UNIVERSIDAD DE SALAMANCA

DOCTORAL THESIS

Effective demand response gathering and deployment in smart grids for intensive renewable integration using aggregation and machine learning

Author:
Cátia Silva

Supervisors:
Prof. Dr. Pedro Faria
Prof. Dr. Juan M. Corchado

Doctor Degree in Informatics Engineering

DEPARTAMENTO DE INFORMÁTICA Y AUTOMÁTICA
FACULTAD DE CIENCIAS

July, 2023

This work received funding from *Fundação para a Ciência e a Tecnologia* (FCT) through the *Programa Operacional Capital Humano* (POCH), supported by *Fundo Social Europeu* and by *Ministério da Ciência, Tecnologia e Ensino Superior* (MCTES) national funds, with an individual Ph.D. scholarship with reference SFRH/BD/144200/2019 from 2019 to 2023.

Thesis Type

This Ph.D. thesis is based on articles published by the author during her Ph.D. work, including international journals, book chapters, and conference proceedings. In order to justify the decision and meet the requirements set by the university, the core research has been published in four internationally recognized journals listed in the Journal Citation Reports (JCR) and the doctoral student is the first author for all of these publications.:

1. C. Silva, P. Faria, and Z. Vale, "Rating the Participation in Demand Response Programs for a More Accurate Aggregated Schedule of Consumers after Enrolment Period," Electronics (Basel), vol. 9, no. 2, p. 349, Feb. 2020, doi: https://doi.org/10.3390/electronics9020349 **(2019 IF:2.412)**

2. C. Silva, P. Faria and Z. Vale, "Rating and Remunerating the Load Shifting by Consumers Participating in Demand Response Programs," in IEEE Transactions on Industry Applications, vol. 59, no. 2, pp. 2288-2295, March-April 2023, doi: 10.1109/TIA.2022.3224414. **(2021 IF: 4.079)**

3. C. Silva, P. Faria, B. Ribeiro, L. Gomes, and Z. Vale, "Demand Response Contextual Remuneration of Prosumers with Distributed Storage," *Sensors*, vol. 22, no. 22, p. 8877, Nov. 2022, doi: 10.3390/s22228877. **(2021 IF: 3.847)**

4. C. Silva, P. Faria, and Z. Vale, "Rating consumers participation in demand response programs according to previous events," Energy Reports, vol. 6, pp. 195–200, Dec. 2020, doi: 10.1016/j.egyr.2020.11.101. **(2019 IF: 3.595)**

Authors Names and Affiliations

Bruno Ribeiro (brgri@isep.ipp.pt): GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) — Polytechnic of Porto (P.Porto), R. Dr. António Bernardino de Almeida, 431, 4200-072 Porto, Portugal.

Cátia Silva (cvcds@isep.ipp.pt): GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) — Polytechnic of Porto (P.Porto), R. Dr. António Bernardino de Almeida, 431, 4200-072 Porto, Portugal.

Luís Gomes (lufog@isep.ipp.pt): GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) — Polytechnic of Porto (P.Porto), R. Dr. António Bernardino de Almeida, 431, 4200-072 Porto, Portugal.

Pedro Faria (pnf@isep.ipp.pt): GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) — Polytechnic of Porto (P.Porto), R. Dr. António Bernardino de Almeida, 431, 4200-072 Porto, Portugal.

Zita Vale (zav@isep.ipp.pt): Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) — Polytechnic of Porto (P.Porto), R. Dr. António Bernardino de Almeida, 431, 4200-072 Porto, Portugal.

STATEMENT

Juan Manuel Corchado Rodríguez, Full Professor, Area of Computer Science and Artificial Intelligence, Department of Computer Science and Automation Control at the University of Salamanca and director of the BISITE (Bioinformatics, Intelligent Systems, and Educational Technology) research group, authorizes that **Cátia Vanessa Costa da Silva** can present her thesis using a collection of previously published works in international journals indexed at JCR as well as international conference proceedings (thesis by papers).

Salamanca, July 10th, 2023

Juan Manuel Corchado Rodríguez

PARECER

Pedro Nuno Silva Faria, Auxiliary Researcher, Area of Electrical and Computer Engineering, GECAD research group, authorizes **Cátia Vanessa Costa da Silva** to present her thesis using a collection of previously published works in international journals indexed at SJR as well as international conference proceedings (thesis by papers).

Porto, July 10th, 2023

Pedro Nuno da Silva Faria

"Be the change you wish to see in the world."

Mahatma Gandhi

Acknowledgments

I would like to take this opportunity to express my profound gratitude and acknowledge the invaluable support to all who have, either directly or indirectly, contributed to the progress and success of my PhD work.

Firstly, I would like to express my heartfelt gratitude towards my parents, sister and grandmother, for their unwavering support and dedication to my growth and development. I am eternally thankful to them for their contributions to my personal journey. Their efforts have not gone unnoticed and have played a significant role in shaping the person I am today. I would also like to extend my deepest appreciation to those family members who, though no longer with us, have left a profound impact on my life.

To my wonderful boyfriend, João, I wish to express my sincere gratitude for the unlimited patience, love, and support that have been indispensable to me. He has been by my side through good and bad times, never giving up on me, and consistently striving to ensure my happiness. I am immensely grateful to him for being a strong pillar of support and for walking with me on this challenging journey that is life.

To my supervisor, Professor Doctor Pedro Faria, I would like to thank for his exceptional support, encouragement, and invaluable contributions throughout my PhD work. His consistent availability and willingness to provide guidance and suggestions have been crucial in my growth as both a researcher and an individual. I am deeply grateful for his mentorship. The merit of this achievement is undoubtedly shared with him, and I will always be grateful for his priceless contributions.

To my supervisor at the University of Salamanca, Professor Doctor Juan Manuel Corchado, I would also like to thank for his support, guidance and availability throughout this PhD work. I am so grateful to him for accepting me at BISITE research group and for helping me feel integrated within the community. The merit of this achievement also belongs to him.

To Professor Zita Vale, who played a significant role in my PhD journey. Her expertise, advice, and contributions were key to achieve this milestone. I am also thankful to the Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) for providing the technical resources necessary to complete this Ph.D. thesis. To all members of GECAD (both present and past) who besides being my coworkers also became my friends. Your support, encouragement, and fellowship have made this journey much more enjoyable and fulfilling. Thank you Brígida, Bruno Canizes, Calvin, Débora, Fernando, Filipe, Francisco, Gabriel, José, Ricardo, and Rúben, for being an essential part of this experience. Moreover, I would also like to express my gratitude to Professor Pedro Campos for his willingness and availability to help me not only with my PhD work but also feeling integrated at LIAAD research group, during my secondment.

To my all dear friends, I would like to express my sincere appreciation. Although you have indirectly followed this PhD journey, your presence and positivity have made the long days and sleepless nights more bearable. I am grateful for the memories we have shared and the moments we have created together.

Finally, I would like to express my gratitude to the Fundação para a Ciência e a Tecnologia (FCT) for the scholarship grant, which provided me with the financial support to pursue and successfully complete my PhD.

Abstract

Distributed generation, namely renewables-based technologies, have emerged as a crucial component in the transition to mitigate the effects of climate change, providing a decentralized approach to electricity production. However, the volatile behavior of distributed generation has created new challenges in maintaining system balance and reliability. In this context, the demand response concept and corresponding programs arise giving the local energy communities prominence.

In demand response concept, it is expected an empowerment of the consumer in the electricity sector. This has a significant impact on grid operations and brings complex interactions due to the volatile behavior, privacy concerns, and lack of consumer knowledge in the energy market context. For this, aggregators play a crucial role addressing these challenges. It is crucial to develop tools that allow the aggregators helping consumers to make informed decisions, maximize the benefits of their flexibility resources, and contribute to the overall success of grid operations. This thesis, through innovative solutions and resorting to artificial intelligence models, addresses the integration of renewables, promoting fair participation among all demand response providers. The thesis ultimately results in an innovative decision support system - MAESTRO, the Machine learning Assisted Energy System management Tool for Renewable integration using demand respOnse. MAESTRO is composed by a set of diversified models that together contribute for handling the complexity of managing energy communities with distributed generation resources, demand response providers, energy storage systems and electric vehicles.

This PhD thesis comprises a comprehensive analysis of state-of-the-art techniques, system design and development, experimental results, and key findings. In this research were published twenty-six scientific papers, in both international journals and conference proceedings. Contributions to international projects and Portuguese projects was accomplished.

Keywords: Aggregation; Decision-support models; Demand Response; Machine Learning; Renewables Integration; Trustworthiness; Uncertainty.

Resumen

La generación distribuida, en particular las tecnologías basadas en energías renovables, se ha convertido en un componente crucial en la transición para mitigar los efectos del cambio climático, al proporcionar un enfoque descentralizado para la producción de electricidad. Sin embargo, el comportamiento volátil de la generación distribuida ha generado nuevos desafíos para mantener el equilibrio y la confiabilidad del sistema. En este contexto, surge el concepto de respuesta de la demanda y los programas correspondientes, otorgando prominencia a las comunidades energéticas locales.

En el concepto de "respuesta a la demanda" (DR por sus siglas en inglés), se espera un empoderamiento del consumidor en el sector eléctrico. Esto tiene un impacto significativo en la operación de la red y genera interacciones complejas debido al comportamiento volátil, las preocupaciones de privacidad y la falta de conocimiento del consumidor en el contexto del mercado energético. Para esto, los agregadores desempeñan un papel crucial al abordar estos desafíos. Es fundamental desarrollar herramientas que permitan a los agregadores ayudar a los consumidores a tomar decisiones informadas, maximizar los beneficios de sus recursos de flexibilidad y contribuir al éxito general de las operaciones de la red.

Esta tesis, a través de soluciones innovadoras y utilizando modelos de inteligencia artificial, aborda la integración de energías renovables, promoviendo una participación justa entre todos los proveedores de respuesta de la demanda. La tesis resulta en última instancia en un sistema de apoyo a la toma de decisiones innovador: **MAESTRO**, *__M__achine learning __A__ssisted __E__nergy __S__ystem management __T__ool for __R__enewable integration using demand resp__O__nse*. MAESTRO está compuesto por un conjunto de modelos diversificados que contribuyen juntos para manejar la complejidad de la gestión de comunidades energéticas con recursos de generación distribuida, proveedores de respuesta de la demanda, sistemas de almacenamiento de energía y vehículos eléctricos.

Esta tesis de doctorado comprende un análisis exhaustivo de las técnicas de vanguardia, el diseño y desarrollo del sistema, los resultados experimentales y los hallazgos clave. En esta investigación se publicaron veintiséis artículos científicos, tanto en revistas internacionales como en actas de conferencias. Se lograron contribuciones a proyectos internacionales y proyectos portugueses.

Palabras clave: Agregación; Aprendizaje Automático; Confianza; Integración de Renovables; Incertidumbre; Modelos de Apoyo a la Decisión; Respuesta de la Demanda.

.

Resumo

A produção distribuída, nomeadamente as tecnologias baseadas em energias renováveis, emergiram como um componente crucial na transição para mitigar os efeitos das alterações climáticas, proporcionando uma abordagem descentralizada à produção de eletricidade. No entanto, o comportamento volátil da geração distribuída criou desafios na manutenção do equilíbrio e da fiabilidade do sistema. Nesse contexto, surge o conceito de resposta à procura e os programas correspondentes, conferindo proeminência às comunidades energéticas locais.

No conceito de resposta à procura, espera-se um empoderamento do consumidor no setor elétrico. Isso tem um impacto significativo nas operações da rede e gera interações complexas devido ao comportamento volátil, preocupações com a privacidade e falta de conhecimento dos consumidores no contexto do mercado energético. Para isso, os agregadores desempenham um papel crucial ao lidar com esses desafios. É fundamental desenvolver ferramentas que permitam aos agregadores ajudar os consumidores a tomar decisões informadas, maximizar os benefícios de seus recursos de flexibilidade e contribuir para o sucesso global das operações da rede.

Esta tese de doutoramento, através de soluções inovadoras e recorrendo a modelos de inteligência artificial, aborda a integração de energias renováveis, promovendo uma participação justa entre todos os fornecedores de resposta à procura. A tese resulta, em última instância, num sistema inovador de apoio à tomada de decisões - **MAESTRO**, *__M__achine learning __A__ssisted __E__nergy __S__ystem management __T__ool for __R__enewable integration using demand resp__O__nse*. A ferramenta MAESTRO é composta por um conjunto de modelos diversificados que, em conjunto, contribuem para lidar com a complexidade da gestão de comunidades energéticas com recursos de geração distribuída, fornecedores de resposta à procura, sistemas de armazenamento de energia e veículos elétricos.

Esta tese de doutoramento abrange uma análise abrangente de técnicas de ponta, design e desenvolvimento do sistema, resultados experimentais e descobertas-chave. Nesta pesquisa, foram publicados vinte e seis artigos científicos, tanto em revistas internacionais como em atas de conferências. Foram realizadas contribuições para projetos internacionais e projetos portugueses.

Palavras-chave: Agregação; Aprendizagem Automática; Confiança, Incerteza; Integração de Energias Renováveis; Modelos de Apoio à Decisão; Resposta da Procura.

.

Contents

List of Figures

List of Tables

Acronyms

ANN	-	Artificial Neural Networks
ARIMA	-	Autoregressive Integrated Moving Average
ARMA	-	Autoregressive Moving Average
BRP	-	Balance Responsible Parties
CCR	-	Contextual Consumer Rate
CR	-	Context Rate
CVaR	-	Conditional Value At Risk
DG	-	Distributed Generation
DLC	-	Direct Load Control
DNN	-	Deep Neural Network
DR	-	Demand Response
DRX	-	Demand Response Exchange
DSO	-	Distribution System Operators
DSS	-	Decision Support System
ESS	-	Energy Storage Systems
EU	-	European Union
EU	-	European Union
EV	-	Electric Vehicle
FIS	-	Fuzzy Inference System
GHG	-	Greenhouse Gas
HEMS	-	Home Energy Management System
HR	-	Historic Rate
kNN	-	K-Nearest Neighbor Method
LER	-	Last Event Rate
MAESTRO	-	**M**achine Learning **A**ssisted **E**nergy **S**ystem Management **T**ool For **R**enewable Integration Using Demand Resp**o**nse
MC	-	Markov Chain
MCS	-	Monte Carlo Simulation
MPC	-	Model-Based Predictive Control
PCCR	-	Preliminary Contextual Consumer Rate
PhD	-	Doctor Of Philosophy
RL	-	Reinforcement Learning
RR	-	Response Rate

SOC	-	State-Of-Charge
TOU	-	Time Of Use
TSO	-	Transmission System Operators
UCCR	-	Updated Contextual Consumer Rate
US	-	United States
V2G	-	Vehicle-To-Grid
XGBoost	-	Extreme Gradient Boosting

Chapter 1

Introduction

1. Introduction

The current chapter is divided into four sub-sections. Chapter 1.1 presents the motivation behind the PhD work development. Moving on to Chapter 1.2, the objectives of the thesis are stated. The key accomplishments of the research and the related publications are discussed in Chapter 1.3. Finally, the organization of the Ph.D. thesis document are outlined in the last chapter.

1.1 Motivation

The energy system is experiencing significant changes to meet climate goals, create sustainable policies, and ensure secure, reliable, and affordable energy supply. To achieve a low-carbon future, the implementation of Distributed Generation (DG) and Demand Response (DR) are present as key in the literature [1]. However, these resources are connected to lower voltage levels. To avoid costly implementations and network reconstruction, it is essential to change the distribution network management, to include all of the associated concepts and new volatile resources [2].

The prior paradigm where the generation follows the demand needs no longer applies on the smart grid concept and the demand-side must provide flexibility throughout DR events [3]. This new chapter of the energy sector predicts a consumer-centric approach, by empowering the small players [4]. Therefore, in the context of the present thesis, an active player defined as any participant that has availability to contribute in a DR event. However, the involvement of active players as an individual remains difficult, uncertain, and at times insufficient to have a significant impact on market transactions [5].

The aggregator is then created to be the entity capable of collecting all the contributions from active players who wish to participate on the power and energy market – both consumers and prosumers [6]. Nevertheless, there is a lack of business models that support the complete and stable introduction of DG and DR resource – which bring to the equation a complicated set of challenges at technical and financial level [7]. In this way, the importance of creating business models considering these questions become urgent.

The United States produced some successful cases of DR, but the potential of small and medium-sized consumers is still mostly unexplored [8]. In the

European Union (EU), DR programs have gained political support through the energy efficiency directives (such as Directive (EU) 2012/27 latter amended by Directive (EU) 2019/944), requiring national regulators and system operators to enable consumer access to markets through DR [9]. However, the member states pace is still slow on incorporating all the elements for the successful operation of DR in their markets [10]. Many justify this fact resorting to regulation barriers: either it was not allowed by the government, or the rules were not clearly defined by the proper entities, or even the existing business cases did not have the suitable characteristics [11].

Besides the regulation obstacles, the incentives for active players to participate in such programs are scarce, and the current compensation for event participation is the same for all types of consumers [12]. In fact, every player has different characteristics that can influence their consumption profile and should be consider as such. In this way, understanding each consumer will be essential for a successful market management [11]. Machine learning algorithms can be an useful tool for DR successful implementation [13]. For instance, by creating an active player profile using historical data or in the case of remuneration, clustering and classification methods can be applied to group consumers with similar characteristics, enabling fair incentivization and decision-making [14].

1.2 Objectives

The main goal from this PhD is to establish a framework, supported by several methodologies, for aggregating DG and DR resources in smart grids. Therefore, the PhD research addresses the identified gaps in the existing literature, answering to the following research question that tackles the previously unexplored aspects of the topic:

Can AI support decisions on DR concept, ensuring renewables integration and fair players participation?

By analyzing the behaviors from these smart grid resources, the idea is to further incorporate them in the power and energy market, enabling the intensive renewable integration resorting to machine learning algorithms and aggregation. With this the following intermediate objectives to achieve this goal were defined and accomplished:

- Identify opportunities for innovative DR models in response to the evolving state-of-the-art;

- Explore the existing research work on DR programs, player modeling, machine learning, and resource management;
- Develop business models suitable for effective DR use by considering appliance management, optimal consumer profiling, and interaction with other aggregated resources such as renewable energy, electric vehicles and energy storage systems;
- Increase the economic value of DR in the energy market for all involved parties, including the aggregator and DR resources, by adjusting remuneration schemes and tariffs;
- Explore optimization models with distinct objectives considering the players perspective:
  - Minimizing operating costs and maximizing profits from the aggregator perspective
  - Decrease the small consumers discomfort and enhance DR performance, considering social welfare and fairness for each player involved;
- Validate the models developed in a realistic manner through a diverse range of case studies based on real-world data;
- Contribute to the United Nations 2030 agenda following goals by improving energy sustainability and involving consumers as key players:
  - Goal 7 – "Ensure access to affordable, reliable, sustainable and modern energy for all";
  - Goal 11 – "Make cities and human settlements inclusive, safe, resilient and sustainable";
  - Goal 12 – "Ensure sustainable consumption and production patterns";
- Refine and enrich the existing literature by providing and exploring the following key contributions:
  - Renewable integration;
  - Energy market;
  - Resource/player profiling/modeling;
  - DR program design;
  - Contextual approaching;
  - Aggregation;
  - Machine learning use;
  - DR gathering;
  - Resource scheduling;
  - DR deployment;

- Remuneration / assessment;
- Real-time simulation;
- Case studies;

Chapter 3 will provide a detailed description of each of the key contributions listed above. Additionally, it will explore the clear relationship between each of the published papers used in this thesis and each of the key contributions.

1.3 Contributions and Publications

The successful DR program implementation to enable the renewable integration in the power and energy system is the primary focus of both the thesis research and work. In this way, a decision support system was created and developed – **MAESTRO**, the **M**achine learning **A**ssisted **E**nergy **S**ystem management **T**ool for **R**enewable integration using demand resp**O**nse, to answer the gaps found on the literature throughout the research question formulated on sub-section 1.2.

Within the scope of this PhD thesis, different contributions to the objectives and results of research projects were achieved. Through the synergy of the combined expertise and resources, under the supervision of Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD), the findings and outcomes influenced several projects under *Fundação para a Ciência e a Tecnologia* (FCT) and H2020 "European Commission Research and Innovation" program. These include:

- Contextual LOad flexibility Remuneration Strategies (COLORS), reference no. PTDC/EEI-EEE/28967/2017. Thesis contributions: load flexibility, contextual DR, remuneration;
- Smart Distribution Grid: a Market Driven Approach for the Next Generation of Advanced Operation Models and Services (DOMINOES), H2020, reference no. 771066. Thesis contributions: DR enabling services, smart metering, aggregation;
- New Markets Design & Models for 100% Renewable Power Systems (TradeRES), reference no. 864276. Thesis contributions: spatial flexibility, electricity markets;

Twenty-six scientific papers were published within the timeline of this thesis, in both international journals and conference proceedings, where another seven are being developed or in the submission process. It is worth to highlight that two of the published articles are literature reviews [11], [15]. Five of the most relevant ones were selected as "Core Publications" ([11], [16]–[19]) and other eight were added as "Other Publications" ([20]–[27]) to support the content of this thesis. From this list, the PhD candidate is first author in twelve out of thirteen publications and five of them were published on international journal indexed at Scientific Journal Rankings.

Full versions of the mentioned publications are available in Appendix A ("Core Publications") and Appendix B ("Other Publications"). This work will be further discussed in Chapter 3.1., exploring each key contribution mentioned above according to Table 3.1.

1.4 Thesis Outline

This thesis is organized into four main chapters. The current introductory chapter discussed the motivations, objectives and contributions within the thesis scope. After this, Chapter 2 is a review on the current state-of-the-art. By focusing on the recent trends of renewable integration, resorting to DR programs, the associated players and the business models developed considering machine learning algorithms and aggregation. Chapter 3 details the list of key contributions resulted from the work developed on this PhD thesis and demonstrates how these contributions were essential to accomplish and answer the research question proposed. With this, both the relation and the role of the published papers is discussed. Finally, Chapter 4 gathers the main outcomes and findings achieved, also providing several paths for future research.

Chapter 2

Background and related literature

2. Background and related literature

This chapter explores how the DR topic can be useful for the renewable energy integration in the sub-section 2.1. After the DR concept is further studied in the sub-section 2.2., followed by a discussion of DR mechanisms and programs. Then, in the sub-section 2.3, machine learning and clustering (for aggregation) algorithms used for DR are explored, showing the potential to optimize the effectiveness of DR programs in the published literature. Finally, in the sub-section 2.4, the importance of the aggregator is highlighted, namely the tools used for DR events, referring the need for effective strategies to manage risk and improve DR outcomes.

2.1 Renewables integration using demand response concept

The growing concern, regarding climate change increases the importance of DG technologies in the power and energy system, namely the renewable-based resources such as wind and solar [28]. Yet, since this resources main source has a volatile behavior, the management complexity increases and, therefore, the current paradigm where the generation follows the demand needs no longer applies [11]. The roles must be reversed, and the demand side should provide flexibility to promote the widespread use of these energy resources in order to reduce the reliance on fossil fuels [29]. It is crucial to place consumers at the center of the business model and consider their flexibility as fundamental for achieving system balance [30]. With this, solutions that deal with this problem and include DR programs should be developed for local grid operators and small consumers actively participate in local electricity markets [31].

In the past, the electricity load from consumers in power and energy systems was viewed as inflexible by system operators [32]. However, each consumer has a set of appliances that can present a flexible behavior, as they do not have a fixed schedule. This assumption has led to the emergence of the concept of DR, which involves consumers adjusting their electricity usage based on signals. This signals might result in the usage of appliances at different times (throughout load shifting) or not at all [33]. It is believed that this bottom-up approach can effectively tap into the potential of DG technologies without compromising the reliability and security of the system [34]. Therefore, for future approaches, the demand side must be empowered. Active players should respond to signals (direct or indirectly) from network operators, aggregators or utility companies to achieve system balance by participating in DR events [35]. It is expected that this approach offers numerous benefits including more and better choices for active players, new opportunities and challenges, competitive pricing, effective investments, improved service standards, supply security, sustainability, and decarbonization of the electrical system [36].

Several designations of DR programs have been proposed in recent years. The definition given on [11] is commonly used and defines this concept as a "…tariff or program … to motivate changes in electric use by end-use customers" where "changes in the price of electricity over time" occur offering "incentive payments", for instance "high market prices" to increase "grid reliability". The definition published in Directive EU 2019/944 [9] is similar and says that DR is a "… change of electricity load by final customers" triggered by "market signals… time-variable electricity prices or incentive payments" where the "final customer's bid to sell demand reduction or increase… alone or through aggregation".

Prior to the emergence of smart grids and DR, active players had low or no direct access to information about market transactions [37]. A consumer-centric approach offers numerous advantages, particularly in flexibility markets where Transmission System Operator (TSO), Distribution System Operator (DSO), Balance Responsible Party (BRP), aggregators, and retailers are the main players [38]. The TSO is responsible for ensuring service and stability in the transmission system, while the DSO is responsible for operating the distribution system. Collaboration between TSOs and DSOs is essential to unlocking the potential of flexibility [39]. Retailers are commercial entities that sell electricity to consumers, while aggregators gather flexibility through active players and those using renewable-based energy sources [9].

It is important, for the definition of DR, to also consider time range for the flexibility [40]. DR programs can operate on different timescales, as depicted in Figure 2.1, ranging from several years (on the left) to real-time (on the right). Programs with a year-long timescale are typically used to improve long-term planning. Shorter timescales are more focused on incentive-based DR programs, such as those that use Direct Load Control (DLC).

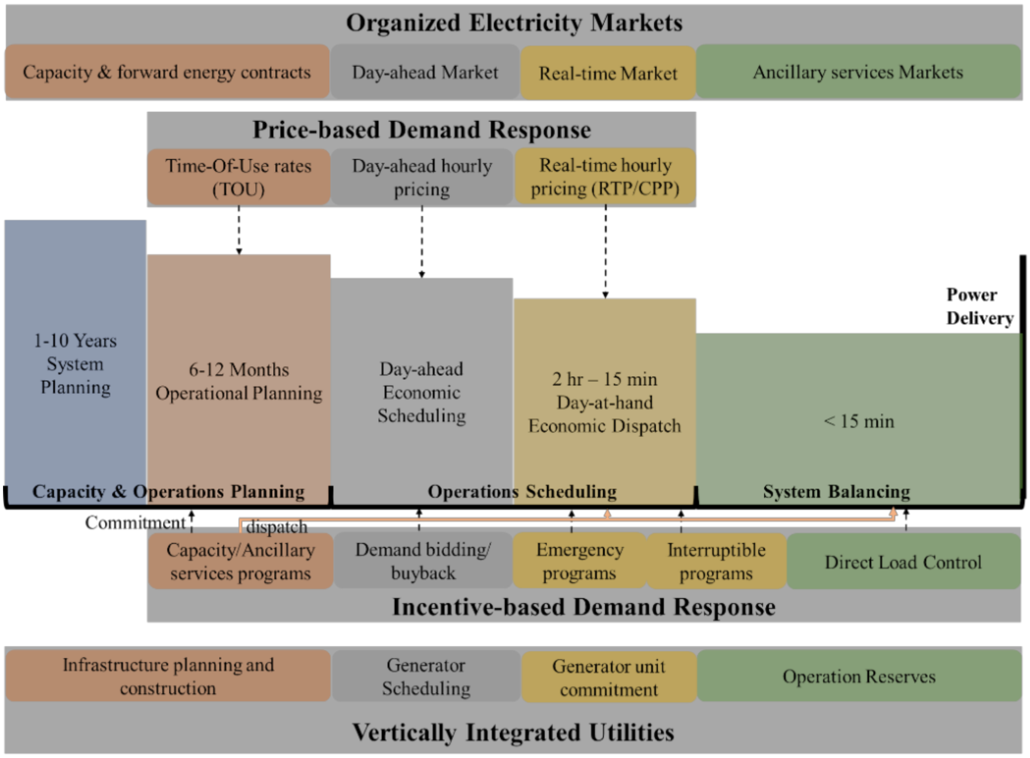


Figure 2.1. Power and Energy System and Demand Response implementation timescales [11].

The implementation timeline for DR is illustrated in Figure 2.2. The DR implementation timeline involves several phases that the aggregator must consider. During the ramp period, active players must reach the contractual DR event baseline. The first phase begins when the aggregator is notified of the DR event and continues until the announcement deadline (δ). During this period, the aggregator and DR program manager exchange information and setpoints regarding the event, assessment duration, and ramp period. The next phase is the ramp period. However, the aggregator faces a challenging task due to the variable duration of the advance notification to players [41].

Communication between the aggregator and active players occurs in different layers, with several iterations, until reaching a goal point (equal to or above the reduction baseline). The Deployment period is when the aggregator initiates the event and collects information regarding DR amounts. In TDR2, two intermediate periods are considered: the activation notification period (αDR2) and actual response period (βDR2). The aggregator notifies the active players of the difference between actual and goal values in αDR2, and those who agree should start the load reduction process demonstrated in βDR2. However, non-response is always a possibility since the participation is voluntary [11].

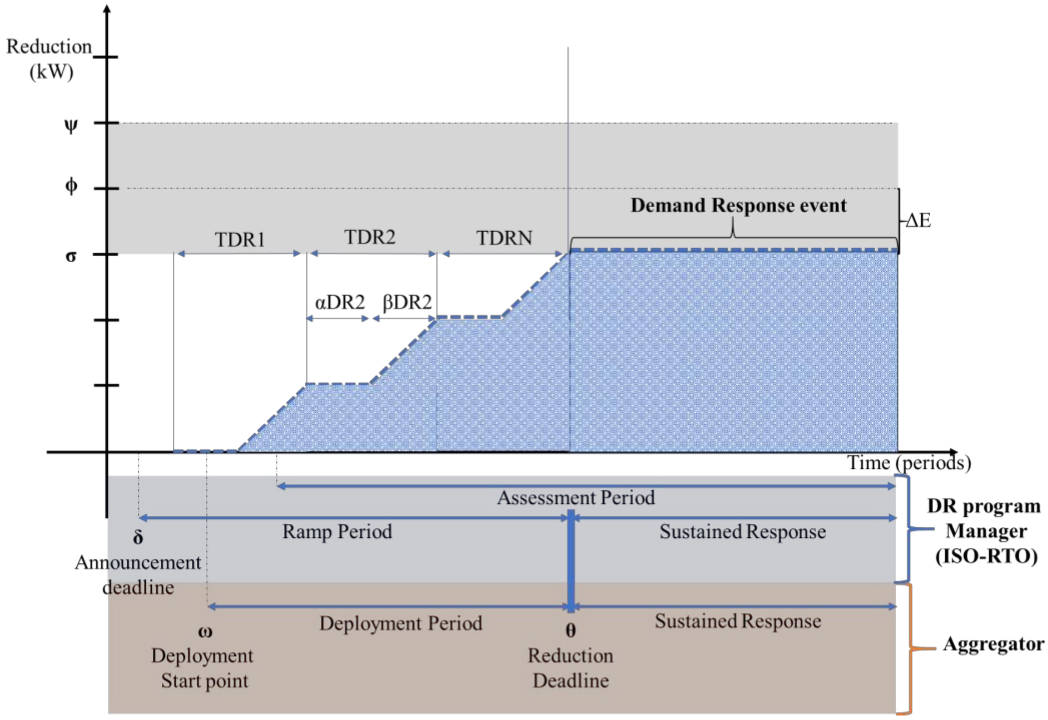


Figure 2.2. Demand Response implementation timeline. Adapted from [42].

Once the forecasted reduction baseline is achieved, the information must be returned to the DR program manager. In the case of insufficient reduction in the actual period, the aggregator can implement a new TDRN until the reduction deadline moment (θ). The DR program manager defines a margin of forecast error (ΔE), and the sustained period can begin if the available reduction capacity exceeds the reduction baseline (σ). The actual DR event starts at this point, and active players that agree to participate must maintain their committed level of reduction to be further remunerated.

With this, the success of DR programs depends heavily on the performance and response of active players to the given signals. In this way, gather correct and clear information on active players' behavior is crucial to provide appropriate signals and remuneration that meet their goals. By accomplishing this target, it is expected to reduce response uncertainty and maintaining system reliability and security [43].

Although various approaches in the literature encourage consumer participation, most of them are profit driven from the grid or aggregator perspective [44]. Behaviors can change according to the type and goals of active player participating in DR events. Residential consumers' response is highly influenced by the level of discomfort they experience during a DR event, sometimes even more important than their profit [45]. While industrial consumers aim to maximize their revenues, while managing any possible discomfort [46]. Therefore, different players result in different behaviors which require different approaches as mentioned on sub-section 1.1. With this, one can conclude that a business model to successfully integrate renewable-based resources resorting to DR must consider various approaches and contexts, according to the current portfolio.

2.2 Demand response mechanisms and programs

DR concept has a wide program portfolio and can be achieved through various mechanisms, each with its own unique characteristics and requirements [47]. Some of the most common DR mechanisms include price-based and incentive-based [48]. In this chapter, these mechanisms and programs will be explored. Also, the discussion some of the emerging DR programs, such as Electric Vehicle (EV) demand response and the Demand Response Exchange (DRX), which have the potential to further increase the flexibility and responsiveness of the demand side of the power grid [49].

In incentive-based DR programs, active players agree to participate based on rules outlined in a contract that includes penalties for non-compliance [50]. Price-based programs, on the other hand, rely on changes in energy prices to encourage active player response, which can result in more unpredictable behavior. In this way, active players have the freedom to choose whether to disconnect their appliances in response to these changes or not [51]. DRX is a new DR scheduling program that relies on bidding entities rather than prices or incentives to motivate changes in load. This implies careful assessment of load profile attributes before submitting a bid to avoid negative outcomes such as reduced load satisfaction, higher electricity bills, and system stress [52].

On the other hand, EVs popularity is increasing. These resources have been identified as a flexible and can play a critical role in balancing supply and demand in the future smart grid [53]. However, security and privacy concerns of EV owners have limited the popularity of EV-based energy management. Some works only refer to these resources without making them the focus of the study. Furthermore, vehicle owners are hesitant to grant authority to control EVs to an aggregator [54].

Before fully commit to a DR program, it is important to provide the proper knowledge to the active players. Both interested parties should learn, use proper tools and make clear statements for building a relationship based on trust so issues, such as privacy and response uncertainty, be avoided.

2.3 Machine learning for demand response

The constant evolving state-of-art from power and energy systems is adopting and employing intelligent systems for DR [55]. Not only due to their ability to automate and optimize the process but also because these systems can make use of various techniques such as machine learning, artificial intelligence, and optimization algorithms to provide real-time monitoring and control of energy consumption [56]. In fact, the goal is to enable automated decision-making and improve the overall efficiency of DR. In this chapter, current research on intelligent algorithms for DR and their potential benefits will be explored where machine learning will have a special focus.

Starting with the Autoregressive Integrated Moving Average (ARIMA), due to its simplicity and ease to use, is commonly used for time series forecasting on the energy sector and it is an extension of the Autoregressive Moving Average (ARMA) model. Hamed Mortaji et al. [57] study showed that utilizing the ARIMA time series prediction model and smart load control could significantly decrease power outages for consumers. Model-based Predictive Control (MPC) algorithm has gained significant attention among researchers in this field due to its prediction capabilities, fast processing speed, and suitability for multivariable control operations. For example, in their study, Farzad Arasteh and Gholam H. Riahy [58] developed a real-time algorithm to coordinate DR programs and energy storage systems operation in wind-integrated power systems based on market mechanisms. Homa Rashidizadeh-Kermani et al. [59] utilized the Conditional Value at Risk (CVaR) as a risk measure embedded in a stochastic program for decision making of DR aggregators, considering various sources of uncertainty. The aim was to control different levels of risk associated with profit volatility.

Probabilistic models utilize probability distributions and random variables to develop a model. A probabilistic model offers a probability distribution as a solution, in contrast to a deterministic model that offers only a single possible solution. For example, Zvi Baum et al. [60] employed MCS to develop a framework that estimates the performance of dynamic-active DR, which models the behavior of the system over time in response to both internal and external influences while reflecting the stochastic characteristics of supply and demand. The Markov Chain (MC) is a probabilistic model commonly used for modeling random processes. Yue Yang [61] applied an MC model at the appliance level to capture correlations in power consumption.

Supervised and unsupervised learning are two of the main topics approached within the machine learning concept. The first one includes well know methods such as Decision Trees (DT), Random Forests (RF) or Artificial Neural Networks (ANN). DT operate by recursively partitioning the input data into smaller subsets based on the values of specific features. This algorithm is also known for its easy interpretability but can be prone to overfitting. Somayeh Dehghan-Dehnavi et al. [62] used DT in their study for industrial load classification in DR programs. RF, on the other hand, are an extension of decision trees that generate a collection of individual trees and aggregate their predictions to arrive at a final output. Other difference from the DT is that RF are capable of handling both categorical and continuous features. Guo-Feng Fan et al. [63] resorted to RF for short-term load forecasting. Regarding ANN, this algorithm has been a fundamental in Artificial Intelligence (AI) and aims to mimic the information analysis and processing abilities of the human brain [64]. In the context of DR, Renzhi Lu et al. [65] utilized both ANN and reinforcement learning techniques to design an energy management approach for different appliances within a Home Energy Management System (HEMS), where ANN was applied for price forecasting.

Unsupervised learning algorithms are widely used methods in power systems to identify patterns in electrical loads like the clustering methods, as demonstrated in a study by Mansour Charwand et al. [66]. The application of fuzzy theory can be beneficial for dealing with imprecise, subjective, and ambiguous judgments in research. For instance, Skrikanth Reddy K et al. [67] used the Fuzzy Inference System (FIS) and compared it with non-fuzzy approaches, demonstrating the superior performance of FIS for processing load profiles and behavior for designing DR bids for market participation. Furthermore, k-means is one of the most used methods of clustering, widely used for in the energy sector for load profiling. For instance, Maria Alejandra Zuñiga Alvarez et al. [68] created an adaptive clustering process, resorting to k-means, that enables the identification of clients who contribute the most to power consumption during peak periods. However, understanding active players is a complex task that goes beyond just predicting their load reduction, especially since prosumers are still evolving. In their study Kang & Lee [88], the authors proposed a data-driven approach that employs the k-nearest neighbor method (kNN) and a weighted ensemble model to address the load prediction problem. Since each consumer may only receive a request for load curtailment a few times a year, the kNN method, which requires small amounts of data, is an appropriate choice. However, due to differences between consumers, a single prediction method may not be sufficient. To address this, the authors used a weighted ensemble model that applies different models for different consumers.

Efforts are being made to add "intelligence" to the power and energy sector business models, however, the primary focus is on topics like time series forecasting or load profiling. Finding ways to reduce the response uncertainty from DR events is still unexplored when resorting to machine learning algorithms.

2.4 Aggregator tools to enhance performance from demand response participants

Like as being reinforced in this chapter, the role of consumers in the energy system is evolving, and they are becoming more active players with a significant impact on system reliability [69]. DR participants have control over their appliances. As such, researchers must consider the availability of these active players to enhance their performance [81]. Performance is defined within the scope of this thesis as the level of success of players in participating in DR events. In other words, when an aggregator sends a signal to change a consumer's load consumption, it is expected that the consumer will comply and participate in the event and be viewed as a trustworthy player [70]. While participation is voluntary, some DR programs require agreements under certain circumstances. To be beneficial for both parties, tools must be developed to aid the two perspectives. Developing proper aggregator's tools are crucial for improving the performance of DR participants [77]. By enabling scalability, simplifying participation, enhance revenue potential, offer technical capabilities, ensure grid integration and reliability, and facilitate energy market engagement. With their expertise and coordination, aggregators maximize the advantages of DR programs for both individual participants and the electricity grid as a whole [78].

However, there is a need to develop tools capable of address uncertainties and enhance performance of demand side players. This chapter will focus on these primary themes.

AI models can be subjected to gamification interactions between participants. The prevailing assumption in the literature is that DR participants are rational and make optimal decisions. To encourage participation, one possible approach is game theory, which is the formal study of the interdependence between adaptive agents and the emergence of cooperation and competition dynamics [82]. In fact, the literature has been considering game theory to be a crucial branch of mathematics for exploring conflicts, collaborations, and strategic interactions between rational players in a single system [71]. In studies like [72], [73], [74], [75] and [76], game theory is utilized to handle DR uncertainty. In this context, agents refer to entities that can make informed choices and autonomously act to affect the environment's state [83]. Interdependence between agents means that the values associated with a particular property of one agent become correlated with those of another. In other words, an agent's goal's achievement becomes correlated with others' goals. Game theory approaches in DR can be categorized into two types: those played between consumers and those played between the utility and consumers [84]. The interdependence between agents can also be defined at micro and macro levels. Looking at the macro-level, all agents need to collaborate to achieve a successful outcome. At the micro-level, active players act in their self-interest by choosing the most competitive aggregator to minimize their payments, assuming that they have perfect information about the price offered by the aggregators [85].

Starting the macro-level, Talwariya, Singh, and Kolhe [75] used MCS to consider uncertainty in consumption and generation, along with a Bayesian Game Theory model to analyze the decisions of active players. However, since active players are self-interested, their behavior needs further study. Niromandfam, Yasdankhah, and Kazemzadeh [44] developed an approach that considered the utility function to maximize individual consumer welfare for DR programs while studying consumer risk aversion behavior. The utility function measures consumer preferences, a critical concept in microeconomics that helps understand how rational consumers make consumption decisions. Classical game theory assumes that players are always rational and try to maximize their payoffs. However, the rules and dynamics of the game may not align with this assumption, and what is rational for the whole may be irrational for the individual [11]. In some situations, human behavior may differ significantly, making it difficult to predict their actions. Various factors such as cultural, financial, natural, or social capital can influence the actions of active players, as highlighted by Ilieva et al. [86].

At the micro level, the assumption that participants always react optimally to utility prices for profit maximization can impact the utility's profit, as it neglects context and only focuses on a single metric. In a competitive environment, players are expected to lower prices to attract more consumers, leading to lower profits. In a study by B. Zhang et al. [87], a contract-based incentive scheme was proposed to encourage consumer and small-scale supplier participation in direct energy trading. However, their behaviors are highly coupled, and a model is needed to analyze interactions and find the Nash Equilibrium.

However, in reality, the active consumer may not always act as a rational and economic agent, as they are new players in the market and may not have enough information to make informed decisions. Thus, the goal must be to provide aid and understanding to enhance their performance in DR events [11]. Uncertainties related to the stochastic variations of variables involved in residential DR, such as load demand, user preferences, environmental conditions, house thermal behavior, and wholesale market trends, can be modeled using the Monte Carlo Simulation (MCS) method, as suggested by Pierluigi Siano and Debora Sarno [79]. By adapting to and learning about player preferences and updating the system, DR implementation can improve consumer comfort, a crucial characteristic for its success in the real world. In fact, as already mentioned, residential participants are often hesitant to sacrifice their comfort to participate in demand response [80].

Numerous DR solutions involve clustering of consumer data to analyze input data for flexibility, including factors such as occupancy, temperature, humidity, and bidding strategy design [89]. However, clustering methods are sensitive to input data and may produce incorrect outputs due to errors from smart equipment [90]. Therefore, preprocessing of the dataset with data mining tools is necessary to provide meaningful information to aggregators, allowing them to handle active players correctly and improve their performance. To mitigate the impact of errors, fuzzy variables were incorporated in a study conducted by Mansour Charwand et al. [66], where intuitionistic fuzzy divergence technique was used to represent the consumer load pattern, modeling the indecision and non-determinacy using the membership, non-membership, and hesitancy function. To cope with future uncertainties and improve performance, Lu and Hong [91] proposed the use of a Deep Neural Network (DNN) to predict unknown prices and energy demands. They also employed RL to determine optimal incentives for different consumers while considering both the service provider's and consumers' profits. The advantage of RL is that it is adaptive, model-free, and can autonomously acquire and adapt incentive rates, considering the uncertainties and flexibilities of the system.

Consumers' willingness to participate in DR programs depends on various psychological factors such as cognitive or experimental judgment biases, which can lead to shifts in their risk attitudes from risk-seeking to risk-averse or risk-neutral. To address this issue, Remani et al. [92] used RL as an efficient tool to solve the decision-making problem under uncertainty. They modeled the problem as a Markov decision process and identified the state, state space, transition function, action, and reward function to solve the load commitment problem considering consumer comfort, stochastic renewable power, and tariff.

Various methods have been employed to improve DR schedules, with the goal of predicting unknown prices and energy demands, enhancing performance, and managing risks associated with doubt. For instance, Mbungu et al. [93] used an adaptive Time of Use (TOU) MPC approach to create a managing system for a real-time electricity pricing environment. Hung Khanh Nguyen et al. [94] used the Nash bargaining theory to achieve maximum social welfare when studying the economic interaction between the DSO and microgrids, and Tushar et al. [76] created an energy planning noncooperative game for residential consumers with at least a Nash Equilibrium in the prediction phase.

Again, the importance of learning and understanding the active players is highlighted for the successful implementation of DR. Now, the assumption of an active player fully aware of the optimal decisions, acting as a rational and economical player, might not be the reality for the energy market. The aggregator, resorting to intelligent methods, is capable of using and also providing useful knowledge regarding the context on which the DR event is triggered. Not only selecting the optimal participants, with this powerful tool, can also aid the active players thriving on their role. This can be beneficial to both parties, since the aggregator reduces the uncertainty of response to have more profit, and the active players become more aware of the market transactions to achieve their own agenda.

2.5 Conclusions

In conclusion, the integration of renewable energy sources into energy sector will lead to new challenges for managing the grid's stability and reliability. DR programs are one of the solutions to tackle these issues, encouraging active players to modify their energy consumption patterns in response to grid conditions or price signals. DR mechanisms and programs vary from traditional to more advanced approaches based on intelligent systems.

These systems leverage machine learning algorithms to predict prices, energy demand and optimize incentives for different consumers. However, uncertainties and flexibilities in the DR system, as well as psychological factors influencing consumer behavior, can impact the overall performance of the program. While improving DR schedules, it is also essential to consider inappropriate strategies that may lead to consumer dissatisfaction and decrease their participation in DR events. Therefore, it is crucial for the managing entity of these new players to "learn" and capture their behavior to provide the right assistance in all situations.

Machine learning widely used in the literature but are unexplored on the DR uncertainty reduction and performance enhancement. Economic incentives could be useful but overall, learning and understanding consumer behavior can be a step towards improving the contribution of these new players in the power and energy market.

Chapter 3

Contributions and MAESTRO tool

3. Contributions and MAESTRO tool

This chapter outlines the contributions made within the thesis work and the role played by each of the published papers in its development. The contributions have been categorized and presented in Chapter 3.1, while Chapter 3.2 focuses on the main contribution and research question, as well as key contributions, which are further elaborated in Chapters 3.3 to 3.15. The chapter concludes with a summary of the main findings and conclusions in Chapter 3.16.

3.1 Introduction

The literature analyzed on Chapter 2 highlights the need to carefully examine the technical and economic aspects of any business models developed for implementing renewable-based technologies before the widespread adoption. Considering this fact, the present thesis shows the created methods by the PhD candidate to effective DR gathering and deployment for intensive renewable integration using aggregation and machine learning. With this, a list of 13 scientific papers (Journal – J, Conference proceedings – C, Book Chapter – B), were carefully selected for this thesis. As already mentioned in sub-section 1.3, five were considered as "Core Publications" (all as first author), and eight more have been selected as "Other Publications" to support the contents of the thesis and to successfully answer to the research question.

Core publications:

[J1] C. Silva, P. Faria, and Z. Vale, "Rating the Participation in Demand Response Programs for a More Accurate Aggregated Schedule of Consumers after Enrolment Period," Electronics (Basel), vol. 9, no. 2, p. 349, Feb. 2020 **(2020 IF: 2.397)** with the reference [16]

[J2] C. Silva, P. Faria, Z. Vale, and J. M. Corchado, "Demand response performance and uncertainty: A systematic literature review," Energy Strategy Reviews, vol. 41, p. 100857, May 2022 **(2021 IF: 10.01)** with the reference [11]

[C1] C. Silva et al., "Optimal management of an active community for fair selection of electric vehicles in a V2G event," CIRED Porto Workshop 2022: E-mobility and power distribution systems, Hybrid Conference, Porto, Portugal, p. 1069-1073, 2022, with the reference [17]

[J3] C. Silva, P. Faria, B. Ribeiro, L. Gomes, and Z. Vale, “Demand Response Contextual Remuneration of Prosumers with Distributed Storage,” Sensors, vol. 22, no. 22, p. 8877, Nov. 2022 **(2021 IF: 3.847)** with the reference [18]

[J4] C. Silva, P. Faria and Z. Vale, "Rating and Remunerating the Load Shifting by Consumers Participating in Demand Response Programs," in IEEE Transactions on Industry Applications, vol. 59, no. 2, pp. 2288-2295, March-April 2023 **(2021 IF: 4.079)** with the reference [19]

Other publications:

[B1] C. Silva, P. Faria, J.M. Corchado, and Z. Vale, “Clustering Methods for the Profiling of Electricity Consumers Owning Energy Storage System,” In Intelligent Data Mining and Analysis in Power and Energy Systems (eds Z. Vale, T. Pinto, M. Negnevitsky and G.K. Venayagamoorthy), 2022 with the reference [20]

[J5] C. Silva, P. Faria, and Z. Vale, “Rating consumers participation in demand response programs according to previous events,” Energy Reports, vol. 6, pp. 195–200, Dec. 2020, **(2021 IF: 6.87)** with the reference [21]

[C2] O. Abrishambaf, C. Silva, P. Faria, and Z. Vale, “An Optimization Based Community Model of Consumers and Prosumers: A Real-Time Simulation and Emulation Approach”, International Conference on Renewable Energy (ICREN), 2021 with the reference [22]

[C3] C. Silva, P. Faria, Z. Vale, “Classification of New Active Consumers Performance According to Previous Events Using Decision Trees”, International Federation of Automatic Control (IFAC), vol. 55, no. 9, 2022, p. 297-302 with the reference [23]

[C4] C. Silva, P. Faria, and Z. Vale, “DR Participants’ Actual Response Prediction Using Artificial Neural Networks,” 17th International Conference on Soft Computing Models in Industrial and Environmental Applications (SOCO) p. 176–185, 2023, with the reference [24]

[C5] C. Silva, P. Faria and Z. Vale, "Using Supervised Learning to Assign New Consumers to Demand Response Programs According to the Context," IEEE International Conference on Environment and Electrical Engineering (EEEIC), Prague, Czech Republic, pp. 1-6, 2022, with the reference [25]

[C6] C. Silva, P. Faria, B. Canizes and Z. Vale, "Real-Time Approach for Managing Power Network by Shifting Electricity Consumers Demand," 2022 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Novi Sad, Serbia, p. 1-5, 2022, with the reference [26]

[C7] C. Silva, P. Campos, P. Faria and Z. Vale, "Exploring Dataset Patterns for New Demand Response Participants Classification," 21st International Conference on Practical Applications of Agents and Multi-Agent Systems (PAAMS), 2023, with the reference [27]

The key contributions defined in Chapter 1.2. are explored within the scope of the previous list of “Core” and “Other” publications and can be seen in Table 3.1. Also, “Support” papers listed in Table 3.1 are auxiliary publications related to the context of this thesis.

Table 3.1. Key contributions according to the core and other publications

Sub-section	**Key contribution**	**Publications**													**Support**
		Core					**Other**								
		J1	J2	C1	J3	J4	B1	J5	C2	C3	C4	C5	C6	C7	
3.3	Renewable integration	x	x	x	x	x			x						
3.4	Energy Market	x		x	x	x			x						
3.5	Resource/Player profiling/modeling	x			x	x	x		x	x	x	x	x	x	
3.6	DR program design	x	x	x	x	x		x							[16]
3.7	Contextual approaching	x		x	x	x		x							[95]
3.8	Aggregation	x		x	x	x				x		x			[96]
3.9	Machine learning use	x		x	x					x[1]	x[2]	x[3]		x[4]	[96], [97]
3.10	DR gathering	x		x	x	x	x								
3.11	Resource Scheduling	x		x	x	x		x	x				x		[98]
3.12	DR deployment	x		x	x	x	x				x				
3.13	Remuneration / Assessment	x		x	x	x									[97]
3.14	Real-time Simulation				x				x						
3.15	Case Studies	x		x	x	x	x	x	x	x	x	x	x	x	

[1] Using classification, namely Decision Trees
[2] Using classification, namely Artificial Neural Networks
[3] Using classification, namely Decision Trees and Random Forests
[4] Using classification (Decision Trees, Random Forests and XGBoost), supervised clustering and subgroup discovery

The research and contributions in the field of renewable integration have been substantial. Considered a core area of focus, emphasizing the need to efficiently integrate renewable energy sources into existing energy system. Although energy market topic is presented in all publications, it was more discussed on the definition of the different business models ([16]–[19]). Additionally, resource and player profiling/modeling have received significant attention and support, as evidenced by numerous publications. These studies aim to understand the characteristics and behaviors of various resources and players in the energy market to enhance decision-making processes.

Another important aspect is the DR programs design, which has been extensively researched and published ([16]–[19]), resulting on several business models. The business models developed resorting to a contextual approaching, which focuses on considering relevant contextual factors in decision-making, have also received significant support and attention throughout the list of publications ([16]–[20], [22]–[26]) and are also considered a core contribution.

Algorithms that provide the "smartness" to business models have also an important role in this thesis. Aggregation techniques have been explored to combine multiple energy resources effectively, as evidenced by the publications ([16]–[19]). Machine learning applications have been widely adopted ([11], [16]–[19], [23]–[26]). DR gathering ([17], [18], [20], [22], [24]), Resource scheduling ([16]–[19]), and DR deployment ([17], [18], [20], [22], [24]) contributed to the various steps of the research. The importance of remuneration and assessment is evident in the core publications. Finally, the real-time simulation ([18], [22]) and case studies ([16]–[20], [22]–[26]) were important for validation and practical implementation.

3.2 Main contribution

The main contribution of this Ph.D. for the current state-of-art was determined based on the need to address the identified gaps on Chapter 2. With the work developed within the PhD timeline, significant advancements have been made to answer the following research question:

Can AI support decisions on DR concept, ensuring renewables integration and fair players participation?

MAESTRO, the **M**achine learning **A**ssisted **E**nergy **S**ystem management **T**ool for **R**enewable integration using demand resp**O**nse is the culmination of all the efforts done. **MAESTRO** is a Decision Support System (DSS) and was designed to help any player with different roles in the power and energy system to become better decision-makers, managing their demand or generation, by making informed decisions based on data analysis and modeling. The system has six overlapping key layers for model management: player, role, DR program, resources, real-time simulation, and tariff and rate definition. The decision support system steps can be seen in Figure 3.1.

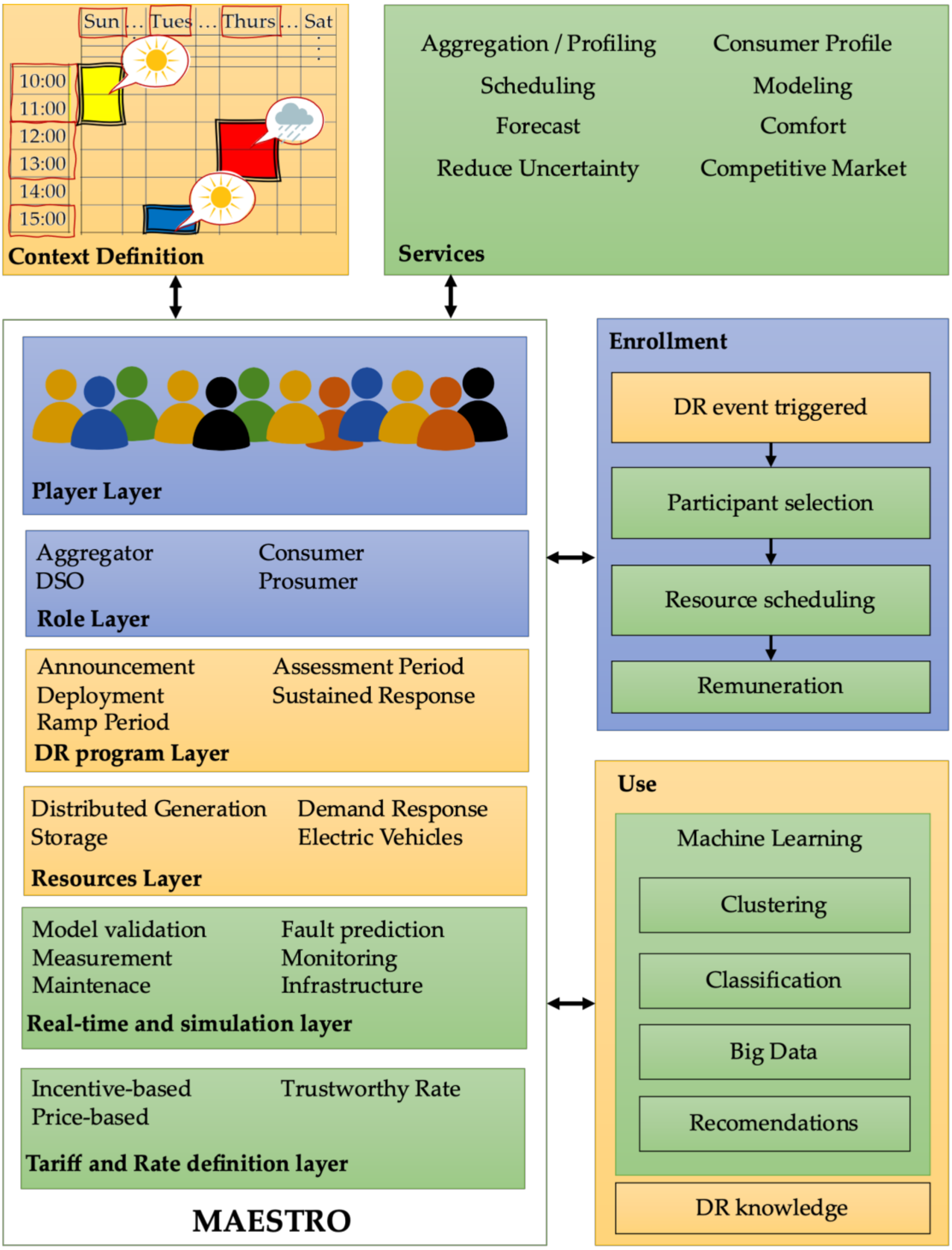


Figure 3.1. MAESTRO decision support system.

In the background, four other layers were designed to ensure the system's proper functioning regarding DR: context definition, services, enrollment, and use. Again, must be highlighted that there is no sequence on any of the layers represented in Figure 3.1 since they are overlapping layers. Each layer is related to one or more key contributions and will be discussed in their respective sub-section.

MAESTRO gathers all the market players, creating the "Role layer" (Figure 3.1), to find their purpose and help improve their performance, successfully integrating renewable resources. Here, the players are distinguished by their roles in power and energy system. MAESTRO considers four main positions: the DSO, the aggregator, the consumers, and the prosumers. Figure 4 shows the role positions considered for the DSS developed in this thesis. The TSO and BRP, although players in the electricity market, are not the focus of this work. As mentioned earlier, the DSO is responsible for the distribution system's operation, capable of handling the remaining positions, according to Figure 3.2.

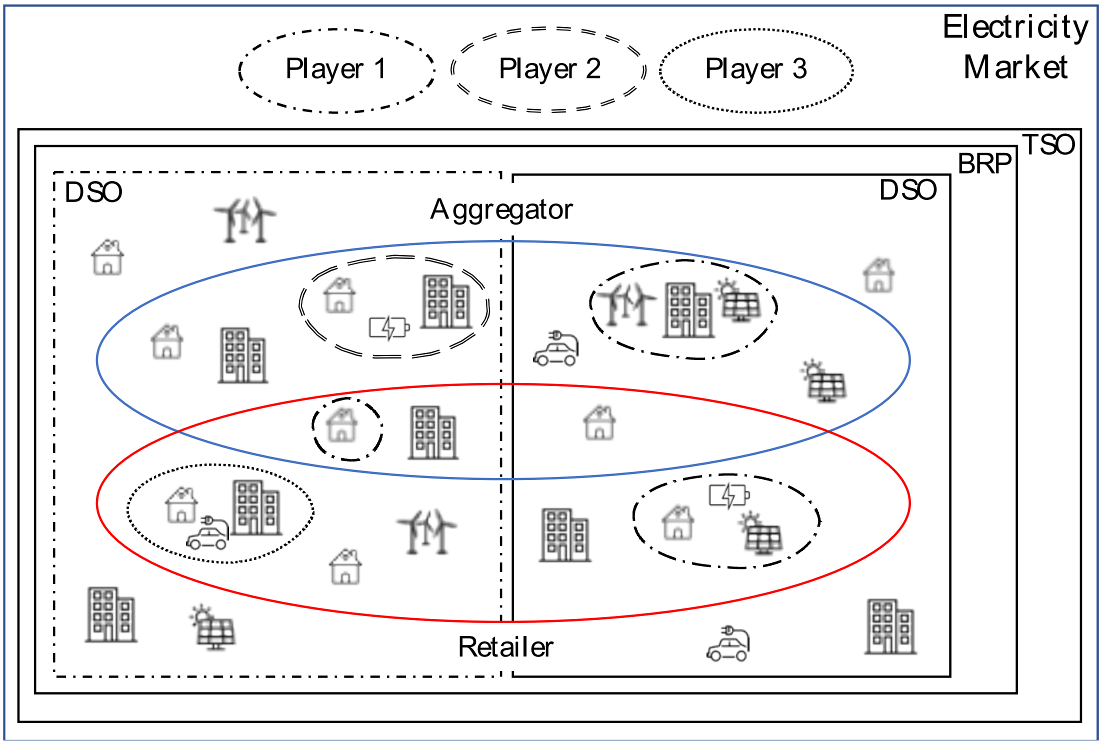


Figure 3.2. MAESTRO players and roles interaction.

When a load reduction is needed – for instance, due to a voltage violation in a grid bus, a request is then sent by DSO to all the aggregators in the local communities nearby. The aggregator then manages the local community and associated resources to suppress this problem, highlighting their unique flexibility during the electricity market negotiations. Active communities might aggregate active players with several roles. A single player can have different roles, for instance, wants to participate in DR programs providing load flexibility or even, as a prosumer that want to be paid for the energy they produce and store. The aggregator then has bidirectional contracts for remuneration and scheduling, with resources and participants in the DR being able to, in some cases, control and monitor both of them.

With this, the following sub-sections will explore each key contribution from the "Core" and "Other" publications to successfully answer to the gap presented in the research question.

3.3 Renewables integration

The intensive renewable integration in the real power and energy markets is the goal of this thesis, resorting to DR programs. Throughout the work, the developed findings indicate that players are unaware of the market transactions and how to be an economic and rational agent, as mentioned on sub-section 2.4. Therefore, the aggregator represents the entity behind the management of active communities, and it is expected to have the proper platform for the combined DR and DG resources and accept players from various regional infrastructures. In fact, with MAESTRO, the active players might choose between more than one aggregator for the DR event, introducing competition between these entities. On the Services layer, topics such as comfort, reduce uncertainty and competitive market can be used within this scope.

MAESTRO has models capable of managing complex community resources optimally and fairly, as Resources Layer on Figure 3.1 points out. The DSS developed in this thesis is qualified to handle the following:

- Players from different types (small, commercial, industrial);
- Players with DG resources such as wind and solar;
- Players with Energy Storage Systems (ESS);
- Players with EV;
- Any combination that can result from the previous players.

As can be seen in Figure 3.2, a player can have more than one role when overlapping "Player" and "Role" layers. For instance, player 1 can be a DSO with resources on another DSO, on the aggregator (blue line), or/and on the retailer (red line). Player 2 only reports to the aggregator, and player 3 only reports to the retailer. The consumers and prosumers are considered the center of the MAESTRO approach as players that will enable the intensive integration of renewables, representing the higher share of DR. Combining with their resources, and the demand-side will be able to fulfill their purpose on the smart grid paradigm successfully, avoiding the use of more fossil fuels on the power and energy system.

The thesis work has focused on managing renewable energy resources and their integration at various levels of the power network, which has been discussed in several publications ([11], [17]–[19], [22]). These publications have explored the challenges of maintaining network balance faced by the aggregator and have proposed several optimal approaches to address them. Although the main focus was the consumer flexibility, the thesis work has provided valuable insights into managing renewable resources and the role they play in network management, especially for small-scale resources, and their impact on demand-side consumers.

In the review done in [11] it was emphasized the significance of consumers in integrating renewable energy through DR programs. It was recommend exploring contextual resource management as an effective approach for implementing DR solutions in the evolving smart grid of the future. For the work developed in [19] it was used load shifting for load allocation during DR events, considering a broader time range to prevent the creation of additional peak loads. The study concludes that this approach brings several benefits.

In the simulated scheduling results presented in [18], the behavior of prosumer load flexibility was minimally affected by contextual energy price changes. However, ESS were frequently utilized when photovoltaic generation was low. The study presented on [20] introduces the perspective of EVs and highlights the advantages and disadvantages of these resources moving within the grid. The study suggests employing different strategies to prevent congestion and the formation of new peaks in the load curve.

The studied from [22] and [20] focus on optimizing the management of these resources and validate their proposed community model using real-time simulation models. They address practical challenges and considerations related to electrical grid conditions. Utilizing real-time simulation and laboratory equipment offers distinct advantages in these studies.

3.4 Energy market

The MAESTRO basis, besides promoting competition and consumer choice, believes that walking towards a future with a more competitive local energy market can also play a crucial role in the integration of renewable energy sources into the power and energy market. By enabling DR programs and energy efficiency measures, the market can help balance the intermittency of renewable energy generation and reduce the need for fossil fuel-based peaking power plants. These new players can offer various energy products and services that can result in lower prices, better service, and more innovation in the energy sector.

The aggregator has been an essential entity within the publications in this thesis scope. The majority has indeed focused on only one aggregator and the complex management of these new resources: DR flexibility ([16], [19]), ESS ([18]), EVs ([17]), and DGs ([16]–[19], [22]). The competition was implicitly created when the trustworthy rate was applied. It was intended for players to enhance their performance if they wanted to be called to participate in DR programs. Furthermore, the availability was also an important parameter for building a trusting relationship. However, the energy market was indirectly mentioned.

3.5 Resource or Player profiling and modeling

To successfully implement DR programs, resource or player profiling/modeling techniques are employed to categorize and identify DR resources or participants based on their behavior and characteristics. In MAESTRO, this categorization is utilized by the aggregator to optimize and coordinate the DR program used in the majority of the core publications, by the system operator to ensure the secure and dependable operation of the power system used in [19], or for any other player that wants to enhance its performance. The "Player layer" from Figure 3.1 works as the data management component where the DSS performs tasks such as collecting, storing, analyzing and retrieving information from the several active players to be further used. This includes data from various sources such as databases, spreadsheets, and external sources (real-time sensors). Services such as profiling, aggregation, forecast or consumer profile modeling can be used within the scope of this layer ([16], [18]–[20], [22]–[26]).

The player profiling in MAESTRO involves grouping DR program participants into categories or segments based on their preferences, constraints, contextual availability and expectations ([19], [22]–[26]). These categories were used in MAESTRO to tailor the DR program according to each scenario needs and players proper and fair motivations, such as financial incentives or environmental benefits for instance on [18].

Resource profiling, on the other hand, was used for analyzing historical data of each DR resource and create a model that predicts its behavior during DR events ([18]–[20], [24]), where the trustworthy rate could also be used as support. With this, the main outcomes withdrawn, and the value created for the literature in this topic must be underlined. The developed model in [24] estimates the potential demand reduction that can be achieved by each resource. Both [19] and [18] emphasize the significance of understanding the behavior of each player throughout the day, as the allocation of load during specific periods is crucial to prevent exceeding load limits. This understanding is particularly important for avoiding load violations. In the case of [17], the profile of EVs is of great importance for their participation in Vehicle to Grid (V2G) programs.

The study from [20] emphasizes the importance of resource grouping based on similarity to improve decision-making processes such as profiling, participation and remuneration. For profiling, it was suggested assembling resources with similar behaviors into groups which can lead to more accurate and fair decisions, especially in real-time scenarios. Additionally, the study discusses the need for finding the optimal number of clusters when aggregating active players, considering the sensitivity of clustering methods to input data. By determining the best number of groups to be implemented, the aggregator can enhance the effectiveness of the aggregation process.

It was proven that profiling techniques allowed the customization of DR programs to achieve greater participation, increased demand response, reduce response uncertainty and more efficient use of resources.

3.6 Demand response programs design

As already mentioned, the consumer centric approach was considered as the solution for the renewable integration in the real power and energy market within the scope of this thesis. Their flexibility is crucial to find balance between load demand and generation. It is, however, essential to find the proper participants to DR events triggered when, for instance, renewable resources are not capable of satisfy the demand requests. Besides, their response it is still voluntary. Although DR programs such as DLC, can directly manage an equipment, the player can turn it on anytime (facing the proper consequences for violating a DR contract).

For this thesis, a reliability rate was then created to avoid discomfort and reduce the response uncertainty and was formulated as a hybrid of incentive and price-based strategies, making it compatible with both approaches. Initially introduced in [16] as a reliability rate used in three different approaches: Basic Rate Method, Cost Rate Method, and Clustering Rate Method, where each one dealt with the uncertainty of the consumer differently. It must be highlighted that the Enrollment layer steps (Figure 3.1) are always present in the proposed methodologies within this thesis.

The Basic Rate Method selects consumers with higher values for scheduling and updates their reliability rate based on past performance and achievement of DR targets. The Cost Rate Method introduces a price fluctuation feature, where consumers can change their reliability prices to increase their rates, and only those with lower prices are selected for DR events. The Clustering Rate Method clusters consumers by reliability rate and contracted reduction, and only those with higher values are considered for scheduling. All three methods update reliability rates based on past performance and achievement of DR targets, with remuneration given as an incentive to participants. The Cost Rate Method allows consumers who were not selected for DR events to change their cost in DR events to increase their chances of being selected. In the end, it was concluded that the context of the DR event impacts the actual response from the participants. In other words, the consumer's comfort and participation during working hours, holidays, weekends, or extreme temperatures may affect their response to DR events.

The DR program design for MAESTRO was then improved and complemented with the core publications ([16]–[19]), resorting to the contextual approach mentioned in the following sub-section 3.7. Overall, the results from [16] highlighted the need for a contextual approach, that was then improved with the work done on [19] and on [21]. The trustworthy rate was also used for the remuneration of prosumers within the scope of [18]. For the selection of EVs for a V2G event using extrinsic and intrinsic factors, one of them this rate, which was very useful since it can avoid privacy issues [17].

3.7 Contextual approaching

In this way, to update this approach, a new version was developed where the context was included so the aggregator could select the proper participants. In the studies from [19], [21], and [95] efforts were made to create a Contextual Consumer Rate (CCR) or trustworthy rate, revising the formulation of the previous reliability rate. The CCR is divided into two rates, the Preliminary Contextual Consumer Rate (PR) and Updated Contextual Consumer Rate (UCCR), which depend on several factors (independent rates), including Context Rate (CR), Historic Rate (HR), Last Event Rate (LER), and Response Rate (RR). Both PCCR and UCCR are formulated in equation 1 and equation 2, respectively.

$$PCCR = \omega_{HR} * HR + \omega_{LER} * LER \tag{1}$$

$$UCCR = \omega_{HR} * HR + \omega_{LER} * LER + \omega_{RR} * RR + \omega_{CR} * CR \tag{2}$$

The weights assigned to each independent rate are defined through ω. Consumers who do not have previous information are assigned the lowest rate and can improve their CCR. The value of each weight one was then evaluated to define the impact of each independent rate.

To fully understand the logic behind this trustworthy rate contextual approach, Figure 3.3 shows the different timelines for the independent rates, regarding time of the day (24-hour format), day of the week (Sun. – Sunday, Mon. – Monday, Tues. – Tuesday), and the weather. Event 1 is represented with the red color, and event 2 is represented with the blue color. Considering event 1, triggered on the Sunday morning, between 10 and 11 AM. For HR, historic data is used where, for instance, this independent rate is the average of the last five performances within the same context. HR is different from the LER in the sense of representing only the last event – which can positively or negatively impact the average from the last performances. In other words, the player might have a good performance in this rate but did not have the availability to participate in the last event: from the PhD candidate perspective, it is not fair to jeopardize all the work done until this point, therefore, LER was created [95]. With this, the aggregator can obtain the PCCR to select the proper participants for the DR event.

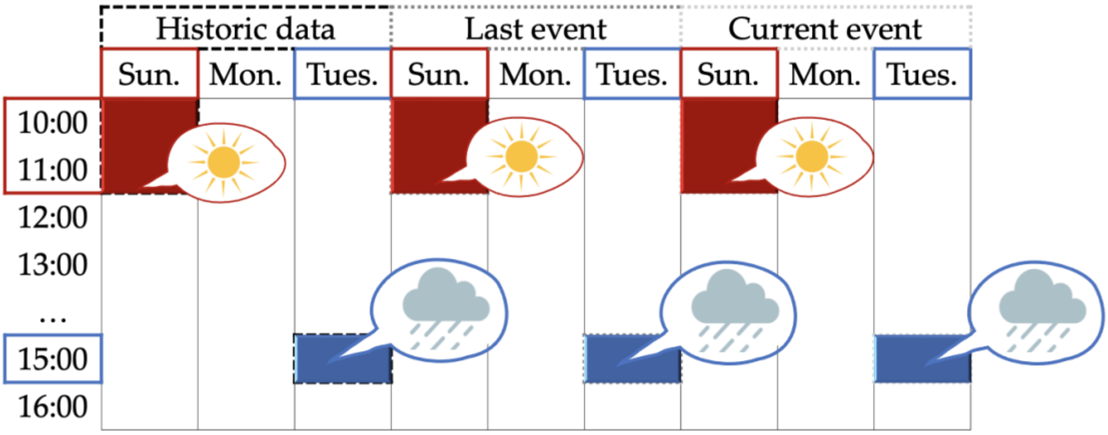


Figure 3.3. Contextual approaching for trustworthy rate.

After the event, and the comparison between requested and actual response, both RR and CR are used to update the performance with UCCR. Regarding core publications studies, it is crucial to highlight the key findings for complementing MAESTRO by adding new players and resources to the equation and offering a wider version of the approach developed. First, the energy storage systems were added to the portfolio in [17], [18]. In this work, a methodology was developed and tested within a real-time simulation following the same lines from the Enrollment layer steps (Figure 3.1).

To complement MAESTRO resource portfolio, another business model was developed. The work from [17] proposes a novel methodology for managing active local communities with volatile resources, specifically focusing on EVs with V2G capability. The methodology includes a V2G perspective to aid the aggregator in managing the resources, a fairness model for prioritizing EV charging based on performance and departure time, criteria for selecting EVs ready for V2G events, aggregation of EVs for events, categorization of EV resources based on a previous response, and collaboration among community members to prioritize local generation and suppress demand. The methodology aims to increase the reliability and accuracy of the management of local energy communities and help achieve distribution system operator reduction targets. Overall, this methodology focusses on fairness and good compensation to motivate continuous participation and reduce uncertainty. Contextual remuneration was also applied to show the importance of the event's context for both parties involved.

Finally, [18] propose a methodology to effectively manage a community, focusing on remunerating community members for the flexibility they provide.

The study compares and evaluates four different approaches, considering contextual tariffs. The results demonstrate that it is possible to enhance the fairness of remuneration, which serves as an incentive and compensation for the loss of comfort. Among the approaches examined, the single fair remuneration approach proved most beneficial to the community manager, as it resulted in lower total remuneration compared to the other approaches. On the other hand, from the prosumers' perspective, employing a clustering method was more advantageous, as it led to a higher distribution of remuneration for the flexibility provided.

3.8 Aggregation

In the scope of this thesis, aggregation is considered as the process of combining of small, distributed energy resources into larger groups with similar characteristics. This allows a better management and utilization of these resources, increasing their value and reducing the overall costs. So, making use of the developed trustworthy rate, the players are aggregated according to their characteristics and their performance for a DR event. MAESTRO has gathered different models to not only predict the group/rate from a new player, but also select the proper ones for a specific DR event context ([16]–[19]). This sub-section is then divided considering the machine learning algorithms used for this goal. The candidate had already published different works that only considered the trustworthy rate for selecting the DR participants assuming a minimum level to participate such as [16] but, as referred in the future works, there was a need for contextual approach to improve the business model.

Firstly, the main works using supervised learning focused on predicting the trustworthy rate for the participants. The study in [23] discusses the use of decision trees to classify new active players based on their performance in previous events. The goal is to identify patterns in consumer behavior that can help predict their performance in future events, using the trustworthy rate created. The publication highlights the benefits of decision trees, which allow for a simple and easy-to-understand visualization of the decision-making process.

Complementing this work, Figure 3.4 presents the proposed methodology from [25] where comparison was made between DT and RF for the same goal as [23], but using different scenarios where the inputs vary.

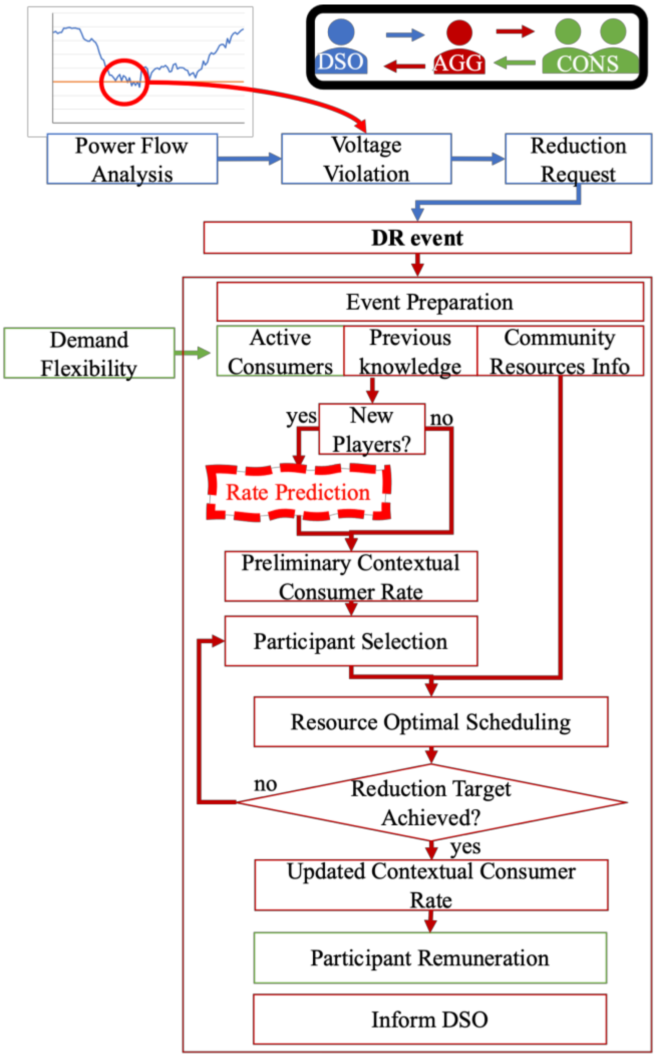


Figure 3.4. Predict the new players trustworthy rate resorting to supervised learning [25].

Concerns regarding the privacy of active players and the impact of their current location on the models were also addressed. However, the results showed that the current location feature was not critical to achieving the goal of classifying new active players. The authors conducted a sensitivity test and found that a decision tree with five leaves could achieve an accuracy value above 50%, which can be a reasonable number for a player with little to no information. This work also emphasizes the importance of balancing the benefits of using machine learning techniques with the privacy concerns of active players. The study from [23] resorted to ANNs to predict the actual response of DR participants, with already contextual and historical performances. The goal is to improve the accuracy of predicting participants' response to DR events, which can help players optimize their operations. The approach can also help identify the most significant factors that influence participants' response to DR events.

Regarding unsupervised clustering, for this thesis, the main uses were participant selection and remuneration by gathering the similar players within compensation groups. In [16], consumers with a higher trustworthy rate and higher values of contracted reduction are selected for the initial scheduling. In this way, consumers are clustered by rate, and the group with the highest sum of pledged reduction is chosen for the next phase. However, the same logic was then used for remuneration in [96]. Focusing on EVs, in [17] clustering was used for a selection based on two different inputs: intrinsic and extrinsic factors. The intrinsic factors consider EV characteristics, such as the value of charge and discharge, while extrinsic factors consider the participation history, period of staying in the park, and status during the stay, such as arrival and departure times and battery status. By considering these inputs, the group with the most interesting typical profile according to the event context is selected. The discharge rate is an important parameter to consider, and the group with the higher value is chosen.

3.9 Machine learning use

Machine learning is a subfield of artificial intelligence that involves creating algorithms and statistical models to create computer systems that can make decisions based on patterns or insights from data. Within the scope of this thesis, supervised and unsupervised learning was used to accomplish different tasks. The most important ones were aggregation and remuneration. However, it must be highlighted the fact that machine learning was a crucial piece to build MAESTRO, for instance, prediction of the trustworthy rate using classification methods ([23]–[25]), selecting participants using clustering ([17], [16], [96]) or attributing a fair remuneration ([18], [97]).

Undoubtedly, it is crucial to highlight the valuable contributions made by these studies to the existing literature in this important and current field. The outcomes derived from these research endeavors have yielded significant advancements and insights. In the study from [23], classification methods were employed to provide a trustworthy rate to a new player without performance information. A decision tree was developed, considering various contextual factors at the time of the DR event.

From the aggregator's perspective, the availability of active consumer data proved to be useful, although privacy concerns may arise. Nevertheless, the results indicated that incorporating this information can improve the outcomes. The work in [25] had same goal, different features, but compared the results from decision trees and random forest. For this case, the scenarios with private features were less important, however the accuracy was above 50%. In the study conducted by [24], artificial neural networks were utilized to predict the actual response of a participant in a DR event, using multiple features. Notably, the inclusion of the consumer's contextual information (such as their geographical location) through the concept of CCR resulted in high accuracy values. While CCR may entail sharing personal information, it can also equip aggregators with the necessary knowledge to predict the actual response of active players in the local community using just one feature. These findings greatly contribute to the literature by introducing effective methodologies for assigning trustworthy rates to new players and enhancing the accuracy of predicting consumer responses in DR events, considering privacy concerns and the significance of contextual information.

Clustering played a significant role within the MAESTRO context. The results from [17] indicated that employing a clustering method would be advantageous for all parties involved. It led to increased event participation, enabled the achievement of state of charge goals for EVs, and resulted in reduced final player bills. While performance is a useful indicator of resource availability, relying solely on performance may not be the most effective approach for selecting EVs for V2G events. Doing so could limit the pool of available resources for event participation. Therefore, incorporating a clustering method provides a more comprehensive and beneficial approach in selecting EVs for V2G events.

Furthermore, used to attribute a fair remuneration, machine learning methods were used in [18], comparing three different ones: decision trees, k-nearest neighbors and artificial networks. The study results indicate that adding more contextual information may reduce the total remuneration and still be fair with the participation compensation. The outcomes are supported by the study in [97] when the optimal number of DR programs and tariffs was defined.

3.10 Demand response gathering

This topic is not commonly discussed in literature related to aggregators. In fact, DR gathering becomes more critical in short and real-time DR events due to the limited time available to achieve the desired reduction baseline. In this thesis was considered that is crucial motivate the participants by discussing remunerations between aggregators and DR participants during the ramp period. The majority of the works developed in the scope of this thesis was designed to close the existing gap on the relationship between these players ([16]–[20]). It is in fact assumed that contractual information is complete, clear and precise to avoid any misunderstandings or legal disputes. It should specify the obligations, responsibilities, and rights of each party involved in the contract. This includes the duration of the contract, the terms and conditions, pricing and payments, and any other relevant details. Having a well-defined contract is particularly important in the case of DR programs, where the aggregation of small resources into larger portfolios requires a high degree of trust and cooperation between the aggregator and the resource owners, as can be seen in [20] where prosumers were grouped according to their similarity.

Considering that uncertainty reduction and performance enhancement are key for MAESTRO, the transparency is essential hence the design of a trustworthy rate – guaranteeing the fairness and minimizing unnecessary expenses. The mentioned works in the Resource Scheduling sub-section considered this assumption. For better understanding, Figure 3.5 presents the different stages of the V2G model developed, partially used for instance in [17]. It is essential to have all the information well-defined from the beginning until the event of the model, in order to guarantee the fairness.

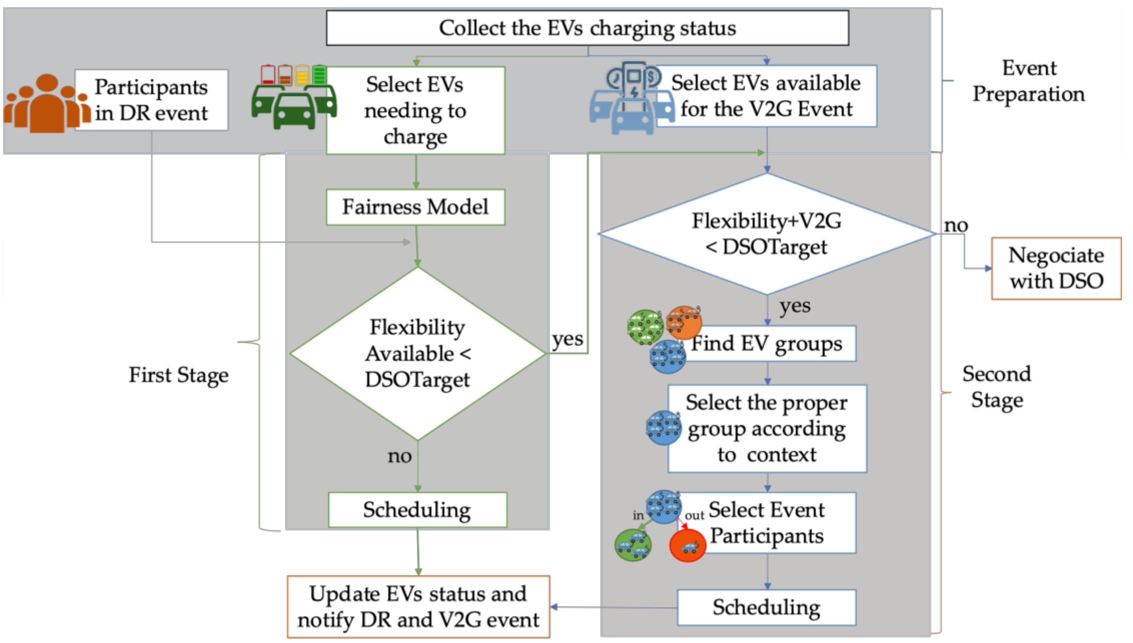


Figure 3.5. DR gathering from an aggregator perspective for the V2G model developed.

Firstly, collect the EVs charging status to select the EVs available for the V2G and the ones that need charging – to apply the fairness model. Actually, in [17], all the EVs had a previously well-defined parameters, both intrinsic and extrinsic. Information such the check-in, check-out, the expected State-Of-Charge (SOC) at the check-out, minimum remuneration for participation, were considered avoiding misleading and discomfort. For the first stage, the load participants for the DR event provide their flexibility available and the aggregator compare if it is enough to suppress the DSO target. If so, the resource scheduling is done, and the information is updated. Otherwise, on the second stage, after the V2G event be triggered, and the total flexibility is confirmed to be enough to suppress the DSO target, it is time to find and gathering groups of EVs. Clustering methods can be used for this purpose. In this case, the EVs on groups with the sum of higher flexibility provided are chosen for participation until achieve the expected flexibility. With this, the model was able to guarantee the expected SOC at the check-out time, managing optimally and fairly the resources.

Again, the innovation from this methodology presented on Figure 3.5 focuses on the contextual approach, by gathering important DR data, to care for the player behavior details – not only the load consumers but also the EV users. This business model was created to be possible to avoid players discomfort, since it is managed to be guaranteed the SOC expected at the check-out time, which can be important to motivate future participations.

3.11 Resource scheduling

The resource scheduling for the active communities was widely implemented throughout this thesis. The MAESTRO developed linear models for optimal scheduling of several types of resources, namely DR participants, DG, ESS, and EV. Mostly in the scope of an aggregator managing a local community where a DR event is triggered, and a reduction target must be achieved ([16]–[19]). The goal is to minimize the operation costs from the perspective of the Aggregator considering the fair remuneration of the participating resources.

The problem of DR and DG scheduling is addressed in [19], [21], [22], [26] with the objective of reducing the operational costs of the aggregator For instance, in [19], a hypothetical situation was considered where a voltage violation is detected by a power flow analysis conducted by the DSO. Aggregators responsible for managing communities located near the affected area would be required to implement load reduction measures. Figure 3.6 shows the proposed methodology developed for [21], where the scheduling was performed with the initially selected consumers for the DR event.

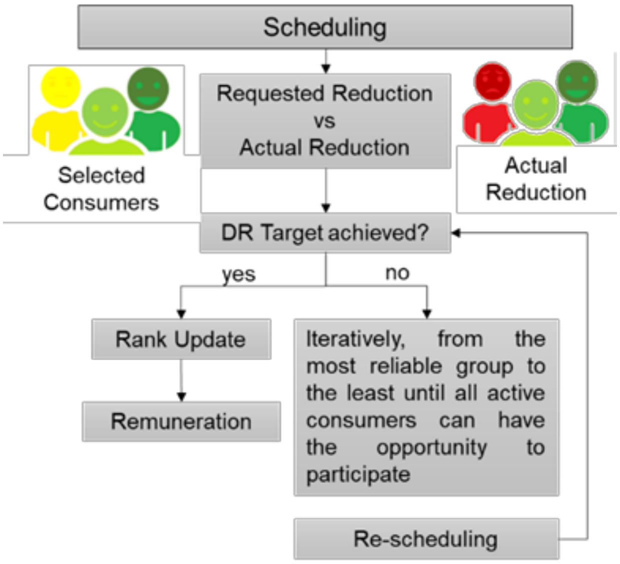


Figure 3.6. Resource scheduling approach [21].

The actual and the requested reduction is compared to understand if the reduction target is achieved. If not, iteratively, new participants are added, and new re-scheduling are performed until the goal is reached.

More punctual contributions resorted to mixed-integer linear programming optimization. In [18], a prosumers community with ESS was optimally scheduled using this technique. On the other hand, [17], simulated a parking lot with V2G, where this option was only implemented in situations where DR participants flexibility was not enough to achieve a DR target. This would allow EV to increase their performance rate if available for participation.

3.12 Demand response deployment

In the context of DR programs, the availability of DR participants plays a crucial role in achieving the desired level of demand reduction during, for instance, peak hours. It is important for aggregators to have a sufficient number of participants and ensure their availability during DR events to meet the contracted capacity. To deploy DR programs successfully, aggregators must conduct careful planning and preparation to ensure the availability of DR participants. This includes identifying and recruiting potential participants, verifying their eligibility, and establishing contracts to formalize their participation. MAESTRO guarantees these with the trustworthy rate classification applied within the scope of most of the works referred in this thesis ([16]–[19]).

In advance, the aggregator communicate the DR event details and requirements to participants, including the start and end times, the expected reduction levels, and the expected incentives for participation. In the study from [20], energy storage systems were used. It must be highlighted that remuneration, depends on the actual response of the participant in MAESTRO. Penalties can be applied for non-responses: reducing the trustworthy rates, lower remuneration or even both. To avoid these, techniques from the aggregator perspective are used to previously select and evaluate each player for the context in which the DR event is triggered, considering previous performances, such as in sub-section 3.7.

Furthermore, as soon as the signal is sent to the DR participants, aggregators continuously monitor the availability of participants and their ability to provide the contracted capacity. With MAESTRO, a comparison between the actual and the requested load reduction is performed like in ([18], [19]). Some of the MAESTRO approaches are also prepared to address any issues or emergencies that may arise during the event, such as equipment failures or unexpected participant dropouts. For instance, [16] considers an initial scheduling and a further rescheduling if the flexibility provided in the first one is not enough to achieve the DR target. The study in [24] was developed a model useful for the aggregator to predict the responses and non-responses from the DR participants.

3.13 Remuneration and Assessment

Finally, the Tariff and Rate definition layer comprehends the real and widely studied DR programs incentive-based and price based. However, for the scope of this thesis, a new way to compensate the participants was designed – the Trustworthy Rate, which was used in the majority of works ([16]–[19]). Regarding the publication's role, in [19], the remuneration value used was according to the schedule in which the DR event was triggered. For [18], k-means clustering method was used for the remuneration step. The proposed methodology aims to group prosumers with similar flexibility profiles using this approach and offer better tariffs to those with higher flexibility, potentially resulting in different tariff values per period as the group with higher flexibility may change. In the same line of thought, [97] also resorted to k-means to form these groups based on actual participation of resources in managing the local market. The main focus was the comparison of methods to find the optimal number of clusters for a given database, highlighting the importance of fair remuneration for small resources. However, the results were inconclusive due to the significant difference in the optimal number of clusters.

3.14 Real-time simulations

In order to implement any business models, it is crucial to validate and test them on reliable and physical simulation platforms. However, conducting simulations solely on computational resources, such as electrical distribution network simulations, can be challenging and costly, and may not produce accurate results. Therefore, employing a real-time simulation strategy can provide a satisfactory solution by combining both simulation results and real-world data to ensure a more realistic representation. This introduces the Real-time simulation layer from (Figure 3.1), where the overlapped layers become understandable since many of these processes can be used in other layers. Measuring, monitoring, maintenance, fault prediction, and the infrastructure can be used on the Player layer (Figure 3.1), to obtain better datasets as input but can also be used for the DR program layer for supervising the different steps. To sum up, this step provides the tools for the other layers to function properly.

This was proved within the [18] work, resorting to prosumers, where five were connected to real BESS that belongs to the GECAD, Instituto Superior Engenharia do Porto research center with a capacity of 2 kW. It was also tested on [22] with a different community, where an optimization-based community model that aggregates small-scale consumers and producers was explored. The model has a central controller or aggregator and multiple local community managers to balance the network locally. Real-time simulation and hardware-in-the-loop devices validate the system's practicality, indicating a difference between simulation and experimental results. Nonetheless, the system performs well in real-time mode using actual devices.

3.15 Case studies

The effectiveness of each MAESTRO approach has been demonstrated through the implementation of relevant case studies that focus on specific parameters, as illustrated in Table 3.2. These parameters were selected based on the key contributions outlined in Chapter 1.2. The table lists various characteristics of publications related to DR programs. The characteristics are grouped into four categories, namely DR program, Players, Decision Tool, and Voltage Limit Violation. Under the DR program category, the publications are classified into three types, namely price-based, incentive-based, and DR target. Under the Players category, the publications are categorized into various groups, such as Aggregator, Consumers, Electric Vehicle, Distributed Generation, and Energy Storage. These groups represent the different stakeholders involved in DR programs within the scope of this thesis. Under the Decision Tool category, the publications are classified into two types, namely optimization and intelligent approach. Finally, the Voltage Limit Violation category, involves a broader approach besides local community management.

Based on the analysis of the Table 3.2, several key outcomes can be observed.

Table 3.2. Case studies summary

Characteristics		**Publications**											
		Core				**Other**							
		J1	C1	J3	J4	B1	J5	C2	C3	C4	C5	C6	C7
DR programs	*Price based*	x		x			x	x	x	x	x		x
	Incentive based	x	x	x	x	x			x	x	x	x	x
	Target	x	x	x	x		x					x	
Players	*Consumers*	20,310	5	19	96	14	20	156	406	406	406	96	406
	Electric Vehicle	0	30	0	0	0	0	0	0	0	0	0	0
	Distributed Generation	548	5	38	0	14	548	108	0	0	0	0	0
	Energy Storage	0	0	19	0	14	0	0	0	0	0	0	0
Decision	*Optimization*	Y	N	Y	Y	N	Y	Y	N	N	N	Y	N
	Intelligent approach	Y	Y	Y	Y	Y	N	N	Y[1]	Y[2]	Y[3]	N	Y[4]
Voltage limit violation		N	N	N	Y	N	N	N	Y	Y	Y	Y	N

[1] Using classification, namely Decision Trees
[2] Using classification, namely Artificial Neural Networks
[3] Using classification, namely Decision Trees and Random Forests
[4] Using classification (Decision Trees, Random Forests and XGBoost), supervised clustering and subgroup discovery

Firstly, the majority of research related to DR programs is focused on consumers, with fewer publications related to other players such as aggregators, electric vehicles, DG, and energy storage. The publication [11] refers to a review paper type so it is not included in the table. The most commonly studied DR program types are both price-based and incentive-based approaches. The trustworthy rate created, as already mentioned, can be used for both approaches but, within the scope of this thesis, was used mainly as incentive. The DR target concept was mentioned in fewer publications ([16]–[18], [21], [23], [26]) despite being frequently used in an implicit manner.

Secondly, the table shows that optimization using mathematical models and algorithms was the main approach for resource scheduling ([16], [18], [19], [21], [22], [26]). However, the table also reveals that intelligent approaches were a main topic within the publications since these methods were very useful for identifying patterns and predicting behaviors in DR programs, leading to more effective implementation and management ([16]–[20], [23], [25], [27]). These approaches have the potential to enhance the accuracy and efficiency of DR program implementation. Finally, the table highlights the importance of addressing voltage limit violations in DR programs, as this is a relevant aspect of program implementation that has been studied in several publications ([19], [23]–[25], [27]).

3.16 Conclusion

The publications developed within this thesis scope have focused on implementing various approaches for DR programs and create a new way to properly select DR participants where the goal was enhancing performance and reduce response uncertainty. It involved several machine learning models to adjust and analyze all the information provided. The thesis also highlights how the key contributions are integrated to fulfill the core contribution of the study and answer to the research question.

The core publications ([11], [16]–[19]) main findings contributed for the current state-of-art on the key topics. Regarding [16], by selecting the proper participants, the aggregator was able to reduce operation costs and avoid a resource re-scheduling in some methods. The review of the literature from [11] explored DR performance and uncertainty topics, useful for the development of MAESTRO business models. Added to the lessons learned with this paper, the

PhD candidate updated the trustworthy rate for a contextual approach, to be further used in [17]–[19]. Firstly, with a V2G approach on the [17] study, the EV users participated in events where the flexibility goal was achieved by the aggregator, and it was also possible to achieve the SOC at the check-out time by all users. Regarding the ESS approach on the [18] study, the remuneration comparison concludes that the trustworthy rate led to fairer results and had a close result to the single fair remuneration plus, has the advantage to increase the remuneration by increasing the rate. Finally, the study from [19], introduced a spatial perspective, providing the aggregator with a wider portfolio. When conjugating this with a contextual trustworthy rate, the approach eases the implementation throughout the grid.

MAESTRO was proposed and developed to enhance the features and benefits of DR implementation in an energy management system, specifically for the intensive renewable integration. Case studies were conducted to support the key contributions of the thesis.

Chapter 4

Conclusions and Future Work

4. Conclusions and Future Work

This chapter provides the final remarks of the thesis by presenting the key findings derived from the research – Chapter 4.1 and suggesting potential areas for future work that build upon the current study – Chapter 4.2.

4.1 Main Findings and Contributions

The transition to a renewable-based energy system is an ongoing and complex process, requiring constant adaptation and innovation. DG using renewable-based technologies has emerged as a crucial component in this transition, but its unpredictable nature creates challenges in maintaining system balance and reliability. To address this, it was concluded that the smart grid concept should prioritize active participation of small consumers and the utilization of local resources. In this work, the PhD candidate focused on the development of DR programs to achieve this goal.

DR plays a crucial role in ensuring the stability and reliability of the electricity grid, especially in the context of increasing integration of renewable energy resources. The DSS developed enables active players to adjust their energy usage in response to changes in grid conditions or market signals. DR provides a valuable tool for balancing supply and demand in real-time, therefore it is the core of DSS. It was learned, by analyzing the literature, that this approach helps to prevent blackouts, reduce energy costs, and improve overall grid efficiency. Additionally, DR approaches incentivizes active players to adopt energy-efficient behaviors and reduce their overall energy consumption, leading to significant environmental benefits.

Despite its importance, it was concluded that, for achieving a smarter grid with DR, requires a solution that deals with the uncertainties introduced by new players. Several factors were considered on the business models developed for empowering consumers, such as their limited access to accurate information, complex actions in the energy market, privacy concerns, and the need for knowledge to support their DR participation.

This thesis main contribution to the innovation in DR programs is the designing and developing of DSS called **MAESTRO**, ***M**achine learning **A**ssisted **E**nergy **S**ystem management **T**ool for **R**enewable integration using demand resp**O**nse*.

The results obtained demonstrate that the MAESTRO methodologies outperformed other methods with which it was compared. The tool has shown its ability to learn and adapt to changing circumstances by utilizing the available resources, such as distinct DSS, resource scheduling, learning and data analysis algorithms.

MAESTRO was developed to choose the best decisions to make in each context and continually improve the way that each player achieves its objectives. By studying the behavior and learning from its performance on DR events, the trustworthy rate developed aids the managing entity make fair decisions to achieve the best outcomes. This capability to learn and adapt allows MAESTRO to demonstrate a clear improvement of active players in performance over time.

When creating a business model to successfully implement DR, one of the lessons learned from the consumer's perspective, it is crucial to consider their comfort, concerns about remuneration, reliability, and the challenges they face when dealing with multiple aggregators in the DR landscape. Small consumers prioritize their comfort and convenience when participating in DR programs, seeking assurance that their preferences and comfort levels are considered. From the results, it is expected from these active players, that aggregator provides fair and transparent compensation for their energy reductions or contributions during DR events. Simplifying the active player experience, ensuring their trust and satisfaction are vital considerations in designing and implementing effective DR strategies. These guidelines were considered in MAESTRO.

Another important lesson learned in this thesis is the need to explore real-time simulation to ensure that the economic solution is technically robust. Resorting and incorporating real-time simulation allowed for a more accurate representation of the dynamic behavior of the smart grid and DR programs, namely with ESS. In fact, real-time simulation provided a platform to validate and fine-tune the technical aspects of this solution, considering factors such as resource availability, and demand variations. By leveraging real-time simulation, can be concluded that market players can assess the feasibility and effectiveness of different DR scenarios, identify potential bottlenecks, and refine strategies to achieve optimal outcomes. Therefore, this approach facilitates a comprehensive understanding of the economic viability of DR programs.

With MAESTRO it was possible to achieve the goals and find the responses to the research questions leading to significant progress in the multidisciplinary fields of AI and power and energy systems. The advancements in AI mainly focused on machine learning and data analysis, while in the power systems domain, they were particularly related to the electricity markets and optimal scheduling. During the research conducted for this thesis, a total of twenty-six scientific papers were published in international journals and conference proceedings. Additionally, seven papers are currently in development or being prepared for submission. Therefore, these findings represent valuable contributions to these fields of study.

4.2 Perspectives of Future Work

This PhD work has made significant contributions to the field of artificial intelligence within the scope of the power and energy sector, making particular use of machine learning to achieve the proposed goals. The core contribution involved the development of MAESTRO, a decision support tool that focuses on leveraging different machine learning techniques to harness their complementary strengths and adapt them to specific application contexts. Additionally, novel methodologies and techniques were introduced to improve the performance of active players in DR events. The progress made in this work will serve as a foundation for proposing new and improved methodologies aimed at more effective and efficient learning with a deeper understanding of the context and dynamics of the applicable circumstances. Several future developments are listed below as some of the most relevant:

- Develop multi-level environment involving negotiations between players from the same or neighboring smart grids at different scales;
- Integration of non-linear optimizations and different metaheuristics approaches for solving the complex management of energy communities;
- Integration of forecasting methods for optimal scheduling approaches, predicting critical factors and improve the model efficiency;
- Enhance the learning process of MAESTRO, by enriching the database and exploring the different behaviors of each resource or player, throughout surveys and other data sources;
- Exploration of additional techniques to improve the effectiveness of remuneration and motivation approaches;
- Improve the triggering of signals for DR programs participation by using, for instance, transactive control methods;
- Testing bigger realistic case studies.

Most of these suggestions for future work have been deemed important not only for the further development of this PhD research, but also as a crucial part of ongoing international research projects. As such, these suggestions ensure the continuity of the research carried out within the scope of this PhD. These ongoing projects include:

- New Markets Design & Models for 100% Renewable Power Systems (TRADERES), reference no. 864276;
- Power and Energy Cyber-Physical Solutions with Explainable Semantic Learning (PRECISE), reference no. PTDC/EEI-EEE/6277/2020 ;

References

References

[1] C.-C. Lin, S. Saponara, D. Stanelyte, N. Radziukyniene, and V. Radziukynas, “Overview of Demand-Response Services: A Review,” *Energies 2022, Vol. 15, Page 1659*, vol. 15, no. 5, p. 1659, Feb. 2022, doi: 10.3390/EN15051659.

[2] B. Canizes, B. Mota, P. Ribeiro, and Z. Vale, “Demand Response Driven by Distribution Network Voltage Limit Violation: A Genetic Algorithm Approach for Load Shifting,” *IEEE Access*, vol. 10, pp. 62183–62193, 2022, doi: 10.1109/ACCESS.2022.3182580.

[3] S. Impram, S. Varbak Nese, and B. Oral, “Challenges of renewable energy penetration on power system flexibility: A survey,” *Energy Strategy Reviews*, vol. 31, p. 100539, Sep. 2020, doi: 10.1016/j.esr.2020.100539.

[4] N. Ahmed, M. Levorato, and G. P. Li, “Residential Consumer-Centric Demand Side Management,” *IEEE Trans Smart Grid*, vol. 9, no. 5, pp. 4513–4524, 2018, doi: 10.1109/TSG.2017.2661991.

[5] S. R. Lopez, G. Gutierrez-Alcaraz, M. S. Javadi, G. J. Osorio, and J. P. S. Catalao, “Flexibility Participation by Prosumers in Active Distribution Network Operation,” in *2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, IEEE, Jun. 2022, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope54979.2022.9854631.

[6] O. Abrishambaf, P. Faria, and Z. Vale, “Ramping of Demand Response Event with Deploying Distinct Programs by an Aggregator,” *Energies (Basel)*, vol. 13, no. 6, p. 1389, Mar. 2020, doi: 10.3390/en13061389.

[7] D. de São José, P. Faria, and Z. Vale, “Smart energy community: A systematic review with metanalysis,” *Energy Strategy Reviews*, vol. 36, p. 100678, Jul. 2021, doi: 10.1016/j.esr.2021.100678.

[8] C. Silva, P. Faria, and Z. Vale, “Demand Response Implementation: Overview of Europe and United States Status,” *Energies (Basel)*, vol. 16, no. 10, 2023, doi: 10.3390/en16104043.

[9] European Parliament and Council of the EU, “Directive (EU) 2019/944 on Common Rules for the Internal Market for Electricity and Amending Directive 2012/27/EU,” *Official Journal of the European Union*, no. 158, p. 18, 2019, doi: http://eur-lex.europa.eu/pri/en/oj/dat/2003/l_285/l_28520031101en00330037.pdf.

[10] A. G. Gaglia *et al.*, “Energy performance of European residential buildings: Energy use, technical and environmental characteristics of the Greek residential sector – energy conservation and CO_2 reduction,” *Energy Build*, vol. 183, pp. 86–104, Jan. 2019, doi: 10.1016/j.enbuild.2018.10.042.

[11] C. Silva, P. Faria, Z. Vale, and J. M. Corchado, “Demand response performance and uncertainty: A systematic literature review,” *Energy Strategy Reviews*, vol. 41, p. 100857, May 2022, doi: 10.1016/j.esr.2022.100857.

[12] C. Ribeiro, T. Pinto, Z. Vale, and J. Baptista, “Dynamic remuneration of electricity consumers flexibility,” *Energy Reports*, vol. 8, pp. 623–627, Jun. 2022, doi: 10.1016/j.egyr.2022.04.056.

[13] N. Hasan and M. Alam, “Envisaging Industrial Perspective Demand Response Using Machine Learning,” *Lecture Notes on Data Engineering and Communications Technologies*, vol. 90, pp. 331–342, 2022, doi: 10.1007/978-981-16-6289-8_28.

[14] A. C. Varghese, P. V., G. Kumar, and S. A. Khaparde, “Smart Grid Consumer Behavioral Model using Machine Learning,” in *2018 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia)*, IEEE, May 2018, pp. 734–739. doi: 10.1109/ISGT-Asia.2018.8467824.

[15] C. Silva, P. Faria, and Z. Vale, “Demand Response Implementation: Overview of Europe and United States Status,” *Energies (Basel)*, vol. 16, no. 10, p. 4043, May 2023, doi: 10.3390/en16104043.

[16] C. Silva, P. Faria, and Z. Vale, “Rating the Participation in Demand Response Programs for a More Accurate Aggregated Schedule of Consumers after Enrolment Period,” *Electronics (Basel)*, vol. 9, no. 2, p. 349, Feb. 2020, doi: 10.3390/electronics9020349.

[17] C. Silva *et al.*, “Optimal management of an active community for fair selection of electric vehicles in a V2G event,” in *CIRED Porto Workshop 2022: E-mobility and power distribution systems*, Institution of Engineering and Technology, 2022, pp. 1069–1073. doi: 10.1049/icp.2022.0878.

[18] C. Silva, P. Faria, B. Ribeiro, L. Gomes, and Z. Vale, “Demand Response Contextual Remuneration of Prosumers with Distributed Storage,” *Sensors*, vol. 22, no. 22, p. 8877, Nov. 2022, doi: 10.3390/s22228877.

[19] C. Silva, P. Faria, and Z. Vale, “Rating and Remunerating the Load Shifting by Consumers Participating in Demand Response Programs,” *IEEE Trans Ind Appl*, vol. 59, no. 2, pp. 2288–2295, Mar. 2023, doi: 10.1109/TIA.2022.3224414.

[20] C. Silva, P. Faria, J. M. Corchado, and Z. Vale, “Clustering Methods for the Profiling of Electricity Consumers Owning Energy Storage System,” in *Intelligent Data Mining and Analysis in Power and Energy Systems*, Wiley, 2022, pp. 129–148. doi: 10.1002/9781119834052.ch6.

[21] C. Silva, P. Faria, and Z. Vale, "Rating consumers participation in demand response programs according to previous events," *Energy Reports*, vol. 6, pp. 195–200, Dec. 2020, doi: 10.1016/j.egyr.2020.11.101.

[22] O. Abrishambaf, C. Silva, P. Faria, and Z. Vale, "An Optimization Based Community Model of Consumers and Prosumers: A Real-Time Simulation and Emulation Approach," *E3S Web of Conferences*, vol. 239, p. 00024, Feb. 2021, doi: 10.1051/e3sconf/202123900024.

[23] C. Silva, P. Faria, and Z. Vale, "Classification of New Active Consumers Performance According to Previous Events Using Decision Trees," *IFAC-PapersOnLine*, vol. 55, no. 9, pp. 297–302, 2022, doi: 10.1016/j.ifacol.2022.07.052.

[24] C. Silva, P. Faria, and Z. Vale, "DR Participants' Actual Response Prediction Using Artificial Neural Networks," in *17th International Conference on Soft Computing Models in Industrial and Environmental Applications (SOCO 2022)*, P. García Bringas, H. Pérez García, F. J. Martinez-de-Pison, J. R. Villar Flecha, A. Troncoso Lora, E. A. de la Cal, Á. Herrero, F. Martínez Álvarez, G. Psaila, H. Quintián, and E. S. Corchado Rodriguez, Eds., Cham: Springer Nature Switzerland, 2023, pp. 176–185.

[25] C. Silva, P. Faria, and Z. Vale, "Using Supervised Learning to Assign New Consumers to Demand Response Programs According to the Context," in *2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, IEEE, Jun. 2022, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope54979.2022.9854646.

[26] C. Silva, P. Faria, B. Canizes, and Z. Vale, "Real-Time Approach for Managing Power Network by Shifting Electricity Consumers Demand," in

2022 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), IEEE, Oct. 2022, pp. 1–5. doi: 10.1109/ISGT-Europe54678.2022.9960318.

[27] C. Silva, P. Campos, P. Faria, and Z. Vale, "Exploring Dataset Patterns for New Demand Response Participants Classification," in *PAAMS*,

[28] C. Cruz, E. Palomar, I. Bravo, and M. Aleixandre, "Behavioural patterns in aggregated demand response developments for communities targeting renewables," *Sustain Cities Soc*, vol. 72, p. 103001, Sep. 2021, doi: 10.1016/j.scs.2021.103001.

[29] B. Canizes, J. Soares, F. Lezama, C. Silva, Z. Vale, and J. M. Corchado, "Optimal expansion planning considering storage investment and seasonal effect of demand and renewable generation," *Renew Energy*, vol. 138, pp. 937–954, Aug. 2019, doi: 10.1016/j.renene.2019.02.006.

[30] J. M. Corchado and S. Trabelsi, "Advances in Sustainable Smart Cities and Territories," *Electronics (Basel)*, vol. 11, no. 8, p. 1280, Apr. 2022, doi: 10.3390/electronics11081280.

[31] D. Yu *et al.*, "Modeling and prioritizing dynamic demand response programs in the electricity markets," *Sustain Cities Soc*, vol. 53, p. 101921, Feb. 2020, doi: 10.1016/j.scs.2019.101921.

[32] J. Sang, H. Sun, and L. Kou, "Deep Reinforcement Learning Microgrid Optimization Strategy Considering Priority Flexible Demand Side," *Sensors*, vol. 22, no. 6, p. 2256, Mar. 2022, doi: 10.3390/s22062256.

[33] O. A. Paramo Rojas, J. C. Rivera, and G. A. Lopez Alvarez, "Effects on Electricity Markets of a Demand Response Model Based on Day Ahead Real Time Prices: Application to the Colombian Case," in *IEEE Latin America Transactions*, 2018, pp. 1416–1423. doi: 10.1109/TLA.2018.8408436.

[34] N. Mahmoudi, E. Heydarian-Forushani, M. Shafie-khah, T. K. Saha, M. E. H. Golshan, and P. Siano, "A bottom-up approach for demand response aggregators' participation in electricity markets," *Electric Power Systems Research*, vol. 143, pp. 121–129, 2017, doi: 10.1016/j.epsr.2016.08.038.

[35] L. de Vries and G. Doorman, "Valuing consumer flexibility in electricity market design," in *Variable Generation, Flexible Demand*, Elsevier, 2021, pp. 287–308. doi: 10.1016/b978-0-12-823810-3.00019-4.

[36] R. Rodríguez, M. Negrete-Pincetic, D. Olivares, Á. Lorca, and N. Figueroa, "The value of aggregators in local electricity markets: A game theory based comparative analysis," *Sustainable Energy, Grids and Networks*, vol. 27, p. 100498, Sep. 2021, doi: 10.1016/J.SEGAN.2021.100498.

[37] A. González-Briones, P. Chamoso, F. L. de Alba, and J. M. Corchado, "Smart Cities Energy Trading Platform Based on a Multi-agent Approach," 2022, pp. 131–146. doi: 10.1007/978-981-19-1434-8_7.

[38] C. Kok, J. Kazempour, and P. Pinson, "A DSO-Level Contract Market for Conditional Demand Response," in *2019 IEEE Milan PowerTech*, IEEE, Jun. 2019, pp. 1–6. doi: 10.1109/PTC.2019.8810943.

[39] C. of the E. U. European Parliament, "Regulation (EU) 2019/943 of the European Parliament and of the Council of 5 June 2019 on the internal market for electricity," 2019. Accessed: Dec. 04, 2020. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32019R0943

[40] W. Huang, N. Zhang, C. Kang, M. Li, and M. Huo, "From demand response to integrated demand response: review and prospect of research and application," *Protection and Control of Modern Power Systems*, vol. 4, no. 1, 2019, doi: 10.1186/s41601-019-0126-4.

[41] O. Abrishambaf, P. Faria, and Z. Vale, “Ramping of Demand Response Event with Deploying Distinct Programs by an Aggregator,” *Energies (Basel)*, vol. 13, no. 6, p. 1389, Mar. 2020, doi: 10.3390/en13061389.

[42] O. Abrishambaf, F. Lezama, P. Faria, and Z. Vale, “Towards transactive energy systems: An analysis on current trends,” *Energy Strategy Reviews*, vol. 26, p. 100418, Nov. 2019, doi: 10.1016/j.esr.2019.100418.

[43] M. Kühnbach, J. Stute, and A. L. Klingler, “Impacts of avalanche effects of price-optimized electric vehicle charging - Does demand response make it worse?,” *Energy Strategy Reviews*, vol. 34, p. 100608, 2021, doi: 10.1016/j.esr.2020.100608.

[44] A. Niromandfam, A. S. Yazdankhah, and R. Kazemzadeh, “Modeling demand response based on utility function considering wind profit maximization in the day-ahead market,” *J Clean Prod*, vol. 251, p. 119317, Apr. 2020, doi: 10.1016/j.jclepro.2019.119317.

[45] M. Kubli, M. Loock, and R. Wüstenhagen, “The flexible prosumer: Measuring the willingness to co-create distributed flexibility,” *Energy Policy*, vol. 114, pp. 540–548, Mar. 2018, doi: 10.1016/j.enpol.2017.12.044.

[46] M. Shafie-Khah, P. Siano, J. Aghaei, M. A. S. Masoum, F. Li, and J. P. S. Catalao, “Comprehensive Review of the Recent Advances in Industrial and Commercial DR,” *IEEE Trans Industr Inform*, vol. 15, no. 7, pp. 3757–3771, 2019, doi: 10.1109/TII.2019.2909276.

[47] N. G. Paterakis, O. Erdinç, and J. P. S. Catalão, “An overview of Demand Response: Key-elements and international experience,” *Renewable and Sustainable Energy Reviews*, vol. 69, pp. 871–891, Mar. 2017, doi: 10.1016/j.rser.2016.11.167.

[48] H. Pereira, R. Faia, L. Gomes, P. Faria, and Z. Vale, "Incentive-based and Price-based Demand Response to Prevent Congestion in Energy Communities," in *2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe)*, IEEE, Jun. 2022, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope54979.2022.9854648.

[49] S. R. K., L. K. Panwar, B. K. Panigrahi, and R. Kumar, "Computational Intelligence for Demand Response Exchange Considering Temporal Characteristics of Load Profile via Adaptive Fuzzy Inference System," *IEEE Trans Emerg Top Comput Intell*, vol. 2, no. 3, pp. 235–245,, doi: 10.1109/TETCI.2017.2739128.

[50] X. Wang, K. Li, X. Gao, F. Wang, and Z. Mi, "Customer Baseline Load Bias Estimation Method of Incentive-Based Demand Response Based on CONTROL Group Matching," in *2nd IEEE Conference on Energy Internet and Energy System Integration, EI2 2018 - Proceedings*, IEEE, Oct. 2018, pp. 1–6. doi: 10.1109/EI2.2018.8582122.

[51] F. Wang *et al.*, "Smart Households' Aggregated Capacity Forecasting for Load Aggregators Under Incentive-Based Demand Response Programs," *IEEE Trans Ind Appl*, vol. 56, no. 2, pp. 1086–1097, 2020, doi: 10.1109/TIA.2020.2966426.

[52] S. R. Konda, A. S. Al-Sumaiti, L. K. Panwar, B. K. Panigrahi, and R. Kumar, "Impact of Load Profile on Dynamic Interactions between Energy Markets: A Case Study of Power Exchange and Demand Response Exchange," *IEEE Trans Industr Inform*, vol. 15, no. 11, pp. 5855–5866, Nov. 2019, doi: 10.1109/TII.2019.2910349.

[53] J. Soares, J. Almeida, L. Gomes, B. Canizes, Z. Vale, and E. Neto, "Electric vehicles local flexibility strategies for congestion relief on distribution networks," *Energy Reports*, vol. 8, pp. 62–69, Jun. 2022, doi: 10.1016/j.egyr.2022.01.036.

[54] J. Kim, J. Lee, and J. K. Choi, "Joint Demand Response and Energy Trading for Electric Vehicles in Off-Grid System," *IEEE Access*, vol. 8, pp. 130576–130587, 2020, doi: 10.1109/ACCESS.2020.3009739.

[55] C. Silva, P. Faria, and Z. Vale, "Defining the Optimal Number of Demand Response Programs and Tariffs Using Clustering Methods," in *2019 20th International Conference on Intelligent System Application to Power Systems (ISAP)*, IEEE, Dec. 2019, pp. 1–6. doi: 10.1109/ISAP48318.2019.9065957.

[56] R. Mehmood, J. M. Corchado, and T. Yigitcanlar, "Developing Smartness in Emerging Environments and Applications with a Focus on the Internet of Things," *Sensors*, vol. 22, no. 22, p. 8939, Nov. 2022, doi: 10.3390/s22228939.

[57] H. Mortaji, S. H. Ow, M. Moghavvemi, and H. A. F. Almurib, "Load Shedding and Smart-Direct Load Control Using Internet of Things in Smart Grid Demand Response Management," *IEEE Trans Ind Appl*, vol. 53, no. 6, pp. 5155–5163, Nov. 2017, doi: 10.1109/TIA.2017.2740832.

[58] F. Arasteh and G. H. Riahy, "MPC-based approach for online demand side and storage system management in market based wind integrated power systems," *International Journal of Electrical Power and Energy Systems*, vol. 106, pp. 124–137, 2019, doi: 10.1016/j.ijepes.2018.09.041.

[59] H. Rashidizadeh-Kermani, M. Vahedipour-Dahraie, M. Shafie-khah, and J. P. S. Catalão, "Stochastic programming model for scheduling demand response aggregators considering uncertain market prices and demands,"

International Journal of Electrical Power and Energy Systems, vol. 113, no. June, pp. 528–538, Dec. 2019, doi: 10.1016/j.ijepes.2019.05.072.

[60] Z. Baum, R. R. Palatnik, O. Ayalon, D. Elmakis, and S. Frant, “Harnessing households to mitigate renewables intermittency in the smart grid,” *Renew Energy*, vol. 132, pp. 1216–1229, Mar. 2019, doi: 10.1016/j.renene.2018.08.073.

[61] Y. Yang, “Real-Time Disaggregation of User Power Consumption Using the Viterbi Algorithm,” in *2018 IEEE International Conference on Communications Workshops (ICC Workshops)*, IEEE, May 2018, pp. 1–6. doi: 10.1109/ICCW.2018.8403781.

[62] S. Dehghan-Dehnavi, M. Fotuhi-Firuzabad, M. Moeini-Aghtaie, P. Dehghanian, and F. Wang, “Decision-Making Tree Analysis for Industrial Load Classification in Demand Response Programs,” *IEEE Trans Ind Appl*, vol. 57, no. 1, pp. 26–35, Jan. 2021, doi: 10.1109/TIA.2020.3032932.

[63] G.-F. Fan, L.-Z. Zhang, M. Yu, W.-C. Hong, and S.-Q. Dong, “Applications of random forest in multivariable response surface for short-term load forecasting,” *International Journal of Electrical Power & Energy Systems*, vol. 139, p. 108073, Jul. 2022, doi: 10.1016/j.ijepes.2022.108073.

[64] A. Shirsat and W. Tang, “Identification of the Potential of Residential Demand Response Using Artificial Neural Networks,” in *2019 North American Power Symposium (NAPS)*, IEEE, Oct. 2019, pp. 1–6. doi: 10.1109/NAPS46351.2019.9000246.

[65] R. Lu, S. H. Hong, and M. Yu, “Demand Response for Home Energy Management Using Reinforcement Learning and Artificial Neural Network,” *IEEE Trans Smart Grid*, vol. 10, no. 6, pp. 6629–6639, 2019, doi: 10.1109/TSG.2019.2909266.

[66] M. Charwand, M. Gitizadeh, P. Siano, G. Chicco, and Z. Moshavash, "Clustering of electrical load patterns and time periods using uncertainty-based multi-level amplitude thresholding," *International Journal of Electrical Power and Energy Systems*, vol. 117, p. 105624, 2020, doi: 10.1016/j.ijepes.2019.105624.

[67] S. Reddy K., L. K. Panwar, B. K. Panigrahi, and R. Kumar, "Computational Intelligence for Demand Response Exchange Considering Temporal Characteristics of Load Profile via Adaptive Fuzzy Inference System," *IEEE Trans Emerg Top Comput Intell*, vol. 2, no. 3, pp. 235–245, Jun. 2018, doi: 10.1109/TETCI.2017.2739128.

[68] M. A. Z. Alvarez, K. Agbossou, A. Cardenas, S. Kelouwani, and L. Boulon, "Demand Response Strategy Applied to Residential Electric Water Heaters Using Dynamic Programming and K-Means Clustering," *IEEE Trans Sustain Energy*, vol. 11, no. 1, pp. 524–533, Jan. 2020, doi: 10.1109/TSTE.2019.2897288.

[69] J. Kang and S. Lee, "Data-Driven Prediction of Load Curtailment in Incentive-Based Demand Response System," *Energies (Basel)*, vol. 11, no. 11, p. 2905, Oct. 2018, doi: 10.3390/en11112905.

[70] Y. Li, Q. Hu, and N. Li, "Learning and Selecting the Right Customers for Reliability: A Multi-Armed Bandit Approach," in *2018 IEEE Conference on Decision and Control (CDC)*, IEEE, Dec. 2018, pp. 4869–4874. doi: 10.1109/CDC.2018.8619481.

[71] B. Zeng, G. Wu, J. Wang, J. Zhang, and M. Zeng, "Impact of behavior-driven demand response on supply adequacy in smart distribution systems," *Appl Energy*, vol. 202, pp. 125–137, Sep. 2017, doi: 10.1016/j.apenergy.2017.05.098.

[72] C. Silva, P. Faria, and Z. Vale, "A Consumer Trustworthiness Rate for Participation in Demand Response Programs," *IFAC-PapersOnLine*, vol. 53, no. 2, pp. 12596–12601, 2020, doi: 10.1016/j.ifacol.2020.12.1825.

[73] A. M. Carreiro, C. H. Antunes, and H. Jorge, "Assessing the robustness of solutions to a multi-objective model of an energy management system aggregator," in *2016 IEEE Symposium Series on Computational Intelligence (SSCI)*, 2016, pp. 1–6. doi: 10.1109/SSCI.2016.7849845.

[74] Ö. Okur, N. Voulis, P. Heijnen, and Z. Lukszo, "Aggregator-mediated demand response: Minimizing imbalances caused by uncertainty of solar generation," *Appl Energy*, vol. 247, no. October 2018, pp. 426–437, Aug. 2019, doi: 10.1016/j.apenergy.2019.04.035.

[75] M. Ghorbanian, S. H. Dolatabadi, and P. Siano, "Game Theory-Based Energy-Management Method Considering Autonomous Demand Response and Distributed Generation Interactions in Smart Distribution Systems," *IEEE Syst J*, vol. 15, no. 1, pp. 905–914, Mar. 2021, doi: 10.1109/JSYST.2020.2984730.

[76] H. A. Mostafa, R. El Shatshat, and M. M. A. Salama, "A correlated equilibrium game-theoretic approach for multiple participants electric distribution systems operation," *IEEE Trans Smart Grid*, vol. 7, no. 1, pp. 32–42, Jan. 2016, doi: 10.1109/TSG.2015.2440419.

[77] D. Ellman and Y. Xiao, "Customer Incentives for Gaming Demand Response Baselines," in *2019 IEEE 58th Conference on Decision and Control (CDC)*, 2019, pp. 5174–5179. doi: 10.1109/CDC40024.2019.9029860.

[78] A. Jamil *et al.*, "An Innovative Home Energy Management Model with Coordination among Appliances using Game Theory," *Sustainability*, vol. 11, no. 22, p. 6287, Nov. 2019, doi: 10.3390/su11226287.

[79] S. Misra, S. Bera, T. Ojha, H. T. Mouftah, and A. Anpalagan, “ENTRUST: Energy trading under uncertainty in smart grid systems,” *Computer Networks*, vol. 110, pp. 232–242, Dec. 2016, doi: 10.1016/j.comnet.2016.09.021.

[80] A. Talwariya, P. Singh, and M. Kolhe, “A stepwise power tariff model with game theory based on Monte-Carlo simulation and its applications for household, agricultural, commercial and industrial consumers,” *International Journal of Electrical Power & Energy Systems*, vol. 111, no. July 2018, pp. 14–24, Oct. 2019, doi: 10.1016/j.ijepes.2019.03.058.

[81] M. H. K. Tushar, A. W. Zeineddine, and C. Assi, “Demand-Side Management by Regulating Charging and Discharging of the EV, ESS, and Utilizing Renewable Energy,” *IEEE Trans Industr Inform*, vol. 14, no. 1, pp. 117–126, Jan. 2018, doi: 10.1109/TII.2017.2755465.

[82] S. J. Kim and G. B. Giannakis, “An Online Convex Optimization Approach to Real-Time Energy Pricing for Demand Response,” in *IEEE Transactions on Smart Grid*, 2017, pp. 2784–2793. doi: 10.1109/TSG.2016.2539948.

[83] A. Jamil, “An Innovative Home Energy Management Model with Coordination among Appliances using Game Theory,” *Sustainability*, vol. 11, no. 22, p. 6287, doi: 10.3390/su11226287.

[84] N. Guo, Y. Wang, and G. Yan, “A double-sided non-cooperative game in electricity market with demand response and parameterization of supply functions,” *International Journal of Electrical Power and Energy Systems*, vol. 126, p. 106565, Mar. 2021, doi: 10.1016/j.ijepes.2020.106565.

[85] I. Ilieva, B. Bremdal, and S. Puranik, “Bringing Business and Societal Impact Together in an Evolving Energy Sector,” *Journal of Clean Energy Technologies*, vol. 7, no. 3, pp. 42–48, 2019, doi: 10.18178/JOCET.2019.7.3.508.

[86] B.-G. Kim, Y. Zhang, M. Schaar, and J.-W. Lee, "Dynamic Pricing and Energy Consumption Scheduling With Reinforcement Learning," *IEEE Trans Smart Grid*, vol. 7, no. 5, pp. 2187–2198,, doi: 10.1109/TSG.2015.2495145.

[87] P. Siano and D. Sarno, "Assessing the benefits of residential demand response in a real time distribution energy market," *Appl Energy*, vol. 161, pp. 533–551, Jan. 2016, doi: 10.1016/j.apenergy.2015.10.017.

[88] H. Liang, J. Ma, R. Sun, and Y. Du, "A Data-Driven Approach for Targeting Residential Customers for Energy Efficiency Programs," *IEEE Trans Smart Grid*, vol. 11, no. 2, pp. 1229–1238, Mar. 2020, doi: 10.1109/TSG.2019.2933704.

[89] L. Sun, K. Zhou, and S. Yang, "An ensemble clustering based framework for household load profiling and driven factors identification," *Sustain Cities Soc*, vol. 53, p. 101958, Feb. 2020, doi: 10.1016/j.scs.2019.101958.

[90] M. Charwand, M. Gitizadeh, P. Siano, G. Chicco, and Z. Moshavash, "Clustering of electrical load patterns and time periods using uncertainty-based multi-level amplitude thresholding," *International Journal of Electrical Power & Energy Systems*, vol. 117, no. August 2019, p. 105624, May 2020, doi: 10.1016/j.ijepes.2019.105624.

[91] R. Lu and S. H. Hong, "Incentive-based demand response for smart grid with reinforcement learning and deep neural network," *Appl Energy*, vol. 236, no. August 2018, pp. 937–949, Feb. 2019, doi: 10.1016/j.apenergy.2018.12.061.

[92] T. Remani, E. A. Jasmin, and T. P. I. Ahamed, "Residential Load Scheduling with Renewable Generation in the Smart Grid: A Reinforcement Learning

Approach," *IEEE Syst J*, vol. 13, no. 3, pp. 3283–3294, Sep. 2019, doi: 10.1109/JSYST.2018.2855689.

[93] N. T. Mbungu, R. C. Bansal, R. Naidoo, V. Miranda, and M. Bipath, "An optimal energy management system for a commercial building with renewable energy generation under real-time electricity prices," *Sustain Cities Soc*, vol. 41, no. November 2017, pp. 392–404, Aug. 2018, doi: 10.1016/j.scs.2018.05.049.

[94] H. K. Nguyen, A. Khodaei, and Z. Han, "Incentive Mechanism Design for Integrated Microgrids in Peak Ramp Minimization Problem," *IEEE Trans Smart Grid*, vol. 9, no. 6, pp. 5774–5785, Nov. 2018, doi: 10.1109/TSG.2017.2696903.

[95] C. Silva, P. Faria, Z. Vale, J. M. Terras, and S. Albuquerque, "Rating the participation in Demand Response events with a contextual approach to improve accuracy of aggregated schedule," *Energy Reports*, vol. 8, pp. 8282–8300, Nov. 2022, doi: 10.1016/j.egyr.2022.06.060.

[96] C. Silva, P. Faria, and Z. Vale, "Rating the Participation of Electricity Consumers in Demand Response Events," *International Conference on the European Energy Market, EEM*, vol. 2020-September, Sep. 2020, doi: 10.1109/EEM49802.2020.9221907.

[97] C. Silva, P. Faria, and Z. Vale, "Defining the Optimal Number of Demand Response Programs and Tariffs Using Clustering Methods," *2019 20th International Conference on Intelligent System Application to Power Systems, ISAP 2019*, Dec. 2019, doi: 10.1109/ISAP48318.2019.9065957.

[98] C. Silva, P. Faria, and Z. Vale, "Aggregation of Prosumers in the Context of Demand Response and Distributed Generation Remuneration and Scheduling," in *2020 IEEE/PES Transmission and Distribution Conference and*

Exposition (T&D), IEEE, Oct. 2020, pp. 1–5. doi: 10.1109/TD39804.2020.9300003.

Appendix

Appendix A. Core Publications

Publication I

C. Silva, P. Faria, and Z. Vale, "Rating the Participation in Demand Response Programs for a More Accurate Aggregated Schedule of Consumers after Enrolment Period," Electronics (Basel), vol. 9, no. 2, p. 349, Feb. 2020 (2020 IF: 2.397)

Resumen

La agregación de consumidores de pequeño tamaño y unidades de Generación Distribuida (DG por sus siglas en inglés) tiene un impacto considerable para aprovechar todo el potencial de flexibilidad en el contexto de los programas de respuesta a la demanda. Se necesitan nuevos mecanismos de incentivos para remunerar adecuadamente a los consumidores y reconocer a aquellos que tienen una participación más confiable. Los autores proponen un enfoque innovador que se puede utilizar en la fase de operación para tratar la incertidumbre en los eventos de respuesta a la demanda, donde se solicita un objetivo específico para una comunidad energética gestionada por el Agregador. El contenido innovador se relaciona con asignar y actualizar una Tasa de Confiabilidad a cada consumidor según la respuesta real en una solicitud de reducción. Se han implementado y comparado tres métodos distintos. Las tasas iniciales se asignan según la participación en los eventos de respuesta a la demanda después de un mes del período de inscripción, y las que tienen una mayor confiabilidad siguen una programación realizada mediante optimización lineal. Los resultados demuestran que utilizando el enfoque propuesto, el administrador de la comunidad energética encuentra a los consumidores más confiables en cada período y se logra el objetivo de reducción en los eventos de respuesta a la demanda. Un algoritmo de agrupamiento es implementado para determinar la tasa final del consumidor para un mes considerando el valor del centroid.

electronics

Article

Rating the Participation in Demand Response Programs for a More Accurate Aggregated Schedule of Consumers after Enrolment Period

Cátia Silva [1,2], Pedro Faria [1,2,*] and Zita Vale [2]

[1] GECAD—Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, Rue Dr.Antonio Bernardino de Almeida 431, 4200-072 Porto, Portugal; cvcds@isep.ipp.pt
[2] Polytechnic of Porto, Rua Dr. Roberto Frias, 712 4200-465 Porto, Portugal; zav@isep.ipp.pt
* Correspondence: pnf@isep.ipp.pt; Tel.: +351-228-340-511; Fax: +351-228-321-159

Received: 1 January 2020; Accepted: 16 February 2020; Published: 19 February 2020

Abstract: Aggregation of small size consumers and Distributed Generation (DG) units have a considerable impact to catch the full flexibility potential, in the context of Demand Response programs. New incentive mechanisms are needed to remunerate consumers adequately and to recognize the ones that have more reliable participation. The authors propose an innovative approach to be used in the operation phase, to deal with the uncertainty to Demand Response events, where a certain target is requested for an energy community managed by the Aggregator. The innovative content deals with assigning and updating a Reliability Rate to each consumer according to the actual response in a reduction request. Three distinct methods have been implemented and compared. The initial rates assigned according to participation in the Demand Response events after one month of the enrolment period and the ones with higher reliability follow scheduling, performed using linear optimization. The results prove that using the proposed approach, the energy community manager finds the more reliable consumers in each period, and the reduction target achieved in DR events. A clustering algorithm is implemented to determine the final consumer rate for one month considering the centroid value.

Keywords: clustering; consumers; demand response; uncertainty

1. Introduction

The energy sector is facing challenges due to the need for more efficiency in energy usage. More reliable and efficient energy networks and markets are desired, empowering players, enabling bidirectional communication, and finding solutions to replace fossil fuels [1–3]. Demand Response (DR) concept is one of the main topics in the literature due to the potential benefits and to the search to overtake the barriers and achieve successful implementation in the energy market.

1.1. Background and Motivation

Directive 2019/944 [4] defines DR as "the change of electricity load by final customers from their normal or current consumption patterns in response to market signals, including in response to time-variable electricity prices or incentive payments, or in response to the acceptance of the final customer's bid to dell demand reduction or increase at a price in an organized market". This directive's primary goal will be finding a way to overcome existing obstacles to the completion of the internal electricity market. Directive 2003/54/EC and Directive 2009/72/EC contributed to the conception of the electricity market as it is currently but, with these new challenges coming from Smart Grids concept introduction, several updates must be done, namely regarding the consumers' role [5,6]. With Directive 2019/944, considering that to achieve the main goals with effectiveness, the innovation must be incentivized, and the flexibility compensated. Only after a fully functional energy market, the possibility of adding renewable energy to the actual grid, ready to deal with the uncertainties associated, can become a reality taking a new step to decarbonize the system.

Currently, and in the context of the work in this paper, the main stakeholders involved in the flexibility markets are Transmission System Operator (TSO), Distribution System Operators (DSO), Balance Responsible Parties (BRPs), Aggregator, and Retailer. TSO is responsible for the service and stability of the transmission system. Regarding DSO, it is the entity responsible for the operation of the distribution system and the power delivery to customers. The BRP role can be played by a market entity (such as wholesale supplier or retailer), or its chosen representative responsible, in charge of dealing with imbalances, paying penalties for deviations from energy schedules. Finally, the Retailer is an existing commercial entity selling electrical energy to consumers.

Regarding the role of the Aggregator in a local community, it depends on the market model. Still, this entity can operate in different parts of the network and use the associated resources for trading electricity and ancillary service markets. The Aggregator can also act as an intermediary for the transactions between small entities, such as consumers, and the wholesale market so it is the entity that accumulates flexibility through renewable-based generation and consumers (through DR), as Figure 1 presents. In the present paper, the Aggregator acts as a Local Energy Community (LEC) manager. In [7], LEC is defined as "*an association, a cooperative, a partnership, a non-profit organization or other legal entity which is effectively controlled by local shareholders or members, generally, value- rather than profit-driven, involved in distributed generation and performing activities of a distribution system operator, supplier or aggregator at local level, including across borders*". Many benefits were previewed from this concept, namely regarding the relationship between the DSO and the communities: DSO is now allowed to manage some of the difficulties associated with the local generation (e.g., by controlling local flexibility resources) which could drastically reduce the network costs.

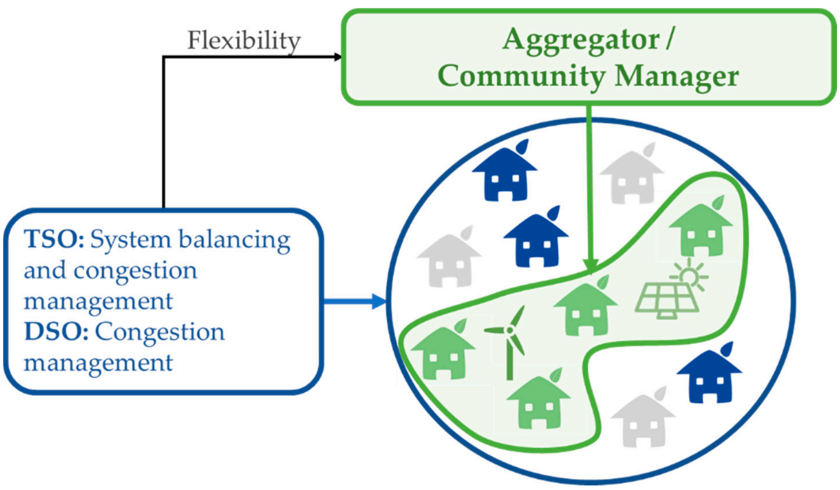


Figure 1. The simplified interaction between different entities.

The consumers' role in this market, although currently less explored and with increasing value, becomes crucial to achieving the required level of flexibility to adjust the current network to recognize a distributed, renewable, and volatile generation [8,9]. Currently, consumers do not have the right tools to access information about their consumption, in real-time or near to real-time, to actively participate in the energy market. Still, consumers are more conscious and worried with climate issues; aware of their capabilities as an active role; searching for the investment in Distributed Generation (DG), for instance in their houses; finding mechanisms to consume in a more clean, efficient, and economical way through DR [10,11].

Therefore, the creation of new players and business models developed to deal with this "new type" of players must exist, considering that not all the consumers have the same behaviour causing uncertainties to the management of the market. Services that produce benefits to only a particular group of the population may bring negative results. In this way, the consumers' characterization and behaviour study is crucial. The referred challenges are the primary motivation for the present work. As already mentioned, being the Aggregator of the entity capable of managing a local energy community, providing the right tools to be successful. However, this entity must have reliable information about the resources to decide which one should participate in the eventuality of a DR event to avoid imbalances. The goal is to create a tool able to answer questions such as: Should the Aggregator rely on all the consumers in the community? If not, is it possible to differentiate them? How? When in a DR event, the consumers who reduce accordingly should they compensate differently? And those who do not answer?

The authors of the present paper designed a methodology that deals with the uncertainty of the small resources, focusing on the consumers with the assignment of a Reliability Rate to optimally manage the local community in cases of DR events. Previous works [12–14] already proposed a business model to help Aggregators, although the doubt associated with the actual response of the consumers was never considered. The action described in the paper is relevant to the operation being a simulation of a real-time reaction by the resources to DR events and how the Aggregator should manage the uncertainties associated.

1.2. Related Literature

The related literature presents distinct approaches to solve the scheduling problem when dealing with the introduction of demand-side in the energy market and how the load diagram can influence network reliability. Muhsen et al. [15] proposed a multi-objective optimization differential evolution method to solve the load scheduling problem in terms of cost and energy saving, creating a set of optimal solutions. Ilo et al. [16] considered a holistic power system architecture that gathers the relevant components in a single structure focusing on the decarbonization of the sector cost-effectively while guaranteeing data privacy and safety against external threats. Li, Dou, and Xu [17] used a firefly optimization algorithm to solve the scheduling problem of a distribution network. The simulation, prediction of the load, travel chain of electric vehicles, and different charging methods were considered to establish a predictive model, and the establishment of demand response sideload. Khalid et al. [18] presented a pricing model to delineate the rates for on-peak and shoulder-peak hours having the goal of charging a per-unit price—taking into account the consumed energy and the extra generation cost. Faria and Vale [19] proposed a method to minimize the operation costs, where the virtual power player manages DR programs and respects the consumption shifting constraints making a comparison between the advantages of DR use and DG. Proving the benefits of DR in the operation of distributed energy resources, namely when considering the lack of supply. Hu, Lu, and Chen [20] formulated a stochastic multi-objective Nash–Cournot competition model to simulate DR in an uncertain energy market. The authors considered that DR programs can reduce peak energy consumption, energy price, and carbon dioxide emissions. The lack of studies connecting the uncertainty and the actual response of the consumer in the scheduling is visible. However, these works prove the increasing influence of this new player in the transactions of the energy market.

The comprehension of the consumer's behaviour is a significant study as their decision power is higher, and they may become the focal point of this sector. Nicholas Good [21] presented research on the suitability of behavioural economics as an approach for modelling demand response. This author reminds us that most of the studies shaped under the demand response topic assume that the end-user is always rational and an active economic agent. In this way, its concluded from this study that centrally coordinated actions may produce the best results since consumers are willing to collaborate and sacrifice thermal comfort without compensation to achieve a common objective—secure operation of the local electricity network. Ruiz et al. [22] contradicting the previous conclusion, presented a bottom-up approach based on physical end-use load models. These authors study the individual responses of combining a random sample of customers building an aggregated load Demand Response model by performing a simulation of the different reactions with an optimization algorithm based on mixed-integer linear programming. It proved that minimizing the electricity bill occurs while maintaining the consumer's comfort level. The results from this study show that the higher the incentive offered by the Aggregator (disagreeing with [21] which believed in the insignificance of compensation for this kind of discomfort), obtain higher load reductions with this approach. Both [21,22] agree, as well as the authors of the present paper that consumers must be willing to participate in the DSM programs. They must also allow the application of more restrictive control actions, over their controllable appliances, although this implies higher losses on their comfort level. However, the authors of the present paper consider it essential to compensate them, incentivizing continuous participation in the management of the local community.

There is a necessity to find techniques to incentivize and support the participation of the small resources to decrease the uncertainty associated with them. Monfared and Ghasemi [23] proposed a value-based hourly pricing approach, concluding that the value of the electricity is not the same to end-users depending on the benefits for each consumer. The objective of the proposed methodology was to improve the effectiveness of price-based Demand Response programs implemented in a smart distribution network. Jiang et al. [24] developed a method to deal with performance and efficiency uncertainties from distributed energy resources. These authors formulate a scenario-based two-stage algorithm to solve the problem, preserving the multiple risks in the entire decision-making process. Khan et al. [25] designed a knowledge-based system for short-term load forecasting where the precision is improved by a different priority index to select similar days.

1.3. Innovations and Contributions

The proposed methodology provides innovative contributions in the field of consumers' response uncertainty, which is a complicated matter. With the novel approach proposed, after the enrolment period, the Aggregator will be able to identify and schedule reliable consumers to participate in DR events, increasing the accuracy and dealing with the doubt. The main goal of the present paper is to provide essential means and knowledge to the entity that manages the LEC to be successful in DR implementation and use. It is critical to understand what extent each consumer can contribute to DR and be more reliable, in each period of the day. In this way, the community manager can appropriately reward the consumer for the discomfort caused by DR events. The following features are listed as innovative aspects of the methodology proposed in the present paper:

- Consider the consumer behaviour from past DR events, during a full month period as the enrolment period;
- Categorize the consumers according to their actual response;
- Remunerate the consumers according to their actual response;
- DR events with DR targets for the community being essential to understand in which consumers the Aggregator can rely on to achieve the goals;
- Collaboration between members of the community regarding local balance, highlighting the importance of the role of the prosumer and the influence of prioritizing the local generation to suppress the demand;
- Comparison between the requested reduction and the actual reduction when on DR event, being a crucial factor to increase or decrease the reliability rate;
- Interactions from the consumers' side to improve the reliability rate, either through higher reductions or with lower tariffs;
- Incentives, through remuneration, according to the reliability rate group inserted;
- Identify the monthly reliability rate of a consumer.

According to the actual response for DR events, in different temporal ranges, a reliability rate is assigned to each consumer. This rate was calculated through three independent rates. The way of using the reliability rate through the proposed methodology depends on three methods: Basic Rate Method, Cost Rate Method, and Clustering Rate Method.

After this introduction, Section 1 presents several related works and the comparison with the proposed methodology detailed in Section 2—Materials and Methods, as well as the case study. Section 3 presents the scenarios selected, the results obtained by the application of the proposed approach to show the feasibility of the methodology and the respective discussion. Finally, Section 4 brings the conclusions from this study.

2. Materials and Methods

The authors implemented a methodology that gives the Aggregator, as the entity that manages the energy community, a tool to optimally manage the resources associated and have some knowledge about their reliability when participating in DR events. With this, Figure 1 shows the proposed methodology. Presenting three approaches—Basic Rate Method, Cost Rate Method, and Clustering Rate Method, and each one deals with the uncertainty of the consumer differently. These methods are applied per DR event and can be used in different contexts, namely different seasons, as the consumers' behaviours change through the year.

In the Basic Rate Method, the selection phase considers only consumers with values higher than the nominated minimum for scheduling, i.e., for example in Figure 2 consumers with more than three "stars", were represented as green faces, chosen to participate in DR event. The initial reliability rate considers two independent rates: Historical Rate (HR) and the Last Day Rate (LDR). The first one takes into account past information from the consumer. The second considers the reliability rate assigned to the consumer in the same period of the previous day. The Aggregator schedules its resources considering a DR target for this community. After, a comparison is made between the actual response and the requested one. In the hypothesis of not achieving the DR target in a first schedule, a re-schedule considering the remaining consumers with DR contracts is performed, allowing their reliability rate to increase by participating in the management of the local community.

The update of the final reliability rate of each consumer considers more than one independent rate related to the actual response. Although Cut-Rate (CR) has some percentage in the formulation, a higher reduction than the requested may not be enough to increase their rate. The other two, HR and LDR, have also weight in the formulation of the final reliability rate of a consumer to control the rate change speed.

In the case of the Cost Rate Method, a feature is added when updating the final reliability rate: The price also fluctuates. The entire process is similar to the primary method but introduces a new strategy for the consumer. They can change their reliability prices to increase their rates. In other words, when each group of resources is called to participate in a DR event, the ones with lower prices are selected (considering minimization of operational costs regarding the Aggregator). If the actual response surpasses the expectations, the possibilities of increasing the final reliability rate arises. The third and final approach is formulated based on clustering: The idea is to compare with the Basic Rate Method. Let's call it the Clustering Rate Method. Mainly, the consumers are also classified by reliability rate and only the ones with a higher rate will be considered in the scheduling. However, an adaptation is considered using clustering: Only the consumers with higher values of contracted reduction are considered for the first scheduling. That is, each rate will be clustered, and the group with the higher sum of pledged reduction follows to the next phase. The remaining process stays the same.

Regarding the scheduling phase, a linear optimization is performed to minimize operation cost from the perspective of Aggregator. The scheduling input needs several parameters, and it is the responsibility of the Aggregator to gather them all to schedule all the associated resources successfully. Information such as the maximum capacity of the DG units, the external suppliers, and the reduction capacity of the consumers belonging to DR programs, as well as the consumption tariffs associated with each resource is needed. The authors considered the existence of two types of external suppliers: Regular and additional.

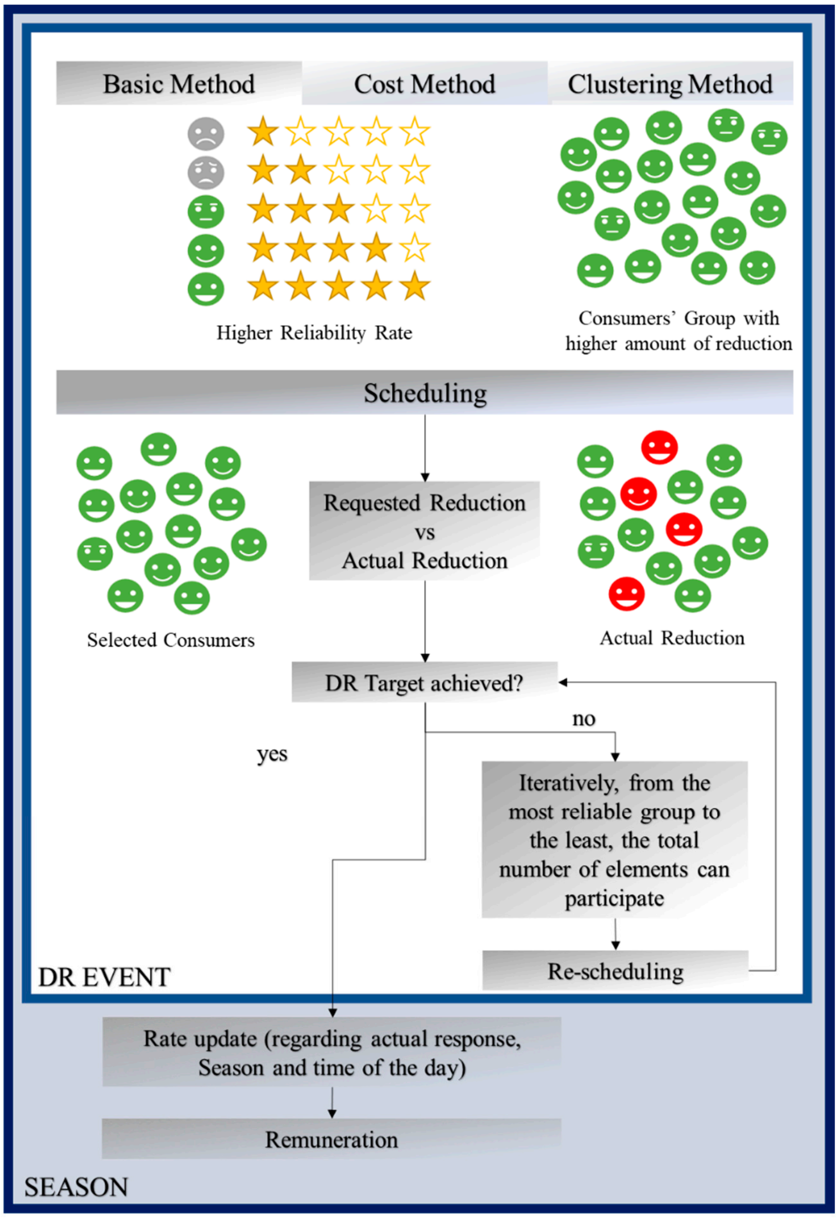


Figure 2. Proposed methodology.

Equation (1) introduces the objective function of the problem:

$$Min\ OS = \sum [P_{DG}(p,t)\, C_{DG}(p,t)] + \sum [P_{IDR}(c,t)\, C_{IDR}(c,t)] + \sum [P_{SUPA}(sa,t)\, C_{SUPA}(sa,t)] + \sum [P_{SUPR}(sr,t)\, C_{SUPR}(sr,t)] + P_{NSP}(t)\, C_{NSP}(t) \quad (1)$$

The optimal scheduling is done for each period t and the different resources in the local community such as DG units (P_{DG}), consumers belonging to DR programs (P_{IDR}) and suppliers, both regular (P_{SUPR}) and additional (P_{SUPA}) are considered. The external suppliers are only applied in the case of DG units that were not able to suppress the total amount of consumption to achieve the network balance, as presented in Equation (2):

$$\sum [P^{initial}(c,t) - P_{IDR}(c,t)] = \sum [P_{DG}(p,t)] + \sum [P_{SUPA}(sa,t)] + \sum [P_{SUPR}(sr,t)] + P_{NSP}(t) \quad (2)$$

This equation is essential and a complex problem for the network operators. The goal is to maintain the value of Non-Supplied Power (NSP)—the amount of demand not satisfied, null proving that the network is being optimally managed. In this way, several options to fulfil the demand ($P^{initial}$) requests are available: DG units and external suppliers are also included in the production side, and DR events are also considered.

Other restrictions were added to the presented optimization: Regarding the consumers who participate in DR events Equation (3) and Equation (4) control, their participation and Equation (5) and Equation (6) defines the DR target for the community. When compared with previous works from the authors, Equations (4)–(6) are an innovation.

The proposed method, as shown in Figure 2, includes a possible rescheduling with all the consumers in the impossibility of the actual response from the selected were not enough to achieve the DR target in the first stage. Giving this, the ones chosen in the scheduling should maintain the requested reduction—considered as the new ${P_{IDR}}^{Min}$ in Equation (4), and only be added to the difference needed being the value of the first scheduling considered as $DRtarget^{min}$ in Equation (6):

$$P_{IDR}\ (c,t) \leq {P_{IDR}}^{Max}\ (c,t) \tag{3}$$

$$P_{IDR}\ (c,t) \geq {P_{IDR}}^{Min}\ (c,t) \tag{4}$$

$$\sum [P_{IDR}\ (c,t)] \leq DRtarget^{Max}\ (c,t) \tag{5}$$

$$\sum [P_{IDR}\ (c,t)] \geq DRtarget^{Min}\ (c,t) \tag{6}$$

Regarding the distributed generation resources in the local community, they are restricted by Equations (7)–(9). Equation (7) represents the upper bound, considering the maximum capacity and Equation (8) the lower bound. The lower bound was considered for specific cases such as type wind units, which must be constrained by the resulting power from the cut-in and cut-out wind. Equation (9) gives the Aggregator more control when using the generation, restricting the amount that can be used. A similar tactic used for external suppliers:

$$P_{DG}\ (p,t) \leq {P_{DG}}^{Max}\ (p,t) \tag{7}$$

$$P_{DG}\ (p,t) \geq {P_{DG}}^{Min}\ (p,t) \tag{8}$$

$$\sum [P_{DG}\ (p,t)] \leq {P_{DG}}^{Total}\ (p,t) \tag{9}$$

The constraints related to external suppliers are presented from Equation (10) to Equation (13). The upper bound is established by Equation (10) for additional suppliers and Equation (12) for regular suppliers. Equation (11) and Equation (13), as in DG units, restrict the total amount of generation from this source:

$$P_{SUPA}\ (sa,t) \leq P_{SUPA}\ (sa,t) \tag{10}$$

$$\sum [P_{SUPA}\ (sa,t)] \leq P_{SUPA}\ (t) \tag{11}$$

$$P_{SUPR}\ (sr,t) \leq P_{SUPR}\ (sr,t) \tag{12}$$

$$\sum [P_{SUPR}\ (sr,t) \leq P_{SUPR}\ (t) \tag{13}$$

After DR target is achieved for the DR event, there is the update of the reliability rate and the remuneration for the participants. The remuneration is considered as an incentive and done according to tariffs existing in the same reliability rate. For the three methods, the reliability rate update is the same: Considering HR, LDR, and CR in the formulation. However, for the Cost Rate Method, the consumers that were not selected for the DR event can change their cost in DR events to be selected.

As soon as the three approaches are compared, a final study is done. The authors propose to find the proper reliability rate per consumer per month, using a clustering method. The task of the clustering object is created from the need of the human to define prominent attributes and identify them as a type. Therefore, several disciplines use this method—from mathematics to biology, the goal is the same: Establishing categories for the objects and assigning individuals to the proper groups within it [26]. In this way, the selected method for the first study is a well-known partitioning clustering method: K-means. The algorithm consists in finding, iteratively, the value that represents each group—centroid. The centroid element is found when the distance between itself and the remaining is minimal. Several techniques are applied to calculate the gap, namely Euclidean distance. The results for one month will be considered, and the consumers will be represented by one reliability rate only.

The proposed methodology was studied resorting to a database formed by a real distribution network, with ten random local communities and a total of 20,310 consumers from five different types classified as Domestic, Small Commerce, Medium Commerce, Large Commerce, and Industrial. Although the consumers are the focus of this work, for the scheduling phase, the generation units were also considered in this study, highlighting Distributed Generation (DG) units, namely Small Hydro, Waste-to-energy, Wind, Photovoltaic, Biomass, Fuel Cell, and Co-generation. Table 1 presents the characterization of all consumers and generation units in the ten local communities.

Table 1. Small resources characterization in the ten communities.

CONSUMPTION					
Type	**Domestic**	**Small Commerce**	**Medium Commerce**	**Large Commerce**	**Industrial**
# elements	10,168	9828	82	85	147
Energy (kWh)	9369.35	7983.35	11,254.75	10,880.48	23,142.48
Max Load Reduction (kW)	4684.7	3991.7	15,756.7	9792.4	20,828.2
Initial Price (m.u./kWh)	0.12	0.18	0.20	0.19	0.15

GENERATION							
Type	**Small Hydro**	**Waste-to-Energy**	**Wind**	**Photovoltaic**	**Biomass**	**Fuel Cell**	**CHP**
# elements	25	7	254	208	25	13	16
Energy (kWh)	214.05	53.10	5866.09	7061.28	2826.57	2457.60	6910.10
Tariff (m.u./kWh)	0.0961	0.0900	0.0988	0.2889	0.1206	0.0945	0.0975

One month of information was considered for the present study. The whole database, consumption, and generation are divided into periods of 15 min, so a day has 96 periods where the first one is at 12 am and 96 is at 12 pm. The chosen historical information used for the creation of scenarios was April 2018. In this way, the database has 2880 periods.

The present study focuses on the reliability of each consumer when requested to participate in DR events. The Aggregator of the local community has DR targets according to the period of the day, and it is expected that consumers with higher reliability rate answer as requested. In the present scenarios, it was considered a DR target of 100 kW for each type of event.

For the three proposed methods, the techniques to calculate the initial and final reliability rate is different and can influence other variables—namely in the Cost Rate Method where the consumers change their cost to be considered in the scheduling. Both initial and final reliability rates have a value between 1 and 5. They are dependent on the consumers' performances in DR events for different periods where independent rates were attributed as Table 2. A Historical Rate (HR) to past information with more than one day; the Previous Day Result Rate in the same period (LDR), and the Actual Reduction Rate for the studied period (CR).

Table 2. Independent rates weights.

	HR	**CR**	**LDR**
Initial	0.4	-	0.6
Final	0.33	0.33	0.33

According to the stage of the method, the weights of these independent rates in the formation of the reliability rate are different. In this way, Table 2 presents the masses considered in the present case study.

3. Results and Discussion

The current section shows a comparison between three methods and the analysis done to understand the behaviour of the consumers over a month regarding the uncertainty of their participation in the management of the community.

Considering 96 periods in a day, to perform scheduling for one period, the solving time for the community as a whole is overly high to be used in a real-time situation, not considering the remaining process. Giving this, the authors opt for presenting the study only for one community: The one with a higher reliability rate, being this one the centre of the case study. In this way, Table 3 presents a survey of the average rate found in the communities and the one with higher value was considered.

Table 3. Average rates from the local communities.

Community	1	2	3	4	5	6	7	8	9	10
Number of Elements	2501	658	3480	406	4982	1598	398	3789	1509	989
Average Rate	2.97	3.03	2.99	3.10	3.01	3.03	2.94	3.01	3.00	2.98

Section 3 is subdivided into five subsections. Firstly, the results from each method which represent three subsections. After, a study of Consumer Reliability Rate Identification for the Month—k-means—where a clustering method is used to assign a reliability month rate for each consumer. Finally, a survey on Reliability Rates over different seasons. The steps taken in the first three subsections are presented in Table 4, as well as the criteria used to compare them. Moreover, in the same table, there is a correspondence between the subsections and the steps taken to clarify the structure of the present section.

Table 4. Study steps and criteria to compare the three methods.

<table>
<tr><th></th><th>Basic Rate Method (Section 3.1)</th><th>Cost Rate Method (Section 3.2)</th><th>Clustering Rate Method (Section 3.3)</th></tr>
<tr><td>Consumer Selection by Initial Rate (Sub-section 3.X.1.)</td><td>Rate ≥ 3</td><td>Rate ≥ 3</td><td>Rate ≥ 3
and
The group with higher reduction according to the clustering method</td></tr>
<tr><td>Scheduling and Re-Scheduling (Sub-section 3.X.2)</td><td colspan="3">Until achieving the target in a DR event
(comparison between how quick the goal can be achieved by understanding the quality of the selected samples—the more reliable consumers)</td></tr>
<tr><td>Rate Update (Sub-section 3.X.3)</td><td>Actual reduction vs. Requested Reduction</td><td>Actual reduction vs. Requested Reduction
and
Cost Update</td><td>Actual reduction vs. Requested Reduction</td></tr>
<tr><td>Remuneration (Sub-section 3.X.3)</td><td colspan="3">Maximum tariff per rate
(final minimum reward in the perspective of the Aggregator)</td></tr>
</table>

In the analysis of the results from the three methods, there are three parts. The first one, Initial Rate, the initial number of elements per period and per group is presented. The Scheduling and Re-scheduling Results, showing the requested and the actual reduction through the month. Finally, Rate Update and Remuneration, where the final reliability rates and the remuneration are presented analyzing per period.

3.1. Basic Rate Method

The Basic Rate Method consists of only selecting the higher reliability rate consumers to the scheduling. Regarding the update of the final reliability rate for each period, considering the three independent rates and the cost associated with the DR events is not revised. Since it is the first method to be analyzed, a more detailed view of the results is done. As mentioned, April 2018 was selected, and the DR events are exhibited in Table 5. As can be seen, two types of events are considered: Event 1 is between 11 am–12 am, and Event 2 is between 6 pm and 7 pm. The frequency of each occurrence in this month is five, having been performed ten events in this study.

Table 5. DR (Demand Response) events.

Day	Event 1 (11:00–12:00)	Event 2 (18:00–19:00)
Sunday, 1	x	-
Thursday, 4	x	-
Saturday, 7	x	-
Tuesday, 10	-	x
Friday, 13	-	x
Monday, 16	-	x
Thursday, 19	x	-
Sunday, 22	-	x
Wednesday, 25	-	x
Saturday, 28	x	-

3.1.1. Initial Reliability Rate

The Initial Reliability Rate considers the HR and the LDR, finding that Day 1 does not have LDR, and the Initial Reliability Rate is equal to the HR. Figure 3 shows the number of elements per group in each event day. Each event has four periods—15 min each.

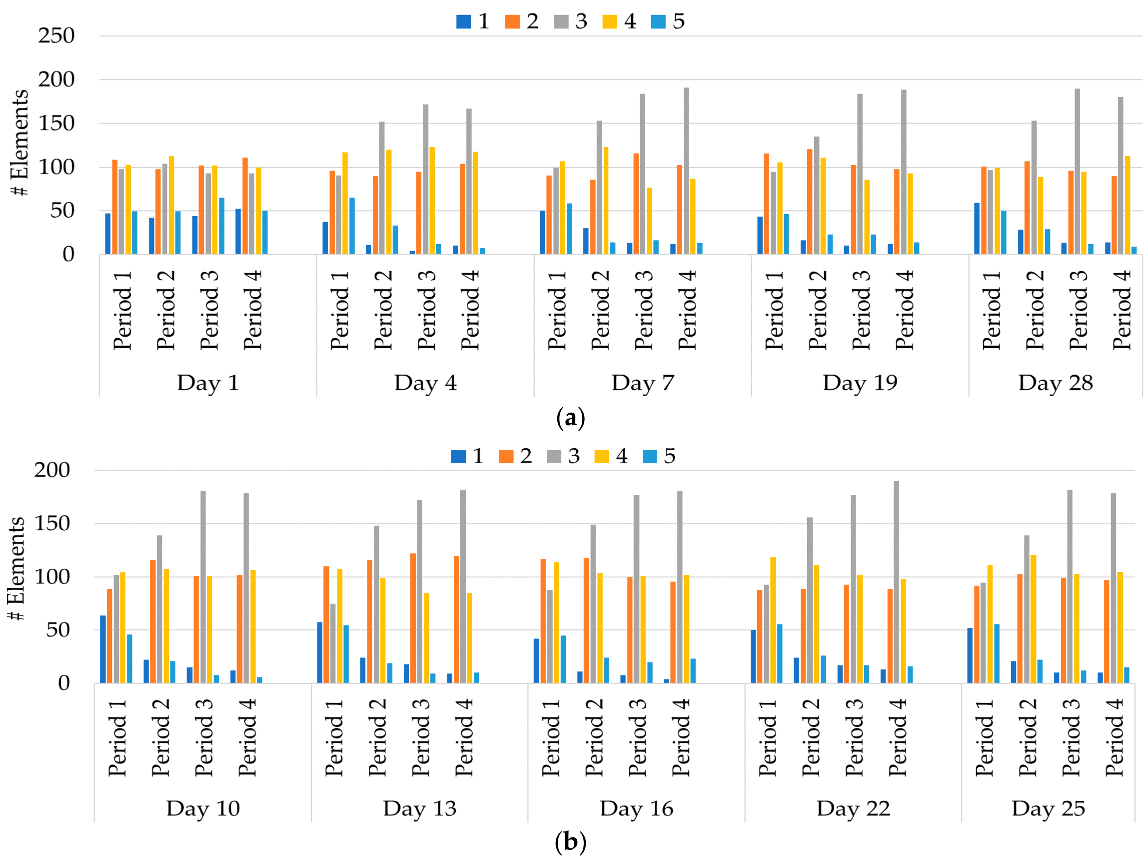


Figure 3. Number of elements per Reliability Rate group considering the Initial Rate being: (**a**) DR event 1; (**b**) DR event 2.

Initially, on the first day of the month, a DR event between 11 am and 12 am happened. For the DR event, in Period 1 only 250 were able to participate; for Period 2 the value increased to 266; for Period 3 and Period 4 the value decreased to 260 and 243, respectively.

For the following days, the actual response in the previous day was impacted by LDR.

Day 4 also had an event between 11 am and 12 am. The Reliability Rate 4 had the highest number of elements in all the periods, counting with 167 in the last one. In this second day of Event 1, more consumers were able to participate: In Period 1 the total was 273, Period 2 was 305, Period 3 was 307 and, finally, Period 4 was the one with the lower number of elements, 292.

On Day 7, Event 1 also occurred. The number of consumers able to participate in Period 1 was 265; in Period 2 were 290; in Period 3 decreased to 277, and in the final period of the event 291 consumers were able to participate. On the third day of Event 1, Reliability Rate 3 had the highest number of elements over time.

On Day 10, the DR event occurred between 6 pm and 7 pm. For the first event of this genre, the HR was the only rate considered in this Initial Rate. For Period 1, there were 253 elements capable of participating in the scheduling; in Period 2, 15 elements were added; Period 3 increased to 22 elements and, finally, for Period 4 the number of elements reached 292.

Day 13 had an Event 2, similar to the previous day. The number of elements in Reliability Rate 1 decreased from 58 to 9 at the end of the DR event. Reliability Rate 2 increased ten elements comparing the initial and the final period. Reliability Rate 3 doubled the number of elements. Regarding Reliability Rate 4 elements, it decreased the number of elements from 108 to 85. Reliability Rate 5 also had a relative decrease in the number of elements comparing the beginning and the end of the event (−82%). Day 16 was also one of the Event 2 days. The third event of this type counted with 247 consumers in the first period of the event, 277 in the second, 298 in the third, and 306 in the final.

Regarding Day 19 from the study month, an event between 11 am and 12 am occurred, being the fourth of Event 1 type. At the beginning of the event, 247 consumers were available to participate. For the following periods, this number increased to 22, 46, and 49 elements.

The final two events from type 2 happened on Day 22 and Day 25. The number of elements increased over time for both situations, with 304 and 299 elements, respectively, being able to participate at the end of the event.

The last event of the studied month was type 1, as can be seen in Table 4. Both Reliability Rate 1 and Reliability Rate 5 decreased the number of elements over time, meaning that consumers' rates were updated to the groups in-between. In this case, the Reliability Rate 3 had the highest number of elements in the final period of the event, and through Event 1 it was possible to notice the impact from the last day in the number of elements per period. In Period 1, when comparing the number of elements in the first day of this type of event with the last one, the total of elements able to participate decreased by 1.60%. Regarding Period 2, the number of elements increased by 1.8%. For Period 3, the impact was higher than the previous ones, increasing by 14.23%. However, Period 4 was the one with a more significant difference (24.28%).

Now, Event 2 had a distinct outcome since the percentual difference between the number of elements in the first day of this type of event (per period) and with the last one did not reach 5% in all periods. Comparing with the other occasion, maybe this period of the day brings more discomfort to the consumers and less are willing to reduce their consumption.

3.1.2. Scheduling and Re-Scheduling Results

In this subsection, the results from the scheduling of the local community according to the method are presented. This method considers that all consumers with reliability rates above the nominated minimum are convoked. Still, the proposed optimization will decide which of those are selected to achieve the DR target for the events. Figure 4 shows the initial load curve for the event days (darker colour) and the values of the DR target (medium colour) and actual reduction (lighter colour) from each period. A more comprehensive chart of the DR event is also presented. Moreover, different colours were applied to ease the distinction between the type of events: One is green, and two is blue.

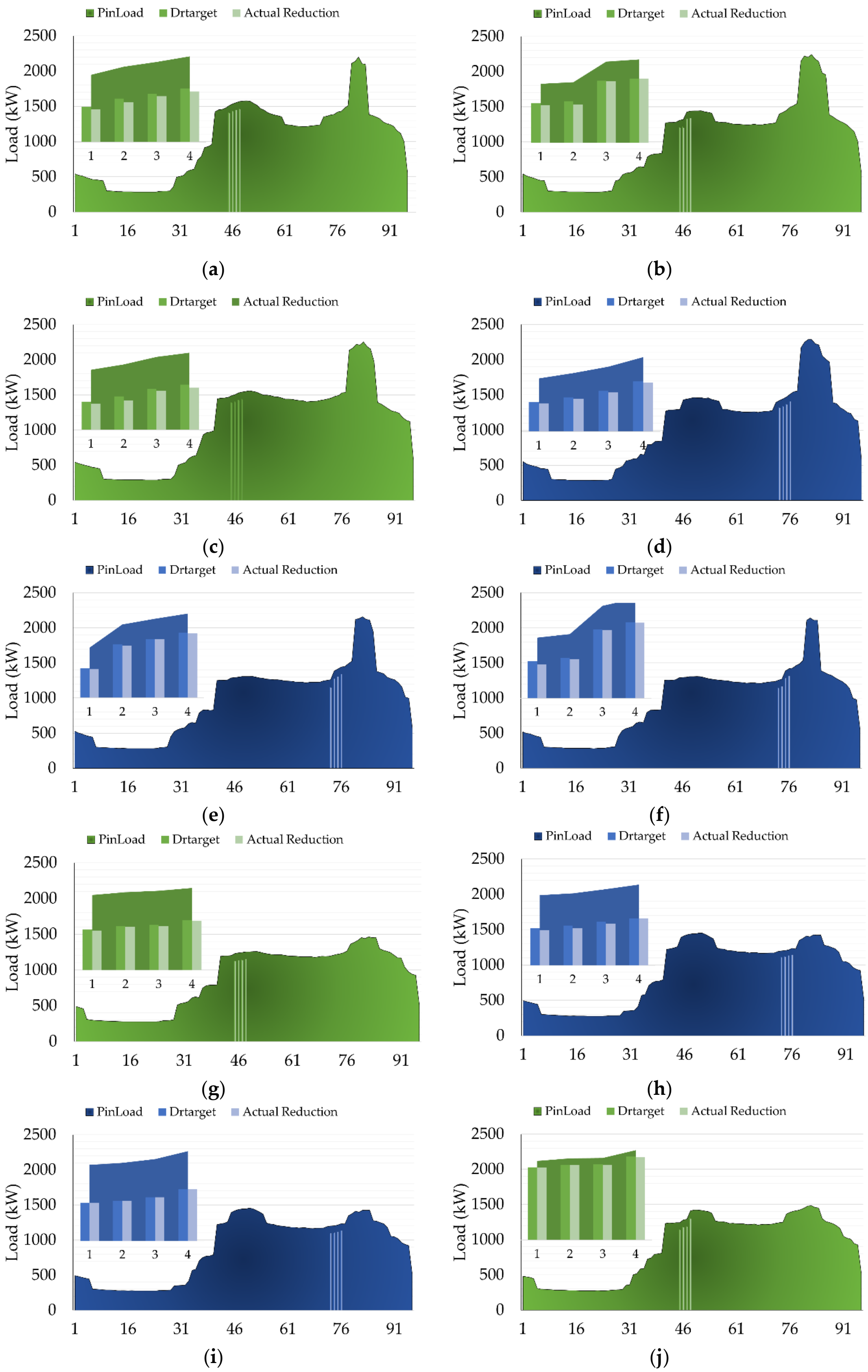


Figure 4. Scheduling results for: (**a**) Day 1, Event 1; (**b**) Day 4, Event 1; (**c**) Day 7, Event 1; (**d**) Day 10, Event 2; (**e**) Day 13, Event 2; (**f**) Day 16, Event 2; (**g**) Day 19, Event 1; (**h**) Day 22, Event 2; (**i**) Day 25, Event 2; (**j**) Day 28, Event 1.

In the Day 1 period of the DR event, the initial load floated between 1510 and 1568 kW, with the DR target of 100 kW being achieved in all the events: Period 1 with 1402 kW; Period 2 with 1425 kW; Period 3 with 1444 kW, and Period 4 with 1459 kW. For Day 4, the initial load curve had a more significant difference between the initial and the final period of the event (1309 and 1437 kW). The actual reduction was always above the DR target—highlighting Period 1 and Period 2, where this value was more than 10 kW higher than the expected. In Day 7, the actual reduction was also above the target passing the load curve from 1489 to 1382 kW in Period 1; from 1506 to 1392 kW in Period 2; from 1529 to 1423 kW in Period 3, and from 1542 to 1432 kW in Period 4.

Between 6 pm and 7 pm on Day 10, the initial load curve increased from 1423 to 1511 kW. In this event, the DR target is achieved, and the maximum actual reduction reached 8 kW higher than the expected. Regarding Day 13, the initial load curve, at the beginning of the event had, for Period 1, 1263 kW and reached 1151 kW with the actual reduction. Regarding Period 2, decreased from 1385 to 1274 kW; Period 3 started with 1415 kW and finished with 1308 kW and, finally, for Period 4 the actual reduction were reduced from 1442 to 1339 kW. As can be seen in Figure 4f, the DR target was achieved in all periods of the event for Day 16—the maximum reduction that was completed in the first period of the event decreased the initial load from 1254 to 1142 kW.

Day 19 returns to the type 1 DR event, with the DR target being also accomplished. For Period 1 the initial load was 1232 kW, and 110 kW were reduced; Period 2 started with 1240 kW and were reduced to 106 kW; Period 3 initially had 1245 kW where 110 kW were reduced; in Period 4, 101 kW were reduced from 1254 kW.

Day 22 and Day 25 had the same type of event (1), and the actual reduction was higher than the DR, not reaching 10 kW higher than the denominated value of DR target.

The last Event 2, Day 28, the actual reduction for Period 1 was 106 kW; for Period 2 was 104 kW; for Period 3 was 107, and for Period 4 was 111 kW.

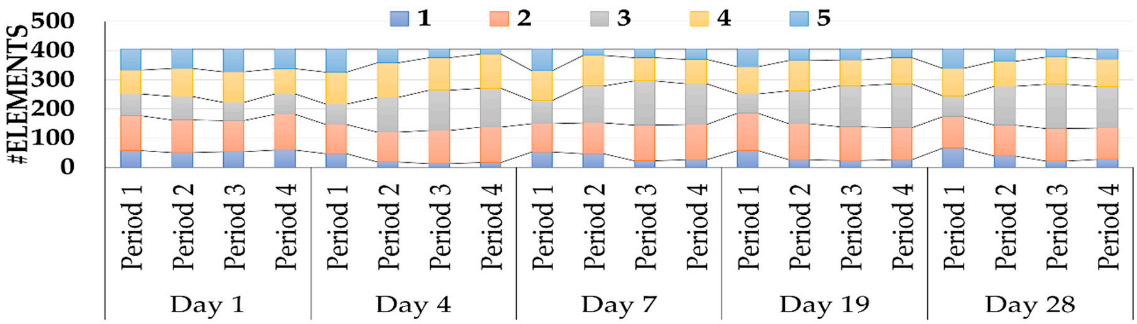
Through this stage of the study and with Method 1, the Aggregator was able to select the proper consumers initially—the ones able to reduce the DR target in the Scheduling phase being not needed to resort to a Re-scheduling in the following days: Day 13, Day 16, Day 28 resorted to Re-scheduling in Period 2 and Period 4. For Day 1 and Day 19, the opposite situation happened (Re-scheduling for Period 1 and Period 3). In Day 4, Day 22, and Day 25, the Scheduling was enough to achieve the DR target for Period 3, Period 2, and Period 4, respectively. Day 7 was the only one where all the periods from the DR event needed a Re-scheduling. In total, the Re-scheduling step was required 25 times.

3.1.3. Rate Update and Remuneration

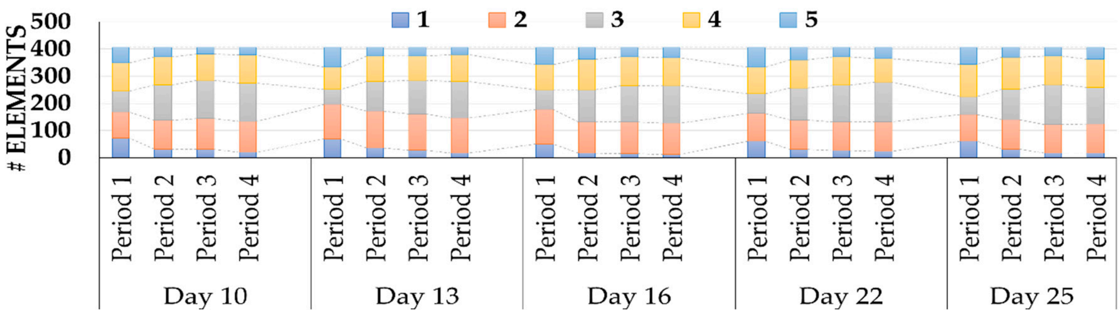
Figure 5 presents the accumulated number of elements in each group per period and day to the two events.

According to the actual response of each consumer, the reliability rate is updated to the final reliability rate of the current period. This rate is considered as LDR for the following day. Additionally with of this value, the Remuneration Rate is found for each Reliability Rate group—regarded as the maximum value detected in each group. When comparing with the results in Figure 3, where the initial number of elements per Reliability Rate was presented, for Event 1, the group with a higher difference was Reliability Rate 3—the number of elements reduced for all the DR event periods when comparing. The second group with the lower number of elements was Reliability Rate 4. For Reliability Rate 1 and Reliability Rate 2, the number of elements floated but always above the initial value. Regarding Reliability Rate 5, the highest difference record achieved an increase of 288.89% from the initial value: Day 28, Period 4—started with nine elements and finished with 35.

Applying the same analysis to the results from Figure 5b, similar conclusions can retreat: Reliability Rate 3 was the one where the frequency of negative percentages (lower number of elements than initial) was higher, followed by Reliability Rate 4. The Reliability Rate 1 and Reliability Rate 2 had increased their number of elements most of the time. The Reliability Rate 5 also had the highest increase—366.67%, on Day 10, Period 4 – started with six elements and finished with 28.



(**a**)



(**b**)

Figure 5. Number of elements per Reliability Rate group considering the final rate being: (**a**) DR event 1; (**b**) DR event 2.

Having the updated rates, Table 6 introduces the remuneration values per period, day and event, and the number of consumers' needs for each period to achieve the DR target (# is the number of elements).

Table 6. Remuneration.

	Day	Period 1		Period 2		Period 3		Period 4		Total Day
		(m.u.)	#	(m.u.)	#	(m.u.)	#	(m.u.)	#	
Event 1	1	27.64	73	28.30	71	27.32	70	28.02	68	111.28
	4	28.33	50	28.84	60	25.06	58	25.39	53	107.62
	7	27.19	73	28.02	72	26.86	70	27.87	71	109.94
	19	28.05	75	27.11	71	27.95	70	24.91	68	108.02
	28	27.00	72	25.83	72	26.59	69	27.17	67	106.59
Total Period		138.21	-	138.10	-	133.78	-	133.36	-	543.45
	Day	Period 1		Period 2		Period 3		Period 4		Total Day
		(m.u.)	#	(m.u.)	#	(m.u.)	#	(m.u.)	#	
Event 2	10	27.13	61	27.05	60	25.87	70	27.20	73	107.25
	13	26.98	73	26.63	73	25.57	58	23.85	60	103.03
	16	26.88	68	25.26	67	24.54	65	24.30	64	100.98
	22	26.44	70	26.16	69	25.84	72	25.28	82	103.72
	25	25.09	69	25.39	75	24.94	75	25.76	74	101.18
Total Period		132.52	-	130.49	-	126.76	-	126.39	-	516.16

According to the total remuneration per period, Period 4 is the one where the Aggregator spends less in the compensation of the participants in the management of the community, for both events. The total remuneration for Event 1 was higher than Event 2 because, in 14 of this event periods, the value of actual reduction was much higher than the DR event (considering values below 105 kW acceptable).

3.2. Cost Rate Method

The Cost Rate Method is a variant from the Basic Rate Method. The consumers that were not able to increase their Reliability Rate may decrease their DR event cost to be selected by the optimization in the Scheduling phase of the next period for the following DR event. As mentioned, this method and the following will not have the same detailed explanation and analysis of the Basic Rate Method.

3.2.1. Initial Reliability Rate

Figure 6 introduces the initial number of elements in a Reliability Rate group per day and period. The assumptions from Basic Rate Method for this phase are now applied: The initial reliability rate considers the HR and the LDR. Moreover, the first day of each event does not have an LDR so, only HR is applied. By analyzing Figure 6a, one of the points that stand out is the reduction of the number of elements from Reliability Rate 5 through the days until it reaches a null value. This fact will have a massive impact on the performance of this method—considering that only the elements with reliability rates above the denominated minimum can join the scheduling phase. If the consumers with Reliability Rate 3 and Reliability Rate 4 do not have enough reduction power available, a Re-scheduling stage will be needed to achieve the DR target. Another highlight is the fact that the number of elements from Reliability Rate 2 highly increased overtime. When comparing the number of elements in the first day of this type of event with the last one, the total of elements able to participate in Period 1 decreased by 1.60%. Regarding Period 2, the number of elements increased by 1.88%. The difference for Period 3 was the highest being −49.62% from the initial value of participants. The amount of Period 4 was also high, being −34.98%.

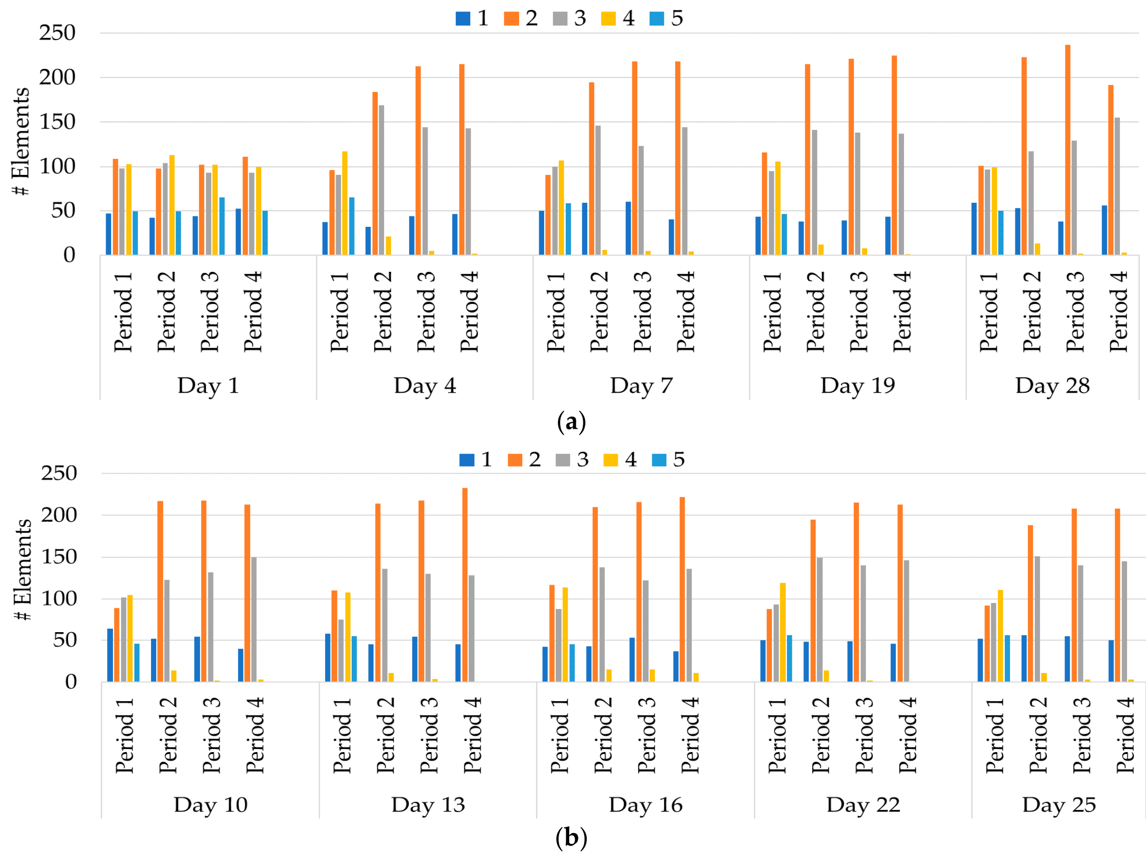


Figure 6. Number of elements per Reliability Rate group considering the initial rate being: (**a**) DR event 1; (**b**) DR event 2.

About Event 2, the reduction of elements for Reliability Rate 5 started right on the first day of the event, unlike Event 1. Giving this, the effect in the comparison between the number of elements in the first day with the last one was not so impactful. From Period 1 to 3, the number of elements floated but always increased. Period 4, instead, decreased by 3.27%.

3.2.2. Scheduling and Re-Scheduling Results

Due to space limitations in this paper, the results are not shown for this method. Anyway, it has been computed, and the rate update and remuneration are given in the next sub-section.

According to Figure 2, when the method that selected the consumers were not able to achieve the DR event in the Scheduling, one or several Re-scheduling must be done. In this case, a maximum of five more iterations was needed to accomplish the DR target. On Day 16 and Day 25, the first two periods were able to meet the goal in the Scheduling. For Day 7, Day 10, Day 13, Day 19, Day 22, only in Period 1 the objective was achieved with a Scheduling. In total, the Re-Scheduling step was needed 31 times.

3.2.3. Rate Update and Remuneration

Figure 7 shows the accumulated number of elements for each Reliability Rate group per period, per day, and event. The missing Reliability Rate 5 for both events can be easily noticed.

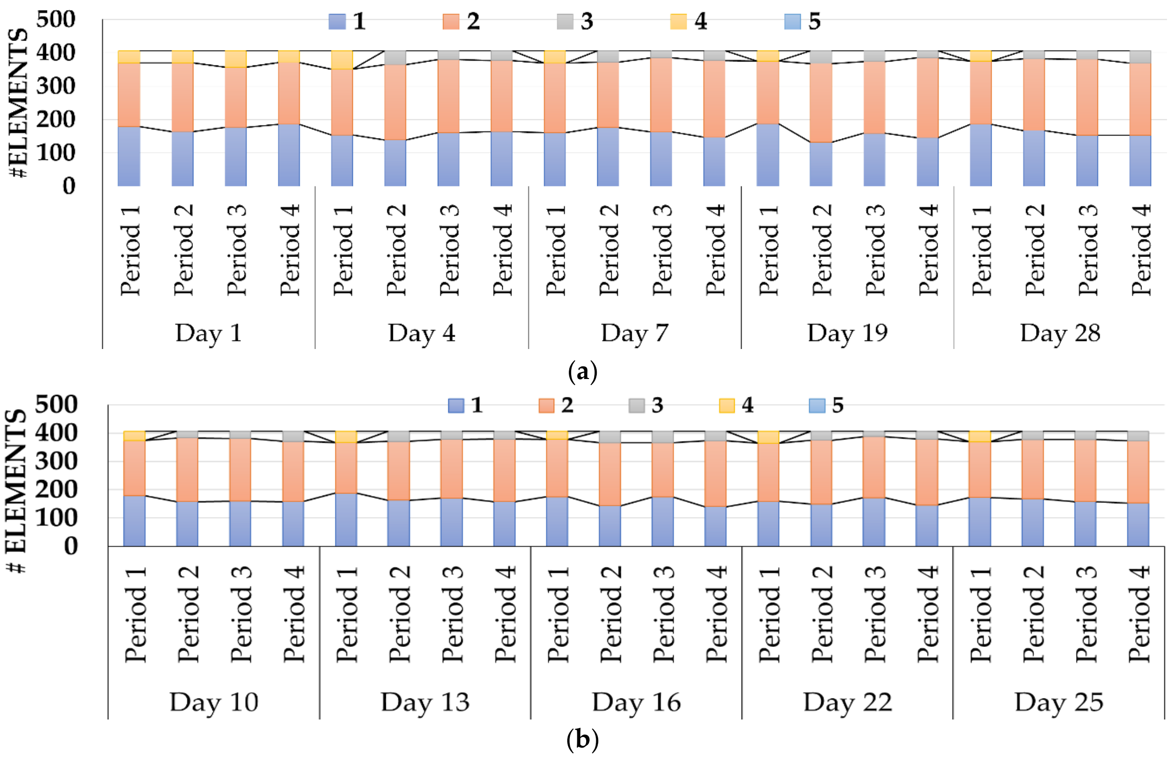


Figure 7. Number of elements per Reliability Rate regarding final rate: (**a**) DR event 1; (**b**) DR event 2.

The formula used to update the reliability rate of each consumer is the same as the Basic Rate Method but, the variant is presented here since the cost from the DR event can be updated according to the reliability rate. In Figure 7a, Reliability Rate 1 was the one with a higher increase of elements when comparing with Figure 6a—starting from +183.33% to +320.93%. Reliability Rate 2 was the other one where this percentage was maintained above 0%. The remaining saw their number of elements reduced. Regarding Figure 7b, the scenario is similar for all days: In the first period, Reliability Rate 4 still had some elements but, over time, tended to null. In this way, the final reliability rate resumed into three groups. The remuneration provided by the Aggregator to the participants and the number of participants per event is in Table 7. The period with a lower value was Period 3 for both events.

Table 7. Remuneration.

	Day	Period 1		Period 2		Period 3		Period 4		Total Day
		(m.u.)	#	(m.u.)	#	(m.u.)	#	(m.u.)	#	
Event 1	1	27.51	73	28.26	71	28.01	70	26.94	68	110.72
	4	28.00	50	27.03	64	25.55	56	27.95	49	108.53
	7	28.30	73	25.67	33	25.48	53	26.93	41	106.38
	19	27.31	75	26.57	30	26.62	44	28.81	38	109.31
	28	28.31	72	27.98	35	26.05	41	28.33	42	110.67
Total Period		139.43	-	135.51	-	131.71	-	138.96	-	545.61
	Day	**Period 1 (m.u.)**		**Period 2 (m.u.)**		**Period 3 (m.u.)**		**Period 4 (m.u.)**		**Total Day**
Event 2	10	25.60	69	25.78	39	25.59	47	25.81	52	102.78
	13	25.85	73	25.04	38	25.82	48	23.96	45	100.67
	16	25.99	68	25.06	52	25.69	48	23.98	59	100.72
	22	24.92	70	23.95	64	24.40	79	25.44	57	98.71
	25	25.58	69	25.87	52	23.96	46	26.56	55	101.97
Total Period		127.94	-	125.7	-	125.46	-	125.75	-	504.85

Regarding the total remuneration per day, the lower value in Event 1 was on Day 7 with 106.38 m.u. and for Event 2 was Day 22 with 98.71 m.u. When comparing Table 7 with Table 6, along with results from the remuneration of the Basic Rate Method, the number of elements needed to achieve the DR target is generally less.

3.3. Clustering Method

The Clustering Method is another variant from the Basic Rate Method. On the contrary to the Cost Rate Method, the final cost stays the same. The only difference is the technique for participant selection—a clustering method is used to split each reliability rate into groups. The one with the higher accumulated reduction from each reliability rate is selected, and all the elements are selected.

3.3.1. Initial Reliability Rate

The logic for the Initial Reliability Rate calculation is the same as previous methods, only the selection of the consumers to participate in DR events is different. In this way, the HR and the LDR are considered except on the first day of each event. Figure 8 introduces the number of elements per Reliability Rate, for each day and per period. It is also separated by type of event. The number of elements that could participate in the management of the community in the first event of type 1, for Period 1 was 250 being reduced by 1.60% by the last day. In Period 2, a little increase was noticed (1.88%) being the Reliability Rate 3 the group with more elements. For Period 3 and Period 4, the number of elements able to be selected increased by 15.77% and 27.16%, respectively.

Forward to Event 2 results in Figure 8b, Period 1 had an increase of 3.56% in the number of elements above the denominated minimum. For Period 2, the number of elements increase was the same as Event 1. Period 3 had the higher growth of elements in this event and to this comparison being 3.041%. Period 4 was the only one with a reduction, where the number of elements able to participate reduced by 0.03%.

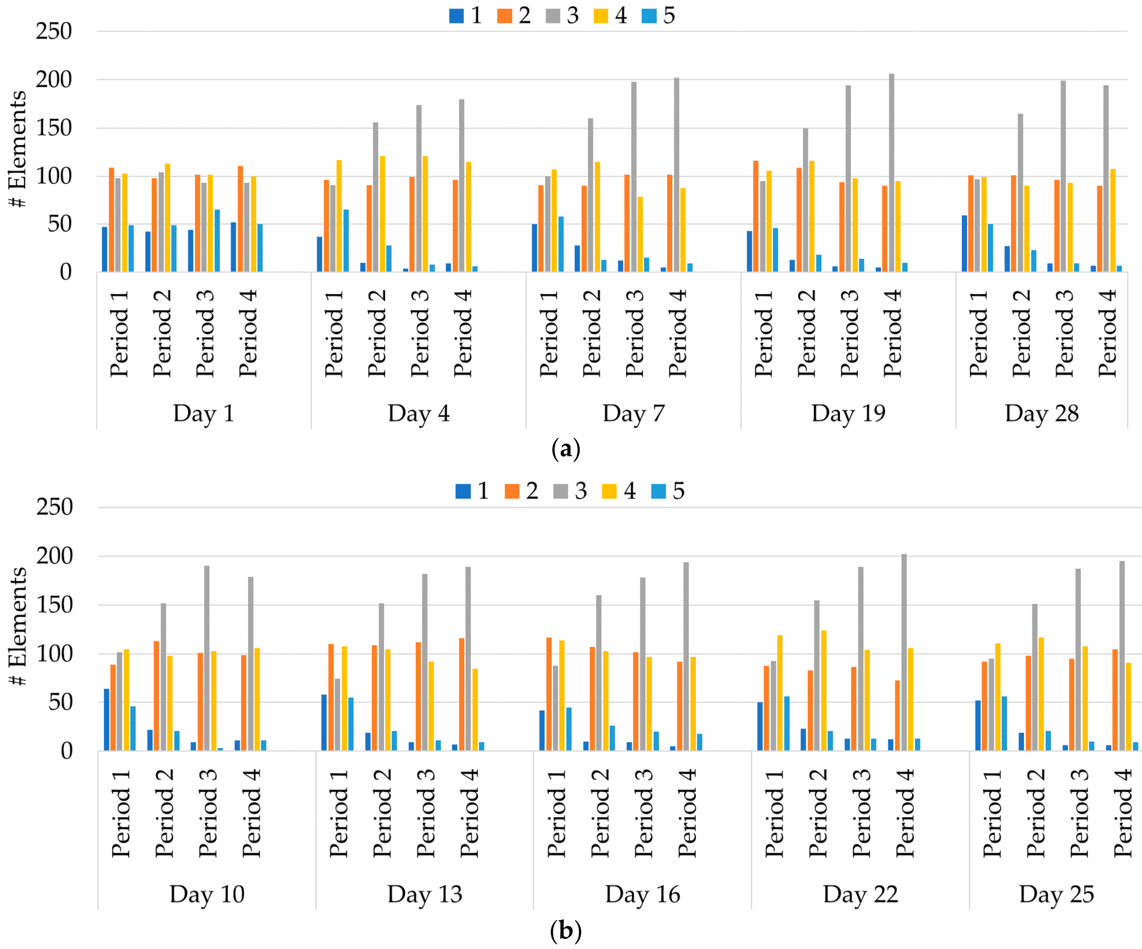


Figure 8. Number of elements per Reliability Rate group considering the initial rate being: (**a**) DR event 1; (**b**) DR event 2.

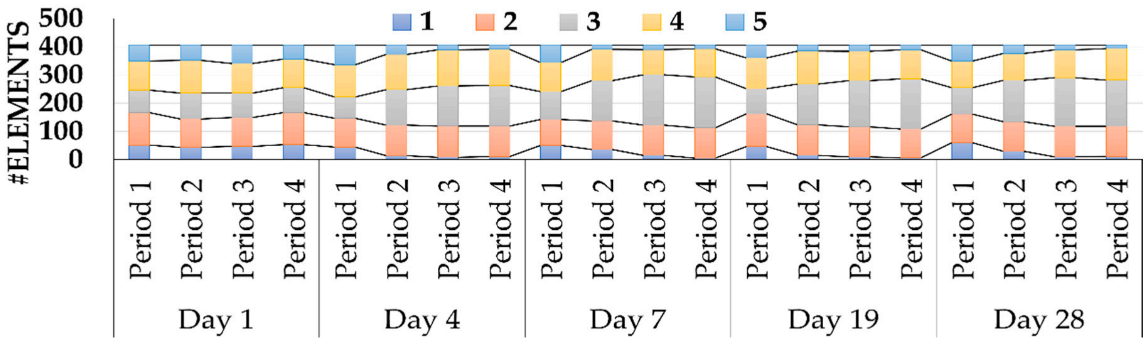
3.3.2. Scheduling and Re-Scheduling Results

The clustering method was applied to each Reliability Rate group above three, and the selected consumers were able to participate in the Scheduling. The days where a Re-scheduling was needed for only one period in the DR event were Day 1, Day 10, and Day 13. Day 4 and Day 16 were the only days where the DR target was achieved with Scheduling in one period, and the remaining needed another iteration. On Day 7, Period 1 and Period 5 went to Re-scheduling. On Day 19 and Day 25, Period 1 and Period 2 went to Re-scheduling. On Day 22, Period 2 and Period 3 went to Re-scheduling. In total, the Re-scheduling step was needed 18 times, the lowest value from the three methods.

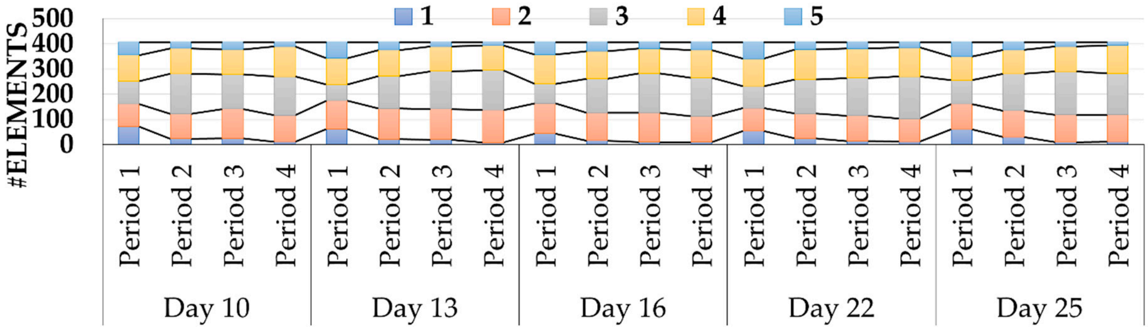
3.3.3. Rate Update and Remuneration

With the results from the Scheduling phase, it is possible to revise the Reliability Rate. The Clustering Method has the same formula and weights as the Basic Rate Method, and no DR event costs are changed. In this way, Figure 9 shows the results from this update. Reliability Rate 3 was the one that suffered more changes negatively, since, in all periods of Event 1, the number of elements reduced when compared with the initial value. Reliability Rate 5 was the one with a higher sum of elements when compared with the initial number; however, the maximum number of elements was never higher than 70, as well as Reliability Rate 1. In this way, most elements are concentrated between Reliability Rate 2 and Reliability Rate 4. Regarding Event 2, the picture is similar: Reliability Rate 1 and Reliability Rate 5 with fewer elements, having the last one the higher increase in Day 10, Period

3 passing from 3 to 28 elements. Over periods, regarding Reliability Rate 5, the tendency seems to increase the percentage of elements.



(**a**)



(**b**)

Figure 9. Number of elements per Reliability Rate regarding final rate: (**a**) DR event 1; (**b**) DR event 2.

Forwarding to the remuneration of the participants, Table 8 presents the compensation values and the number of elements needed to achieve the DR event target. For the analysis of Event 1, the most expensive period was the first one. Still, over time the value reduced being the last one the cheapest from the perspective of the Aggregator—also, fewer members were needed to achieve the target.

Table 8. Remuneration.

	Day	**Period 1**		**Period 2**		**Period 3**		**Period 4**		**Total Day**
		(m.u.)	**#**	**(m.u.)**	**#**	**(m.u.)**	**#**	**(m.u.)**	**#**	
Event 1	1	27.85	52	32.60	23	29.57	15	25.61	28	115.63
	4	31.16	28	28.00	28	26.27	25	27.29	22	112.72
	7	32.67	9	29.24	19	29.79	15	25.99	11	117.69
	19	30.93	9	29.21	9	25.67	31	26.98	24	112.79
	28	26.07	12	26.79	24	24.50	20	28.82	22	106.18
Total Period		148.68		145.84		135.80		134.69	-	565.01
Event 2	10	28.28	20	25.58	22	25.68	74	25.63	14	105.17
	13	24.03	31	24.03	32	24.06	28	25.53	17	97.65
	16	24.25	30	28.67	33	25.40	32	25.82	39	104.14
	22	24.93	34	24.02	30	24.75	43	24.59	17	98.29
	25	24.07	35	24.02	31	27.44	27	23.99	26	99.52
Total Period		125.56	-	126.32	-	127.33	-	125.56	-	504.77

In Event 2, the final remuneration per period was around 125 m.u., the lowest value achieved in both Period 1 and Period 4. This event was also the cheapest to the Aggregator (in days: 504.77 m.u.).

3.4. Consumer Reliability Rate Identification for Month—k-Means

A clustering method was used to identify a Month Reliability Rate to each consumer. This approach was already applied for Clustering Rate Method. The idea is to study the centroid value to assign proper rates according to the performance of that consumer over the entire month, for both events. In this way, per consumer, a monthly curve per event was designed, and the rate was designated with the maximum value found in the mentioned curve.

Figure 10 presents the total elements per Reliability Rate. The three methods were compared, and the groups with null values were hidden. Considering that the Basic Rate Method is Method 1, Cost Rate Method is Method 2, and the Clustering Rate Method is Method 3. Starting with Method 1, Figure 10a finds the more significant number of elements between Reliability Rate 3 and Reliability Rate 4 with a total of 394 elements. The other 12 elements were attributed to Reliability Rate 2 and Reliability Rate 5.

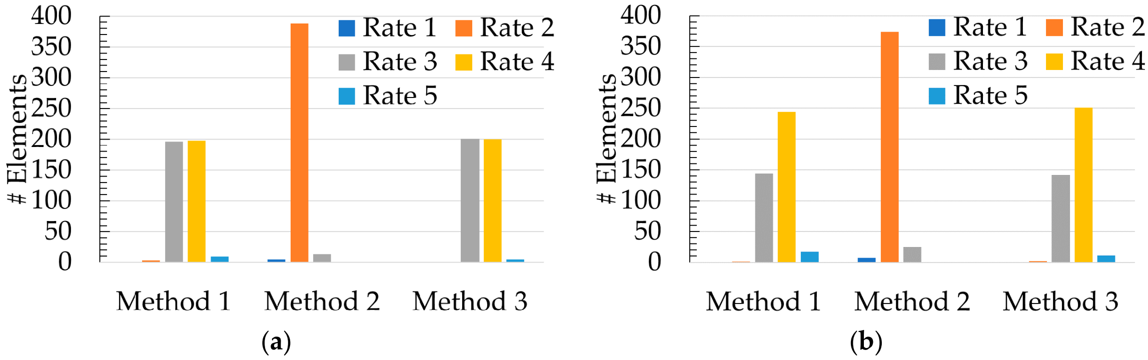


Figure 10. The number of elements per Reliability Rate over a month, being (**a**) DR event 1; (**b**) DR event 2.

The results from Figure 10b are similar, although Reliability Rate 4 has more elements this time: 244 elements. Moreover, Reliability Rate 4 increased the number of elements. Method 2 has the highest number of elements in Reliability Rate 2 for both events: Event 1 with 388 and Event 2 with 374. The remaining consumers were attributed to Reliability Rate 1 and Reliability Rate 3. Finally, Method 3 results were similar to Method 1. In Figure 10a, most consumers are centered between Reliability Rate 3 and Reliability Rate 4, where the remaining were assigned to the higher reliability rate. Regarding Figure 10b, Reliability Rate 4 has 251 elements when comparing with the 142 of Reliability Rate 3. The missing 13 were assigned to Reliability Rate 2 and Reliability Rate 5. To justify these results and understand the behaviour of some consumers the following Tables 9–11 present the results from five selected consumers for Method 1, Method 2, and Method 3, respectively.

Table 9. Final Reliability Rate from selected consumers when using Method 1.

Consumer ID	Final Month Rate		Reliability Rate 1	Reliability Rate 2	Reliability Rate 3	Reliability Rate 4	Reliability Rate 5
	Event 1	Event 2					
41	4.40 (4)	4.00 (4)	8	12	2	3	15
119	3.20 (3)	3.00 (3)	0	12	18	10	0
162	4.00 (4)	4.00 (4)	1	6	17	13	3
232	3.00 (3)	4.20 (4)	7	14	6	6	7
356	3.40 (3)	3.00 (3)	6	9	14	11	0

Table 10. Final Reliability Rate from selected consumers when using Method 2.

Consumer ID	Final Month Rate		Reliability Rate 1	Reliability Rate 2	Reliability Rate 3	Reliability Rate 4	Reliability Rate 5
	Event 1	Event 2					
41	1.80 (2)	2.00 (2)	16	24	0	0	0
119	2.00 (2)	1.80 (2)	16	20	4	0	0
162	2.00 (2)	2.40 (2)	11	25	2	2	0
232	1.60 (2)	2.00 (2)	23	16	0	1	0
356	2.20 (2)	2.00 (2)	16	19	5	0	0

Table 11. Final Reliability Rate from selected consumers when using Method 3.

Consumer ID	Final Month Rate		Reliability Rate 1	Reliability Rate 2	Reliability Rate 3	Reliability Rate 4	Reliability Rate 5
	Event 1	Event 2					
41	4.00 (4)	4.40 (4)	3	9	8	12	8
119	3.20 (3)	3.00 (3)	1	12	17	10	0
162	4.00 (4)	4.00 (4)	1	6	17	13	3
232	2.80 (3)	3.60 (4)	7	17	8	5	3
356	3.40 (3)	3.00 (3)	6	9	14	11	0

Consumer 41 and Consumer 162 were assigned to Reliability Rate 4 for both events in Method 1 and Method 3. In Method 2, both decreased two levels. Consumer 119 and Consumer 356 were assigned by Method 1 and Method 3 to Reliability Rate 3 and by Method 2 to Reliability Rate 2. Consumer 232, in Method 1, was assigned to Reliability Rate 3 in Event 1 and Reliability Rate 4 in Event 2. In Method 2, the Reliability Rate 2 was attributed to this consumer. Finally, Method 3 was assigned the Reliability Rate 3 in both events.

3.5. Reliability Rates over Different Seasons

From the previous sub-sections, one consumer was chosen by the authors to examine the behaviour and the possibility of reliability change throughout the year. In this way, prior results from April were compared with a month in another season with October in Autumn being chosen. October 2018, in Portugal, was classified as usual regarding air temperature and as dry concerning precipitation. The month of April 2018 was pouring and normal regarding air temperature.

Figure 11 presents both initial and final rates for Consumer 41 to the ten different events simulated in these months. The highlight rates (black outline) represent the times when the consumer was selected to participate in the scheduling. Method 1, for both months, was the one that considered more times in the management of the local community.

On the contrary, Method 3 only chooses this costumer one time. Using a clustering approach where only the ones with the higher value of reduction are adopted, it can be concluded that a re-scheduling was needed in the DR event from October 28, also considering the consumers with Reliability Rate 4. In this way, the detailed overview of Method 1 and Method 2 was done. Regarding the comparison between the initial and final rate for both months, studying the availability and the possibility of reliability change through seasons, for Method 1, for the selected consumer the results were inferior in October since there was a decrease in the reliability rate 30% across the several DR events comparing with 18% from April. The highest share is represented by the equal reliability rate: 45% in October and 55% in April and the periods where the reliability rate increased represent 25% and 28% for October and April, respectively. However, the actual response from this consumer did not have a considerable difference between the selected months and seasons. The authors of the present paper consider that further studies must be done regarding the number of days submitted to DR programs, differences between periods of the day and compensation. Regarding Method 2, the values were worst in April since 70% of the reliability rates decrease over the DR events.

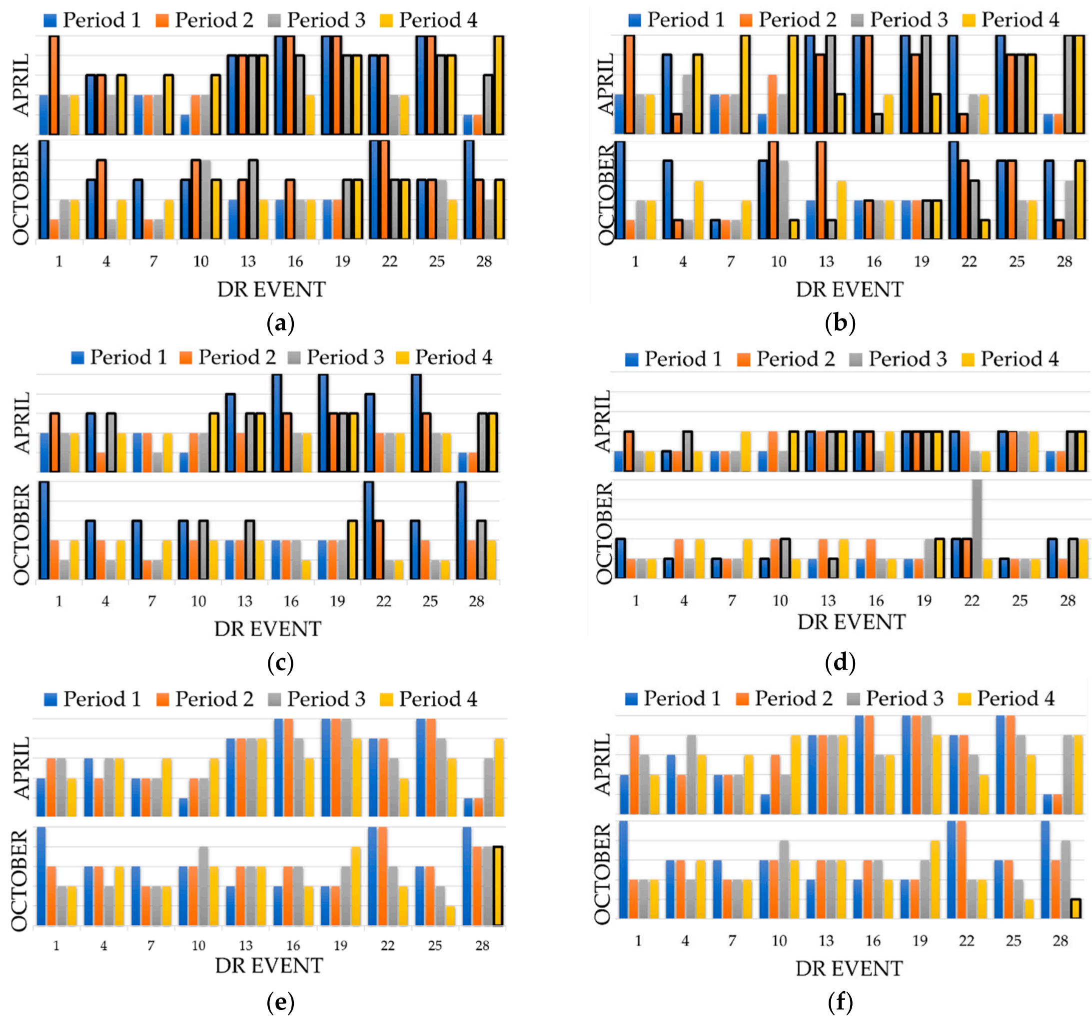


Figure 11. Season comparison for Consumer 41: April vs. October. (**a**) Method 1—initial rate; (**b**) Method 1—final rate; (**c**) Method 2—initial rate; (**d**) Method 2—final rate; (**e**) Method 3—initial rate; (**f**) Method 3—final rate.

The authors are aware that this study did not represent all communities but goes according to what was said by Srivastava et al. [27] in their research understanding the willingness of the consumers to accept limits on the use of smart appliance-based DR program in return for a recompense. One of the main conclusions from these authors was that consumers are motivated by the amount of compensation they would receive for the flexibility given. Since one of the main focuses of the small consumers is the comfort—the abdication of this goal would require high remuneration. Therefore, this method must be reformulated.

4. Conclusions

The solution proposed in the present paper has as the main goal of defining a proper approach to aid the Aggregator in the complex management of small resources in a local community, taking into account the uncertainty associated with the demand response. The literature presents fewer approaches considering this problem. Hence, the authors introduce, as a noble factor from previous works, a Reliability Rate that will be useful to decide which consumers this entity may trust in a certain period for a DR event with a specific DR target. The goal is to minimize the operation costs, for the Aggregator, with an optimization to manage all the resources associated with this entity—small consumers and DG are considered, and still achieve the DR target when DR events occur. The case study had a dataset with information from all the resources for a whole month. Regarding the

Scheduling phase, the proposed methodology is suitable to be used as a tool to aid the Aggregator in the management of a local community where DR targets are applied. Although some periods need Re-scheduling, it is considered as a successful approach to deal against the uncertainty of the consumers and a step forward when comparing with previous works by the authors since the DR target was always achieved. The technique of aggregate consumers with higher reduction power between the rates with more reliability was the one with lower failures. Additionally, from the perspective of the Aggregator, the one with lower remuneration costs.

By analyzing results from three methods, the duration of the DR event as an impact on the actual response of the consumers. Independent of the event, when comparing the first period and the remaining, a notorious increase of Reliability Rate 3 can be noticed. Several conclusions can be withdrawn from this study:

- A 15-min interval between actualizations of the actual response is a bearable time for a DR event to have more reliable answers and understand the condition of each consumer;
- The Aggregator, as a community manager, must take into account not only the past information but also the actual response for the previous event in the calculation of the initial rate to consider the results of earlier events. Although the historic quota is relevant, the behaviour of the consumer and recent information may indicate a change useful for the reliability;
- The remuneration for participating in DR programs is essential. When the value of compensation decreases, the consumers were less willing to contribute to the balance of the local community.

Overall, the approach implemented in this paper is found to be useful in assessing and rewarding the consumers' performance, giving reliability signals to the Aggregator after the enrolment phase, in opposition to traditional approaches where consumer participation in DR is assessed in each event individually.

Anyway, more improvements and further studies are needed. As future work, authors intend to investigate: The behaviour of consumer—according to the period of the day, day of the week, and month or even to an entire season. The ways to incentivize their participation is to increase their reliability rate since the consumption habits can vary through the year and the right remuneration is crucial.

Author Contributions: Conceptualization, Z.V.; data curation, C.S.; formal analysis, C.S. and P.F.; investigation, C.S. and P.F.; methodology, P.F. and Z.V.; resources, Z.V.; visualization, C.S.; writing—original draft, C.S.; writing—review and editing, P.F. and Z.V. All authors have read and agreed to the published version of the manuscript.

Funding: The present work was done and funded in the scope of the following projects: UIDB/00760/2020 and CEECIND/02887/2017funded by FEDER Funds through the COMPETE program. This work has also received funding from the European Union's Horizon 2020 research and innovation programme under project DOMINOES (grant agreement No 771066). Cátia Silva is supported by national funds through Fundação para a Ciência e a Tecnologia (FCT) with PhD grant reference SFRH/BD/144200/2019.

Conflicts of Interest: The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

References

1. Paterakis, N.G.; Erdinç, O.; Catalão, J.P.S. An overview of Demand Response: Key-elements and international experience. *Renew. Sustain. Energy Rev.* **2017**, *69*, 871–891. [CrossRef]
2. Espe, E.; Potdar, V.; Chang, E.; Espe, E.; Potdar, V.; Chang, E. Prosumer Communities and Relationships in Smart Grids: A Literature Review, Evolution and Future Directions. *Energies* **2018**, *11*, 2528. [CrossRef]
3. Siano, P.; Sarno, D. Assessing the benefits of residential demand response in a real-time distribution energy market. *Appl. Energy* **2016**, *161*, 533–551. [CrossRef]
4. European Parliament and Council of the EU. Directive (EU) 2019/944 on Common Rules for the Internal Market for Electricity and Amending Directive 2012/27/EU. *Off. J. Eur. Union* **2019**, *158*, 18.

5. Kok, K.; Widergren, S. A Society of Devices: Integrating Intelligent Distributed Resources with Transactive Energy. *IEEE Power Energy Mag.* **2016**, *14*, 34–45. [CrossRef]
6. Faria, P.; Spínola, J.; Vale, Z. Aggregation and Remuneration of Electricity Consumers and Producers for the Definition of Demand-Response Programs. *IEEE Trans. Ind. Inform.* **2016**, *12*, 952–961. [CrossRef]
7. Commissioner Europea. *Proposal for a Directive of the European Parliament and of the Council on Common Rules for the Internal Market in Electricity (Recast)*; (COM (2016) 864 final/2); Commissioner Europea: Brussels, Belgium, 2016; Volume 0380.
8. Wei, W.; Liu, F.; Mei, S. Energy Pricing and Dispatch for Smart Grid Retailers Under Demand Response and Market Price Uncertainty. *IEEE Trans. Smart Grid* **2015**, *6*, 1364–1374. [CrossRef]
9. Vallés, M.; Bello, A.; Renesas, J.; Frías, P. Probabilistic characterization of electricity consumer responsiveness to economic incentives. *Appl. Energy* **2018**, *216*, 296–310. [CrossRef]
10. Villar, J.; Bessa, R.; Matos, M. *Flexibility Products and Markets: Literature Review*; Electric Power Systems Research; Elsevier: Amsterdam, The Netherlands, 2018; Volume 154, pp. 329–340.
11. Ilieva, I.; Bremdal, B.; Puranik, S. Bringing Business and Societal Impact Together in an Evolving Energy Sector. *J. Clean Energy Technol.* **2019**, *7*, 42–48.
12. Silva, C.; Faria, P.; Vale, Z. Demand response and distributed generation remuneration approach considering planning and operation stages. *Energies* **2019**, *12*, 2721. [CrossRef]
13. Silva, C.; Faria, P.; Vale, Z. Multi-Period Observation Clustering for Tariff Definition on a Weekly Basis Remuneration of Demand Response. *Energies* **2019**, *12*, 1248. [CrossRef]
14. Silva, C.; Faria, P.; Vale, Z. Discussing Different Clustering Methods for the Aggregation of Demand Response and Distributed Generation. In Proceedings of the 2018 IEEE Symposium Series on Computational Intelligence (SSCI), Bangalore, India, 18–21 November 2018.
15. Muhsen, D.H.; Haider, H.T.; Al-Nidawi, Y.; Khatib, T. Optimal Home Energy Demand Management Based Multi-Criteria Decision Making Methods. *Electronics* **2019**, *8*, 524. [CrossRef]
16. Albana, I.A.; Ricardo, P.; Goran, S.; Spyros, G.; Gareth, R.B.; Kulmala, A.I.; Norela, C. *Natalie, S. Holistic Architectures for Future Power Systems*; ETIP-SNET: Brussels, Belgium, 2019.
17. Li, F.; Dou, C.; Xu, S. Optimal Scheduling Strategy of Distribution Network Based on Electric Vehicle Forecasting. *Electronics* **2019**, *8*, 816. [CrossRef]
18. Khalid, A.; Javaid, N.; Mateen, A.; Ilahi, M.; Saba, T.; Rehman, A. Enhanced Time-of-Use Electricity Price Rate Using Game Theory. *Electronics* **2019**, *8*, 48. [CrossRef]
19. Faria, P.; Vale, Z. A Demand Response Approach to Scheduling Constrained Load Shifting. *Energies* **2019**, *12*, 1752. [CrossRef]
20. Hu, M.-C.; Lu, S.-Y.; Chen, Y.-H. Stochastic-multiobjective market equilibrium analysis of a demand response program in energy market under uncertainty. *Appl. Energy* **2016**, *182*, 500–506. [CrossRef]
21. Good, N. Using behavioural economic theory in modelling of demand response. *Appl. Energy* **2019**, *239*, 107–116. [CrossRef]
22. Ruiz, N.; Claessens, B.; Jimeno, J.; López, J.A.; Six, D. Residential load forecasting under a demand response program based on economic incentives. *Int. Trans. Electr. Energy Syst.* **2015**, *25*, 1436–1451. [CrossRef]
23. Monfared, H.J.; Ghasemi, A. Retail electricity pricing based on the value of electricity for consumers. *Sustain. Energy Grids Netw.* **2019**, *18*, 100205. [CrossRef]
24. Jiang, Y.; Wan, C.; Chen, C.; Shahidehpour, M.; Song, Y. A Hybrid Stochastic-Interval Operation Strategy for Multi-Energy Microgrids. *IEEE Trans. Smart Grid* **2019**, *11*, 440–456. [CrossRef]
25. Khan, M.; Javaid, N.; Naseem, A.; Ahmed, S.; Riaz, M.S.; Akbar, M.; Ilahi, M. Game Theoretical Demand Response Management and Short-Term Load Forecasting by Knowledge-Based Systems on the basis of Priority Index. *Electronics* **2018**, *7*, 431. [CrossRef]
26. Rokach, L.; Maimon, O. Clustering Methods. In *Data Mining and Knowledge Discovery Handbook*; Springer: New York, NY, USA, 2019; pp. 321–352.
27. Srivastava, A.; Van Passel, S.; Kessels, R.; Valkering, P.; Laes, E. Reducing winter peaks in electricity consumption: A choice experiment to structure demand response programs. *Energy Policy* **2019**, 111183. [CrossRef]

Publication II

C. Silva, P. Faria, Z. Vale, and J. M. Corchado, "Demand response performance and uncertainty: A systematic literature review," Energy Strategy Reviews, vol. 41, p. 100857, May 2022, doi: 10.1016/j.esr.2022.100857. (2021 IF: 10.01)

Resumen

La presente revisión se ha llevado a cabo utilizando la metodología PRISMA y analizando 218 artículos publicados. Se ha realizado un análisis exhaustivo del papel del consumidor en el mercado energético. Además, se han revisado los métodos utilizados para abordar la incertidumbre en la respuesta a la demanda y las estrategias utilizadas para mejorar el rendimiento y motivar la participación. Los autores encuentran que los participantes estarán dispuestos a cambiar su patrón de consumo y comportamiento siempre que tengan plena conciencia del entorno del mercado y busquen la decisión óptima. También se encuentra que una solución contextual, que brinde las señales adecuadas según los diferentes comportamientos y los diferentes tipos de participantes en el evento de respuesta a la demanda, puede mejorar el rendimiento de la participación de los consumidores, proporcionando una respuesta confiable. La respuesta a la demanda es un medio de gestión del lado de la demanda, por lo que ambos conceptos se abordan en el presente artículo. Finalmente, se discuten las direcciones futuras para la investigación.

Energy Strategy Reviews 41 (2022) 100857

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.elsevier.com/locate/esr

Demand response performance and uncertainty: A systematic literature review

C. Silva [a,b], P. Faria [a,b], Z. Vale [a,b,*], J.M. Corchado [c]

[a] GECAD, 4249-015, Porto, Portugal
[b] Polytechnic of Porto, 4249-015, Porto, Portugal
[c] BISITE Research Centre, University of Salamanca (US), Calle Espejo, 12, 37007, Salamanca, Spain

ARTICLE INFO

Keywords:
Active consumer
Behavior
Demand response
Load flexibility
Performance
Uncertainty

ABSTRACT

The present review has been carried out, resorting to the PRISMA methodology, analyzing 218 published articles. A comprehensive analysis has been conducted regarding the consumer's role in the energy market. Moreover, the methods used to address demand response uncertainty and the strategies used to enhance performance and motivate participation have been reviewed. The authors find that participants will be willing to change their consumption pattern and behavior given that they have a complete awareness of the market environment, seeking the optimal decision. The authors also find that a contextual solution, giving the right signals according to the different behaviors and to the different types of participants in the DR event, can improve the performance of consumers' participation, providing a reliable response. DR is a mean of demand-side management, so both these concepts are addressed in the present paper. Finally, the pathways for future research are discussed.

1. Introduction

In the local electricity markets, bottom-up approaches have been proposed to boost the involvement of local grid operators and encourage the active participation of small consumers [1]. These tactics are crucial to successfully penetrate Distributed Generation (DG) technologies in the current network, avoiding the use of fossil fuels. So, by focusing on the empowerment of the local resources, namely active consumers' flexibility, the potential of renewable energy resources can be explored without jeopardizing the system's reliability and security.

Progressing towards a future where the demand side has greater importance in the system, consumers should follow the signals from network or utility companies. To achieve system balance, their response is crucial [2]. Many advantages come from this approach, such as real choices to end-users, new opportunities and challenges, more competitive prices; effective investments; higher service standards; security of supply, sustainability; and the decarbonization of the electrical system [2,3]. The Demand Response (DR) concept and the respective programs were then defined [4]. Nevertheless, it is important to enabling technologies such as the Internet of Things (IoT) to be used to raise the consumers' awareness and their contribution to market transactions [5].

1.1. Contextualization and background

In the former paradigm, the system operator considered the load from electricity consumers in power and energy systems as rigid. However, each consumer has a set of appliances that do not have a fixed schedule and can be used flexibly by introducing the DR definition [6]. This concept means that following the different signals, the consumer uses them at different times or does not use them. In recent years, numerous definitions of DR have been proposed. A commonly used definition says [7]: "*… tariff or program … to motivate changes in electric use by end-use customers … changes in the price of electricity over time, … incentive payments … high market prices … grid reliability …*". A more recent one, published in European Directive 2019/944, says [8]: "*… change of electricity load by final customers … market signals … time-variable electricity prices or incentive payments, …final customer's bid to sell demand reduction or increase … market … alone or through aggregation*".

Until introducing the smart grid concept and DR, the consumer had no direct information regarding the market transactions. With the growing concern regarding climate change, the role of this new player must be empowered. Due to the volatile behavior of DG, it is crucial to make the consumers the center of the business model and consider their flexibility as fundamental to achieve the system balance. A consumer-centric approach has countless advantages, for example, for flexibility

* Corresponding author. GECAD, 4249-015, Porto, Portugal.
E-mail address: zav@isep.ipp.pt (Z. Vale).

https://doi.org/10.1016/j.esr.2022.100857
Received 4 October 2021; Received in revised form 25 March 2022; Accepted 4 May 2022
Available online 12 May 2022

Abbreviations

AMI	Advanced Metering Infrastructure
ANN	Artificial Neural Network
ARMA	Autoregressive Moving Average
ARIMA	Autoregressive integrated moving average
BRPs	Balance Responsible Parties
CBL	Consumer Baseline Load
CC	Capacity Credit
CDR	Correlated Demand Response
CVaR	Conditional Value at Risk
DG	Distributed Generation
DLC	Direct Load Control
DNN	Deep Neural Network
DR	Demand Response
DSM	Demand Side Management
DSO	Distribution System Operator
EMS	Energy Management Scheme
EU	European Union
FIS	Fuzzy Inference System
HVAC	Heating, Ventilating, and Air Conditioning
IoT	Internet of Things
ISO	Independent System Operator
kNN	K-Nearest Neighbor Method
LEC	Local Energy Community
MCS	Monte Carlo Simulation
MF	Membership Function
MPC	Model Predictive Control
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PV	Photovoltaic Systems
RE	Roth-Erev
RF	Response Frequency
RI	Response Intensity
RL	Reinforcement Learning
RTO	Regional Transmission Organization
TLP	Typical Load Pattern
TOU	Time of Use
TSO	Transmission System Operator
VaR	Value at Risk

markets, where the main players are [1]: Transmission System Operators (TSO), Distribution System Operators (DSO), Balance Responsible Parties (BRPs), aggregators, and retailers. The TSO is responsible for the service and stability of the transmission system, while the DSO is the entity responsible for the distribution system's operation. TSO/DSO collaboration is crucial to unleashing the potential of flexibility [9,10]. The retailer is a commercial entity selling electricity to consumers. The aggregator gathers flexibility through renewable-based and active consumers [11].

In this way, the DR definition must also comply with time flexibility. Thus, DR programs have different timescales, as presented in Fig. 1, and range from several years (on the left) to real-time (on the right). Year-long timescales are usually applied to improve long-term planning. Shorter timescales are more devoted to incentive-based DR programs, e.

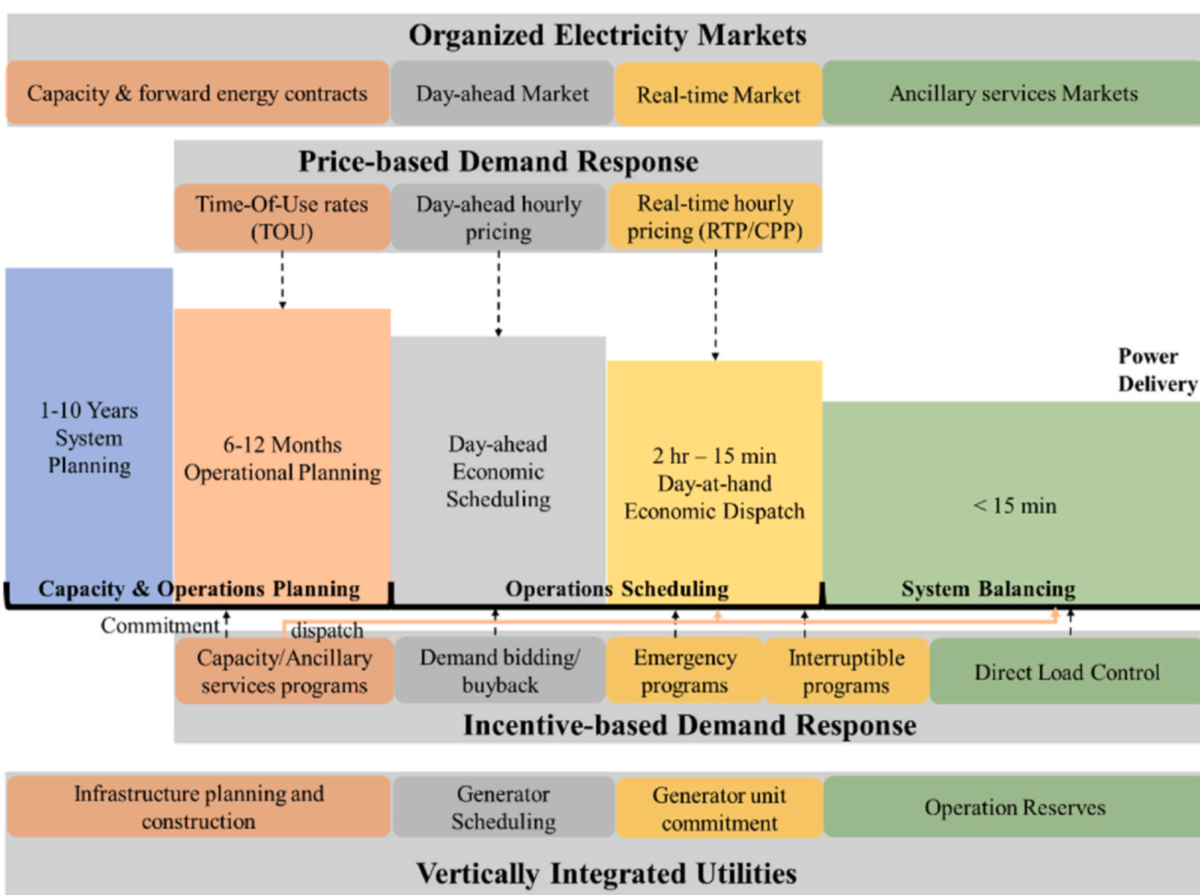


Fig. 1. Electric Power System and Demand Response implementation timescales.

g., applying Direct Load Control (DLC).

The performance from consumers' participation and how they react to a given signal are critical topics to successfully implement DR programs [6]. From the perspective of the entity requesting DR, gathering this type of information to give the right signals to the right consumers and the proper remuneration that will fit their needs is the right path to reduce the response uncertainty and maintain the system reliable and secure [6]. From the active consumers' perspective, the type of consumer participating in this type of event matters. The residential consumer's response is highly affected by the level of discomfort caused during a DR event [12]. However, industrial consumers' goal is to maximize their profits when participating in these programs and while managing any discomfort [13].

For this reason, different objectives require different approaches. Thus, it is necessary to respond to the consumers by adopting different approaches and contexts. Although approaches in the literature encourage consumer participation, most of them are profit-driven [14–16].

1.2. Motivation and contributions

The main motivation of the present literature review is to understand the current state-of-art of approaches to the uncertainty, performance, and reliability of consumer participation in DR programs. Some of the questions are: Is it important to deliberate methods to reduce uncertainty and enhance consumers' participation in DR programs? Should the distinct types of active consumers be treated differently? Should the individual behavior be analyzed to find proper methods of incentivizing each consumer's response? The authors have found interest in these questions after analyzing the related literature, as explained from now on, and finding the need for it doing their research.

The authors want to understand the implications of adding such an uncertain player into the current system. In the previous paradigm, consumer contributions were indirect, having little or no knowledge regarding this matter. Gathering different algorithms, solutions, and conclusions into a single document summarizing the current state of the art regarding this topic can be useful to create better-quality models. As far as the authors' knowledge, the DR concept has already been applied in some real markets but is still fresh in others. These new players should be further studied and understood to achieve a successfully implemented solution throughout the system. Their response is uncertain and could impact the performance of the remaining players in the market, jeopardizing the security and reliability of the system. For instance, in the review carried out by *Ivana Dusparic* et al. [17], whose focus was the residential DR, several algorithm characteristics have been discussed, concluding that performance concerning the algorithm for a particular DR implementation has been discussed energy use should be considered. The conclusion of this study emphasizes that a DR approach may use more than one algorithm that can be combined to meet the implementation requirements. Each solution must be tailored to a particular context.

Thus, context is also an important topic addressing DR programs that need to be customized. For instance, the type of consumer, their energy patterns be influenced by climate, and many more in the review published by *Miadreza Shafie-khah* et al. [13] where the recent advances in DR for industrial and commercial sectors were studied, as well as the benefits and barriers associated with their role. The authors categorized the different business models and objective functions. Consumer behavior was mentioned referring to trust level among parties – high trust levels should be sufficient to prevent any barriers to viewing DR as a reliable source, and widespread adoption of DR programs – lack of understanding of the benefits of DR can cause less investment by different parties.

A broader review of the barriers and enablers of DR in the Smart Grid was conducted by *Nicholas Good, Keith Ellis, and Pierluigi Mancarella* [18]. The barriers were categorized into fundamental and secondary, producing a comprehensive and discrete classification. The first ones include challenges related to intrinsic human nature, namely social/-economic barriers and enabling essential technology. The second type of barrier is related to anthropogenic institutions, such as regulations entities or markets, or even the resulting behaviors from feedback in response to DR participation, known as physical constraints. One of the study's important highlights is behavioral economics, which indicates that individual factors play a critical role in shaping consumers' decisions. In the paper, these authors refer to those behavioral aspects attracting more interest more recently. The focus is especially for residential and small commercial consumers, where the uncertainty has been emphasized as a particularly inflexible barrier to the exploitation of DR.

Furthermore, with an emphasis in terms of social welfare losses, *Marilena Minou, George D. Stamoulis, and Thanasis G. Papaioannou* [15] study considers that appropriate policies and demand reduction strategies exploiting altruism can benefit consumers (mainly in contracted-based Automated DR (ADR) programs and considering the consumers' preferences external contexts). Regarding the ADR provider perspective, the benefits will come in terms of incentive costs. However, the leveraging of altruists should be performed carefully. They are saddle with high energy reductions. Moreover, although yielding in small values of total incentives, they can yet prove inefficient for the social welfare of the system.

Consequently, with introducing these new concepts, the policies must be updated. Policymakers are making advances to create common rules for the new paradigm. In Europe, the Directive (EU) 2019/944 [11] recasts Directive 2012/27/EU on common rules used in the internal electricity market. It puts citizens at the center as they take ownership of energy transition and take advantage of innovative technologies to decrease costs by actively participating in the market, with the most vulnerable consumers being protected. Also, it was mentioned that the retail market should serve consumers better, notably by improving the links between the wholesale and retail markets, allowing all consumers to participate in the transition of energy and contribute to the overall reduction of energy consumption by providing efficient solutions. This results in more flexible markets and fully integrates all market players, including renewable energy producers, new energy service providers, energy storage, and flexible demand.

The present literature review discusses the uncertainty, performance, and reliability of consumer participation in DR programs. An innovative exploration is made into the behavior of active consumers and the aspects that may impact their response – which is highly uncertain and difficult to predict – and, consequently, impacts their performance and energy management reliability. Thus, the authors consider as a hypothesis, that the need for a more in-depth study of the influence of the context on the response should be explored and the different compensation techniques for the distinct types of active participants. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology is used.

The present paper is then organized into seven sections. An introduction is provided in section 1. Then, in section 2, the methodology followed to carry out this research review is described. Section 3 and Section 4 show, respectively, mechanisms to control DR and techniques and methods applied to DR. This is followed by Section 5, where consumer response uncertainty, performance, and reliability for DR are presented. Section 6 discusses the findings. Final remarks are presented in section 7.

2. Methodology

A systematic literature review has been performed considering the PRISMA methodology [19]. The present literature review started with formulating the research questions in the first phase: Should the distinct types of active consumers be treated differently? Should the authors analyze individual behavior in-depth to find proper methods for incentivizing their response? How the consumers' performance can be improved in DR programs? The current study focuses on finding answers to these questions in the reviewed literature.

The second phase of a systematic review involves the inclusion and exclusion criteria. The research results were obtained considering the following:

1. Include
   a. Describe any Demand Response tactics and other related consumer concepts (namely Demand Side Management or Consumer Flexibility).
   b. Consumer Behavior analysis considering their performance or response uncertainties.
   c. Document related to the Demand Response topic or similar, referring to the keywords considered as important by the authors (refer to Table 1).
2. Exclude
   a. No access to the full paper.
   b. Written in a language other than English or Portuguese.

The authors selected the online research tools and the multiple databases in the third phase. The five chosen databases were Web of Science, Science Direct, SciELO, IEEEX, and ACM. Table 1 presents the definition of the keywords and expressions that have been used.

Clarification of definition comparison for "performance" and "behavior" should be done. When the authors refer to consumer behavior, it means the players' actions to respond to a DR event in a certain context. Performance is related to the actual consumer response quantification, i.e., how much KW or KWh of reduction was provided.

A research equation must be formulated according to the language of each tool. For instance, Science Direct does not support the substitution symbol, also known as wildcard, represented by a "?" or truncation symbol represented by a "*." Both symbols are useful for substituting letters within a word or retrieving words with the same origin. However, all the remaining research tools supported the utilization of Boolean operators for the formulation of research equations, for instance ("Demand Response" AND Uncertainty* AND Real-time). The quotation marks mean that the word must be contained within the resulting document.

Several levels, resulting in different combinations of keywords or expressions, have been applied and are presented in Fig. 2.

In this way, the keywords in the first three levels must exist within the full paper searching these fields: title, abstract, keywords, or 'all fields' (search simultaneously in all record fields). The research finished in May 2021, so the listed references are published until this date. Therefore, the studies considered in this literature review have been published no farther than five years before this research. This assures that only the most recent studies have been considered.

Level 4 was considered for online research tools such as Science Direct, which does not support wildcards, for instance, when there were important related words within level 3, in plural form, or varying in spelling (American English vs. the United Kingdom English) like behavior and behavior.

Moving on to evaluating the obtained results, Fig. 3 represents a systematic review of the information flow. In the Identification stage, the agglomerated number of the identified records is too high (3,148,838 records). Still, it must be highlighted that there were five databases, several combinations of keywords, and the number also includes duplicate material and papers from different languages and areas. However, after analyzing the results, the research equations where most of the non-related documents were found included the keyword "flexibility" – should be reformulated as "load flexibility" or "consumer flexibility" to avoid an excessive number of references from other areas.

During the screening stage, the duplicates, non-related references, and documents in languages other than Portuguese and English were excluded reducing the total to 6,784 records. After that, to filter the

Table 1
Keywords and expressions (ordered by relevance).

Keyword	Definition
Demand Response (Flexibility, Program, Participation, Performance, Uncertainty, Reliability)	According to the Directive 2019/944 (EU), the definition of Demand Response is "*the change of electricity load by final customers from their normal or current consumption patterns in response to market signals, including in response to time-variable electricity prices or incentive payments, or in response to the acceptance of the final customer's bid to sell demand reduction or increase at a price in an organized market* "[11]. Thanks to real-time information exchange, active consumers can schedule their appliances according to signals designed to induce lower consumption, for instance, when system reliability is jeopardized. Their performance in these events will define the success of the DR implementation in real markets. So, the response uncertainty must be mitigated to increase reliability from the systems perspective [15,20–25].
Demand Side Management (DSM)	Demand-side management is a portfolio of procedures to enhance energy systems' utilization on the demand-side to meet several goals. These measures may include the management of consumption patterns of smart appliances, renewable energy systems, and home energy management systems to improve energy utilization efficiency [26–28].
Compensation (Remuneration, Incentive, Payment, reward)	Benefits are given to a person to reward participation in a DR event to motivate continuous participation. Several types can be used, such as economic remuneration, for instance, discounts on the energy bill or shopping vouchers to be used in stores of the consumer's choice, etc. This benefit should be fair and consider the remaining participants [29].
Penalty (Penalties)	Punishment for not fulfilling the agreement on a DR program, where penalty policies may also exist for violating contract obligation [30,31].
Behavior (Behavior, Behavior, Behaviours)	A set of reactions in response to the stimulus provided in a DR event. These can be signals sent to the active consumer to change the consumption in response to variations in the electricity price, incentives applied in high market prices, or when system reliability needs improvement [32].
Real-time	According to the Directive 2019/944 (EU), in the DR area and the context of smart metering: "*a short time period, usually down 2 s or up to the imbalance settlement period in the national market*" [11].
Community (Communities, Local Community, Local Communities)	In a DR context, an active community is a group of individuals working together for the same goal. In this way, distributed generation and consumer empowerment have made local energy communities effective and cost-efficient to meet consumers' needs and expectations regarding energy sources, services, and local participation. In addition, these communities offer inclusive options for all consumers to directly produce, consume, or share energy [8].
Electricity Market	Unlike other markets, electricity markets involve trading a service that cannot be easily stored and produced using a large variety of generating installations. Therefore, incorporating electricity markets requires a high level of collaboration among system operators, market participants, and regulatory authorities, particularly where electricity is traded via market coupling in the DR context [11].
Local Electricity Market	Considering the electricity market definition, the local electricity market can be defined for a particular region. So, it can be thought of as a sub-market for a commodity that serves a specific purpose for that local community, including in DR programs [33].

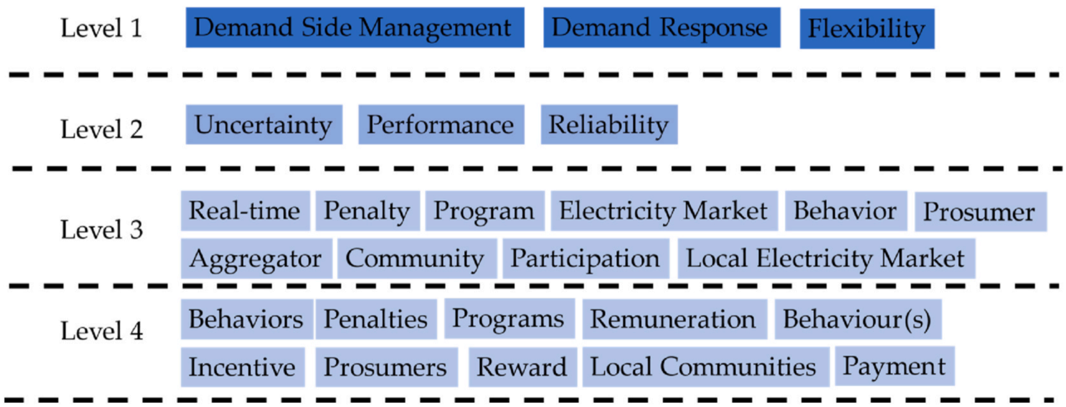


Fig. 2. Keywords combinations.

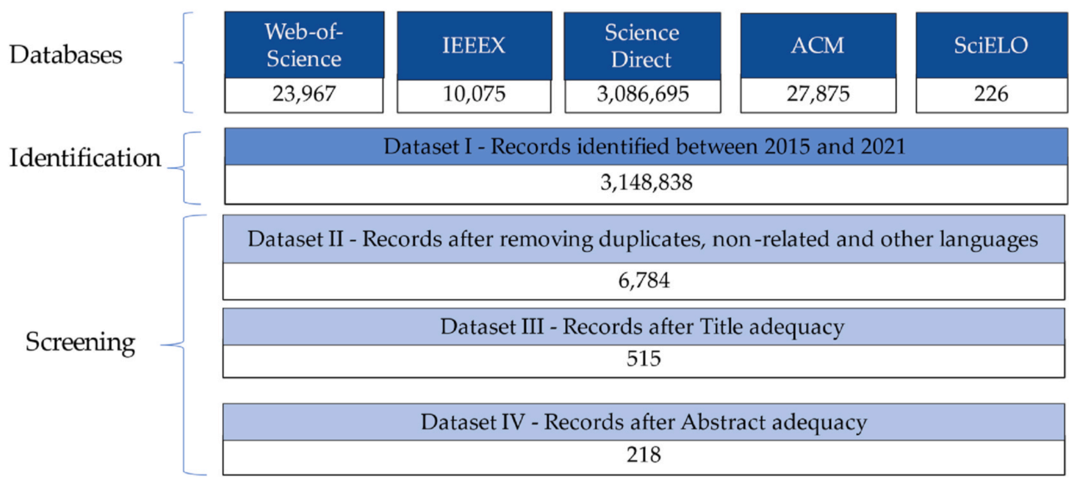


Fig. 3. A number of records in the dataset at each step.

articles that were not within the scope of this research, the title and abstract adequacy were verified. Finally, the records were subjected to a fluctuating reading guaranteeing their relationship with the study.

According to Fig. 4 and Dataset II in Fig. 3, “Demand Response” has the highest influence in the dataset of level 1 keywords, with an influence of more than 55%.

For level 2 keywords, “uncertainty” has the highest level of influence and exceeds “performance” by 4.5%. These two keywords have a higher level of influence than “reliability.” Unfortunately, the trustworthiness of the active consumer’s response to demand-side management methods is not yet addressed in the literature.

The resulting dataset, Dataset IV, as defined in Fig. 3, was analyzed, and nine factors were highlighted as important for the role of active consumers in the electricity market. The keywords were grouped and are

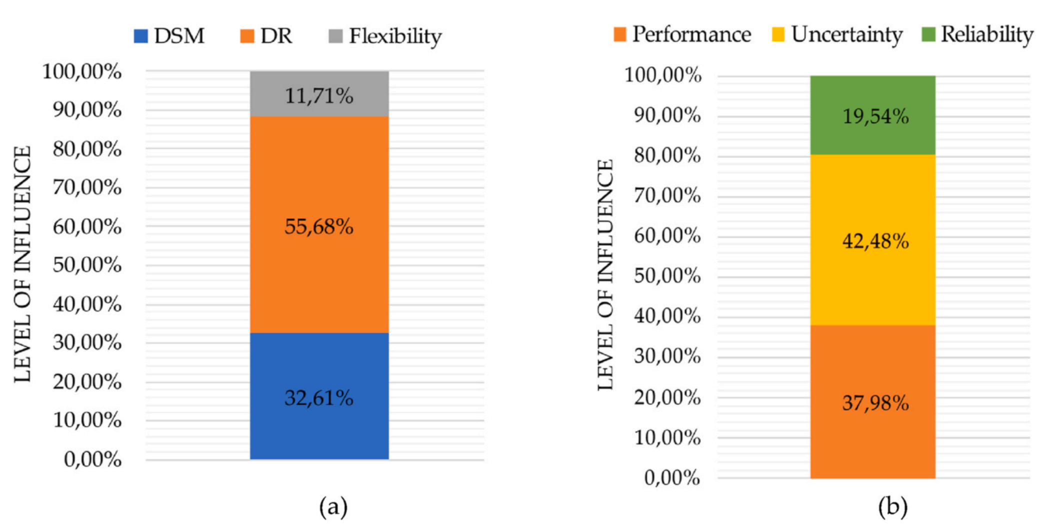


Fig. 4. Keywords in Dataset II: a) related to level 1; b) related to level 2.

listed in Table 2.

The following sections present the extraction, analysis, and interpretation of the information found, the discussion, and conclusions from this systematic review.

3. Mechanisms to control DR

The present section organizes the reviewed papers according to the type of DR they addressed, indicating the ones that contributed to DR Uncertainty, Performance, and Reliability research. The detailed exploration of the works gathered in the dataset will be further discussed in section 5. Although many other DR programs can be defined, the authors selected those with higher mentions in the publications from the resulting dataset. Price and Incentive-based are the types of DR with the most references in the resulting dataset. Demand Response Exchange (DRX) and Electric Vehicles (EV) were the least referenced types of DR in the dataset. However, as mentioned by Zhiwei Xu et al. [119], the flexible resources from the demand-side can play a critical role in balancing the supply and the demand in the future smart grid, namely providing various DR services. One of these resources is the EV. However, as Bhagya Nahali Silva, Murad Khan, and Kijun Han [223] emphasize, EV owners' security and privacy concerns is another challenge that limits the popularity of EV-based energy management because, although it is a hot topic, there are w low number of publications in the resulting dataset regarding uncertainty ([1,20,47,69,164,224–226]), performance ([59,104]) and reliability ([167]), as can be seen. Some of these works only refer to these resources, and it is not the focus of the study. Vehicle owners are hesitant to grant authority to control EVs to an Aggregator.

3.1. Incentive-based

Under incentive-type programs, consumers agree to participate according to rules by signing contracts. These usually determine that penalties are applied to the consumer in case of lack of response in the contractual terms. J. Meng et al. [213] consider an incentive-based DR in their study and used a multi-dimensional DR evaluation method considering the several affecting factors such as response speed and response duration that can comprehensively evaluate the response performance of users on the power demand side and effectively quantify the contribution of its response to grid load regulation. In work done by Ioannis Konstantakopoulos et al. [178], they created an adaptive model that learns active consumers' preferences and how they change over time to generate the appropriate incentives to ensure active participation. The uncertainty topic, regarding the incentive-based programs, were mentioned on [1,20,69,77,86,140,164,177,226]. The performance was an important topic in Refs. [14,21,84,115,125,140,144,146,147,195,213,215,227–229]. Lastly, fewer works mentioned reliability, namely [14,84,87,213,228].

Table 2
Main topics in the dataset IV.

Keywords	References
Aggregator	[13,34–67]
Behavior	[21–23,30,32,68–97]
Prosumer	[20,25,55],[98–138]
Community	[139–151]
Compensation/Penalty	[22,85–88,152]
Electricity Market/Local Electricity Market	[41–44,46,153]
Participation	[16,24,29,31,33,38,154–183]
Program	[14,16,26,43,48,184–215]
Real-time	[26,185,186,193,194,196,198–200,202–205,207,209,210,214,216–222]

3.2. Price-based

Moving to Price-based, these programs are based on the energy price change, looking for the consumers' response to those changes. This could lead to more randomness in consumer behavior when compared to incentive-based programs, for which the contractual rules determine predefined response behaviors. Still, there is always the freedom of choice from the perspective of the active consumer who has the power to disconnect the appliance.

Active consumers can receive discounts by reducing energy demand during critical peak periods, as in the work done by Gerardo Osorio et al. [135]. Namely, Real-time Pricing programs are deeply intertwined with the wholesale market price, varying in real-time throughout the day. In the straightforward approach used by Byung-Gook Kim et al. [20], with dynamic consider the decision from the active players in their environment and learn the dynamics of the entire system and find its optimal energy consumption scheduling based on the observations. Reliability was the keyword least mentioned for this type of DR program: [22,106,135,171,213,228,230]. The performance was started in 13 works: [40,117,158,186,192,195,202,205,213,228,231–233]. Finally, uncertainty was a mentioned in the following works: [[20,29,36,40,43,46,47,65,98,100,106,112,116,118,119,121,133,156,161,185,186,214,231,232].

3.3. Both incentive and price based

By analyzing the combination of these two types of DR programs in the resulting dataset can be concluded that performance and Reliability were mentioned in less than five works when combining these two types of DR programs: [195,213,228]. Two of them refer to these topics in their studies. The uncertainty was highlighted in Refs. [14,23,30,54,55,77,84,86,88,111,115,132,192].

3.4. Demand Side Management (DSM)

DSM can be defined as the modification of consumers' demand. As Julián Valbuena et al. [190] refer, DSM modeling at the building sector is challenging since the existing models are not flexible enough to incorporate a wide set of modeling features and guiding principles, while including all important aspects of end-use. The performance was the keyword with more mentions in the dataset gathered: [27,59,61,113,123,127,155,158,164,187,192,196,205,234–236]. Uncertainty was reported in Refs. [20,109,116,137,158,164,168,187,235] and the Reliability concept in Refs. [28,190,201,206].

3.5. Demand Response Exchange (DRX)

DRX refers to a new DR scheduling program. Derived from the market clearing mechanism, the motivation for change in load is dependent on a bidding entity and not price or incentive. Therefore, load profile attributes should be assessed carefully before submitting any bid to avoid losing load satisfaction, higher electricity bills, system stress, etc. [195]. With this, only a few works refer to this DR program and only consider uncertainty and performance topics: [31,149,195].

3.6. Load shifting

In this DR program, the Aggregator has permission to use consumers' loads for DR within pre-specified limits for internal balancing. So, it is defined as shifting electricity consumption to another period. Pedro Faria et al. [32] proposed scheduling load-shifting opportunities performed by a VPP. The main advantage is modeling the consumption shifting constraints (limits for each period/set of periods) from the VPP and the consumer standpoints.

Mellouk et al. [187] scheduled energy consumption profiles for each active consumer. They are treated independently to determine the optimal distribution of devices' operating time among different periods to avoid peak hours generally characterized by the highest values for the cost coefficient. Load shifting is one of the types of DR with more studies regarding the performance topic: [32]. The reliability was not mentioned, and uncertainty has a total of 6 publications in the resulting database: [58,120,122,136,163,207].

3.7. Others

Other less known DR types were found in the gathered publications. The keyword with more mentions was the uncertainty: [13,14,18,23,29, 31,32,34,36,37,44,47,55,58,69,84,85,87,103,110,112,113,117–120, 126,129,134,137,144–146,149,159,164,171,172,176,180,186,190, 193,195,198,201,206,210,211,214,225,228,231,232,235,237–244]. For instance, Chen et al. [29] proposed a framework to encourage the new active players and their resources, such as parking lots with high penetration of electric vehicles, to participate directly in the real-time retail electricity market based on an integrated eVoucher program. As the authors mentioned, this program can work for various scenarios involving economic or physical extreme events.

To study and select the right participants for a DR event, Yingying Li, Qinran Hu, and Na Li [77] formulate the DR problem as a combinatorial multi-armed bandit (CMAB) problem with a reliability goal. These authors believe that the multi-armed bandit (MAB) method emerges as a natural framework to handle intrinsic and heterogeneous uncertainties associated with small consumers such as residential.

Reliability was the second one with more mentions: [13,14,22,30,38, 77,83,84,87,100,106,109,111,112,121,167,171,173,197,201,213,228, 230,241,243,245]. As can be seen, some of the references were mentioned in both keywords search. Shuai Fan et al. [144] focused on large-scale DR. These authors mention that current incentive-based DR schemes are unsuitable for large-scale DR due to their centralized formulation, jeopardizing the system reliability. With this, propose a consumer directrix load (CDL), which is a desired load profile, to replace the customer baseline load (CBL). The authors refer that the uniqueness of this solution makes it more suitable for distributed schemes, while numerous CBLs must be calculated in a centralized manner to ensure fairness.

The performance was the least mentioned keyword in the others point: [21,27,31,37,84,85,115,140,145,170,192,193,213,215,228, 229]. One concern that has become major in the DR program design topic is resource privacy and preserving the managing entity. Amir Ghasemkhani et al. [246] affirm that active consumers' privacy protection is being ignored when designing DR programs since their behavior patterns can be easily recognized when interacting with the managing entity. The proposed and commonly used solution incorporates perturbations in users' load measurements. However, although it can protect the active consumers' privacy, this modification would reduce the managing tools' performance in achieving an optimal incentive strategy. Therefore, further studies should be developed to include privacy-preserving solutions.

4. Technics and methods applied to DR

Discussing the methods found in the resulting database, Artificial Intelligence (AI) methods were reviewed first and then non-AI methods. Although some methods can be converted into AI approaches, the presented studies used the method in their original form.

4.1. Artificial Neural Networks

Artificial Neural Networks (ANN) methods are the foundation of AI methods and are designed to simulate how the human brain analyzes and processes information. In the DR Uncertainty topic, as mentioned in Refs. [104,185] and for DR performance [77,180,196,209,215,247]. None of these works mentioned reliability. Renzhi Lu et al. [202] resort to both ANN and Reinforcement Learning (RL) to design an hour-ahead energy management scheme for different appliances within a HEMS, where ANN was used for price forecasting.

4.2. Reinforcement Learning

RL is characterized by Machine learning models trained to make a sequence of decisions to achieve a goal in an uncertain, potentially complex environment. All the keywords from level 2 were included in the RL works in the gathered dataset: uncertainty ([20,40,87,108,112, 180,202]), performance ([20,77,87,180]) and reliability ([20,77]). For instance, Amir Ghasemkhani and Lei Yang [112] leverage RL to learn the users' response functions. In theory, AI models can be subjected to gamified interactions between participants.

4.3. Game theory

Game Theory is considered the most vital mathematical branch was exploring the conflicts, collaborations, and strategic interactions between rational players within a single system by several authors such as Haytham A. Mostafa, Ramadan El Shatshat, and M. M. A. Salama [175]. Their study considered a participant system to achieve rational and independent interaction with several players, improving the distribution system. The works using this algorithm mentioned uncertainty ([47,54, 59,85,113,125,144]), performance ([20,158,164,178]) but not reliability.

4.4. Autoregressive Moving Average

The autoregressive integrated moving average (ARIMA) is one of the easiest and most effective Machine Learning algorithms for performing time series forecasting. It is a generalization of the Autoregressive Moving Average (ARMA) model. The study of Hamed Mortaji et al. [48] indicated that load shedding using the ARIMA time series prediction model and smart, direct load control could remarkably reduce consumers' power outage. In the resulting database from the present paper, the uncertainty keyword ([21,36,44,58,65,115,173,202,214]), the performance keyword ([21,58,87,115,124,202]) and the reliability keyword ([21,58,87,115,124,202]) were mentioned when using these algorithms.

4.5. Clustering methods

Researchers use Clustering Methods extensively in the power system, mainly to find patterns in electrical loads, as in the study conducted by Mansour Charwand et al. [91]. The cluster analysis was mentioned works where the uncertainty keyword ([115,143,150]), performance keyword ([73,215]) and the reliability ([26,126,137,139,146–148,151, 214]) were referred. The last one has a higher number of publications.

4.6. Fuzzy theory

Fuzzy theory can also be applied, and the research approach can deal with ambiguous, subjective, and imprecise judgments. In the resulting dataset, when looking for fuzzy theory algorithms, uncertainty ([91,107, 149,163,195]), performance ([83,91,124,149,163,186,195,248]), and reliability ([13,83,117,121,248]) keywords were found. For example, Fuzzy Inference System (FIS) was used and compared with other non-fuzzy approaches by Skrikanth Reddy K et al. [149], where the superior performance of FIS concludes the efficacy of this type of model for processing load profiles and behavior (willingness) in designing the DR bids for market participation.

4.7. Model-based predictive control

Model-based predictive control (MPC) has attracted the researchers' attention to this area due to its prediction abilities, quick processing capacity, and suitability for multivariable control operations. However, few works mentioned this algorithm, including only uncertainty ([86, 122,123]) and performance ([86]). For instance, Farzad Arasteh and Gholam H. Riahy [123] developed a real-time algorithm to systematically coordinate the DR programs and ESS operation in market-based wind integrated power systems.

4.8. Conditional Value at risk

In the DR perspective, Conditional Value at Risk (CVaR) can be used for the stochastic program for decision making of DR aggregator considering various sources of uncertainty, as done by Homa Rashidizadeh-Kermani et al. [55]. Since CVaR as a risk measure was embedded in the problem to control different levels of risk associated with profit volatility. Works using this algorithm also mentioned DR uncertainty ([36,55,121,211]), DR performance ([86,119,121,131]) and DR reliability ([119,228]).

4.9. Monte Carlo Simulation

Probabilistic models incorporate random variables and probability distributions into the model. Confronting this stochastic solution with a deterministic model with only a single possible, a probabilistic model gives a probability distribution as a solution. Many works mentioned probabilistic models also including uncertainty ([65,98,110,120,133, 136,191]), performance ([77,140]) and reliability ([47,154]). One of the best-known probabilistic methods is the Monte Carlo Simulation (MCS). Zvi Baum et al. [14] resort to MCS the of design a convenient framework to estimate Dynamic-Active DR's performance in which the stochastic characteristics of supply and demand can be reflected and the behavior of the system over time, in response to both external and internal influences, can be modeled. This algorithm was also mentioned in publications with uncertainty ([14,25,106,109,159,214]), performance ([38,41,56,98,119,180,190]) and reliability ([59,98,137,154,180]) were highlighted.

4.10. Markov Chain

Also, the Markov Chain (MC) follows probabilistic rules and is a common, relatively simple means of modeling statistically random processes. Yue Yang generates an MC model at an appliance level to capture temporal and inter-device correlations in power consumption. Further works with MC refer to uncertainty ([24,111,137]), performance ([86,137]) and reliability ([13,86,101,123]).

4.11. Others

Other algorithms were also found in the resulting database, however, they only refer to uncertainty keyword ([21,23,29,30,34,43,46,58,60, 69,77,83,84,88,105,116–118,126,132,134,140,152,156,157,161,186, 192,207,231,232]).

5. Uncertainty, performance, and reliability of the DR participants

The role of the consumer is changing. These new players are becoming more active participants with a great influence on system reliability, so their performance must be enhanced, and the response uncertainty dealt with. The focus of the present section is the main keywords found in the studies from the dataset obtained: uncertainty, performance, and reliability.

5.1. DR uncertainty

DR resources' load reduction process is stochastic, statistical, and stationary [169]. Many approaches are used in the literature, but many consider probabilistic distribution regarding the participation uncertainty dilemma and how it was dealt with. According to Bo Zeng and Xuan Wei [107] study, where the Capacity Credit (CC) from DR is assessed, which accommodates probabilistic and possibilistic uncertainties. The definition of CC was developed to quantify DG resources' capability to offer the capacity to power systems. However, the DR participants' flexibility could play a similar role in the Smart Grids concept, so the definition was extended. These authors resort to the fuzzy theory to express the uncertainty introduced by incomplete information and probabilistic propagation technique to describe the human-related uncertainties, standardizing them under the same framework. Consequently, the value of participation level changes with the decision-making during operation, making the formulation a time-dependent model. In the case of Smriti Singh and Ashwani Kumar [100], the MCS was used to model the uncertainty in consumers' participation, extracting samples that correspond to the most probable event. Since the active consumer often fails to reduce their load due to some external factors, the authors developed a probabilistic load model based on a normal distribution function according to the available historical load data. The uncertainties related to the stochastic variations of the variables involved in residential DR include load demand, user preferences, environmental conditions, house thermal behavior, and wholesale market trends. As Pierluigi Siano and Debora Sarno [214] believed, they can be modeled using the MCS method.

As mentioned earlier, besides MCS, MC is a stochastic process in which the present status is quite independent of past or future ones being suitable for modeling the uncertainty introduced by DR participants [123]. Abbas Tabandeh, Amir Abdollahi, and Masoud Rashidinejad [111] share this opinion and mention the importance of Advanced Metering Infrastructure (AMI) for this process. A failure from these technologies can influence the consumers' participation. In their study, the MC model is used for a DR resource to determine the consumers' participation by splitting the participation percentage into finite states – from 0 to 100% with a step of 25%. However, by distinguishing appliances and resorting to individual smart plugs, Zhai et al. [24] applied the same state logic with MC. These authors divided into two main types to define the corresponding flexibilities: appliances working in cycles and appliances working at fixed state. By understanding the habits and routines of this new player, starting with the appliances, the models can be more robust and capable of reducing the response uncertainty. In this way, Chia-Shing Tai, Jheng-Huang Hong, and Li-Chen Fu [108] develop a real-time multi-agent deep RL-based approach to solve the DSM problem and consider user behavior. Again, focusing on the state extraction part of the appliances, three different groups were created to understand the degree of influence of the state of the appliance on the user and the tolerance of frequent switching. First, the Heavy Conflict group includes appliances whose stat switching would lead to a less severe but still strong impact on the user experience. Finally, Less Conflict group, the operation time is less conflicting for the consumer and can be scheduled later - washing machine, dish dryer. The ability to adapt to and learn about user preferences and update the system repeatedly can improve one of the crucial characteristics of implementing DR in the real world: consumer comfort.

As mentioned earlier, for the residential type, comfort is crucial for their participation. This type of the participant is less willing to give up on certain equipment in a specific context just to participate in the market transactions. Nevertheless, the problem can be even more complex. In the study done by Liang et al. [211], the relationship between two pieces of equipment is a particular example of correlated DR (CDR). Gaming PCs and Heating, Ventilating, and Air Conditioning (HVAC) systems were presented. The authors believe these two appliances created a new factor in the management problem: CDR relationships considering heating and cooling demand. So, with the expected increase of power consumption from Gaming PCs, this appliance generates wasted heat along the DR process, requiring the Air Conditioner (AC) system to consume more power to maintain the indoor temperature in summer, which makes the original DR effect worse. However, in winter, the AC system consumes less power to maintain the indoor temperature when the gaming PC performs DR and generates waste heat, which improves the DR effect. In the presented model, the CDR unit consists of two parts: an uncertain and uncontrollable internal heat source – Gaming PC, and an HVAC system that provides DR independently. Considered a whole, the internal heating source brings uncertainty into the entity. Thus, the CDR decisions were operated properly by a risk management scheme considering a CVaR incorporated with a stochastic approach between many other uncertainties. The results confirm that the stochastic approach is more capable of handling uncertainties than the deterministic approach, reinforcing the approach of previous methods.

Still, the active consumers are responsible for the appliances. Participation is voluntary, and although penalties can be applied, they have total control to change their minds. In this way, the authors must focus on the active consumers' behavior. The assumption of DR participants as rational is widely accepted in many studies from the literature. The optimizations from many works look at active consumers as economic agents who always make the "right" decisions and understand the market transactions [109]. However, should the consumer be considered a rational agent who makes an optimal decision?

Bearing in mind, one of the main approaches to encourage others is Game Theory. Defined as the formal study of interdependence between adaptive agents and the dynamics of cooperation and competition that emerge from this [249]. In this case, the term agents refer to an entity with the capacity to make informed choices and act upon those choices autonomously to affect the state of the environment [237]. The interdependence between these adaptive agents means that the values associated with some property of one element become correlated with those of another. In other words, and for this context, the achievement of a goal of one agent becomes correlated with others. For instance, in this topic, game theory approaches can be categorized into two kinds, one is played between consumers, and the second is played between the utility and consumers. Also, two different levels can be defined for the interdependence between agents: the micro and the macro level.

5.1.1. *Macro-level perspective*

From a macro-level perspective, all the agents must work cooperatively to achieve an overall successful outcome at the macro level. Pondering the work from Akash Talwariya, Pushpendra Singh, and Mohan Kolhe [54], where these authors use the Monte Carlo Simulation (MCS) to consider uncertainty in both consumption and generation but also build a Stepwise Power Tariff model with Bayesian Game Theory to consider the active consumer's decisions. In this situation, it is expected that agents do not want to share their best strategy with other players, as happens in non-cooperative games. However, it can be drawn from the results that the best response is when consumers share full information about energy consumption with energy retailers and consumers.

Active consumers are selfish, so their behavior should be further studied in this situation [172]. Maximizing the individual consumer welfare DR programs by building an approach that considered the utility function and studying the consumer risk aversion behavior was the goal of Amir Niromandfam, Ahmad Sadeghi Yasdankhah, and Rasool Kazemzadeh [110] work. The utility function measures consumers' preferences. This is an important concept in microeconomics since it can understand how rational consumers make consumption decisions. Again, a central assumption in classical game theory is that players are always rational and strive to maximize their hyper–rationality payoffs [144]. However, the rules and dynamics may not be aligned with this assumption because what is rational for the whole is irrational for the individual. These agents, assumed to be rational, consistently act to improve their payoff without the possibility of making mistakes. They also fully know other players' interactions and have an infinite capacity to calculate all possibilities beforehand [250]. So, agents have accurate information, and any uncertainty is reduced to a probability distribution. However, this prediction may not be applied in certain situations as humans' behavior differs dramatically.

With this, numerous reasons may impact the active consumer actions: cultural, financial, natural, or social capital (that is, the relationships with other people and their roles within a social group) [251]. From this perspective, it is not the concept that players are trying to optimize. Their payoff needs to be adjusted for the different market options. Instead, the narrow definition of rationality as optimization according to a single metric needs to be expanded within several contexts involving social interaction.

Many examples can support this view of "perfect" agents in many other methods. Homa Rashidizadeh-Kermani et al. [55] created an interface between the market and the active consumers in a competitive environment. These authors designed a decision-making model for the DR aggregator. In day-ahead energy and balancing markets, the aggregators offer selling prices to the active consumers to maximize their expected profit, considering consumers' reactions to the rivals' prices. From the utility perspective, the risk aversion was modeled using CVaR. As in game theory, the players also have their agendas in this work, and two different levels are considered. First, the competition between the aggregator and the rivals offers a better price at the upper level. After, the active consumers act out of self-interest in the lower level and choose the most competitive aggregator to minimize their payments. At this level, it is considered that decisions are made with perfectly accurate information regarding the price offered by the aggregators.

Participants were deemed to react optimally to the utility prices for the profit maximization problem. This assumption will impact the utility's profit since, instead of providing to their active consumers, in a competitive environment, the players are expected to move to lower prices, which consider only a single metric (the pursuit of profit) without context awareness from each participant. For instance, in the study conducted by Billing Zhang et al. [172], a contract-based incentive scheme was proposed to encourage consumers and small-scale suppliers to participate in direct energy trading. Based on their achievements, consumers', and suppliers' behaviors, affect each other, and their strategies are highly coupled. Therefore, there is a need for a model where the utilities are defined, the interactions are analyzed, and the Nash Equilibrium is found. However, under asymmetric information, the problem becomes more complex. Jianwei Gao, Zeyang Ma, and Fengjia Guo [109] wanted to define risk-behavior awareness to focus on the risk from the demand side when participating in DR programs. Both organizations and individuals have different attitudes toward risk-taking. A utility function can be considered feasible to illustrate consumer risk attitudes toward gain or loss, focusing mainly on power, exponential, and logarithmic models. However, the authors pointed out that classical utility functions do not consider consumers' psychological factors.

5.1.2. *Micro-level perspective*

At the micro-level, individual agents pursue their agendas according to their cost-benefit analysis. Again, it should be highlighted that the standard economic theory assumes that all individuals act solely out of self-interest. As an illustration of this point of view, the study presented by Shuai Fan et al. [144] designed a model for DR consumers to choose an ideal rebate ratio to maximize their welfare. The process is designed as a non-cooperative game in which the Nash Equilibrium exists. The so-called Gossip algorithm used in this study was improved for a socially connected network. In this way, consumers can exchange information with familiar DR participants to estimate global information. In the end, it impacts as individuals and as a group but always finds the best option. For instance, to deal with energy retail market price and develop a win-win situation between consumers from several sectors and the utility, Akash Talwariya et al. [54] designed a stepwise power tariff using a game theory model for DR. The results showed that when consumers shared full information on energy consumption with energy retailers and other consumers, the best response was found. Perhaps, some information can be useful to share instead of a non-cooperative approach.

Still, besides the energy price, many other factors can also influence the participation decision, and, again, the context is crucial to understanding their actions. Özge Okur et al. [122] introduce a comprehensive MPC to update and reduce individual imbalances based on input data. From the utility perspective, the results found considerable season discrepancies – the influence of the context in which the event is triggered. June and December were the months with a higher and lower total amount of imbalances, respectively. These authors intend to explain this difference resorting to the absolute solar generation forecast errors: smaller due to lower solar generation. Besides this conclusion, Özge Okur et al. [122] found that the type of consumers can impact the imbalance. So, while demand profiles from residential consumers peak in the early morning and evening hours, the commercial sector peak occurs during daytime hours, coinciding with the highest fundamental imbalances. Nevertheless, the authors also prove that, although this is beneficial for the power system, reducing those imbalances may not benefit financially from the aggregator's point of view. However, these conclusions can help understand and build a model to reduce the response uncertainty.

The complexity of defining and understanding the active consumers is not just related to the amount of load they reduce – which is quite difficult to predict, mainly due to sparse data and each consumer's characteristics. Since it is still in development, their empowerment also includes the prosumer concept – where a consumer can also produce their energy and sell to the market. In work developed in Ref. [115], the authors proposed a data-driven methodology considering the k-nearest neighbor method (kNN) and a weighted ensemble model to deal with the load prediction problem. First, kNN requires small amounts of data, and considering that each consumer may receive a request for load curtailment only a few times a year, the method is adequate. Regarding the disparity between consumers, a single prediction method may not cover all the consumers – it provides a remarkable prediction operation for one consumer but is poor for the remainder. The authors used a weighted ensemble model to apply distinct models for different consumers. Following the same line of thought, Wang et al. [143] focused on the uncertainty related now to the prosumers, the increasing installation of photovoltaic systems (PV), how load patterns become more random, and the consumer baseline load (CBL) difficult to estimate. Especially hard to distinguish between increased PV output power and decreased actual load power. However, in this case, the k-means algorithm was used to divide the consumers into control groups, after calculating a curve similarity index where each DR participant was matched with the most similar cluster based on the similarity between its load curve and cluster centroids during periods when the distributed photovoltaic output power was equal to zero.

Several issues were addressed throughout the uncertainty topic, and the models were used to provide suitable solutions in each authors' opinion. The topic is highly complex. The active consumers' participation is very hard to predict since it depends on several factors. Some authors tried to predict their contribution and deal with uncertainty using probabilistic models [100,107,123,214] since the process is stochastic, statistical, and stationary. However, both AMI failures and appliances participation context impact the response [24,108,111,211]. A focus on ways to incentive their participation and anticipate their schedule to avoid discomfort or losses must be included in the final solution to implement DR. Still, the active consumers have control over these appliances, and some consider that they act as rational and economic agents, always to achieve their individual goal [110,172,250]. However, some studies found that sharing the information may benefit individual and group perspectives [54,144]. Nevertheless, including the prosumer definition may also be valuable since the definition of active consumer is changing [143].

5.2. DR performance

The performance definition throughout the present paper refers to the level of success of the consumers regarding their participation in DR events. In other words, when the managing entity sends a signal to change its load consumption, it is expected to comply and participate in the event, considering this active consumer as a trustworthy player. Even though the participation is voluntary, some DR programs require participation in a certain context, agreed by both parties. And although in the previous section, the active consumer is considered a rational and economic agent, always striving to achieve their goals in a "perfect" way, the reality may be different. As new players, they have low information regarding the market transactions and often do not have the availability to decide the proper approach. Aid, understanding, and enhancing their performance in DR events are goals.

5.2.1. Impact of the consumer behavior

The following works consider the complex non-deterministic nature of consumer behavior regarding performance in DR events. For instance, Konda et al. [195] proposed an adaptive fuzzy inference system (FIS) strategy to improve the performance of DR schedules. The fuzzy method is not new for analyzing consumer behavior in responsive loads – regarding load type, sectoral and seasonal variation. However, in the actual scheduling implementations, the inappropriate strategies may lead to consumer dissatisfaction and the consequent decrease of their participation in DR events. These authors bet on FIS for DR scheduling considering this key aspect: rule-based development and membership function (MF) parameter setting/adjustment. However, the idea that MF parameters must be tuned using expert knowledge or intelligent computational approaches should be reinforced. Thus, the results demonstrated improved convergence and performance compared to the traditional random willingness assignment methodology regarding consumer availability for market participation.

Still focusing on the importance of FIS in the investigation of the impact of consumer behavior, impact of load profile, and temporal characteristics of load profile by load sector and load type, the same author published another research [149] contemplating the utilization factor and availability factors for modeling consumer behavior using linear, non-linear, and exponential functions. Firstly, in the Linear Response Behavior, the relation of the utilization factor and cost factor is linearly proportionate. The Non-linear Response Behavior approach is represented as the product between the utilization and availability factors. The results revealed the non-linearity/non-smooth nature of load profile attributes combined with consumers' willingness.

Hence, due to the unclear response characteristics, it would be beneficial for the profit-oriented managing entity to employ non-linear tools instead of a linear method. Dehghanpour et al. [185] presented an Artificial Neural Network (ANN) approach to capture the loads' behavior using a non-linear ANN-based model to capture the non-linearities from loads' aggregate behavior. Based on the study results, these authors believe that as the penetration level of price-sensitive appliances increases in the system, the higher the improbability. Their methodology was based on a multiagent framework with machine learning that allows these authors to address interoperability and decision-making under incomplete information in a system that maintains data privacy, which can be crucial for active consumers to participate in DR programs.

5.2.2. Consumer behavior learning and prediction

ANN and ARMA prediction techniques to identify unclear load profiles. In work done by Mahmud et al. [104] and according to the results, day-ahead energy management mitigates indecision by implementing preventive measures. So, by considering a "learning" approach, the DR could be defined as automated as in the Aras Sheikhi, Mohammad Rayati, and Ali Mohammad Ranjbar [180] study. These authors consider the participant a price taker consumer with a fully automated energy management scheme (EMS) based on Reinforcement Learning (RL) to minimize their energy bills simultaneously. The EMS learns behaviors over time, the insecurity of energy prices, and appliance efficiency into making optimal decisions in a stochastic environment. The extracted information from AMI technologies can be used in a panoply of situations, namely, DR programs, load profiling, consumer consumption prediction, or even theft detection. Thus, the effects of the imprecise and incomplete information from failures in AMI technologies may condition outcomes from an approach, namely clustering algorithms.

However, many DR implementation solutions include consumer clustering to process consumer input data for possible flexibility such as occupancy, temperature, humidity, bidding strategy design, etc. Focusing on the AMI from the perspective of the residential consumer, Table 3 organizes studies that used clustering methods to analyze information from smart metering data. The table contains the number of participants, the data source, the location of the study, the clustering method, and the data size.

Some of the studies have a big dataset. However, as already mentioned, clustering is sensible to the input information, and errors from smart equipment may result in erroneous outputs. Thus, the a priori processing of the dataset with adequate data mining tools is crucial. This enables the aggregator to access meaningful information that helps deal with active consumers properly and enhance their performance. The incorporation of fuzzy variables to mitigate impact was suitable in the study conducted by Mansour Charwadn et al. [91]. This study aimed to represent the consumer load pattern, modeling the indecision and non-determinacy (hesitation) using the intuitionistic fuzzy divergence technique, which contains the membership, non-membership, and hesitancy function. Hence, this thresholding method considers each consumer's load pattern as an image, and each load value is assigned as a pixel. A minimization procedure is required to guarantee high separation accuracy for indecision in the consumer's pattern. Each consumer's Typical Load Pattern (TLP) is extracted using neighbor information (2-dimensional daily load values). The results evidenced that, with fewer thresholds, the simulation time is reduced and TLP accuracy.

5.2.3. Economic influence in the DR events

Employing a Deep Neural Network (DNN) to predict the unknown prices and energy demands can be useful to overcome future uncertainties and enhance performance, according to the Renzhi LU and Seung Ho Hong [87] work. In cooperation with DNN, RL is adopted to obtain the optimal incentives for different consumers considering both service providers and consumers' profits. RL is model-free, adaptive, and concise. Contrarily to the previous methods, the service provider does not need prior knowledge. Instead, it discovers the optimal incentive rates by "learning" from direct interaction with each active consumer.

Table 3
Clustering methods applied to residential consumers' smart metering data.

Ref.	#	Location	Method	Data size
[53]	197	UK, Bulgaria	Bayesian non-parametric	9 months
[50]	1.057	US	Dynamic Time wrapping	1 month
[219]	1.200	China	FCM clustering	1 Month
[252]	3.622	Ireland	Finite mixture model	1 year
[221]	300	–	Hierarchical clustering	104 days
[222]	265	Portugal	Hierarchical clustering	2 months
[51]	656	Switzerland	k-means	1 year
[52]	197	UK, Bulgaria	k-means	1 year
[218]	4.181	China	k-means and spectral clustering	1 Month
[217]	218.090	–	K-Means, Hierarchical Clustering	3 years
[220]	4.232	Portugal	k-means, Logistic Regression, Decision trees	1 year and 6 months

Moreover, the incentive rates are acquired and adapted autonomously, considering the uncertainties and flexibilities of the system. Finally, it is based on a look-up table, its implementation in the real world becomes much easier. As mentioned earlier, consumers are finitely rational as agents. However, due to psychological factors, such as cognitive or experimental judgment biases, consumers' positive outlook on participating in a DR program (viewing it as either loss or gain) depends on the reference point. So, their risk attitudes – risk-seeking, risk-averse, or risk-neutral, will shift. Remani T., E. A. Jasmin, and T. P. Imthias Ahamed [40] also consider RL an efficient tool for solving the decision-making problem under doubt. Their study intends to solve a load commitment problem considering consumer comfort, stochastic renewable power, and tariff. The problem was modeled as a Markov decision process. To use RL, state, state space, transition function, action, and reward function were identified.

Furthermore, other algorithms were also used to overcome this problem. Nsilulu Mbungu et al. [131] used an adaptive Time of Use (TOU) Model Predictive Control (MPC) approach to create a managing system for a real-time electricity pricing environment, integrating both solar energy generation and an energy storage system in an isolated power grid. The authors achieved good results in managing energy consumption by prioritizing some loads while centralizing the power supply as a demand function. In this approach, the consumer had the opportunity to keep track of their fee and decide on the use of the energy.

The Nash bargaining theory can be used to achieve the overall system's maximum social welfare when studying the economic interaction between the DSO and microgrids. In work performed by Hung Khanh Nguyen et al. [125], the authors concluded that when the system's social welfare is positive – the saving cost from the peak ramp reduction of the DSO is greater than the total cost of microgrids – the bargaining problem is feasible. Mosaddek Hossain Kamal Tushar et al. [59] created an energy planning noncooperative game for residential consumers with at least a Nash Equilibrium in the prediction phase. It was considered that, according to the Nash theorem, every noncooperation game with a finite number of players and action profile has at least one mixed strategy with a Nash equilibrium. So, the game ends when the equilibrium state is achieved, and no consumers are willing to change their strategy, reducing their payoff.

A fuzzy stochastic CVaR can be used to manage the risk associated with doubt, mainly focusing on price-based DR. The study done by Jiafu Yin and Dongmei Zhao [121] established that the price elastic response curve is inaccurate, the fuzzy characteristics of consumer behaviors are visible. Hence, to mathematically characterize the indecision of DR, the authors introduced the concept of self–elastic to formulate the response behavior-changing percentage of demand reduction concerning the changing percentage in incentive price during the same time interval. To assess the probabilistic risk, the authors pointed to the popularity of the stochastic CVaR criterion and the necessity to design a coherent risk measure in this fuzzy environment. Furthermore, the evidence that compared with the Value at Risk (VaR) method, the unit commitment model based on the CVaR expands the required reserves to minimize the complexity of indecision, protect against the operational risk and meet the system trustworthiness requirement.

Although several methods are used to improve the performance of DR schedules, namely fuzzy methods [149,195], it is important to deliberate those inappropriate strategies that may lead to consumer dissatisfaction and the consequent decrease of their participation in DR events. So, the managing entity of these new players must "learn" and capture their behavior to be able to provide the correct assistance in all situations [104,180,185]. Another approach considered in the former works was the clustering method, that although it has input problems, is widely used in the literature, as can be seen in Table 3. It was also noticed that the economic incentives could be useful for enhancing DR performances [40,59,125]. So, learning and understanding consumer behavior is a step forward to improving the contribution of these new players in the power and energy market.

5.3. DR reliability

In the literature, reliability is defined by the system being in a certain operating state and measured through indicators such as discontinuity duration, interruptions frequency, or not supplied energy [190]. The present paper is described from the system operator perspective regarding the DR events and all the intervenient. The previous two keywords mainly focus on active consumers, empowerment, and ways to enhance their role in the energy market. But the introduction of these new players will impact the system operation. In this way, the authors intend to understand the influence of DR on system security and reliability. Reliability will refer to the quality of being trustworthy or performing consistently well in such events, avoiding further problems.

Focusing on the perspective service provider, the randomness of DR responses caused by the consumers' volatile behavior when achieving a DR target can impact the system's reliability. Amir Ghasemkhani and Lei Yang [112] approach involve incurring a penalty on the participants. The authors mentioned that current research on pricing-based DR assumes that consumers' response functions are available to this player or maybe predicted by it. The RL-based algorithm was then used to aid the serving entity in learning the customers' aggregated behaviors to determine an optimal pricing strategy instead of using pre-defined response functions.

The non-necessity of gathering a priori information to allow each service provider and consumer to understand their position in the grid is supported by Byoung-Gook Kim et al. [20] when developing an RL to overcome the challenges of implementing dynamic pricing and energy consumption schedule. The authors compared two distinct scenarios in their study: the consumers with learning capability and the second involves myopic consumers. Not all consumers in the microgrid are not necessarily strategic. For them, it is more important to learn the dynamics of the entire system and find its optimal energy consumption scheduling based on the observations. However, Byoung-Gook Kim et al. [20] did not discard studying the strategic behaviors of the rational agents and their impact on system operation. Xiaodong Yang et al. [103] designed an adaptive MPC scheduling strategy to dynamically deal with predicted errors and update decision strategies according to the system's latest status and short-term predicted values. Three objectives were set: finding an optimal trajectory for power trade between the cooperating microgrids system and the main grid, addressing supply and demand uncertainties, and operating with outage events during emergency conditions. After several attempts, it was proven that supply-demand balance could be enhanced by implementing shift loads in each microgrid and can be adjusted by exchanging power with the adjacent microgrids.

Online MPC can be suitable for high indecision regarding the renewable generation and consumer responses. In the study performed by Farzad Arasteh and Gholam Riahy [123], this method was used for optimal real-time operation of wind integrated power systems, including coordinating energy storage systems and DR programs. In addition, these authors believed that the possibility of shifting load to off-peak hours makes the controller more flexible, resulting in a lower amount of load shedding and improvement of supply management. In the Prajwal Khadgi and Lihui Bai [86] case, MPC was interested in consumer response to DR events when applied to control the new active players. In this case, the consumers determined their optimal consumption by maximizing a multi-attribute utility function based on changing electricity prices, temperature, and thermal comfort. The results obtained by the authors indicate that among various static variable pricing schemes, the TOU rate is the most robust in achieving a higher Coincident Load Factor – the ratio of average load over a household's contribution to the system peak load in a daily cycle and reducing the costs from the perspective of the consumer.

Regarding the distinct dynamic variable pricing schemes, the former improves when comparing Demand Charge with Flat Rate. At the same time, Sudip Misra et al. [47] used a robust game theory to account for energy management constraints associated with indecision since it generally impacts the algorithms in this area. In this way, imperfect information was considered regarding all the indecision issues to optimize energy trading in the smart grid. Although, as a result, the consumers and the network act as players and the payoff values are optimized, the results showed an improvement compared to the existing energy management models.

However, although some appliances may belong to the same category, they can belong to different consumers, so flexibility is quite different because of power consumption and the owners' habits. Therefore, the authors determined that analyzing the DR potential by only considering appliance type and power consumption is irrational because consumer behavior strongly affects consumption, leading to big variations in the energy consumed by the same type of appliance. Therefore, the human factor cannot be discarded. To prove this view, a more specific study was presented by Maomao Hu and Fu Xiao [137] using the Markov Chain Monte Carlo model to quantify indecision in the aggregate energy flexibility considering stochastic occupancy and occupant behavior which characterizes the randomness of people entering or leaving a specified space at a particular time – influencing the appliances. As affirmed by these authors, the Markov-chain technique is widely used to simulate this process and generate stochastic occupancy patterns.

A negative impact of the active consumers in the network can lead to loss of security and jeopardize the system's reliability. So, many authors opt for economic strategies to test the trustworthiness of the participants in DR events using penalties [112] or distinct DR programs [20,86,103], some in real-time [123]. The game theory approach was still mentioned but explored imperfect information [47]. Again, the human factor cannot be discarded, and the different factors that may impact their decisions must be widely studied.

6. Discussion of the identified challenges and future Research

The active consumers that emerge in power systems are complex, and their actions rarely follow the traditional theory of decision-making, which makes their behavior hard to predict from this standpoint. Instead, psychology and behavioral economics must be employed for greater prediction accuracy. Contrasting both theories, traditional economic models expect consumers to make optimal decisions that result in optimal outcomes. On the other hand, behavioral economics considers that consumer choices can be improved by providing more information and other options to influence the consumers' behavioral patterns.

A growing number of scientific research intends to demystify traditional economic theory and point to the importance of understanding the context in which the consumer operates so that solutions can be found to influence their behavior, to make the desired decision easier, quicker, and more convenient from their perspective, minimizing the physical and psychological effort and reducing the perceived doubt. This can be achieved by, for instance, providing the consumer with comparisons between themselves and the other players' performances, possessions, and wellbeing. By demonstrating that consumers with a profile like theirs (the same power contract, the same consumer type, etc.) are using less energy and taking energy-saving actions that are beneficial, the consumer will be more encouraged to follow these positive energy-saving norms and reduce their consumption accordingly.

Moreover, implementing fair rewards and monetary incentives can motivate the DR event participation regarding intrinsic and extrinsic compensation. Finally, the trust factor is important to give the right message for the demand side to make the right decisions – if they seem skeptical can either disengage or react defensively to the information. Using simple and easy-to-understand messages to communicate with consumers who have limited knowledge of the energy market can help increase confidence in the solution. If there is doubt around the electricity supply, market prices, government policies, and long-term financial payoffs, investment in this approach may seem risky for many consumers.

Furthermore, there is a need to upgrade to smart equipment to enable communication between the active consumer and the energy market. The active consumers must improve and integrate technologies capable of, for instance, being controlled by the local community manager or equipment to simply receive the proper signals to participate in the market transactions. Focusing on each appliance instead of considering the whole building may reduce doubt in DR events. Thanks to advances in AMI technologies and the extracted information, the managing entity can delineate and understand its strategy to succeed in the energy market by persuading active consumers to opt for cooperation instead of rivalry.

The above discussion evidence that context-awareness approaches are necessary to handle consumer participation more accurately [1]. Activating consumers according to the context and providing adequate performance evaluation, for example, through key performance indicators [253], makes the consumer better integrated into the process, increasing their motivation and understanding of the rewards process. Moreover, contracts between consumers and entities requesting DR should be drawn up according to the preferences and interests of each player [254]. Aggregators will play a key role in collecting the available DR from small consumers and establishing contracts using the potential of DR to the fullest [122]. Moreover, Artificial Intelligence methods help support decisions on DR management, namely load forecasting [255, 256]. This method helps understand future consumption, which is crucial when estimating potential flexibility in managing a DR event.

Moreover, learning approaches can be used to learn about consumer behaviors. These approaches learn from events and apply them to similar future events. This enables them to make more accurate decisions in the future [257].

In summary, with all the information studied through the present paper, the authors believe that future lines of research should focus on the consumer side, emphasizing comfort and behavioral aspects, privacy-awareness in the DR programs definition, and the contextual management of the resources to implement DR solution in the future smart grid successfully.

7. Final remarks

The role of the end-user is changing together with the gradual implementation of the Smart Grid concept. This concept urges for greater consumer flexibility: consumers who can control and change their consumption according to signals given by the energy market. However, this new paradigm also enables on-site production for small entities. The new active consumer will have more power over the transactions on the market, and thus, understanding and dealing with their decisions will be crucial to a successful implementation. Consumer empowerment will have an impact on the operation of the grid. If the right solution were designed to include all the necessary features to deal with the uncertainty introduced by new players, a huge step would be taken towards developing a smarter grid. However, when empowering the consumers' many factors should be considered:

- Consumers should not be considered agents that have access to perfectly accurate information – the behavior of real people tends to differ dramatically. Although, after the discussion, the authors believe that participants will always be active and willing to change their strategy and consider them as "perfect" economic and rational agents with complete awareness of the market environment, seeking the optimal decision may be a faulty assumption. To solve this problem and reduce the response uncertainty, the authors suggest a contextual solution: giving the right signals according to the different behaviors and the different types of participants in the DR event.
- The DR participants' actions in the energy market will be complex and rarely follow the traditional economic decision-making theory. So, they are considered hard to predict from this standpoint but are rather predictable from psychology and behavioral economics. In the authors' opinion, implementing DR in the market should discover what influences the participants: the social influence, intrinsic and extrinsic rewards, and trust may play a key role.
- Sharing the full information between players, retailers, and other consumers leads to better results. However, privacy concerns can be raised. The authors believe that trust should be crucial and instigated from both sides. Therefore, define limits and boundaries regarding which information should or not be shared.
- Approaches must consider non-linear tools regarding load profiles' uncertain nature combined with consumers' willingness to participate. Several study results prove that a stochastic approach can handle more uncertainties than a deterministic approach. In this case, the authors believe that each type of active consumer has its characteristics and should be treated accordingly.
- Focus on the appliances for DR, through Advanced Metering Infrastructures, instead of solutions where all the consumers' flexibility is considered. By understanding the functioning of the appliance and the impact of the consumer comfort, since it has freedom of choice to disconnect any time, the uncertainty of the response can be reduced. However, another problem derived from this perspective is the correlated DR relationships. For instance, in a load shifting approach, an appliance that generates heat may require other cooling equipment to maintain the consumers' comfort. For this case, the authors believe that all the appliances should be listed in the DR contract and further define their relationship and consequences.
- Despite several existing approaches in DR and DSM field, it has been found that the consumers deserve more knowledge to support their decisions in DR participation instead of reacting to incentives and prices. Given that the knowledge is self-reported, there may be a considerable divergence between attitudes and observable behaviors, for example, the consumers who still depend on non-renewable resources, do not rely on public transport, and make heavy use of their vehicles, neglect recycling, and any other actions that harm the environment. The authors believe that more information should be shared on social media, new policies including and giving more awareness on the impacts of this concept.

Thus, influencing the behaviors of active consumers and their decisions to reduce uncertainty and enhance their performance on DR events can bring several advantages for all the players involved in market transactions and facilitate the penetration of renewable resources in the system. Therefore, more projects should focus on understanding how to influence and reduce uncertainty on the consumer side.

Funding

This article is a result of the project RETINA (NORTE-01-0145-FEDER-000062), supported by Norte Portugal Regional Operational Programme (NORTE 2020), under the PORTUGAL 2020 Partnership Agreement, through the European Regional Development Fund (ERDF). We also acknowledge the work facilities and equipment provided by GECAD research center (UIDB/00760/2020) to the project team, and grants CEECIND/02887/2017 and SFRH/BD/144200/2019.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] C. Silva, P. Faria, Z. Vale, Rating the participation in demand response programs for a more accurate aggregated schedule of consumers after enrolment period, Electronics 9 (2) (Feb. 2020) 349, https://doi.org/10.3390/electronics9020349.
[2] P. Bertoldi, P. Zancanella, B. Boza-Kiss, Demand Response Status in EU Member States, 2016, https://doi.org/10.2790/962868.
[3] Energy Union | Energy, Mar. 08, 2017. https://ec.europa.eu/energy/topics/energy-strategy/energy-union_en#five-dimensions-of-the-energy-union. (Accessed 4 December 2020). accessed.
[4] M. Kühnbach, J. Stute, A.-L. Klingler, Impacts of avalanche effects of price-optimized electric vehicle charging - does demand response make it worse? Energy Strategy Rev. 34 (Mar. 2021) 100608, https://doi.org/10.1016/j.esr.2020.100608.
[5] K. Wohlfarth, A.-L. Klingler, W. Eichhammer, The flexibility deployment of the service sector - a demand response modelling approach coupled with evidence from a market research survey, Energy Strategy Rev. 28 (Mar. 2020) 100460, https://doi.org/10.1016/j.esr.2020.100460.
[6] M. Kühnbach, J. Stute, T. Gnann, M. Wietschel, S. Marwitz, M. Klobasa, Impact of electric vehicles: will German households pay less for electricity? Energy Strategy Rev. 32 (Nov. 2020) 100568, https://doi.org/10.1016/j.esr.2020.100568.
[7] S. Zheng, Y. Sun, B. Li, B. Qi, X. Zhang, F. Li, Incentive-based integrated demand response for multiple energy carriers under complex uncertainties and double coupling effects, Appl. Energy 283 (June 2020) (2021) 116254, https://doi.org/10.1016/j.apenergy.2020.116254.
[8] European Parliament and Council of the Eu, Directive (EU) 2019/944 on common rules for the internal market for electricity and amending directive 2012/27/EU, Off. J. Eur. Union (158) (2019) 18. http://eur-lex.europa.eu/pri/en/oj/dat/2003/l_285/l_28520031101en00330037.pdf.
[9] Delta H2020 Homepage | DELTA Project." https://www.delta-h2020.eu/ (accessed Dec. 04, 2020).
[10] EUR-Lex - 32019R0943 - EN - EUR-Lex." https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32019R0943 (accessed Dec. 04, 2020).
[11] European Parliament, Directive (EU) 2019/944 on common rules for the internal market for electricity, Off. J. Eur. Union (L 158) (2019) 18.
[12] M. Kubli, M. Loock, R. Wüstenhagen, The flexible prosumer: measuring the willingness to co-create distributed flexibility, Energy Pol. 114 (2018), https://doi.org/10.1016/j.enpol.2017.12.044.
[13] M. Shafie-khah, P. Siano, J. Aghaei, M.A.S. Masoum, F. Li, J.P.S. Catalao, Comprehensive review of the recent advances in industrial and commercial DR, IEEE Trans. Ind. Inf. 15 (7) (Jul. 2019) 3757–3771, https://doi.org/10.1109/TII.2019.2909276.
[14] Z. Baum, R.R. Palatnik, O. Ayalon, D. Elmakis, S. Frant, Harnessing households to mitigate renewables intermittency in the smart grid, Renew. Energy 132 (Mar. 2019) 1216–1229, https://doi.org/10.1016/j.renene.2018.08.073.
[15] M. Minou, G.D. Stamoulis, T.G. Papaioannou, The effect of altruism in automated demand response for residential users, in: 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), 2018-Janua, Sep. 2017, pp. 1–6, https://doi.org/10.1109/ISGTEurope.2017.8260336.
[16] A.G. Thomas, L. Tesfatsion, Braided cobwebs: cautionary tales for dynamic pricing in retail electric power markets, IEEE Trans. Power Syst. 33 (6) (Nov. 2018) 6870–6882, https://doi.org/10.1109/TPWRS.2018.2832471.
[17] I. Dusparic, A. Taylor, A. Marinescu, F. Golpayegani, S. Clarke, Residential demand response: experimental evaluation and comparison of self-organizing techniques, Renew. Sustain. Energy Rev. 80 (December 2016) (Dec. 2017) 1528–1536, https://doi.org/10.1016/j.rser.2017.07.033.
[18] N. Good, K.A. Ellis, P. Mancarella, Review and classification of barriers and enablers of demand response in the smart grid, Renew. Sustain. Energy Rev. 72 (May 2017) 57–72, https://doi.org/10.1016/j.rser.2017.01.043.
[19] A. Liberati, et al., The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration, PLoS Med. 6 (7) (Jul. 2009) e1000100, https://doi.org/10.1371/journal.pmed.1000100.
[20] B.-G. Kim, Y. Zhang, M. van der Schaar, J.-W. Lee, Dynamic pricing and energy consumption scheduling with reinforcement learning, IEEE Trans. Smart Grid 7 (5) (Sep. 2016) 2187–2198, https://doi.org/10.1109/TSG.2015.2495145.
[21] D. Liu, Y. Sun, Y. Qu, B. Li, Y. Xu, Analysis and accurate prediction of user's response behavior in incentive-based demand response, IEEE Access 7 (2019) 3170–3180, https://doi.org/10.1109/ACCESS.2018.2889500.
[22] Y. Li, W. Gao, Y. Ruan, Y. Ushifusa, Demand response of customers in Kitakyushu smart community project to critical peak pricing of electricity, Energy Build. 168 (Jun. 2018) 251–260, https://doi.org/10.1016/j.enbuild.2018.03.029.
[23] A. Wang, R. Li, S. You, Development of a data driven approach to explore the energy flexibility potential of building clusters, Appl. Energy 232 (September) (Dec. 2018) 89–100, https://doi.org/10.1016/j.apenergy.2018.09.187.
[24] S. Zhai, Z. Wang, X. Yan, G. He, Appliance flexibility analysis considering user behavior in home energy management system using smart plugs, IEEE Trans. Ind. Electron. 66 (2) (Feb. 2019) 1391–1401, https://doi.org/10.1109/TIE.2018.2815949.
[25] W. Zeng, M. Sun, B. Chen, W. He, Y. Huang, K. Yu, Load cluster management considering response uncertainty, in: 2018 China International Conference on Electricity Distribution (CICED), Sep. 2018, pp. 2865–2869, https://doi.org/10.1109/CICED.2018.8592587, 201805270000002.
[26] Z.A. Khan, D. Jayaweera, H. Gunduz, Smart meter data taxonomy for demand side management in smart grids, in: 2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Oct. 2016, pp. 1–8, https://doi.org/10.1109/PMAPS.2016.7764143.
[27] P. Warren, Demand-side policy: global evidence base and implementation patterns, Energy Environ. 29 (5) (Aug. 2018) 706–731, https://doi.org/10.1177/0958305X18758486.
[28] J.S. Nutma, G. Hoogsteen, A. Molderink, W.E. Wijbrandi, J.L. Hurink, G.J. M. Smit, On integrating device level schedules into market based control, in: 2017 IEEE Manchester PowerTech, Jun. 2017, pp. 1–6, https://doi.org/10.1109/PTC.2017.7980984.
[29] T. Chen, H. Pourbabak, Z. Liang, W. Su, An integrated eVoucher mechanism for flexible loads in real-time retail electricity market, IEEE Access 5 (2017) 2101–2110, https://doi.org/10.1109/ACCESS.2017.2659704.
[30] B. Zeng, D. Zhao, C. Singh, J. Wang, C. Chen, Holistic modeling framework of demand response considering multi-timescale uncertainties for capacity value estimation, Appl. Energy 247 (February) (Aug. 2019) 692–702, https://doi.org/10.1016/j.apenergy.2019.03.121.
[31] D.P. Zhou, M. Balandat, M.A. Dahleh, C.J. Tomlin, Eliciting private user information for residential demand response, in: 2017 IEEE 56th Annual Conference on Decision and Control, CDC 2017 2018-Janua, Dec. 2018, pp. 189–195, https://doi.org/10.1109/CDC.2017.8263664.
[32] P. Faria, Z. Vale, A demand response approach to scheduling constrained load shifting, Energies 12 (9) (May 2019) 1752, https://doi.org/10.3390/en12091752.
[33] S.S. Torbaghan, et al., A market-based framework for demand side flexibility scheduling and dispatching, Sustain. Energy Grids Networks 14 (Jun. 2018) 47–61, https://doi.org/10.1016/j.segan.2018.03.003.
[34] N. Mahmoudi, E. Heydarian-Forushani, M. Shafie-khah, T.K. Saha, M.E. H. Golshan, P. Siano, A bottom-up approach for demand response aggregators' participation in electricity markets, Elec. Power Syst. Res. 143 (Feb. 2017) 121–129, https://doi.org/10.1016/j.epsr.2016.08.038.
[35] S. Chen, R.S. Cheng, Operating reserves provision from residential users through load aggregators in smart grid: a game theoretic approach, IEEE Trans. Smart Grid 10 (2) (Mar. 2019) 1588–1598, https://doi.org/10.1109/TSG.2017.2773145.
[36] N. Mahmoudi, T.K. Saha, M. Eghbal, Demand response application by strategic wind power producers, IEEE Trans. Power Syst. 31 (2) (Mar. 2016) 1227–1237, https://doi.org/10.1109/TPWRS.2015.2424409.
[37] O. Abrishambaf, P. Faria, Z. Vale, Ramping of demand response event with deploying distinct programs by an aggregator, Energies 13 (6) (Mar. 2020) 1389, https://doi.org/10.3390/en13061389.
[38] E. Mahboubi-Moghaddam, M. Nayeripour, J. Aghaei, Reliability constrained decision model for energy service provider incorporating demand response programs, Appl. Energy 183 (Dec. 2016) 552–565, https://doi.org/10.1016/j.apenergy.2016.09.014.
[39] B. Wang, J.A. Camacho, G.M. Pulliam, A.H. Etemadi, P. Dehghanian, New reward and penalty scheme for electric distribution utilities employing load-based reliability indices, IET Gener., Transm. Distrib. 12 (15) (Aug. 2018) 3647–3654, https://doi.org/10.1049/iet-gtd.2017.1809.
[40] T. Remani, E.A. Jasmin, T.P.I. Ahamed, Residential load scheduling with renewable generation in the smart grid: a reinforcement learning approach, IEEE Syst. J. 13 (3) (Sep. 2019) 3283–3294, https://doi.org/10.1109/JSYST.2018.2855689.
[41] S. Wang, C. Shao, Y. Ding, J. Yan, Operational reliability of multi-energy customers considering service-based self-scheduling, Appl. Energy 254 (June) (Nov. 2019) 113531, https://doi.org/10.1016/j.apenergy.2019.113531.
[42] H.-S. Lee, C. Tekin, M. van der Schaar, J.-W. Lee, Contextual learning for unit commitment with renewable energy sources, in: 2016 IEEE Global Conference on Signal and Information Processing (GlobalSIP), Dec. 2016, pp. 866–870, https://doi.org/10.1109/GlobalSIP.2016.7905966.
[43] H.J. Monfared, A. Ghasemi, A. Loni, M. Marzband, A hybrid price-based demand response program for the residential micro-grid, Energy 185 (Oct. 2019) 274–285, https://doi.org/10.1016/j.energy.2019.07.045.
[44] I. Marneris, P. Biskas, A. Bakirtzis, Stochastic and deterministic unit commitment considering uncertainty and variability reserves for high renewable integration, Energies 10 (1) (Jan. 2017) 140, https://doi.org/10.3390/en10010140.
[45] M. Najafi, S. Ahmadi, M. Dashtdar, Simultaneous Energy and Reserve Market Clearing with Consideration of Interruptible Loads as One of Demand Response Resources and Different Reliability Requirements of Consumers, 2019, https://doi.org/10.1515/ijeeps-2019-0018.
[46] D.M. Minhas, R.R. Khalid, G. Frey, Activation of electrical loads under electricity price uncertainty, in: 2017 IEEE International Conference on Smart Energy Grid Engineering (SEGE), Aug. 2017, pp. 373–378, https://doi.org/10.1109/SEGE.2017.8052828.
[47] S. Misra, S. Bera, T. Ojha, H.T. Mouftah, A. Anpalagan, ENTRUST: energy trading under uncertainty in smart grid systems, Comput. Network. 110 (Dec. 2016) 232–242, https://doi.org/10.1016/j.comnet.2016.09.021.
[48] H. Mortaji, S.H. Ow, M. Moghavvemi, H.A.F. Almurib, Load shedding and smart-direct load control using internet of things in smart grid demand response management, IEEE Trans. Ind. Appl. 53 (6) (Nov. 2017) 5155–5163, https://doi.org/10.1109/TIA.2017.2740832.
[49] H. Mortaji, Ow Siew Hock, M. Moghavvemi, H.A.F. Almurib, Smart grid demand response management using internet of things for load shedding and smart-direct load control, in: 2016 IEEE Industry Applications Society Annual Meeting, Oct. 2016, pp. 1–7, https://doi.org/10.1109/IAS.2016.7731836.

[50] T. Teeraratkul, D. O'Neill, S. Lall, Shape-based approach to household electric load curve clustering and prediction, IEEE Trans. Smart Grid 9 (5) (Sep. 2018) 5196–5206, https://doi.org/10.1109/TSG.2017.2683461.

[51] S. Yilmaz, J. Chambers, S. Cozza, M.K. Patel, Exploratory study on clustering methods to identify electricity use patterns in building sector, J. Phys. Conf. 1343 (Nov. 2019) 12044, https://doi.org/10.1088/1742-6596/1343/1/012044.

[52] R. Granell, C.J. Axon, D.C.H. Wallom, Impacts of raw data temporal resolution using selected clustering methods on residential electricity load profiles, IEEE Trans. Power Syst. 30 (6) (Nov. 2015) 3217–3224, https://doi.org/10.1109/TPWRS.2014.2377213.

[53] R. Granell, C.J. Axon, D.C.H. Wallom, Clustering disaggregated load profiles using a Dirichlet process mixture model, Energy Convers. Manag. 92 (Mar. 2015) 507–516, https://doi.org/10.1016/j.enconman.2014.12.080.

[54] A. Talwariya, P. Singh, M. Kolhe, A stepwise power tariff model with game theory based on Monte-Carlo simulation and its applications for household, agricultural, commercial and industrial consumers, Int. J. Electr. Power Energy Syst. 111 (July 2018) (Oct. 2019) 14–24, https://doi.org/10.1016/j.ijepes.2019.03.058.

[55] H. Rashidizadeh-Kermani, M. Vahedipour-Dahraie, M. Shafie-khah, J.P. S. Catalão, Stochastic programming model for scheduling demand response aggregators considering uncertain market prices and demands, Int. J. Electr. Power Energy Syst. 113 (June) (Dec. 2019) 528–538, https://doi.org/10.1016/j.ijepes.2019.05.072.

[56] S. Talari, M. Shafie-khah, F. Wang, J. Aghaei, J.P.S. Catalao, Optimal scheduling of demand response in pre-emptive markets based on stochastic bilevel programming method, IEEE Trans. Ind. Electron. 66 (2) (Feb. 2019) 1453–1464, https://doi.org/10.1109/TIE.2017.2786288.

[57] S. Wang, F. Luo, Z.Y. Dong, Z. Xu, Coordinated residential energy resource scheduling with human thermal comfort modelling and renewable uncertainties, IET Gener., Transm. Distrib. 13 (10) (2019) 1768–1776, https://doi.org/10.1049/iet-gtd.2018.5355.

[58] D. Wu, B. Wang, D. Precup, B. Boulet, Multiple Kernel learning-based transfer regression for electric load forecasting, IEEE Trans. Smart Grid 11 (2) (Mar. 2020) 1183–1192, https://doi.org/10.1109/TSG.2019.2933413.

[59] M.H.K. Tushar, A.W. Zeineddine, C. Assi, Demand-side management by regulating charging and discharging of the EV, ESS, and utilizing renewable energy, IEEE Trans. Ind. Inf. 14 (1) (Jan. 2018) 117–126, https://doi.org/10.1109/TII.2017.2755465.

[60] C. Wu, W. Tang, K. Poolla, R. Rajagopal, Predictability, constancy and contingency in electric load profiles, in: 2016 IEEE International Conference on Smart Grid Communications (SmartGridComm), Nov. 2016, pp. 662–667, https://doi.org/10.1109/SmartGridComm.2016.7778837.

[61] S. Welikala, C. Dinesh, M.P.B. Ekanayake, R.I. Godaliyadda, J. Ekanayake, Incorporating appliance usage patterns for non-intrusive load monitoring and load forecasting, IEEE Trans. Smart Grid 10 (1) (Jan. 2019) 448–461, https://doi.org/10.1109/TSG.2017.2743760.

[62] D. Li, S.K. Jayaweera, Uncertainty modeling and price-based demand response scheme design in smart grid, IEEE Syst. J. 11 (3) (2017) 1743–1754, https://doi.org/10.1109/JSYST.2014.2369451.

[63] S.J. Kim, G.B. Giannakis, An online convex optimization approach to real-time energy pricing for demand response, IEEE Trans. Smart Grid 8 (6) (2017) 2784–2793, https://doi.org/10.1109/TSG.2016.2539948.

[64] P. Theile, et al., Day-ahead electricity consumption prediction of a population of households: analyzing different machine learning techniques based on real data from RTE in France, in: 2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), Oct. 2018, pp. 1–6, https://doi.org/10.1109/SmartGridComm.2018.8587591.

[65] S. Lokhande, V.P. Menon, Y.K. Bichpuriya, Modelling of demand response for utility's loac forecasting, in: International Conference on the European Energy Market, EEM, Jun. 2017, pp. 1–6, https://doi.org/10.1109/EEM.2017.7981985.

[66] J. Jose, V. Margaret, K.U. Rao, Impact of demand response contracts on short-term load forecasting in smart grid using SVR optimized by GA, in: 2017 Innovations in Power and Advanced Computing Technologies, I-PACT 2017, 2017-Janua, Apr. 2017, pp. 1–9, https://doi.org/10.1109/IPACT.2017.8244928.

[67] C. Ziras, C. Heinrich, H.W. Bindner, Why baselines are not suited for local flexibility markets, Renew. Sustain. Energy Rev. 135 (Jan. 2021) 110357, https://doi.org/10.1016/j.rser.2020.110357.

[68] K. Li, J. Che, B. Wang, J. Zhang, F. Wang, Z. Mi, A meta-heuristic optimization based residential load pattern clustering approach using improved Gravitational Search Algorithm, in: 2018 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Feb. 2018, pp. 1–5, https://doi.org/10.1109/ISGT.2018.8403401.

[69] Y. Xiong, B. Wang, C. Chu, R. Gadh, Vehicle grid integration for demand response with mixture user model and decentralized optimization, Appl. Energy 231 (September) (Dec. 2018) 481–493, https://doi.org/10.1016/j.apenergy.2018.09.139.

[70] G.M.U. Din, A.U. Mauthe, A.K. Marnerides, Appliance-level short-term load forecasting using deep neural networks, in: 2018 International Conference on Computing, Networking and Communications, ICNC 2018, 2018, pp. 53–57, https://doi.org/10.1109/ICCNC.2018.8390366.

[71] N. Ahmed, S. Member, M. Levorato, G.P. Li, Residential Consumer-Centric Demand Side Management 9, 2018, pp. 4513–4524, 5.

[72] G. Le Ray, P. Pinson, E.M. Larsen, Data-driven Demand Response Characterization and Quantification, 2017, https://doi.org/10.1109/PTC.2017.7981009.

[73] A.C. Varghese, P V, G. Kumar, S.A. Khaparde, Smart grid consumer behavioral model using machine learning, in: 2018 IEEE Innovative Smart Grid Technologies - Asia (ISGT Asia), May 2018, pp. 734–739, https://doi.org/10.1109/ISGT-Asia.2018.8467824.

[74] C. Eksin, H. Delic, A. Ribeiro, Demand response with communicating rational consumers, IEEE Trans. Smart Grid 9 (1) (2016) 469–482, https://doi.org/10.1109/tsg.2016.2613993.

[75] D. Leiva, C. Araya, G. Valverde, J. Quiros-Tortos, Statistical representation of demand for GIS-based load profile allocation in distribution networks, in: 2017 IEEE Manchester PowerTech, Jun. 2017, pp. 1–6, https://doi.org/10.1109/PTC.2017.7981065.

[76] P. Herath, G. Venayagamoorthy, A Study on Demand Response Potential of a Residential Area Using Census Data, 2019, https://doi.org/10.1109/PSC.2018.8664048.

[77] Y. Li, Q. Hu, N. Li, Learning and selecting the right customers for reliability: a multi-armed bandit approach, in: 2018 IEEE Conference on Decision and Control (CDC), 2018-Decem, Dec. 2018, pp. 4869–4874, https://doi.org/10.1109/CDC.2018.8619481. Cdc.

[78] S. Chen, C.C. Liu, From demand response to transactive energy: state of the art, J. Modern Power Syst. Clean Energy 5 (1) (2017) 10–19, https://doi.org/10.1007/s40565-016-0256-x.

[79] S. Haben, C. Singleton, P. Grindrod, Analysis and clustering of residential customers energy behavioral demand using smart meter data, IEEE Trans. Smart Grid 7 (1) (Jan. 2016) 136–144, https://doi.org/10.1109/TSG.2015.2409786.

[80] M. Lindèn, J. Helbrink, M. Nilsson, D. Pogosjan, J. Ridenour, A. Badano, Categorisation of electricity customers based upon their demand patterns, CIRED - Open Access Proc. J. 2017 (1) (Oct. 2017) 2628–2631, https://doi.org/10.1049/oap-cired.2017.0878.

[81] O.A. Paramo Rojas, J.C. Rivera, G.A. Lopez Alvarez, Effects on electricity markets of a demand response model based on day ahead real time prices: application to the Colombian case, in: IEEE Latin America Transactions, 16, 2018, pp. 1416–1423, https://doi.org/10.1109/TLA.2018.8408436, 5.

[82] X. Xu, C. Chen, A. Washizu, H. Ishii, H. Yashiro, Willingness to pay for home energy management system: a cross-country comparison, in: 2018 IEEE Power & Energy Society General Meeting (PESGM) 2018-Augus, Aug. 2018, pp. 1–5, https://doi.org/10.1109/PESGM.2018.8586275.

[83] B. Zeng, X. Wei, B. Sun, F. Qiu, J. Zhang, X. Quan, Assessing capacity credit of demand response in smart distribution grids with behavior-driven modeling framework, Int. J. Electr. Power Energy Syst. 118 (July 2019) (Jun. 2020) 105745, https://doi.org/10.1016/j.ijepes.2019.105745.

[84] B. Zeng, G. Wu, J. Wang, J. Zhang, M. Zeng, Impact of behavior-driven demand response on supply adequacy in smart distribution systems, Appl. Energy 202 (Sep. 2017) 125–137, https://doi.org/10.1016/j.apenergy.2017.05.098.

[85] D. Ellman, Y. Xiao, Customer incentives for gaming demand response baselines, in: 2019 IEEE 58th Conference on Decision and Control (CDC), 2019-Decem, Dec. 2019, pp. 5174–5179, https://doi.org/10.1109/CDC40024.2019.9029860. Cdc.

[86] P. Khadgi, L. Bai, A simulation study for residential electricity user behavior under dynamic variable pricing with demand charge, IISE Transactions 50 (8) (Aug. 2018) 699–710, https://doi.org/10.1080/24725854.2018.1440671.

[87] R. Lu, S.H. Hong, Incentive-based demand response for smart grid with reinforcement learning and deep neural network, Appl. Energy 236 (August 2018) (Feb. 2019) 937–949, https://doi.org/10.1016/j.apenergy.2018.12.061.

[88] Y. Weng, J. Yu, R. Rajagopal, Probabilistic baseline estimation based on load patterns for better residential customer rewards, Int. J. Electr. Power Energy Syst. 100 (August 2017) (Sep. 2018) 508–516, https://doi.org/10.1016/j.ijepes.2018.02.049.

[89] Learning-Based Demand Response for Privacy-Preserving Users.".

[90] Z. Jiang, R. Lin, F. Yang, Incremental electricity consumer behavior learning using smart meter data, in: Proceedings of the 2019 4th International Conference on Big Data and Computing - ICBDC 2019, 2019, pp. 54–59, https://doi.org/10.1145/3335484.3335517.

[91] M. Charwand, M. Gitizadeh, P. Siano, G. Chicco, Z. Moshavash, Clustering of electrical load patterns and time periods using uncertainty-based multi-level amplitude thresholding, Int. J. Electr. Power Energy Syst. 117 (August 2019) (May 2020) 105624, https://doi.org/10.1016/j.ijepes.2019.105624.

[92] L. Cheng, et al., Behavioral decision-making in power demand-side response management: a multi-population evolutionary game dynamics perspective, Int. J. Electr. Power Energy Syst. 129 (Jul. 2021) 106743, https://doi.org/10.1016/j.ijepes.2020.106743.

[93] S.V. Oprea, A. Bâra, B.G. Tudorică, M.I. Călinoiu, M.A. Botezatu, Insights into demand-side management with big data analytics in electricity consumers' behaviour, Comput. Electr. Eng. 89 (Jan. 2021) 106902, https://doi.org/10.1016/j.compeleceng.2020.106902.

[94] N. Guo, Y. Wang, G. Yan, A double-sided non-cooperative game in electricity market with demand response and parameterization of supply functions, Int. J. Electr. Power Energy Syst. 126 (Mar. 2021) 106565, https://doi.org/10.1016/j.ijepes.2020.106565.

[95] C. Stagnaro, S. Benedettini, Who are the customers with flexible demand, and how to find them?, in: Variable Generation, Flexible Demand Elsevier, 2021, pp. 125–145, https://doi.org/10.1016/b978-0-12-823810-3.00016-9.

[96] W. Zhong, K. Xie, Y. Liu, C. Yang, S. Xie, Y. Zhang, Distributed demand response for multienergy residential communities with incomplete information, IEEE Trans. Ind. Inf. 17 (1) (Jan. 2021) 547–557, https://doi.org/10.1109/TII.2020.2973008.

[97] K. Gamma, R. Mai, C. Cometta, M. Loock, Engaging customers in demand response programs: the role of reward and punishment in customer adoption in Switzerland, Energy Res. Social Sci. 74 (Apr. 2021) 101927, https://doi.org/10.1016/j.erss.2021.101927.

[98] S. Poorvaezi Roukerd, A. Abdollahi, M. Rashidinejad, Uncertainty-based unit commitment and construction in the presence of fast ramp units and energy storages as flexible resources considering enigmatic demand elasticity, J. Energy Storage 29 (February) (Jun. 2020) 101290, https://doi.org/10.1016/j.est.2020.101290.

[99] S. Tiwari, R. Sabzehgar, M. Rasouli, Load balancing in a microgrid with uncertain renewable resources and loads, in: 2017 IEEE 8th International Symposium on Power Electronics for Distributed Generation Systems (PEDG), Apr. 2017, pp. 1–8, https://doi.org/10.1109/PEDG.2017.7972505.

[100] S. Singh, A. Kumar, Demand response program solution to manage congestion in transmission network considering uncertainty of load, in: 8th International Conference on Computing, Communications and Networking Technologies, ICCCNT 2017, Jul. 2017, pp. 1–6, https://doi.org/10.1109/ICCCNT.2017.8203983.

[101] W. Zeng, M. Sun, Risk warning of important power user based on electricity load characteristic, in: 2017 2nd International Conference on Power and Renewable Energy (ICPRE), Sep. 2017, pp. 681–684, https://doi.org/10.1109/ICPRE.2017.8390621.

[102] Evaluation of Reliability in Risk-Constrained Scheduling of Autonomous Microgrids with Demand Response and Renewable Resources.''.

[103] X. Yang, H. He, Y. Zhang, Y. Chen, G. Weng, Interactive energy management for enhancing power balances in multi-microgrids, IEEE Trans. Smart Grid 10 (6) (2019) 6055–6069, https://doi.org/10.1109/TSG.2019.2896182.

[104] K. Mahmud, A.K. Sahoo, J. Ravishankar, Z.Y. Dong, Coordinated multilayer control for energy management of grid-connected AC microgrids, IEEE Trans. Ind. Appl. 55 (6) (Nov. 2019) 7071–7081, https://doi.org/10.1109/TIA.2019.2931490.

[105] M. Shafie-Khah, P. Siano, A stochastic home energy management system considering satisfaction cost and response fatigue, IEEE Trans. Ind. Inf. 14 (2) (Feb. 2018) 629–638, https://doi.org/10.1109/TII.2017.2728803.

[106] M.J. Salehpour, S.M. Moghaddas Tafreshi, The effect of price responsive loads uncertainty on the risk-constrained optimal operation of a smart micro-grid, Int. J. Electr. Power Energy Syst. 106 (November 2018) (Mar. 2019) 546–560, https://doi.org/10.1016/j.ijepes.2018.10.027.

[107] B. Zeng, X. Wei, Capacity credit assessment of demand response based on a rigorous uncertainty modeling framework, in: 2018 IEEE Industry Applications Society Annual Meeting (IAS), Sep. 2018, pp. 1–8, https://doi.org/10.1109/IAS.2018.8544715.

[108] C. Tai, J. Hong, L. Fu, A real-time demand-side management system considering user behavior using deep Q-learning in home area network, in: 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC), Oct. 2019, pp. 4050–4055, https://doi.org/10.1109/SMC.2019.8914266.

[109] J. Gao, Z. Ma, F. Guo, The influence of demand response on wind-integrated power system considering participation of the demand side, Energy 178 (Jul. 2019) 723–738, https://doi.org/10.1016/j.energy.2019.04.104.

[110] A. Niromandfam, A.S. Yazdankhah, R. Kazemzadeh, Modeling demand response based on utility function considering wind profit maximization in the day-ahead market, J. Clean. Prod. 251 (Apr. 2020) 119317, https://doi.org/10.1016/j.jclepro.2019.119317.

[111] A. Tabandeh, A. Abdollahi, M. Rashidinejad, Reliability constrained congestion management with uncertain negawatt demand response firms considering repairable advanced metering infrastructures, Energy 104 (Jun. 2016) 213–228, https://doi.org/10.1016/j.energy.2016.03.118.

[112] A. Ghasemkhani, L. Yang, Reinforcement learning based pricing for demand response, in: 2018 IEEE International Conference on Communications Workshops (ICC Workshops), May 2018, pp. 1–6, https://doi.org/10.1109/ICCW.2018.8403783. February.

[113] A. Jamil, et al., An innovative home energy management model with coordination among appliances using game theory, Sustainability 11 (22) (Nov. 2019) 6287, https://doi.org/10.3390/su11226287.

[114] J. Kang, J.H. Lee, Data-driven optimization of incentive-based demand response system with uncertain responses of customers, Energies 10 (10) (2017), https://doi.org/10.3390/en10101537.

[115] J. Kang, S. Lee, Data-driven prediction of load curtailment in incentive-based demand response system, Energies 11 (11) (Oct. 2018) 2905, https://doi.org/10.3390/en11112905.

[116] H.J. Monfared, A. Ghasemi, Retail electricity pricing based on the value of electricity for consumers, Sustain. Energy Grids Networks 18 (Jun. 2019) 100205, https://doi.org/10.1016/j.segan.2019.100205.

[117] S. Yu, F. Fang, Y. Liu, J. Liu, Uncertainties of virtual power plant: problems and countermeasures, Appl. Energy 239 (August 2018) (Apr. 2019) 454–470, https://doi.org/10.1016/j.apenergy.2019.01.224.

[118] J. Zazo, S. Zazo, S. Valcarcel Macua, Robust worst-case analysis of demand-side management in smart grids, IEEE Trans. Smart Grid 8 (2) (2016), https://doi.org/10.1109/TSG.2016.2559583, 1–1.

[119] Z. Xu, Z. Hu, Y. Song, J. Wang, Risk-averse optimal bidding strategy for demand-side resource aggregators in day-ahead electricity markets under uncertainty, IEEE Trans. Smart Grid 8 (1) (Jan. 2017) 96–105, https://doi.org/10.1109/TSG.2015.2477101.

[120] L. Xu, S. Wang, F. Xiao, An adaptive optimal monthly peak building demand limiting strategy considering load uncertainty, Appl. Energy 253 (July) (Nov. 2019) 113582, https://doi.org/10.1016/j.apenergy.2019.113582.

[121] J. Yin, D. Zhao, Fuzzy stochastic unit commitment model with wind power and demand response under conditional value-at-risk assessment, Energies 11 (2) (Feb. 2018) 341, https://doi.org/10.3390/en11020341.

[122] Ö. Okur, N. Voulis, P. Heijnen, Z. Lukszo, Aggregator-mediated demand response: minimizing imbalances caused by uncertainty of solar generation, Appl. Energy 247 (October 2018) (Aug. 2019) 426–437, https://doi.org/10.1016/j.apenergy.2019.04.035.

[123] F. Arasteh, G.H. Riahy, MPC-based approach for online demand side and storage system management in market based wind integrated power systems, Int. J. Electr. Power Energy Syst. 106 (September 2018) (Mar. 2019) 124–137, https://doi.org/10.1016/j.ijepes.2018.09.041.

[124] A. Jozi, T. Pinto, I. Praça, Z. Vale, Decision support application for energy consumption forecasting, Appl. Sci. 9 (4) (Feb. 2019) 699, https://doi.org/10.3390/app9040699.

[125] H.K. Nguyen, A. Khodaei, Z. Han, Incentive mechanism design for integrated microgrids in peak ramp minimization problem, IEEE Trans. Smart Grid 9 (6) (Nov. 2018) 5774–5785, https://doi.org/10.1109/TSG.2017.2696903.

[126] A.M. Carreiro, C.H. Antunes, H. Jorge, Assessing the robustness of solutions to a multi-objective model of an energy management system aggregator, in: 2016 IEEE Symposium Series on Computational Intelligence (SSCI), Dec. 2016, pp. 1–6, https://doi.org/10.1109/SSCI.2016.7849845.

[127] G. Ifrim, S.V. Oprea, A. Bara, Shifting optimization algorithm for flattening the electricity consumption peak of residential communities, in: 2019 23rd International Conference on System Theory, Control and Computing (ICSTCC), Oct. 2019, pp. 703–708, https://doi.org/10.1109/ICSTCC.2019.8885831.

[128] S. Zalzar, E.F. Bompard, An incentive-based settlement mechanism for participation of flexible demands in day-ahead markets, in: 2019 International Conference on Smart Energy Systems and Technologies (SEST), Sep. 2019, pp. 1–6, https://doi.org/10.1109/SEST.2019.8849038.

[129] G. Wen, X. Yu, Z.-W. Liu, W. Yu, Adaptive consensus-based robust strategy for economic dispatch of smart grids subject to communication uncertainties, IEEE Trans. Ind. Inf. 14 (6) (Jun. 2018) 2484–2496, https://doi.org/10.1109/TII.2017.2772088.

[130] B. Liang, W. Liu, L. Sun, Z. He, B. Hou, An aggregated model for energy management considering crowdsourcing behaviors of distributed energy resources, IEEE Access 7 (2019) 145757–145766, https://doi.org/10.1109/ACCESS.2019.2945288.

[131] N.T. Mbungu, R.C. Bansal, R. Naidoo, V. Miranda, M. Bipath, An optimal energy management system for a commercial building with renewable energy generation under real-time electricity prices, Sustain. Cities Soc. 41 (November 2017) (Aug. 2018) 392–404, https://doi.org/10.1016/j.scs.2018.05.049.

[132] B. Neupane, T.B. Pedersen, B. Thiesson, Utilizing device-level demand forecasting for flexibility markets, in: Proceedings of the Ninth International Conference on Future Energy Systems, Jun. 2018, pp. 108–118, https://doi.org/10.1145/3208903.3208922.

[133] L. Zhang, N. Chapman, N. Good, P. Mancarella, Exploiting electric heat pump flexibility for renewable generation matching, in: 2017 IEEE Manchester PowerTech, Jun. 2017, pp. 1–6, https://doi.org/10.1109/PTC.2017.7981266.

[134] A. Majzoobi, A. Khodaei, Application of microgrids in supporting distribution grid flexibility, IEEE Trans. Power Syst. 32 (5) (Sep. 2017) 3660–3669, https://doi.org/10.1109/TPWRS.2016.2635024.

[135] G.J. Osório, M. Shafie-khah, M. Lotfi, B.J.M. Ferreira-Silva, J.P.S. Catalão, Demand-side management of smart distribution grids incorporating renewable energy sources, Energies 12 (1) (Jan. 2019) 143, https://doi.org/10.3390/en12010143.

[136] H. Shao, C. Gao, S. Chen, H. Yan, D. Li, Decision-making method for demand side resources to participate in demand response scenarios considering uncertainty of renewable energy generation, in: 8th Annual IEEE International Conference on Cyber Technology in Automation, Control and Intelligent Systems, CYBER 2018, Jul. 2019, pp. 1317–1321, https://doi.org/10.1109/CYBER.2018.8688285.

[137] M. Hu, F. Xiao, Quantifying uncertainty in the aggregate energy flexibility of high-rise residential building clusters considering stochastic occupancy and occupant behavior, Energy 194 (Mar. 2020) 116838, https://doi.org/10.1016/j.energy.2019.116838.

[138] A. Mashlakov, E. Pournaras, P.H.J. Nardelli, S. Honkapuro, Decentralized cooperative scheduling of prosumer flexibility under forecast uncertainties, Appl. Energy 290 (May 2021) 116706, https://doi.org/10.1016/j.apenergy.2021.116706.

[139] E. Lee, K. Lee, H. Lee, E. Kim, W. Rhee, Defining virtual control group to improve customer baseline load calculation of residential demand response, Appl. Energy 250 (January) (Sep. 2019) 946–958, https://doi.org/10.1016/j.apenergy.2019.05.019.

[140] X. Jian, L. Zhang, X. Miao, Y. Zhang, X. Han, Designing interruptible load management scheme based on customer performance using mechanism design theory, Int. J. Electr. Power Energy Syst. 95 (Feb. 2018) 476–489, https://doi.org/10.1016/j.ijepes.2017.09.006.

[141] J. Jazaeri, T. Alpcan, R. Gordon, M. Brandao, T. Hoban, C. Seeling, Baseline methodologies for small scale residential demand response, in: IEEE PES Innovative Smart Grid Technologies Conference Europe, 2016, pp. 747–752, https://doi.org/10.1109/ISGT-Asia.2016.7796478.

[142] H. Liang, J. Ma, R. Sun, Y. Du, A data-driven approach for targeting residential customers for energy efficiency programs, IEEE Trans. Smart Grid 11 (2) (Mar. 2020) 1229–1238, https://doi.org/10.1109/TSG.2019.2933704.

[143] F. Wang, X. Gao, K. Li, X. Ge, Y. Hou, PV- load decoupling based demand response baseline load estimation approach for residential customer with distributed PV system, in: 2019 IEEE Industry Applications Society Annual Meeting, Sep. 2019, pp. 1–8, https://doi.org/10.1109/IAS.2019.8911969.

[144] S. Fan, G. He, K. Jia, Z. Wang, A novel distributed large-scale demand response scheme in high proportion renewable energy sources integration power systems, Appl. Sci. 8 (3) (Mar. 2018) 452, https://doi.org/10.3390/app8030452.

[145] S. Fan, Z. Li, L. Yang, G. He, Customer directrix load-based large-scale demand response for integrating renewable energy sources, Elec. Power Syst. Res. 181 (December 2019) (Apr. 2020) 106175, https://doi.org/10.1016/j.epsr.2019.106175.

[146] F. Wang, K. Li, C. Liu, Z. Mi, M. Shafie-Khah, J.P.S. Catalao, Synchronous pattern matching principle-based residential demand response baseline estimation: mechanism analysis and approach description, IEEE Trans. Smart Grid 9 (6) (Nov. 2018) 6972–6985, https://doi.org/10.1109/TSG.2018.2824842.

[147] X. Wang, K. Li, X. Gao, F. Wang, Z. Mi, Customer baseline load bias estimation method of incentive-based demand response based on CONTROL group matching, in: 2nd IEEE Conference on Energy Internet and Energy System Integration, EI2 2018 - Proceedings, Oct. 2018, pp. 1–6, https://doi.org/10.1109/EI2.2018.8582122.

[148] S. Mohajeryami, M. Doostan, A. Asadinejad, P. Schwarz, Error analysis of customer baseline load (CBL) calculation methods for residential customers, IEEE Trans. Ind. Appl. 53 (1) (Jan. 2017) 5–14, https://doi.org/10.1109/TIA.2016.2613985.

[149] S. Reddy K, L.K. Panwar, B.K. Panigrahi, R. Kumar, Computational intelligence for demand response exchange considering temporal characteristics of load profile via adaptive fuzzy inference system, IEEE Transact. Emerging Topics Comput. Intel. 2 (3) (Jun. 2018) 235–245, https://doi.org/10.1109/TETCI.2017.2739128.

[150] S. Mohajeryami, M. Doostan, A. Asadinejad, An investigation of the relationship between accuracy of customer baseline calculation and efficiency of Peak Time Rebate program, in: 2016 IEEE Power and Energy Conference at Illinois (PECI), Feb. 2016, pp. 1–8, https://doi.org/10.1109/PECI.2016.7459237.

[151] S. Mohajeryami, R. Karandeh, V. Cecchi, Correlation between predictability index and error performance in Customer Baseline Load (CBL) calculation, in: 2017 North American Power Symposium, NAPS 2017, Sep. 2017, pp. 1–6, https://doi.org/10.1109/NAPS.2017.8107200.

[152] T.G. Papaioannou, G.D. Stamoulis, M. Minou, Personalized feedback-based customer incentives in automated demand response, in: 2018 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), Oct. 2018, pp. 1–7, https://doi.org/10.1109/SmartGridComm.2018.8587590.

[153] M. Najafi, S. Ahmadi, M. Dashtdar, Simultaneous Energy and Reserve Market Clearing with Consideration of Interruptible Loads as One of Demand Response Resources and Different Reliability Requirements of Consumers, 2019, https://doi.org/10.1515/ijeeps-2019-0018.

[154] H. Jia, Y. Ding, C. Singh, Reliability assessment of power systems considering flexible demand management, in: 2018 IEEE Power & Energy Society General Meeting (PESGM), Aug. 2018, pp. 1–6, https://doi.org/10.1109/PESGM.2018.8586295.

[155] C. Ogwumike, M. Short, F. Abugchem, Heuristic scheduling of multiple smart home appliances: utility planning perspective, in: 2016 International Conference for Students on Applied Engineering, ICSAE 2016, Oct. 2017, pp. 237–241, https://doi.org/10.1109/ICSAE.2016.7810195.

[156] S. Sekizaki, I. Nishizaki, T. Hayashida, Decision making of electricity retailer with multiple channels of purchase based on fractile criterion with rational responses of consumers, Int. J. Electr. Power Energy Syst. 105 (September 2018) (Feb. 2019) 877–893, https://doi.org/10.1016/j.ijepes.2018.09.011.

[157] A. Shirsat, W. Tang, Identification of the potential of residential demand response using artificial neural networks, in: 2019 North American Power Symposium (NAPS), Oct. 2019, pp. 1–6, https://doi.org/10.1109/NAPS46351.2019.9000246.

[158] K. Steriotis, G. Tsaousoglou, N. Efthymiopoulos, P. Makris, E.(Manos, Varvarigos, A novel behavioral real time pricing scheme for the active energy consumers' participation in emerging flexibility markets, Sustain. Energy Grids Networks 16 (Dec. 2018) 14–27, https://doi.org/10.1016/j.segan.2018.05.002.

[159] Q. Xu, Y. Ding, Q. Yan, A. Zheng, P. Du, Day-ahead load peak shedding/shifting scheme based on potential load values utilization: theory and practice of policy-driven demand response in China, IEEE Access 5 (2017) 22892–22901, https://doi.org/10.1109/ACCESS.2017.2763678.

[160] Z. Yahia, P. Kholopane, A binary integer programming model for optimal load scheduling of household appliances with consumer's preferences, in: 2018 International Conference on the Domestic Use of Energy, DUE 2018, 2018, pp. 1–8, https://doi.org/10.23919/DUE.2018.8384381.

[161] H. Yang, J. Zhang, J. Qiu, S. Zhang, M. Lai, Z.Y. Dong, A practical pricing approach to smart grid demand response based on load classification, IEEE Trans. Smart Grid 9 (1) (Jan. 2018) 179–190, https://doi.org/10.1109/TSG.2016.2547883.

[162] P. Yazdkhasti, S. Ray, C.P. Diduch, L. Chang, Using a cluster-based method for controlling the aggregated power consumption of air conditioners in a demand-side management program, in: 2018 International Conference on Smart Energy Systems and Technologies, SEST 2018 - Proceedings, 2018, https://doi.org/10.1109/SEST.2018.8495749.

[163] D. Yu, H. Liu, C. Bresser, Peak load management based on hybrid power generation and demand response, Energy 163 (Nov. 2018) 969–985, https://doi.org/10.1016/j.energy.2018.08.177.

[164] G. Yuan, C.-W. Hang, M.N. Huhns, M.P. Singh, A mechanism for cooperative demand-side management, in: 2017 IEEE 37th International Conference on Distributed Computing Systems (ICDCS), Jun. 2017, pp. 361–371, https://doi.org/10.1109/ICDCS.2017.300.

[165] L. Zhang, S. Ren, C. Wu, Z. Li, A truthful incentive mechanism for emergency demand response in geo-distributed colocation data centers, in: ACM Transactions on Modeling and Performance Evaluation of Computing Systems, 1, 2016, https://doi.org/10.1145/2950046, 4.

[166] D. Zhu, C. Gao, T. Lu, F. Liu, Y. Han, J. Zhang, Assistant analyzer for the characteristics of electricity behavior based on big data technology, in: Proceedings of the 5th IEEE International Conference on Electric Utility Deregulation, Restructuring and Power Technologies, DRPT 2015, Nov. 2016, pp. 704–711, https://doi.org/10.1109/DRPT.2015.7432326.

[167] C. Li, et al., Optimal spatio-temporal scheduling for Electric Vehicles and Load Aggregators considering response reliability, Elec. Power Syst. Res. 162 (December 2017) (Sep. 2018) 183–193, https://doi.org/10.1016/j.epsr.2018.05.007.

[168] Q. Li, Y. Su, W. Nie, M. Tan, Robust unit commitment with high penetration of renewable energy based on demand response and power consumption contract of electrical vehicles, in: 2016 International Symposium on Electrical Engineering (ISEE), Dec. 2016, pp. 1–6, https://doi.org/10.1109/EENG.2016.7845983.

[169] Federal Energy Regulatory Commission, Assessment of Demand Response and Advanced Metering, Aug. 2006.

[170] S. Zalzar, E.F. Bompard, Assessing the impacts of demand-side flexibility on the performance of the europe-wide integrated day-ahead electricity market, in: 2019 International Conference on Smart Energy Systems and Technologies (SEST), Sep. 2019, pp. 1–6, https://doi.org/10.1109/SEST.2019.8849137.

[171] H. Jalili, M.K. Sheikh-El-Eslami, M.P. Moghaddam, P. Siano, Modeling of demand response programs based on market elasticity concept, J. Ambient Intell. Hum. Comput. 10 (6) (Jun. 2019) 2265–2276, https://doi.org/10.1007/s12652-018-0821-4.

[172] B. Zhang, C. Jiang, J.-L. Yu, Z. Han, A contract game for direct energy trading in smart grid, IEEE Trans. Smart Grid 9 (4) (Jul. 2018) 2873–2884, https://doi.org/10.1109/TSG.2016.2622743.

[173] E. Mahboubi-Moghaddam, M. Nayeripour, J. Aghaei, A. Khodaei, E. Waffenschmidt, Interactive robust model for energy service providers integrating demand response programs in wholesale markets, IEEE Trans. Smart Grid 9 (4) (Jul. 2018) 2681–2690, https://doi.org/10.1109/TSG.2016.2615639.

[174] J.R. Schaperow, S.A. Gabriel, M. Siemann, J. Crawford, A simulation-based model for optimal demand response load shifting: a case study for the Texas power market, J. Energy Markets 12 (4) (2019) 53–80, https://doi.org/10.21314/JEM.2019.199.

[175] H.A. Mostafa, R. El Shatshat, M.M.A. Salama, A correlated equilibrium game-theoretic approach for multiple participants electric distribution systems operation, IEEE Trans. Smart Grid 7 (1) (Jan. 2016) 32–42, https://doi.org/10.1109/TSG.2015.2440419.

[176] K. Ma, S. Hu, J. Yang, C. Dou, J. Guerrero, Energy trading and pricing in microgrids with uncertain energy supply: a three-stage hierarchical game approach, Energies 10 (5) (May 2017) 670, https://doi.org/10.3390/en10050670.

[177] S. Chouikhi, L. Merghem-Boulahia, M. Esseghir, H. Snoussi, A game-theoretic multi-level energy demand management for smart buildings, IEEE Trans. Smart Grid 10 (6) (2019) 6768–6781, https://doi.org/10.1109/TSG.2019.2911129.

[178] I.C. Konstantakopoulos, L.J. Ratliff, M. Jin, S.S. Sastry, C.J. Spanos, A robust utility learning framework via inverse optimization, IEEE Trans. Control Syst. Technol. 26 (3) (May 2018) 954–970, https://doi.org/10.1109/TCST.2017.2699163.

[179] M. Sheha, K. Powell, Using real-time electricity prices to leverage electrical energy storage and flexible loads in a smart grid environment utilizing machine learning techniques, Processes 7 (12) (Nov. 2019) 870, https://doi.org/10.3390/pr7120870.

[180] A. Sheikhi, M. Rayati, A.M. Ranjbar, Demand side management for a residential customer in multi-energy systems, Sustain. Cities Soc. 22 (Apr. 2016) 63–77, https://doi.org/10.1016/j.scs.2016.01.010.

[181] P.D. Haghighi, S. Krishnaswamy, Role of Context-Awareness for Demand Response Mechanisms, 6868, 2011, pp. 136–149, https://doi.org/10.1007/978-3-642-23447-7_13.

[182] H. Liang, J. Ma, Separation of residential space cooling usage from smart meter data, IEEE Trans. Smart Grid 11 (4) (2020) 3107–3118, https://doi.org/10.1109/TSG.2020.2965958.

[183] N. Qi, et al., Smart meter data-driven evaluation of operational demand response potential of residential air conditioning loads, Appl. Energy 279 (2020) 115708, https://doi.org/10.1016/j.apenergy.2020.115708.

[184] I. Mamounakis, N. Efthymiopoulos, D.J. Vergados, G. Tsaousoglou, P. Makris, E. M. Varvarigos, A pricing scheme for electric utility's participation in day-ahead and real-time flexibility energy markets, J. Modern Power Syst. Clean Energy 7 (5) (2019) 1294–1306, https://doi.org/10.1007/s40565-019-0537-2.

[185] K. Dehghanpour, M. Hashem Nehrir, J.W. Sheppard, N.C. Kelly, Agent-based modeling of retail electrical energy markets with demand response, IEEE Trans. Smart Grid 9 (4) (Jul. 2018) 3465–3475, https://doi.org/10.1109/TSG.2016.2631453.

[186] A. Najafi-Ghalelou, K. Zare, S. Nojavan, Risk-based scheduling of smart apartment building under market price uncertainty using robust optimization approach, Sustain. Cities Soc. 48 (July 2018) (Jul. 2019) 101549, https://doi.org/10.1016/j.scs.2019.101549.

[187] L. Mellouk, M. Boulmalf, A. Aaroud, K. Zine-Dine, D. Benhaddou, Genetic algorithm to solve demand side management and economic dispatch problem, Procedia Comput. Sci. 130 (2018) 611–618, https://doi.org/10.1016/j.procs.2018.04.111.

[188] J.C. Galvis, A. Costa, Demand side management using time of use and elasticity price, IEEE Latin America Transactions 14 (10) (Oct. 2016) 4267–4274, https://doi.org/10.1109/TLA.2016.7786304.
[189] H. Mortaji, Ow Siew Hock, M. Moghavvemi, H.A.F. Almurib, Smart grid demand response management using internet of things for load shedding and smart-direct load control, in: 2016 IEEE Industry Applications Society Annual Meeting, Oct. 2016, pp. 1–7, https://doi.org/10.1109/IAS.2016.7731836.
[190] G. Julián Valbuena, R. Mateo Mancera, A. Pavas, Reliability improvement in an isolated microgrid considering demand side management, in: 2017 3rd IEEE Workshop on Power Electronics and Power Quality Applications, PEPQA 2017 - Proceedings, May 2017, pp. 1–6, https://doi.org/10.1109/PEPQA.2017.7981665.
[191] A.C. Melhorn, A. Dimitrovski, A. Keane, Probabilistic load flow: a business park analysis, utilizing real world meter data, in: 2016 International Conference on Probabilistic Methods Applied to Power Systems (PMAPS), Oct. 2016, pp. 1–6, https://doi.org/10.1109/PMAPS.2016.7763932.
[192] K.O. Aduda, T. Labeodan, W. Zeiler, G. Boxem, Y. Zhao, Demand side flexibility: potentials and building performance implications, Sustain. Cities Soc. 22 (Apr. 2016) 146–163, https://doi.org/10.1016/j.scs.2016.02.011.
[193] L. Shen, Z. Li, Y. Sun, Performance evaluation of conventional demand response at building-group-level under different electricity pricings, Energy Build. 128 (Sep. 2016) 143–154, https://doi.org/10.1016/j.enbuild.2016.06.082.
[194] S.N. Makhadmeh, A.T. Khader, M.A. Al-Betar, S. Naim, Multi-objective power scheduling problem in smart homes using grey wolf optimiser, J. Ambient Intell. Hum. Comput. 10 (9) (Sep. 2019) 3643–3667, https://doi.org/10.1007/s12652-018-1085-8.
[195] S.R. Konda, A.S. Al-Sumaiti, L.K. Panwar, B.K. Panigrahi, R. Kumar, Impact of load profile on dynamic interactions between energy markets: a case study of power exchange and demand response exchange, IEEE Trans. Ind. Inf. 15 (11) (Nov. 2019) 5855–5866, https://doi.org/10.1109/TII.2019.2910349.
[196] I.-Y. Joo, D.-H. Choi, Distributed optimization framework for energy management of multiple smart homes with distributed energy resources, IEEE Access 5 (2017) 15551–15560, https://doi.org/10.1109/ACCESS.2017.2734911.
[197] C.N. Papadimitriou, A. Anastasiadis, C.S. Psomopoulos, G. Vokas, Demand response schemes in energy hubs: a comparison study, Energy Proc. 157 (2018) (Jan. 2019) 939–944, https://doi.org/10.1016/j.egypro.2018.11.260.
[198] E. Leo, S. Engell, Integrated day-ahead energy procurement and production scheduling, Automatisierungstechnik 66 (11) (Nov. 2018) 950–963, https://doi.org/10.1515/auto-2018-0016.
[199] G.S. Ledva, L. Balzano, J.L. Mathieu, Real-time energy disaggregation of a distribution feeder's demand using online learning, IEEE Trans. Power Syst. 33 (5) (Sep. 2018) 4730–4740, https://doi.org/10.1109/TPWRS.2018.2800535.
[200] V. Kapsalis, L. Hadellis, Optimal operation scheduling of electric water heaters under dynamic pricing, Sustain. Cities Soc. 31 (May 2017) 109–121, https://doi.org/10.1016/j.scs.2017.02.013.
[201] Y. Mou, A. Papavasiliou, P. Chevalier, Application of priority service pricing for mobilizing residential demand response in Belgium, in: International Conference on the European Energy Market, EEM, Jun. 2017, pp. 1–5, https://doi.org/10.1109/EEM.2017.7981860.
[202] R. Lu, S.H. Hong, M. Yu, Demand response for home energy management using reinforcement learning and artificial neural network, IEEE Trans. Smart Grid 10 (6) (Nov. 2019) 6629–6639, https://doi.org/10.1109/TSG.2019.2909266.
[203] F. Luo, G. Ranzi, G. Liang, Z.Y. Dong, Stochastic residential energy resource scheduling by multi-objective natural aggregation algorithm, in: 2017 IEEE Power & Energy Society General Meeting, 5, Jul. 2017, pp. 1–5, https://doi.org/10.1109/PESGM.2017.8274308.
[204] Y. Chen, et al., Quantification of electricity flexibility in demand response: office building case study, Energy 188 (Dec. 2019) 116054, https://doi.org/10.1016/j.energy.2019.116054.
[205] J. Lizana, D. Friedrich, R. Renaldi, R. Chacartegui, Energy flexible building through smart demand-side management and latent heat storage, Appl. Energy 230 (August) (Nov. 2018) 471–485, https://doi.org/10.1016/j.apenergy.2018.08.065.
[206] H. Jin, Z. Li, H. Sun, Q. Guo, B. Wang, Coordination on industrial load control and climate control in manufacturing industry under TOU prices, IEEE Trans. Smart Grid 10 (1) (Jan. 2019) 139–152, https://doi.org/10.1109/TSG.2017.2733578.
[207] X. Ran, K. Liu, Robust scatter index method for the appliances scheduling of home energy local network with user behavior uncertainty, IEEE Trans. Ind. Inf. 15 (7) (Jul. 2019) 4129–4139, https://doi.org/10.1109/TII.2019.2897126.
[208] T.G. Papaioannou, G.D. Stamoulis, M. Minou, Adequate feedback-based customer incentives in automated demand response, in: E-Energy 2018 - Proceedings of the 9th ACM International Conference on Future Energy Systems, 2018, pp. 38–42, https://doi.org/10.1145/3208903.3208933.
[209] F. Luo, G. Ranzi, Z. Dong, Rolling horizon optimization for real-time operation of thermostatically controlled load aggregator, J. Modern Power Syst. Clean Energy 5 (6) (Nov. 2017) 947–958, https://doi.org/10.1007/s40565-017-0329-5.
[210] K.O. Aduda, T. Labeodan, W. Zeiler, Towards critical performance considerations for using office buildings as a power flexibility resource-a survey, Energy Build. 159 (Jan. 2018) 164–178, https://doi.org/10.1016/j.enbuild.2017.10.096.
[211] Z. Liang, Q. Alsafasfeh, T. Jin, H. Pourbabak, W. Su, Risk-Constrained optimal energy management for virtual power plants considering correlated demand response, IEEE Trans. Smart Grid 10 (2) (Mar. 2019) 1577–1587, https://doi.org/10.1109/TSG.2017.2773039.
[212] U.K. Jha, N. Soren, A. Sharma, An Efficient HEMS for Demand Response Considering TOU Pricing Scheme and Incentives, 2019, https://doi.org/10.1109/EPETSG.2018.8659338.
[213] J. Meng, X. Huang, Y. Feng, B. Xu, W. Zhao, M. Luo, A comprehensive evaluation method and incentive mechanism for demand response, in: 2018 International Conference on Power System Technology (POWERCON), Nov. 2018, pp. 703–707, https://doi.org/10.1109/POWERCON.2018.8602333, 3.
[214] P. Siano, D. Sarno, Assessing the benefits of residential demand response in a real-time distribution energy market, Appl. Energy 161 (Jan. 2016) 533–551, https://doi.org/10.1016/j.apenergy.2015.10.017.
[215] F. Wang, et al., Smart households' aggregated capacity forecasting for load aggregators under incentive-based demand response programs, IEEE Trans. Ind. Appl. 56 (2) (Mar. 2020) 1086–1097, https://doi.org/10.1109/TIA.2020.2966426.
[216] U.K. Jha, N. Soren, A. Sharma, An Efficient HEMS for Demand Response Considering TOU Pricing Scheme and Incentives, 2019, https://doi.org/10.1109/EPETSG.2018.8659338.
[217] J. Kwac, J. Flora, R. Rajagopal, Lifestyle segmentation based on energy consumption data, IEEE Trans. Smart Grid 9 (4) (Jul. 2018) 2409–2418, https://doi.org/10.1109/TSG.2016.2611600.
[218] L. Sun, K. Zhou, S. Yang, An ensemble clustering based framework for household load profiling and driven factors identification, Sustain. Cities Soc. 53 (Feb. 2020) 101958, https://doi.org/10.1016/j.scs.2019.101958.
[219] K. Zhou, S. Yang, Z. Shao, Household monthly electricity consumption pattern mining: a fuzzy clustering-based model and a case study, J. Clean. Prod. 141 (Jan. 2017) 900–908, https://doi.org/10.1016/j.jclepro.2016.09.165.
[220] J.L. Viegas, S.M. Vieira, R. Melício, V.M.F. Mendes, J.M.C. Sousa, Classification of new electricity customers based on surveys and smart metering data, Energy 107 (Jul. 2016) 804–817, https://doi.org/10.1016/j.energy.2016.04.065.
[221] A. Rajabi, et al., A pattern recognition methodology for analyzing residential customers load data and targeting demand response applications, Energy Build. 203 (Nov. 2019) 109455, https://doi.org/10.1016/j.enbuild.2019.109455.
[222] J.P. Gouveia, J. Seixas, Unraveling electricity consumption profiles in households through clusters: combining smart meters and door-to-door surveys, Energy Build. 116 (Mar. 2016) 666–676, https://doi.org/10.1016/j.enbuild.2016.01.043.
[223] B.N. Silva, M. Khan, K. Han, Futuristic sustainable energy management in smart environments: a review of peak load shaving and demand response strategies, challenges, and opportunities, Sustainability 12 (14) (Jul. 2020) 5561, https://doi.org/10.3390/su12145561.
[224] J. Kang, J.H. Lee, Data-driven optimization of incentive-based demand response system with uncertain responses of customers, Energies 10 (10) (2017), https://doi.org/10.3390/en10101537.
[225] X. Dai, Y. Li, K. Zhang, W. Feng, A robust offering strategy for wind producers considering uncertainties of demand response and wind power, Appl. Energy 279 (February) (2020) 115742, https://doi.org/10.1016/j.apenergy.2020.115742.
[226] Z. Song, J. Shi, S. Li, Z. Chen, W. Yang, Z. Zhang, Day ahead bidding of a load aggregator considering residential consumers demand response uncertainty modeling, Appl. Sci. 10 (20) (2020) 1–21, https://doi.org/10.3390/app10207310.
[227] J. Kang, J.-H. Lee, Data-driven optimization of incentive-based demand response system with uncertain responses of customers, Energies 10 (10) (Oct. 2017) 1537, https://doi.org/10.3390/en10101537.
[228] S. Chen, C.-C. Liu, From demand response to transactive energy: state of the art, J. Modern Power Syst. Clean Energy 5 (1) (Jan. 2017) 10–19, https://doi.org/10.1007/s40565-016-0256-x.
[229] E. Lee, J. Kim, D. Jang, Load profile segmentation for effective residential demand response program: method and evidence from Korean pilot study, Energies 13 (6) (Mar. 2020) 1348, https://doi.org/10.3390/en13061348.
[230] Long Zhao, Zhiyong Yang, Wei-Jen Lee, Effectiveness of zero pricing in TOU demand reponses at the residential level, in: 2017 IEEE/IAS 53rd Industrial and Commercial Power Systems Technical Conference (I&CPS), May 2017, pp. 1–8, https://doi.org/10.1109/ICPS.2017.7945095.
[231] B. Chai, Z. Yang, K. Gao, T. Zhao, Iterative learning for optimal residential load scheduling in smart grid, Ad Hoc Netw. 41 (May 2016) 99–111, https://doi.org/10.1016/j.adhoc.2016.01.005.
[232] S.-J. Kim, G.B. Giannakis, An online convex optimization approach to real-time energy pricing for demand response, IEEE Trans. Smart Grid 8 (6) (Nov. 2017) 2784–2793, https://doi.org/10.1109/TSG.2016.2539948.
[233] J. Yao, P. Venkitasubramaniam, Stochastic games of end-user energy storage sharing, in: 2016 IEEE 55th Conference on Decision and Control (CDC), Dec. 2016, pp. 4965–4972, https://doi.org/10.1109/CDC.2016.7799028. Cdc.
[234] H.S.V.S. Kumar Nunna, N.A. Binte Aziz, D. Srinivasan, A smart energy management framework for distribution systems with perceptive residential consumers, in: 2018 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC) 2018-Octob, Oct. 2018, pp. 434–438, https://doi.org/10.1109/APPEEC.2018.8566646.
[235] I. Mamounakis, N. Efthymiopoulos, D.J. Vergados, G. Tsaousoglou, P. Makris, E. M. Varvarigos, A pricing scheme for electric utility's participation in day-ahead and real-time flexibility energy markets, J. Modern Power Syst. Clean Energy 7 (5) (Sep. 2019) 1294–1306, https://doi.org/10.1007/s40565-019-0537-2.
[236] Y. Yang, Real-time disaggregation of user power consumption using the viterbi algorithm, in: 2018 IEEE International Conference on Communications Workshops (ICC Workshops), May 2018, pp. 1–6, https://doi.org/10.1109/ICCW.2018.8403781.
[237] S.J. Kim, G.B. Giannakis, An online convex optimization approach to real-time energy pricing for demand response, IEEE Trans. Smart Grid 8 (6) (2017) 2784–2793, https://doi.org/10.1109/TSG.2016.2539948.

[238] M. MacDougall, H.S. Cameron, S.R.J. Maxwell, Medical graduate views on statistical learning needs for clinical practice: a comprehensive survey, BMC Med. Educ. 20 (1) (Dec. 2019), https://doi.org/10.1186/s12909-019-1842-1.
[239] I. Mamounakis, N. Efthymiopoulos, D.J. Vergados, G. Tsaousoglou, P. Makris, E. M. Varvarigos, A pricing scheme for electric utility's participation in day-ahead and real-time flexibility energy markets, J. Modern Power Syst. Clean Energy 7 (5) (2019) 1294–1306, https://doi.org/10.1007/s40565-019-0537-2.
[240] S. Chen, C.C. Liu, From demand response to transactive energy: state of the art, J. Modern Power Syst. Clean Energy 5 (1) (2017) 10–19, https://doi.org/10.1007/s40565-016-0256-x.
[241] S.R. Kuppannagari, R. Kannan, V.K. Prasanna, An ILP based algorithm for optimal customer selection for demand response in SmartGrids, in: 2015 International Conference on Computational Science and Computational Intelligence (CSCI), Dec. 2015, pp. 300–305, https://doi.org/10.1109/CSCI.2015.140.
[242] X. Chen, Y. Nie, N. Li, Online residential demand response via contextual multi-armed bandits, IEEE Control Syst. Lett. 5 (2) (2020), https://doi.org/10.1109/lcsys.2020.3003190, 1–1.
[243] H.W. Qazi, D. Flynn, Analysing the impact of large-scale decentralised demand side response on frequency stability, Int. J. Electr. Power Energy Syst. 80 (Sep. 2016) 1–9, https://doi.org/10.1016/j.ijepes.2015.11.115.
[244] R. Yin, S. Kiliccote, M.A. Piette, Linking measurements and models in commercial buildings: a case study for model calibration and demand response strategy evaluation, Energy Build. 124 (Jul. 2016) 222–235, https://doi.org/10.1016/j.enbuild.2015.10.042.
[245] J. Chen, D. Ye, S. Ji, Q. He, Y. Xiang, Z. Liu, A truthful FPTAS mechanism for emergency demand response in colocation data centers, in: IEEE INFOCOM 2019 - IEEE Conference on Computer Communications, 2019-April, Apr. 2019, pp. 2557–2565, https://doi.org/10.1109/INFOCOM.2019.8737468, 4.
[246] A. Ghasemkhani, L. Yang, J. Zhang, Learning-based demand response for privacy-preserving users, IEEE Trans. Ind. Inf. 15 (9) (2019) 4988–4998, https://doi.org/10.1109/TII.2019.2898462.
[247] Y.-H. Lin, S.-K. Hung, M.-S. Tsai, Study on the influence of voltage variations for non-intrusive load identifications, in: 2018 International Power Electronics Conference (IPEC-Niigata 2018 -ECCE Asia), May 2018, pp. 1575–1579, https://doi.org/10.23919/IPEC.2018.8507762.
[248] H. Mortaji, S.H. Ow, M. Moghavvemi, H.A.F. Almurib, Load shedding and smart-direct load control using internet of things in smart grid demand response management, IEEE Trans. Ind. Appl. 53 (6) (Nov. 2017) 5155–5163, https://doi.org/10.1109/TIA.2017.2740832.
[249] M. Ghorbanian, S.H. Dolatabadi, P. Siano, Game theory-based energy-management method considering autonomous demand response and distributed generation interactions in smart distribution systems, IEEE Syst. J. 15 (1) (Mar. 2021) 905–914, https://doi.org/10.1109/JSYST.2020.2984730.
[250] T.G. Papaioannou, G.D. Stamoulis, M. Minou, Adequate feedback-based customer incentives in automated demand response, in: E-Energy 2018 - Proceedings of the 9th ACM International Conference on Future Energy Systems, 2018, pp. 38–42, https://doi.org/10.1145/3208903.3208933.
[251] I. Ilieva, B. Bremdal, S. Puranik, Bringing business and societal impact together in an evolving energy sector, Clean Energy Technol. 7 (3) (2019), https://doi.org/10.18178/jocet.2019.7.3.508.
[252] S. Haben, C. Singleton, P. Grindrod, Analysis and clustering of residential customers energy behavioral demand using smart meter data, IEEE Trans. Smart Grid 7 (1) (Jan. 2016) 136–144, https://doi.org/10.1109/TSG.2015.2409786.
[253] P. Faria, F. Lezama, Z. Vale, M. Khorram, A methodology for energy key performance indicators analysis, Energy Informatics 4 (1) (Apr. 2021) 1–15, https://doi.org/10.1186/S42162-021-00140-0, 2021 4:1.
[254] P. Faria, Z. Vale, Distributed energy resources scheduling with demand response complex contract, J. Modern Power Syst. Clean Energy (2020) 1–13, https://doi.org/10.35833/MPCE.2020.000317.
[255] D. Ramos, M. Khorram, P. Faria, Z. Vale, Load forecasting in an office building with different data structure and learning parameters, Forecasting 3 (1) (Mar. 2021) 242–255, https://doi.org/10.3390/FORECAST3010015, 2021, Vol. 3, Pages 242-255.
[256] D. Ramos, B. Teixeira, P. Faria, L. Gomes, O. Abrishambaf, Z. Vale, Use of sensors and analyzers data for load forecasting: a two stage approach, Sensors 20 (12) (Jun. 2020) 3524, https://doi.org/10.3390/S20123524, 2020, Vol. 20, Page 3524.
[257] L. Gomes, C. Almeida, Z. Vale, Recommendation of workplaces in a coworking building: a cyber-physical approach supported by a context-aware multi-agent system, Sensors 20 (12) (Jun. 2020) 3597, https://doi.org/10.3390/S20123597, 2020, Vol. 20, Page 3597.

Publication III

C. Silva et al., "Optimal management of an active community for fair selection of electric vehicles in a V2G event," CIRED Porto Workshop 2022: E-mobility and power distribution systems, Hybrid Conference, Porto, Portugal, p. 1069-1073, 2022

Resumen

El concepto de Smart Grids permite el desarrollo de nuevas tecnologías, como la interacción de Vehículo a Red (V2G por sus siglas en inglés), lo que hace posible transferir energía desde un Vehículo Eléctrico (EV por sus siglas en inglés) a la red y viceversa, facilitando así la implementación de la movilidad eléctrica. Sin embargo, la confiabilidad y seguridad del sistema pueden estar en peligro al surgir estos jugadores inciertos. Para ayudar a la gestión compleja de comunidades locales activas y reducir la incertidumbre en la respuesta, los autores proponen una metodología capaz de lidiar tanto con los consumidores activos como con los vehículos eléctricos, eligiendo los participantes adecuados mediante un modelo de equidad de acuerdo al contexto en el que se desencadenan los eventos. Además, los autores introdujeron un mecanismo contextual de remuneración para incentivar la participación de los usuarios y fomentar una respuesta óptima en situaciones de demanda.

OPTIMAL MANAGEMENT OF AN ACTIVE COMMUNITY FOR FAIR SELECTION OF ELECTRIC VEHICLES IN A V2G EVENT

Cátia SILVA, Pedro FARIA, Zita VALE
Polytechnic of Porto, Porto, Portugal
cvcds@isep.ipp.pt; pnf@isep.ipp.pt; zav@isep.ipp.pt

Susete ALBUQUERQUE, José SOUSA, Sara CARDOSO, Emilie GOMES
E-REDES, Portugal
susete.albuquerque@e-redes.pt; joseeduardo.sousa@e-redes.pt; susete.sara.cardoso@e-redes.pt; emilie.gomes@e-redes.pt

ABSTRACT

Smart Grids concept allows the development of new technologies, such as Vehicle to Grid (V2G) interaction, making it possible to transfer energy from an Electric Vehicle (EV) to the grid and vice versa, thus facilitating the implementation of electric mobility. However, the system's reliability and security can be jeopardized by emerging such uncertain players. To aid the complex management of active local communities and reduce the response uncertainty, the authors propose a methodology capable of dealing with both active consumers and EV by choosing the proper participants using a fairness model according to the context in which the events are triggered. Furthermore, the authors introduced a contextual remuneration for continuous participation, studying the impact from the Aggregator perspective.

INTRODUCTION

Moved by the increasing number of electric vehicles (EVs), the literature considers this resource part of the solution [1]. In this way, one of the explored approaches to achieve the climate goals can be the electric vehicle to grid (V2G) interaction technology since it can improve the utilization of renewable energy and stabilize its grid connection [2]. However, if the necessary measures are not taken, the high penetration of EVs can bring problems to the grid, namely decreased performance and power failure [3]. Thus, considering this context, it is essential to apply innovative technologies such as Smart Grid (SG) since it makes it possible to improve the efficiency and quality of grids through bidirectional communication [4].

With V2G technology, EVs can be seen as relevant entities in energy management systems, where they can, through the charging and discharging process, bring various benefits to the grid, such as system services [5]. These system services range from voltage and frequency regulation, peak shaving, valley filling, and improving distributed generation integration [6]. Furthermore, t efficient control of the respective EV charging and discharging processes can be performed by an aggregator, where it can implement strategies depending on the EV owners' preferences, personal or grid objectives, and the generation availability [7].

The H2020 DOMINOES project implemented a complete analysis of the impact of local energy markets (LEM) in the active participation of consumers for grid support. Looking at the role of Distribution System Operator (DSO) in the energy transition at a local level, the assessment of possible services to be provided to the DSO in future grid scenarios of high Renewable Energy Sources (RES) integration is needed to realize not only if these services can match the grid needs, but as well if the consumers or communities have the right incentives and/or motivation for market participation.

Distributed Generation (DG) has high randomness of energy output. The discomfort caused and the uncertainty of the response from these new players is a matter of concern from the managing entity perspective [8]. Therefore, the authors created a concept that intend to fairly select the proper participants (both active consumers and EVs) for a DR event. To clarify the idea, instead of calling all the active consumers, a rate is attributed to each resource providing information to the Aggregator regarding the performance of the local community members for the event context. In the study, the viability of the proposed methodology is tested, highlighting the remuneration phase for a continuous participation, the duration and the context in which the event is triggered.

The present paper is divided into five main sections. First, the introduction to the topic shows its importance and the innovation presented with the proposed methodology. The procedure is then detailed in the following section. After, the case study and the discussion of results are presented in Section 3 and Section 4. Finally, the conclusions were withdrawn.

PROPOSED METHODOLOGY

A detailed explanation regarding the proposed methodology is introduced. First, a reduction request is required from the DSO to all the aggregators managing the local communities associated and by introducing the V2G option. In this way, Figure 1 represents the different steps.

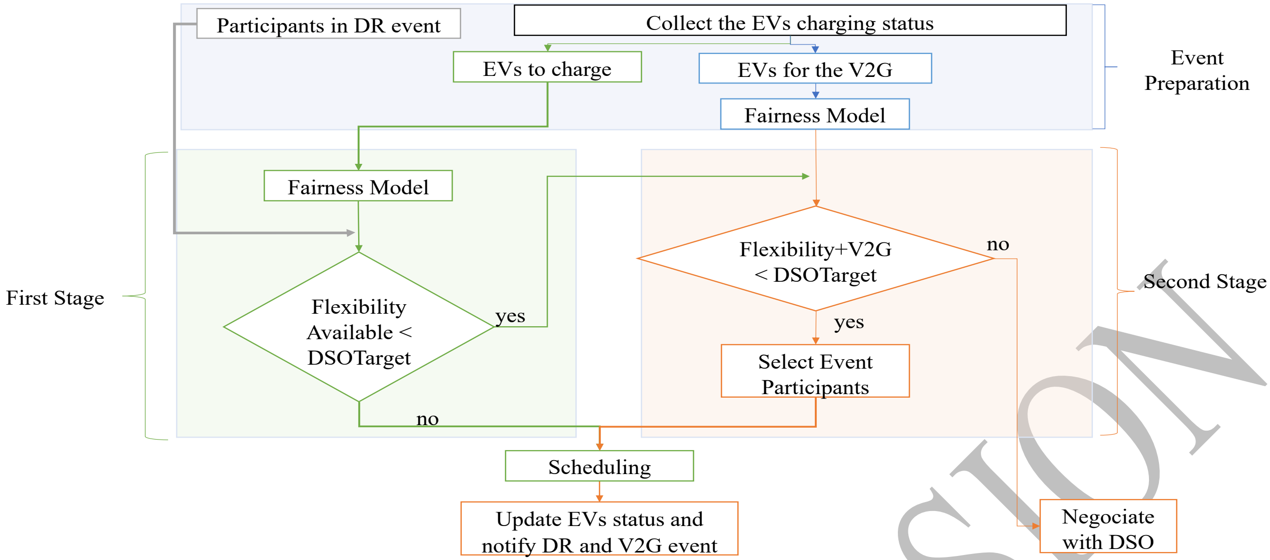


Figure 1. Proposed Methodology

It is necessary to update the EVs status for each period – Event Preparation. Several parameters should be considered. After, a Fairness Model is applied, selecting the order of charging. This model assumes that the ones with higher values of participation in previous events have priority if their check-out period is close.

Gathered all the resources for the First Stage test before the Scheduling step was performed. Is the DSO target for reduction higher than the flexibility provided by the active consumers in the community?

In the positive case, the Scheduling phase is performed, all the EVs charging statuses are updated, and the DR participants are notified. Otherwise, the V2G event is triggered in the Second Stage.

In the scheduling phase, resorting to a mixed-integer linear programming optimization, the goal is to minimize the operation costs from the perspective of the aggregator considering the fair remuneration of the participating resources. The objective function of the problem is introduced by Equation 1. For each period t, let P_{DG} be the power for each Distributed Generation (DG) p resource; P_{DR} is the flexibility from each c consumer; P_{EVD} is the power discharged from each EV who participated in the V2G event; P_{SUP} is the power from an external supplier and P_{NSP} be the Non-Supplied Power (NSP). The respective costs are attached to these variables.

$$\begin{aligned} Min\ OS = & \sum [P_{DG}\ (p,t) C_{DG}\ (p,t)] \\ & + \sum [P_{DR}\ (c,t) C_{DR}\ (c,t)] \\ & + \sum [P_{EVD}\ (ed,t)\ C_{EVD}(ed,t)] \\ & + \sum [P_{SUP}\ (s,t)\ \ C_{SUP}\ (s,t)\ ] \\ & + P_{NSP}\ (t) C_{NSP}\ (t) \end{aligned} \tag{1}$$

The scheduling phases can work with a wide variety and quantity of resources. In this case, both active consumers for a local community and their EV are highlighted – the constraints associated with the last one can be seen in Equation 2 to Equation 5. However, the proposed methodology can deal with prosumers with generation or storage resources if needed.

$$E_{(v,t)}^{evmin} \le E_{(v,t)}^{ev} \le E_{(v,t)}^{evmax}, \forall t \in \{1, \dots, T\}, v \in \{1, \dots, V\} \tag{2}$$

$$0 \le P_{EVc(ec,t)} \le P_{EVc(ec,t)}^{max} \cdot X_{(ec,t)}^{evch}, X_{(ec,t)}^{evch} \in \{0,1\}, \forall t \in \{1, \dots, T\}, v \in \{1, \dots, V\} \tag{3}$$

$$0 \le P_{EVD(ed,t)} \le P_{EVD(ed,t)}^{max} \cdot X_{(ed,t)}^{evdch}, X_{(ed,t)}^{evdch} \in \{0,1\}, \forall t \in \{1, \dots, T\}, v \in \{1, \dots, V\} \tag{4}$$

$$E_{(v,t)}^{ev} = E_{(v,t-1)}^{ev} + P_{EVc(v,t)} + P_{EVd(v,t)}, \forall t \in \{1, \dots, T\}, v \in \{1, \dots, V\} \tag{5}$$

Equation (2) represents the operation capacity limits, Equation (3) the charge needed per period, and Equation (4) the discharge limits per period – flexibility provided for the V2G event. Finally, Equation (5) is introduced to maintain the power balance – the previous state of charged and discharged, also known as State-of-charge (SoC).

So, the Second Stage introduces the V2G event. However, earlier, the aggregator in the Event Preparation already had information regarding the EVs ready for the V2G event. The fairness model applied here divides these resources according to previous events in the same context. The justice factor will then be applied, organizing the participants in different performance groups. The authors applied the same logic to active consumers to reduce the response uncertainty in a DR event [9].

Like the First Stage, a flexibility test is performed before the Scheduling step. For example, is the DSO target for reduction higher than the community's active consumers' flexibility and the EVs available for the event? If so, the aggregator must negotiate with the DSO the reduction terms according to the results found.

Otherwise, the model moves to the following stage. First, in the Select Event participants stage, the groups will be clustered according to their characteristics. This is an important phase to differentiate if the event is fast (15min) or slow (more than 15min) – the aggregator must understand which ones are available and keep continuous participation for the last case. Then, the V2G event participants were found, the Scheduling phase was performed, all the EVs charging statuses were updated, and both DR participants were notified.
The following section will present an analysis and discussion of the results for all the phases in the proposed methodology.

CASE STUDY

As an innovation from previous works, the authors intend to introduce the V2G option reasonably, promoting the continuous participation of active consumers, using their several resources, fighting the uncertainty of the response. The case study was developed to prove the viability of the proposed methodology. In this case, the database is composed of a local community, namely office buildings with private parking lots. Each building consumption throughout the day and the respective flexibility can be seen in Figure 2. The days are divided into a 15-minute base. If a whole week whole considered, it would start on Monday. In this way, a day has 96 periods and a week 652. However, in this study, the authors selected a dataset of a working day. The expected consumption for the week in the study can be seen in Figure 2.

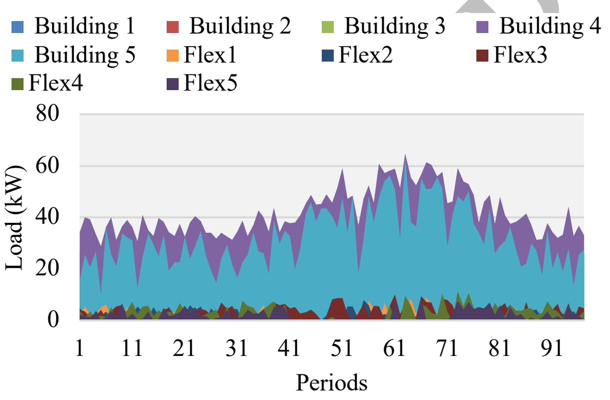


Figure 2. Initial Load Consumption and Flexibility provided by the active consumers.

The parking lot located in this community operates between 8 AM and 8 PM. There are charging stations for electric vehicles associated with each building, thus enabling the implementation of the V2G technology. It is assumed that each one has three sockets. For each building, it is considered that six EVs can participate in V2G events, and their characteristics are shown in Table 1. Their personal information, such as check-in, check-out, percentage before leaving, among others, depends on the owner.

Table I. EV participants main characteristics

ID	Brand	Model	Battery Capacity (kWh)	Average Minimum SOC (%)
1	Renault	ZOE	41	50
2	Renault	ZOE	41	15/20
3	Nissan	Leaf	24	50
4	Renault	ZOE	22	40
5	Renault	ZOE	22	15
6	Nissan	Leaf	30	45

The authors consider that remuneration is crucial for motivating continuous participation in DR and V2G events. However, the motivation must be different according to the context in which the event is triggered. Therefore, the authors followed a schedule with three zones: peak, valley, and off-valley.
According to the parking lot operation hours, the valley zone is excluded in this scenario.

Table II. V2G participation incentive schedule.

Schedule	Peak	Off-valley	Valley
00:00AM – 08:00AM			x
08:00AM – 10:30AM		x	
10:30AM – 01:00PM	x		
01:00PM – 07:30PM		x	
07:30PM – 09:00PM	x		
09:00PM – 10:00PM		x	
10:00PM – 00:00AM			x

Therefore, if a V2G participant collaborated in a peak hour, the incentive should be higher. The contribution for a reliable and secure network balance should be extremely encouraged. Otherwise, although continuous participation is equally important, the incentive is inferior for a valley zone. Table III presents the values used in the current case study.

Table III. V2G participation incentive value.

	Peak	Off-valley	Valley
Incentive (m.u./kW)	0. 2468	0.1515	0. 1124

To keep the participation both fair and able to reduce the uncertainty, the authors added a performance rate, already used in other resources by the authors [10]. The performance rate range is between 1 and 5. Normally, a minimum to participate is added and is performance rate 3. As mentioned, groups will be formed to select the proper consumers according to the type of V2G event. The clustering method used was k-means [11].

RESULTS AND DISCUSSION

In the present section, the authors discuss and analyze the results from the case study used to prove the viability of the proposed methodology. Firstly, Figure 3 shows the number of V2G events triggered throughout the day.

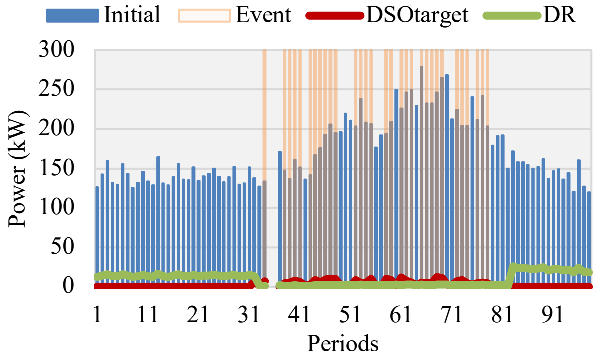


Figure 3. V2G events triggered throughout the day.

It should be mentioned this type of event can only be triggered during the parking lot operation hours, assuming that outside these periods, there is no EV parked. The events identified in Figure 3 are where the flexibility provided by the active consumers – in this case, the office buildings, is not enough to suppress the reduction target requested by the DSO. With this, a total of 31 periods with events were recognized. The authors also want to highlight that 89% were slow events. – in this case, with more than 15 minutes and less than 1 hour and 30 minutes. Table IV shows the total number of events and the actual duration.

Table IV. V2G events identified their duration and type.

Type	Duration (Periods)	Duration (minutes)	Number of occurrences
Fast	1	15	1
Slow	2	30	1
Slow	3	45	3
Slow	4	60	2
Slow	5	75	1
Slow	6	90	1

In this way, due to space limitation, the authors select two events to analyze in-depth: one fast event (with 15 minutes long) and one slow event (the one with the longest duration).

Fast event

In this scenario, only one fast event was identified. This V2G event was triggered on period 34 (8:30 AM). Table V shows the results: how many EVs per performance rate in this group is proper for fast events according to the clustering selection. The EVs selected were previously filtered in the Event Preparation phase and separated from those that needed to charge in this period.
Above the denominated minimum rate to participate, the total count of participants is 11 EVs; however, the flexibility provided from these players is enough to suppress the reduction target needed – 5.34 kW vs. 5.57 kW. With this approach, the aggregator avoids unnecessary costs, and the active consumers, with their EV, avoid discomfort.

Table V. Fast event flexibility results.

Rate	Available	Selected	Flexibility (kW)	Actual Flex. (kW)	V2G Target (kW)
1	5	0	3.511	0	5.344
2	4	0	1.575	0	
3	2	2	1.184	1.184	
4	4	4	1.717	1.717	
5	5	5	2.668	2.668	

In this way, these players were called to participate, being remunerated with an off-valley zone incentive. Table VI shows the remuneration values for this period per performance rate.

Table VI. Fast event remuneration results.

Rate	Count	Remuneration (m.u.)	Zone	Incentive (m.u./kW)
3	2	0.179	Off-valley	0.1515
4	4	0.260		
5	5	0.404		

For this event, the aggregator compensates the participants with 0.844 m.u. Confronting with the approach where all the available players were called to participate, the aggregator saves a total of 0.771 m.u.

Slow event

Moving to the slow event perspective, the one selected, as already mentioned, was the one with the longest duration – a total of 1 hour and 30 minutes. This event happens between period 41 (10:15 AM) inclusive and period 47 (11:45 AM) exclusive. Table VII shows the main characteristics of this event.

Table VII. Slow event characteristics.

Periods	41	42	43	44	45	46
V2G Target (kW)	1,413	6,671	3,517	7,699	8,225	7,818
Zone	off-valley	off-valley	peak	peak	peak	peak

The slow event happens between two zones – off-valley and peak. In the first-mentioned zone, which has two periods in the event, the reduction needed is 8.084 kW. On the other side, the event in the peak zone has four periods, and the flexibility needed from the EVs is 27,259 kW. According to these values and for each period, Table VIII shows the total flexibility results for this event and the remuneration. For period 41 and period 43, only elements from performance rate 5 were selected gathering the enough reduction to achieve the V2G target, receiving a total of 0.272 m.u. and 0.903 m.u. respectively.

Table VIII. Slow event flexibility and remuneration results.

Periods	V2G Target (kW)	Actual Flex. (kW)	Remuneration (m.u.)	Total Selected
41	1.413	1.795	0.272	2
42	6.671	6.770	1.026	9
43	3.517	3.660	0.903	7
44	7.699	7.792	1.923	12
45	8.225	8.482	2.093	13
46	7.818	8.023	1.980	11

For period 42 and period 44, the aggregator needed to call participants from performance rate 3 until rate 4 to achieve the goal – a total of 9 and 12 EVs. In the last two periods, and to suppress the needs, all the rates were called to participate.

CONCLUSION

Considering the demand side as the center of the successful approach to implementing the Smart Grids concept in the real world, dealing with the associated resources must be the focus. In this way, the authors propose a methodology capable of dealing with both active consumers participating in demand response events as well as the vehicle to grid (V2G) interaction.

The authors believe that fairness and good compensation will motivate continuous participation and reduce the response uncertainty from these new and uniformed players. In this way, each resource is classified according to a performance rate to aid the aggregator in selecting the proper participants for the event.

In the present paper, the authors focus on two different types of V2G events: fast (within 15 minutes duration) and slow (more than 15 minutes). For the discussion, the authors compare the reduction target and the flexibility provided by the selected groups, proving the approach's viability.

Also, contextual remuneration was applied, proving that the context in which the event is triggered can be important for both parties involved.

Acknowledgments

This paper results from an integrative and collaborative partnership between the GECAD Research Group from the Polytechnic of Porto (ISEP/PP) and E-REDES developed within the Horizon 2020 Project DOMINOES (grant agreement No771066). The present work was done and funded in the scope of the following projects: UIDB/00760/2020, CEECIND/02887/2017, and SFRH/BD/144200/2019 supported by national funds through FCT.

This work is co-financed by the ERDF – European Regional Development Fund through the Operational Programme for Competitiveness and Internationalisation - COMPETE 2020 under the PORTUGAL 2020 Partnership Agreement, and through the Portuguese National Innovation Agency (ANI) as a part of project NEXTSTEP: POCI-01-0247-FEDER-018006

REFERENCES

[1] M. Kühnbach, J. Stute, T. Gnann, M. Wietschel, S. Marwitz, and M. Klobasa, "Impact of electric vehicles: Will German households pay less for electricity?," Energy Strategy Reviews, vol. 32, p. 100568, Nov. 2020, doi: 10.1016/j.esr.2020.100568.

[2] H. Lund and W. Kempton, "Integration of renewable energy into the transport and electricity sectors through V2G," Energy Policy, vol. 36, no. 9, pp. 3578–3587, Sep. 2008, doi: 10.1016/j.enpol.2008.06.007.

[3] R. Shi, S. Li, P. Zhang, and K. Y. Lee, "Integration of renewable energy sources and electric vehicles in V2G network with adjustable robust optimization," Renewable Energy, vol. 153, pp. 1067–1080, Jun. 2020, doi: 10.1016/j.renene.2020.02.027.

[4] H. Morais, P. Faria, and Z. Vale, "Demand response design and use based on network locational marginal prices," International Journal of Electrical Power & Energy Systems, vol. 61, pp. 180–191, Oct. 2014, doi: 10.1016/j.ijepes.2014.03.024.

[5] C. Li et al., "Optimal spatio-temporal scheduling for Electric Vehicles and Load Aggregators considering response reliability," Electric Power Systems Research, vol. 162, no. December 2017, pp. 183–193, Sep. 2018, doi: 10.1016/j.epsr.2018.05.007.

[6] P. Faria and Z. Vale, "A Demand Response Approach to Scheduling Constrained Load Shifting," Energies, vol. 12, no. 9, p. 1752, May 2019, doi: 10.3390/en12091752.

[7] Q. Li, Y. Su, W. Nie, and M. Tan, "Robust unit commitment with high penetration of renewable energy based on demand response and power consumption contract of electrical vehicles," in 2016 International Symposium on Electrical Engineering (ISEE), Dec. 2016, pp. 1–6. doi: 10.1109/EENG.2016.7845983.

[8] I. Ilieva, B. Bremdal, S. Ødegaard Ottesen, J. Rajasekharan, and P. Olivella-Rosell, "Design characteristics of a smart grid dominated local market," in CIRED Workshop 2016, 2016, pp. 185 (4 .)-185 (4 .). doi: 10.1049/cp.2016.0785.

[9] C. Silva, P. Faria, and Z. Vale, "Finding the Trustworthy Consumers for Demand Response Events by Dealing With Uncertainty," in 2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), Sep. 2021, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope51590.2021.9584667.

[10] C. Silva, P. Faria, and Z. Vale, "Rating the Participation in Demand Response Programs for a More Accurate Aggregated Schedule of Consumers after Enrolment Period," Electronics, vol. 9, no. 2, p.

349, Feb. 2020, doi: 10.3390/electronics9020349.
[11] K. P. Sinaga and M.-S. Yang, "Unsupervised K-Means Clustering Algorithm," IEEE Access, vol. 8, pp. 80716–80727, 2020, doi: 10.1109/ACCESS.2020.2988796.

Publication IV

C. Silva, P. Faria and Z. Vale, "Rating and Remunerating the Load Shifting by Consumers Participating in Demand Response Programs," in IEEE Transactions on Industry Applications, vol. 59, no. 2, pp. 2288-2295, March-April 2023, doi: 10.1109/TIA.2022.3224414. (2021 IF: 4.079)

Resumen

Los consumidores efectivos y activos que brindan flexibilidad a través de programas de Respuesta a la Demanda (DR) tienen tres aspectos importantes: clasificar a cada consumidor según su participación anterior, remunerar esa participación y determinar el efecto de rebote del consumo después del evento. En este artículo, los autores diseñan una tasa para clasificar y seleccionar a los participantes adecuados para un evento de DR considerando el contexto en el que se desencadena el evento. El agregador estima el desplazamiento del consumo a períodos posteriores al evento y se estima la remuneración correspondiente bajo diferentes escenarios. Este desplazamiento se puede realizar en varios marcos de tiempo en el futuro. Los escenarios se desarrollan para probar el rango de tiempo aceptable en el que se debe asignar la carga según el efecto de rebote. Los resultados muestran que un mayor rango de tiempo puede evitar un consumo pico excesivo, optimizando la operación del sistema con beneficios para los consumidores, el DSO y el agregador.

sensors

MDPI

Article

Demand Response Contextual Remuneration of Prosumers with Distributed Storage

Cátia Silva, Pedro Faria, Bruno Ribeiro, Luís Gomes and Zita Vale *

Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD), Intelligent Systems Associated Laboratory (LASI), Polytechnic of Porto, 4200-072 Porto, Portugal
* Correspondence: zav@isep.ipp.pt

Abstract: Prosumers are emerging in the power and energy market to provide load flexibility to smooth the use of distributed generation. The volatile behavior increases the production prediction complexity, and the demand side must take a step forward to participate in demand response events triggered by a community manager. If balance is achieved, the participants should be compensated for the discomfort caused. The authors in this paper propose a methodology to optimally manage a community, with a focus on the remuneration of community members for the provided flexibility. Four approaches were compared and evaluated, considering contextual tariffs. The obtained results show that it was possible to improve the fairness of the remuneration, which is an incentive and compensation for the loss of comfort. The single fair remuneration approach was more beneficial to the community manager, since the total remuneration was lower than the remaining approaches (163.81 m.u. in case study 3). From the prosumers' side, considering a clustering method was more advantageous, since higher remuneration was distributed for the flexibility provided (196.27 m.u. in case study 3).

Keywords: contextual remuneration; battery energy storage; demand response; optimal management; smart grids

Citation: Silva, C.; Faria, P.; Ribeiro, B.; Gomes, L.; Vale, Z. Demand Response Contextual Remuneration of Prosumers with Distributed Storage. *Sensors* **2022**, *22*, 8877. https://doi.org/10.3390/s22228877

Academic Editors: Emmanuel Karapidakis, Pompodakis Evangelos and Fco Javier Rodríguez

Received: 29 September 2022
Accepted: 15 November 2022
Published: 17 November 2022

1. Introduction

1.1. Background

Climate change demands a change in the power and energy sector. It is essential to find solutions that properly introduce these greener approaches to reduce fossil fuel use and decrease air pollution and greenhouse effects [1]. The smart grid concept focuses on the consumer side and their flexibility. However, management tools and knowledge must be provided to take a step forward towards successful implementation in the real market [2].

1.2. Challenges

Although slow, there have been advances in this area [3]. However, the management of energy systems is more complex due to the integration of Distributed Generation (DG), namely renewable-based resources with their volatile behavior, and the addition of energy prosumers as players in energy market transactions [4]. Not only do they provide flexibility by participating in Demand Response (DR) events with their appliances, but also as prosumers, with DG to suppress their own needs or sell their surplus [5]. Still, the flexibility provided by these new and active communities should be properly managed to avoid consumer discomfort, and reduce response uncertainty, rebound effect, and unsupplied power, among other grid problems [6]. It becomes crucial to define a tool to optimally manage resource scheduling to surpass this challenge; namely, using the BES capacity.

Many solutions are being developed to deal with the complex management of local communities and their new and complex resources [7]. Indeed, with the concept of the Internet of Things (IoT), different equipment (sensors and actuators, among others) can be applied to gather information on the consumer side and provide proper solutions [8]. Nevertheless, dealing with big data is one of the major issues in the literature, but progress has been made [9,10]. Prabadevi B et al. [11] analyze the possibility of deep learning approaches for tackling this challenge, leaving the inaccuracies in electricity load forecast as an open issue, where the lack of evaluation of real-time data was at issue. According to these authors, information (both historical and real-time data) is crucial for making wise and optimal decisions, so there is a challenge for the community manager: decide which knowledge is useful since, as mentioned, real-time approaches can be challenging and require fast responses to grid issues.

1.3. Literature Review

System operators require a scheduling model that considers security and economic issues when using energy storage systems, as Meysam Khojasteh et al. [12] highlight. These authors proposed a linear optimization model for synchronous generators and BES in the collective energy and reserve market. Their proposal reduced the total operating costs and provided adequate security by deploying energy storage systems. In [13], the authors introduced the aggregated scheduling of energy storage systems and wind power resources in the same joint markets. For this case study, results indicate that the day-ahead and real-time markets can be considered the optimal options for buying and selling energy storage systems' energy.

Nevertheless, sharing a large capacity battery across a group of small prosumers in a community can alleviate the economic deterrents but also exploit the fact that behavior patterns do not necessarily overlap, as Jiyun Yao and Parv Venkitasubramaniam [14] believe. However, this introduces competition [15]. These authors introduce a stochastic, general-sum, game-theoretical framework to solve this problem and capture the competitive behaviors managing charging and discharging based on the received, sometimes incomplete, information. The results provided a close-to-optimal performance using the strategy with real electricity usage and pricing data.

With this, it is crucial to take a step forward to implement energy storage systems in local communities, namely the ones with residential prosumers with renewable-based resources, as a means to increase their self-consumption [16]. Lisa Calearo et al. [17] stress this fact in their work, where a comparison was made between the benefits of a PV prosumer with an EV under two options: installing a BES or applying smart charging. Furthermore, Farzad Arasteh and Gholam H. Riahy [18] developed an online model-based predictive-control approach for optimal real-time operation of wind-integrated power systems, including DR and energy storage systems facilities. In the results, the authors could reduce operational costs through optimal uncertainty management.

The proper knowledge must be selected from a large amount of data provided by IoT devices. In the study from [19], the authors used a contextual approach to improve the accuracy of aggregated schedules considering DR performances from previous event experiences in the same context (weather conditions and period). The goal was to understand which factor impacts the final performance rate attributed to participants and improve the overall method. However, only direct load control and load appliances were contemplated in the DR events, disregarding prosumers. A previous work [20] did contemplate this type of prosumer. Still, the main goal was fair remuneration for DR participants by understanding the benefits of considering them as individuals or unique players using clustering methods. Along the same line, the study developed [21] a remuneration structure comparing hierarchical and fuzzy c-means, considering the maximum tariff in each group to compensate the DR participants. However, the participant trustworthiness level was not considered; the prosumers have uncertain behaviors and might not participate as requested. Considering them as economic and rational agents might lead to misleading results [22].

Table 1 summarizes the important topics referred to in the literature reviewed previously, considered to be used for motivation for the current work. Regarding the table: prosumers were rarely used; the main Demand Response programs used are incentive-based; the chosen energy storage system is the battery; the horizon most used in these works is real-time; only one work considers fair remuneration of DR participants.

Table 1. The literature review summarized (✓ means that the topic is covered by the reference).

Ref.	Prosumers	Demand Response	Energy Storage System	Horizon	Remuneration
[12]	-	-	✓	Real-time	-
[13]	-	-	✓	Real-time	-
[15]	-	-	✓	Real-time	-
[17]	✓	-	✓	-	-
[18]	-	Incentive	✓	Real-time	-
[19]	-	Incentive	-	Planning	✓
[20]	-	Incentive	-	Planning	✓
[21]	-	Incentive	-	Planning	-
This work	✓	Incentive and price	✓	Planning and Real-time	✓

In the present paper, the authors aim to gather all these concepts with the proposed methodology.

1.4. Scopes

The present study falls into the scope of optimal resource scheduling, considering a contextual approach for DR event participants. In this way, the authors aim to address and solve problems related to fair and contextual remuneration, reduce response uncertainty, BES optimal management, and self-consumption.

1.5. Motivation

Considering the works analyzed previously, the authors' main motivation is to provide innovative contributions for local community management of several resources with uncertain and volatile behavior. Furthermore, dealing with big data issues by selecting contextual information could be useful in characterizing DR performances. And finally, the authors contemplate not only load flexibility prosumers, but also prosumers with more resources beneficial for the grid functioning, properly managed and well-motivated by using fair and contextual remuneration.

1.6. Contributions

With this motivation and the mentioned challenges, the authors address the problem in this paper: how to fairly remunerate prosumers for participating in DR events providing flexibility with several resources and considering different energy price schemes. The following features are listed as innovative aspects of the methodology proposed in the present paper:

- Optimizing prosumer behavior in a distributed management, considering past DR events to predict and classify their response to an event;
- Evaluate several approaches to increase remuneration fairness;
- Compare several energy price schemes to understand the benefits from the community manager and the prosumer perspectives.

1.7. Organization of Paper

The present paper is organized into five main sections. Section 1 presents the present work's background, motivations, related works, and innovations. Then in Section 2, the proposed methodology is presented in detail. The case studies and several scenarios are presented in Section 3 to be further discussed in the results and discussion section. Finally, Section 5 brings forth the conclusions from this study.

2. Proposed Methodology

The authors developed a methodology to optimally manage the resources in a community, such as Distributed Generation (DG), prosumers, load flexibility, and energy storage systems. Believing that context is an important matter, bringing intelligence to the models developed, the authors believe introducing this concept will improve the solution compared with previous works [23]. For the present paper, besides the inclusion of BES in the prosumer's portfolio, the authors intend to evaluate ways to motivate participation in DR events and reduce the operating costs from the community manager by selecting only the proper participants for a certain context, following the proposed methodology in Figure 1.

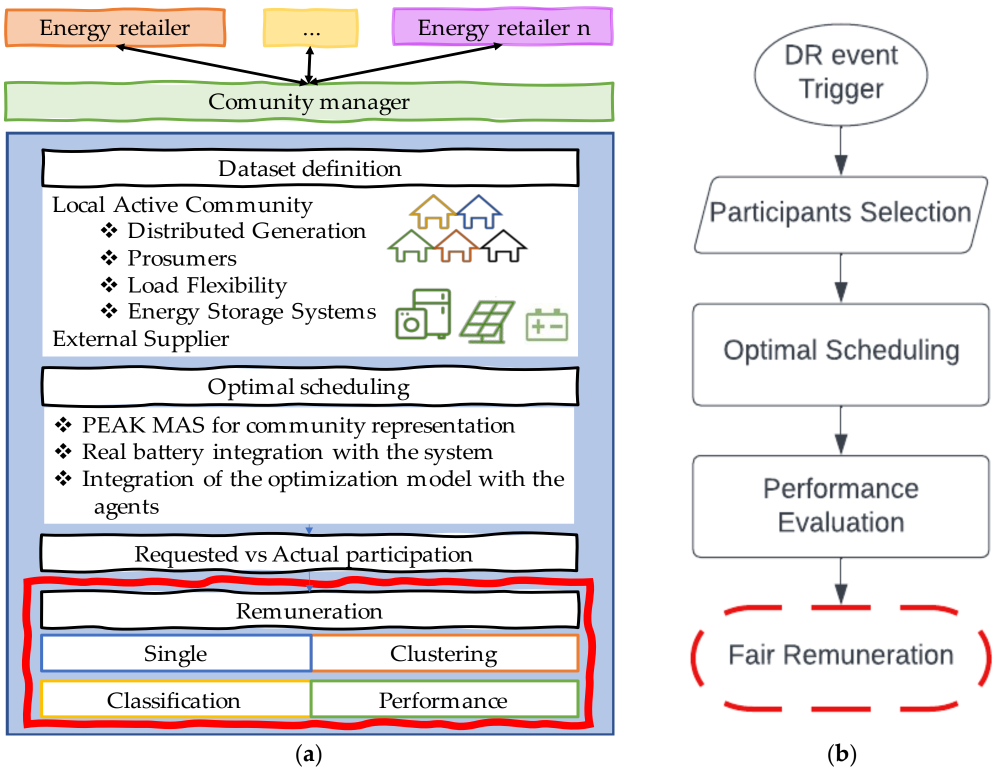


Figure 1. Proposed methodology: (**a**) diagram, (**b**) flowchart.

For a community manager, several offers are being made from the energy retailers as a competitive market is introduced. Furthermore, dealing with the new and uninformed prosumers as market players with a more direct impact on the market transactions increases the complexity of managing active communities.

Following Figure 1b, the participants are selected to attend, starting with the DR event triggered in a specific context. To maintain continuity with previous works, the authors used a rate designed to classify the participants' performance on a DR event: Consumer Trustworthy Rate (CTR), defined according to Figure 2. Three yellow stars in Figure 2 means three out of five.

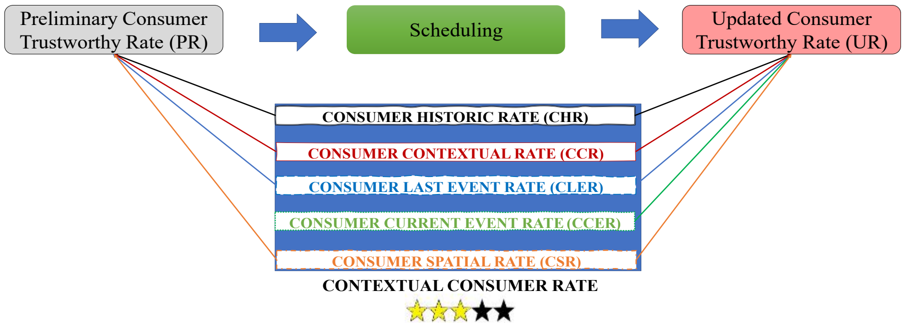


Figure 2. CTR in the scope of the proposed methodology.

Before scheduling, information is gathered regarding DR events in the same context—for instance, the same hour, day of the week, or even the temperature registered for each participant. This rate will be useful for understanding which prosumers are more willing to participate in each situation. However, privacy matters could be raised since prosumers might share sensitive information regarding their appliances to participate in DR events. Before the event, the community manager and the participants should agree on the data provided, since this is a contextual approach. For instance, in load-shifting programs, the appliance schedule might be shared to be optimally attributed to a different period, avoiding consumer discomfort and rebound effect.

To avoid privacy issues, the proposed methodology-optimal schedule in the present paper is performed in a distributed way, so the aggregator does not have any private information on a real-time basis or any other horizon. Each prosumer building does their own internal management with the optimal schedule proposed and does not provide private information regarding a specific appliance's availability or behavior. The aggregator has only the sum of actual flexibility response from each consumer at the end of the month to update the CTR and proceed for DR participation remuneration.

Participants with high values of CTR are usually the more trustworthy. The formulation of the CTR changes according to the needed step: before (preliminary consumer trustworthy rate as PR) or after (updated consumer trustworthy rate as UR) the scheduling. To select the participants for DR events, the PR is defined according to the consumer historic rate (CHR), the consumer contextual rate (CCR), the consumer last event rate (CLER), and the consumer spatial rate (CSR). The first one is the average of the last five performances in the same period. CCR is divided into two different perspectives: time and weather. The participant's performance according to these indicators will result in the CCR. After that, the CLER differs from the CHR to update the CTR according to the last performance. Finally, CSR is only used if the aggregator has knowledge regarding the participant's current location on the grid. For cases where a voltage violation is detected, the participants closer to the faulty bus must have priority. In the present paper, CSR was not considered since it was not the focus of the study. Further privacy issues regarding CTR were already discussed by the authors in prior works with additional consumer information [24], so this topic will not be approached in the present paper. After the scheduling is performed and the comparison between the requested and the actual flexibility is made, the CTR must be updated with the performance from the current period—CCER.

As soon as the participants are selected, the optimal scheduling phase starts. Equation (1) represents the objective function from the mixed-integer linear programming optimization. Since the tariffs are defined hourly, the term Δt was added to adjust the consumption for a different time basis.

$$\min EB = \sum_{t-1}^{T} [\left(P^{grid_{in}}_{(t)}.C^{grid_{in}}_{(t)} - P^{grid_{out}}_{(t)}.C^{grid_{out}}_{(t)}\right).\tfrac{1}{\Delta t} + \sum_{c=1}^{C} P^{DR}_{(c,t)}.W^{DR}_{(c,t)}]$$
$$\begin{cases} P^{grid_{in}}_{(t)} = P^{grid}_{(t)},\ if\ P^{grid}_{(t)} > 0 \\ P^{grid_{out}}_{(t)} = P^{grid}_{(t)},\ if\ P^{grid}_{(t)} < 0 \\ \forall t \in \{1,\ldots,T\} \end{cases} \tag{1}$$

Equation (2) represents the balance that must exist between the consumption and generation resources in the community. Equation (3) shows the upper and lower limits for grid usage. As can be seen, the sign of $P^{grid}_{(t)}$ changes according to the transactions done: if the energy is bought, the value is positive. Otherwise, it is negative.

$$\sum_{p=1}^{P} P^{PV}_{(p,t)} + P^{grid}_{(t)} + \sum_{c=1}^{C} P^{DR}_{(c,t)} + \sum_{s=1}^{S} P^{dch}_{(s,t)} = P^{load}_{(t)} + \sum_{s=1}^{S} P^{ch}_{(s,t)}, \forall t \in \{1,\ldots,T\} \tag{2}$$

$$-P^{gridmax_{out}}_{(t)} \le P^{grid}_{(t)} \le P^{gridmax_{in}}_{(t)}, \forall t \in \{1,\ldots,T\} \tag{3}$$

Regarding the flexibility provided by the participants in the DR events, it is represented with $P^{DR}_{(c,t)}$ and is limited according to upper and lower limits shown on Equation (4). Also, the authors considered that loads are connected to relays and only when activated—using the binary variable $X^{DR}_{(c,t)}$, the loads can be shed according to Equation (5).

$$0 \le P^{DR}_{(c,t)} \le P^{DRmax}_{(c,t)}, \forall t \in \{1,\ldots,T\}, c \in \{1,\ldots,C\} \tag{4}$$

$$P^{DR}_{(c,t)} = P^{DRmax}_{(c,t)}.X^{DR}_{(c,t)}, X^{DR}_{(c,t)} \in \{0,1\}, \forall t \in \{1,\ldots,T\}, c \in \{1,\ldots,C\} \tag{5}$$

Energy storage systems considered in the methodology are limited by several constraints represented from Equations (6)–(10). Equation (6) represents the upper and lower limits of the energy storage system operation capacity. Equations (7) and (8) represent the charge and discharge limits per period, respectively, associated with binary variables. So with Equation (9), the aggregator can guarantee the impossibility of charging and discharging with these binary variables $X^{ch}_{(s,t)}$ and $X^{dch}_{(s,t)}$ in the same period. Finally, Equation (10) represents the state of charge of the energy storage system maintaining the power balance—the sum of the previous state and what was charged or what was discharged for the current period.

$$E^{stormin}_{(s,t)} \le E^{stor}_{(s,t)} \le E^{stormax}_{(s,t)}, \forall t \in \{1,\ldots,T\}, s \in \{1,\ldots,S\} \tag{6}$$

$$0 \le P^{ch}_{(s,t)} \le P^{chmax}_{(s,t)}.X^{ch}_{(s,t)}, X^{ch}_{(s,t)} \in \{0,1\}, \forall t \in \{1,\ldots,T\}, s \in \{1,\ldots,S\} \tag{7}$$

$$0 \le P^{dch}_{(s,t)} \le P^{dchmax}_{(s,t)}.X^{dch}_{(s,t)}, X^{dch}_{(s,t)} \in \{0,1\}, \forall t \in \{1,\ldots,T\}, s \in \{1,\ldots,S\} \tag{8}$$

$$X^{dch}_{(s,t)} + X^{ch}_{(s,t)} \le 1, \forall t \in \{1,\ldots,T\}, s \in \{1,\ldots,S\} \tag{9}$$

$$E^{stor}_{(s,t)} = E^{stor}_{(s,t-1)} + P^{ch}_{(s,t)} + P^{dch}_{(s,t)}, \forall t \in \{1,\ldots,T\}, s \in \{1,\ldots,S\} \tag{10}$$

Once finished with the scheduling, the following stage is represented on Figure 2b as "Performance Evaluation", where a comparison between the actual and the requested participation is made to properly assign the remuneration tariffs to the ones that contributed to the DR event.

The fair remuneration phase is the focus of this study. The authors proposed four approaches: single, clustering, classification, and performance. The single approach considers that flexibility is remunerated according to the energy price applied for the current period. Several schedules were considered for dividing, for instance, the day into peak, valley, and off-valley periods. Each period has a different tariff, and the flexibility is compensated with the same value.

For the clustering approach, the authors opt for one of the well-known partitional methods—k-means. The algorithm aims to find a centroid value representing each group, comparing the distance between elements until the minimum value is found. The k-means clustering method was already studied and widely used with various extensions in the literature. For the proposed methodology, the authors intend to aggregate prosumers with similar flexibility profiles and remunerate higher values with better tariffs, which may lead to different tariff values per period, since the group with higher flexibility can also change. By getting the output data from the method in which a group is assigned to each participant, the authors want to create the proper rules and then attribute the group to other participants without performing the clustering method each period. In this way, classification methods can be used. Three different methods were tested within the scope of the present paper: decision tree, k-nearest neighbors (KNN), and artificial neural networks (ANN). These methods were then compared and evaluated using accuracy and mean absolute error (MAE).

Finally, the UR is used for the remuneration since it contains the information from the actual performance. Each rate is tariff-associated, and the higher the rate, the better the compensation.

The novelty from previous works relies on the contextual change of energy price and remuneration. The authors believe proper compensation is crucial to motivate continuous participation and make this transaction known to prosumers. It will take time, education, and resources to make the prosumers better power and energy market players. Still, the authors believe continuous participation and experience will also be important to progress. With higher knowledge regarding the community come better results in managing community resources. It will also benefit the prosumers, since their load can be changed to other periods when the energy price is lower. Comparing several approaches to remunerate properly and fairly can be useful for developing a tool capable of taking a step forward to apply DR in the real market with optimal results.

3. Case Study

To test and validate the optimization model, it was used with a novel multi-agent system conceived and developed by the authors called Python-based Ecosystem for Agent Communities (PEAK) [25]. PEAK is a multi-agent framework that aims to support and manage the development of multi-agent ecosystems in a simple way, based on the Python programming language. This framework can create simulation environments and provide a feasible solution for a pilot deployment. PEAK can integrate real devices, such as energy resources, loads, and IoT devices, using specific drivers for each communication protocol. Furthermore, it is possible to integrate mathematical and machine learning models within the agents. By default, a system created with PEAK registers every interaction inside the ecosystem for posterior debugging and analysis.

The paper uses Multi-Agent Systems (MAS) to model and represent smart grid entities. The authors consider the approach a good fit, as they can decentralize the computational effort among agents. The proposed MAS solution uses the open-source PEAK framework (www.gecad.isep.ipp.pt/peak, accessed on 3 November 2022), which enables easy and fast development and deployment of MAS in simulated and real scenarios. As for the optimization model, it is distributed among agents, and each agent responsible for the optimization of its own resources.

Energy storage in the literature has been identified with several options, such as ultra-capacitor, super magnetic, flywheel, compressed air, pumped hydro energy storage systems, and Battery Energy Storage Systems (BESS) [26]. In the present paper, BESS has been selected. As concluded in [26], combining BESS with DR can significantly reduce the size of conventional energy storage systems and improve power quality. For the present case study, a total of 19 prosumers/agents were considered, and five of those prosumers are connected to real BESS, while the others use simulated BESS, and both are constrained by (6) to (10). These real BESS belong to the GECAD/ISEP research center and can be seen in Figure 3, with a capacity of 2 kW. The developed PEAK agents for the proposed model do not represent a threat to the equipment when using data simulation. To avoid damage to the equipment, the PEAK was executed in real-time (running the case study for 24 h) while compliant with the physical limitations of BESS. Also, the BESS used, a Victron inverter, was configured to set charging, discharging, and state of the charge limits to avoid physical threats to the equipment. Regarding computational complexity, this framework uses multiprocessing and multithreading to increase simulation processing speed, enabling computation processing distribution between different machines.

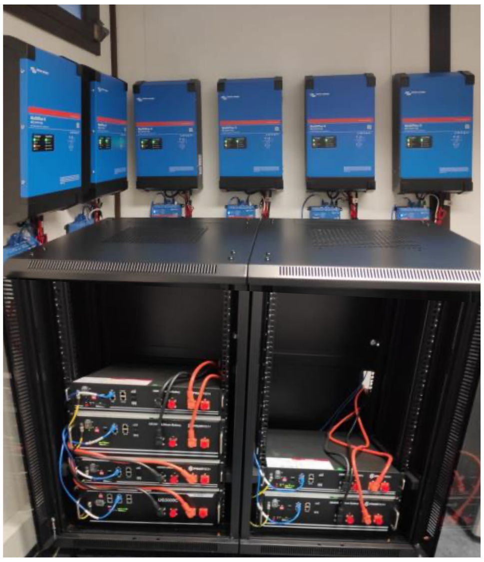


Figure 3. A real BESS from GECAD/ISEP was used for implementing the proposed methodology.

At the beginning of the simulation, the real BESS starts at full capacity. Furthermore, to communicate with the BESS, the agents use the protocol ModBus/TCP. Regarding the optimization model, the authors integrated with the multi-agent system's agents and optimized each period where the model is executed in each agent. The proposed model allows BESS configuration. In this way, for the case study in the present paper, the actual BESS may have a configuration like the simulated BESS.

Focusing on the contextual change of energy prices for resource scheduling, three case studies were created considering the tariff values from Table 2 and the schedule represented in Figure 4. The feed-in tariff was not considered for the case studies—values applied are currently considered by the main Portugal DSO. Only prosumers below 20.7 kW of contracted power were considered for this study. The 19 prosumers mentioned above with contracts as DR participants will provide flexibility. Moreover, these prosumers also use photovoltaic (PV) generation and a BESS associated with each one of them, being able to suppress their load consumption or sell the excess to the grid. The Portuguese DSO from which Table 2 tariffs were withdrawn considers two different schedule options: daily and weekly. However, this fact does not affect the tariff values, only the schedules in which they are applied; for the weekly schedule, the season matters.

Table 2. Energy tariffs for the scheduling phase.

Tariff	Peak (m.u./kWh)	Off-Valley (m.u./kWh)	Valley (m.u./kWh)
Flat	0.1815	0.1815	0.1815
Bi-hourly	0.1865	0.1865	0.1669
Tri-hourly	0.2724	0.1686	0.1561

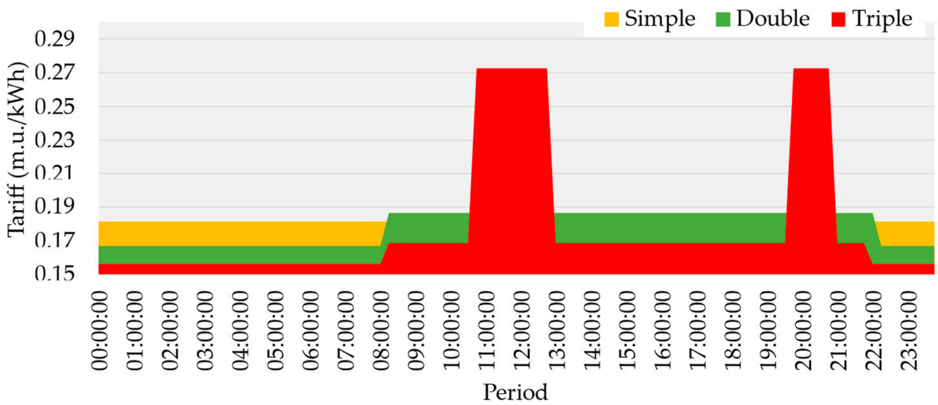


Figure 4. Schedule for the different tariffs.

The four remuneration approaches were then compared using the Figure 4 schedule for the different types of tariffs.

First, the single approach where the same tariffs from Table 2 are used for remunerating the participants in the DR event is the single approach where the same tariffs from Table 2 are used to remunerate the DR event participants. Then, a clustering approach is applied, aggregating the participants with similar behaviors. For this scenario, the number of clusters to be formed will equal three. The tariffs are attributed according to the context in which the DR event is triggered, following the schedule from Figure 4 according to the tri-hourly one. The classification scenario will create several rules to assign a tariff to the participants according to the context. And finally, the authors decided to apply a different approach. The CTR was used for the remuneration fees regarding participation in the DR event, as seen in Table 3.

Table 3. Consumer contextual trustworthy rate tariffs applied.

Rate	Peak (m.u./kWh)	Off-Valley (m.u./kWh)	Valley (m.u./kWh)
1	0.1815	0.1686	0.1561
2	0.2042	0.1718	0.1625
3	0.2270	0.1751	0.1688
4	0.2497	0.1783	0.1752
5	0.2724	0.1815	0.1815

Considering the values from Table 2, for the CTR scenario, the authors attribute the higher tariff value to each scheduled period (i.e., peak, off-valley, and valley) and divide according to the rate. So with higher rate values, the prosumer will receive more compensation for their participation, sometimes enough to pay for their load consumption for the current period and have profits. The approach's main goal is to improve performance and encourage continuous participation, giving more benefits to the prosumer for participating in the market transactions. The dataset used for each case study is in Appendix A.

4. Results and Discussion

In the present section, the authors discuss the proposed methodology results when applied to the previously presented case study. The scheduling was performed for all the prosumers in the community considering (1) to (10). The prosumer resources flexible results can be seen in Figure 5a–f, from load reduction values (constrained by (4) and (5)) and BES discharging (constrained by (8)).

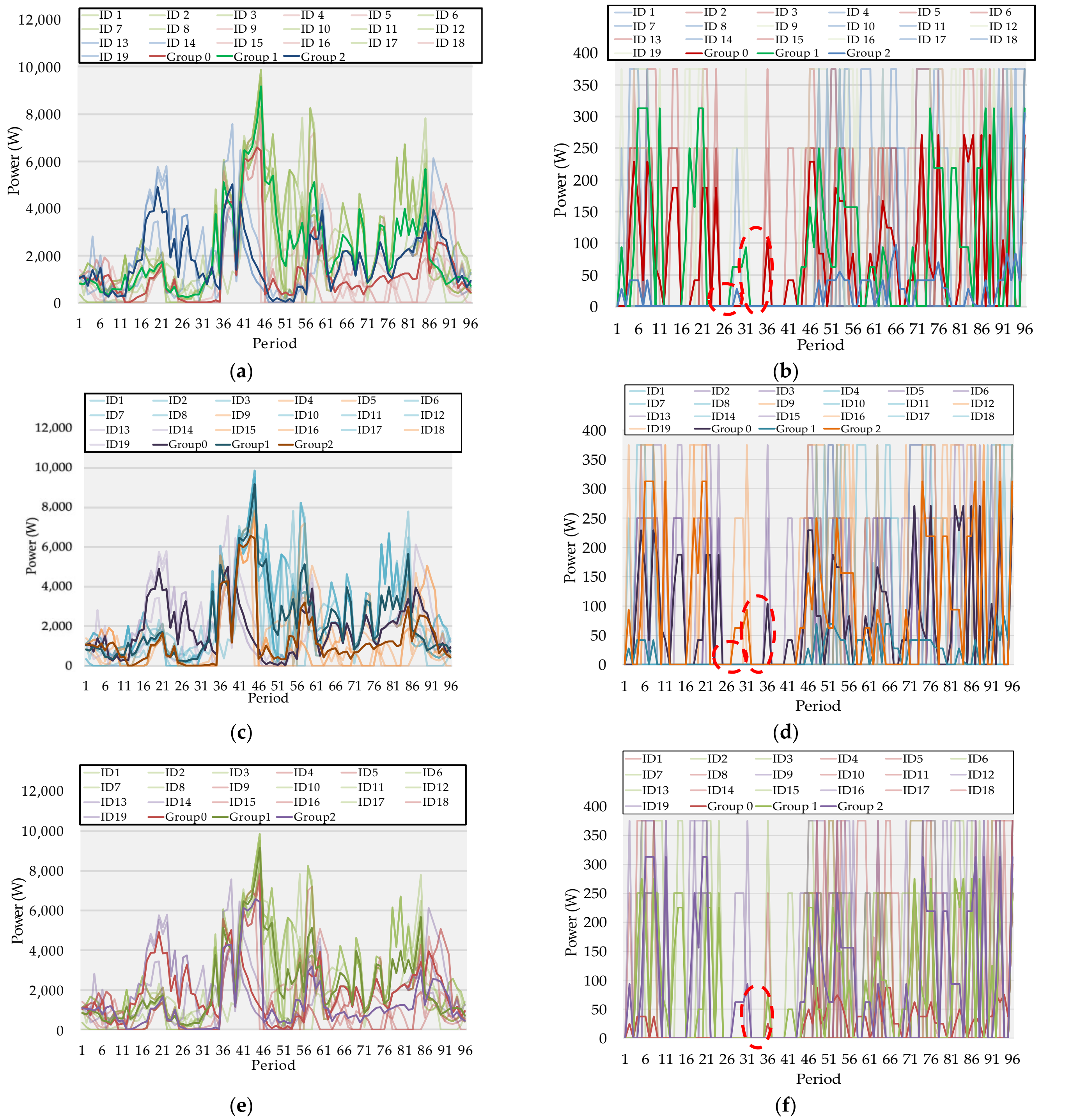


Figure 5. Scheduling results for case studies divided according to clustering method: (**a**) prosumers' load flexibility per period for case study 1, (**b**) prosumers' BES discharging per period for case study 1, (**c**) prosumers' load flexibility per period for case study 2, (**d**) prosumers' BES discharging per period for case study 2, (**e**) prosumers' load flexibility per period for case study 3, (**f**) prosumers' BES discharging per period for case study 3.

The results were then aggregated into three groups using the k-means clustering method to find the similarity between the load profiles. This consumer modeling technique was used by the authors for ease the analysis—the colors were also changed in the group according to each ID assigned, but with higher values of opacity.

Figure 5a,b represent the scheduling results for case study 1 (flat energy price tariff). Figure 5a clustering results show that Group 0 gathers the prosumers with low values of flexibility outside the peak zone, namely when compared with Group 2. From period 40 until period 58, Group 0 (represented by the red curve) had higher values of flexibility than Group 2 (represented by the blue curve), which prevailed mostly higher in the remaining periods. Regarding Group 1, before period 35, it was also below the blue line but remained superior to the others until around period 85. It must be highlighted that Group 0 had six prosumers, Group 1 gathered ten different participants, and the remaining were attributed to Group 2.

Results from Figure 5b achieved the maximum discharge value (375 W) for many periods and kept that value for no more than four consecutive periods. Nevertheless, the participant that contributed with this type of flexibility for the most periods was ID 16, keeping the maximum for four consecutive periods and then decreasing to 95 W. This participant was then assigned to Group 1, the four prosumers that have higher values of contribution for most of the time; namely, when there is no PV generation. Assigned to Group 0 were six different participants: ID2, ID3, ID5, ID6, ID13, and ID15. Group 2 has nine participants with lower values of contribution.

Figure 5c,d represent the scheduling results for the second case study that considers a bi-hourly tariff, meaning there are times of the day considered as valley and off-valley (including the peak hours) where the energy price is different, as seen in Table 2. As suggested by the Portuguese DSO, the bi-hourly tariff is ideal for the prosumers, with 40% of their daily consumption spent between 10 p.m. and 8 a.m. Still, the authors wanted to understand if these tariffs impact the flexibility in the community schedule—are two different energy tariffs enough to move the load consumption to lower price schedules?

Figure 5c flexibility results are similar to Figure 5a. Group 0 was assigned ID12, ID14, and ID19 (represented with purple curves), reducing by a total of 518 W for the whole day—the group with fewer members and less provided flexibility overall. For Group 1, the clustering method allocated ten participants to this group, which reduced the day by 2164 W. Finally, in Group 2, the reduction value was 773 W between the six participants within the group. Regarding the BES discharging results, some disparities can be found in Figure 5b. For instance, period 29 is highlighted with the red dotted circle on both figures—the discharging value from Group 2 in Figure 5b is null.

Figure 5e,f represent the results for the final case study where a tri-hourly tariff is considered, meaning three different values are assigned to periods, such as peak, off-valley, and valley, according to Table 2. However, applying the tri-hourly tariff did not affect the flexibility provided by the participants differently from the previous ones. Still, differences could be seen on the BES discharging chart marked with a red dotted circle in period 36, where the discharging value was slightly lower than the remaining cases.

The simulated values had differences between the three case studies regarding the BESS perspective. To prove the viability and robustness of the proposed model, case study 3, with more tariffs, was tested in a real-time environment. The real state of charge for the five BES considered can be seen in Figure 6, according to the PEAK execution. When comparing both expected and real results, most of the time, the real values are above the expected, although it follows the same tendency. Regarding Figure 6a, between periods 40 and 60, a major difference can be seen between both curves—expected to charge and after discharge. Still, the real value kept above 500 W. Moving on to Figure 6b, from period 60, the battery was expected to discharge, but that did not happen in the real curve, similar to Figure 6c–e. The expected results were constrained by (7).

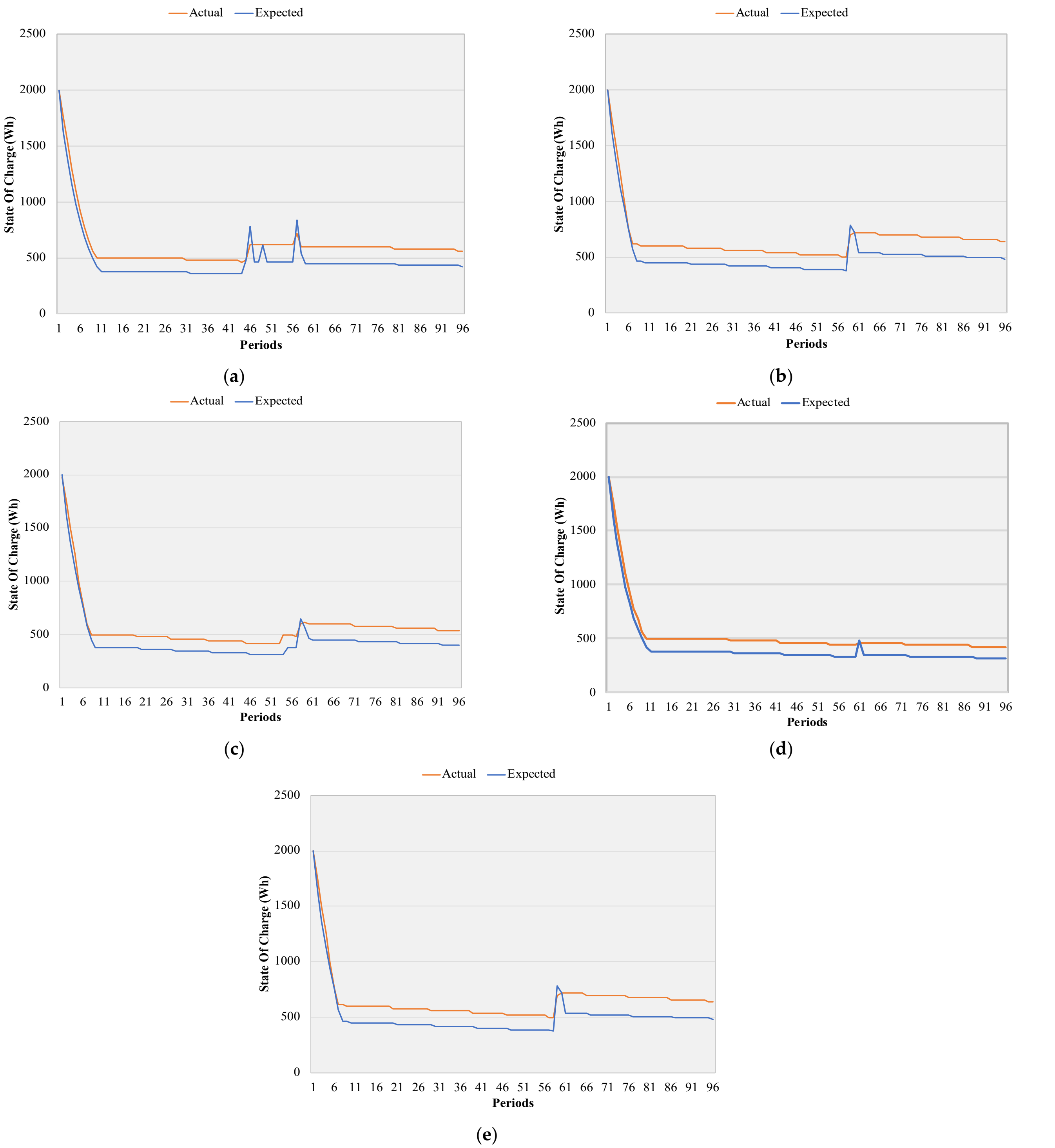


Figure 6. Comparison between the expected and the real state of charge from different batteries: (**a**) battery ID 0, (**b**) battery ID 1, (**c**) battery ID 2, (**d**) battery ID 3, (**e**) battery ID 4.

Moving on to the second phase of the study, regarding fair remuneration, the results for the first approach can be seen in Table 4 regarding the total flexibility of the prosumers' load and the total BES discharging. By analyzing this table, the authors can conclude that the total compensation increased from case study 1 to case study 3. BES discharging remuneration decreased from case study 1 to case study 2 but achieved the maximum in case study 3 with 4.53 m.u.

Table 4. Total remuneration according to a single approach.

Case Study	Actual Flexibility (m.u.)	BESS Discharging (m.u.)
1	156.84	4.45
2	157.76	4.41
3	163.81	4.53

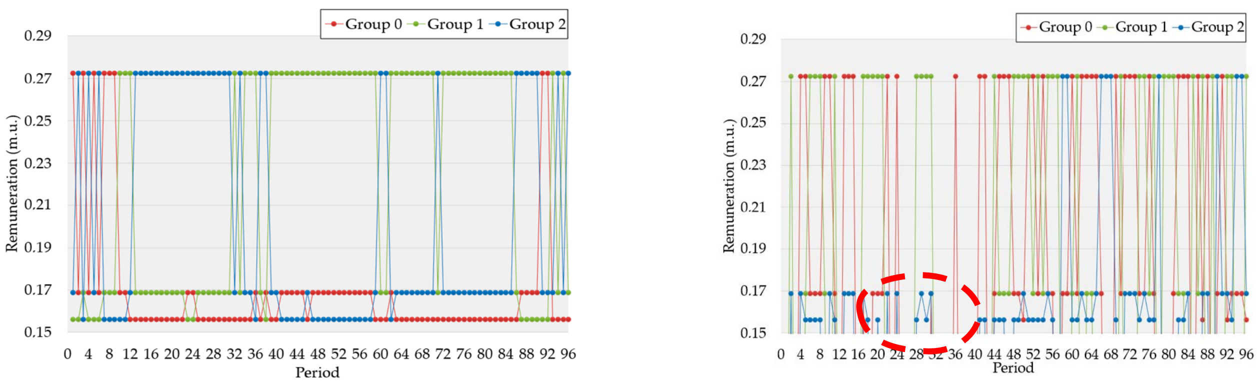
When participating in DR events, the prosumers will benefit from changing their consumption to other periods with cheaper energy prices or even using PV resources for self-consumption. Furthermore, they will be fairly remunerated for helping with market transactions. For instance, according to Table 4, if the community prosumers did not participate, a maximum of 163.81 would be attributed, and grid problems might not be solved.

The results from the fair remuneration clustering approach can be seen in Figure 8 for both prosumers' load flexibility and BESS discharging.

The remuneration tariffs were assigned according to groups with a higher value of flexibility for each period. In other words, the ones with higher accumulated flexibility will be assigned higher remuneration. It must be highlighted that remuneration tariffs were defined according to the tri-hourly tariff used previously. In this way, the group tariffs resulting from the prosumers' flexibility are similar for the three case studies, according to Figure 7a,c,e. Disparities can be, however, found regarding the BES discharging results. Focusing again between periods 20 and 40, marked with a red dotted circle in Figure 7, there were differences between case studies. Firstly, for case study 1, group 2 changed tariffs twice—from 0.1561 (m.u./kW) to 0.1686 (m.u./kW). Regarding case study 2, group 1 increased their remuneration price from 0.1561 (m.u./kW) to 0.1686 (m.u./kW). Finally, similar to case study 2, group 0 from case study 3 increased the remuneration but also participated in period 36, achieving the second-best tariff. In contrast to the results from Figure 7, Table 5 was created to compare the daily remuneration obtained per group and case study.

Table 5. Total remuneration according to clustering method.

Case Study	Actual Flexibility (m.u.)			Total	BES Discharging (m.u.)			Total
	Group 0	Group 1	Group 2		Group 0	Group 1	Group 2	
1	33.22	134.67	28.38	196.27	2.75	2.21	0.84	5.80
2	33.22	134.67	28.38	196.27	2.75	0.87	2.20	5.82
3	33.22	134.67	28.38	196.27	1.08	2.40	2.22	5.70



(a) (b)

Figure 7. *Cont.*

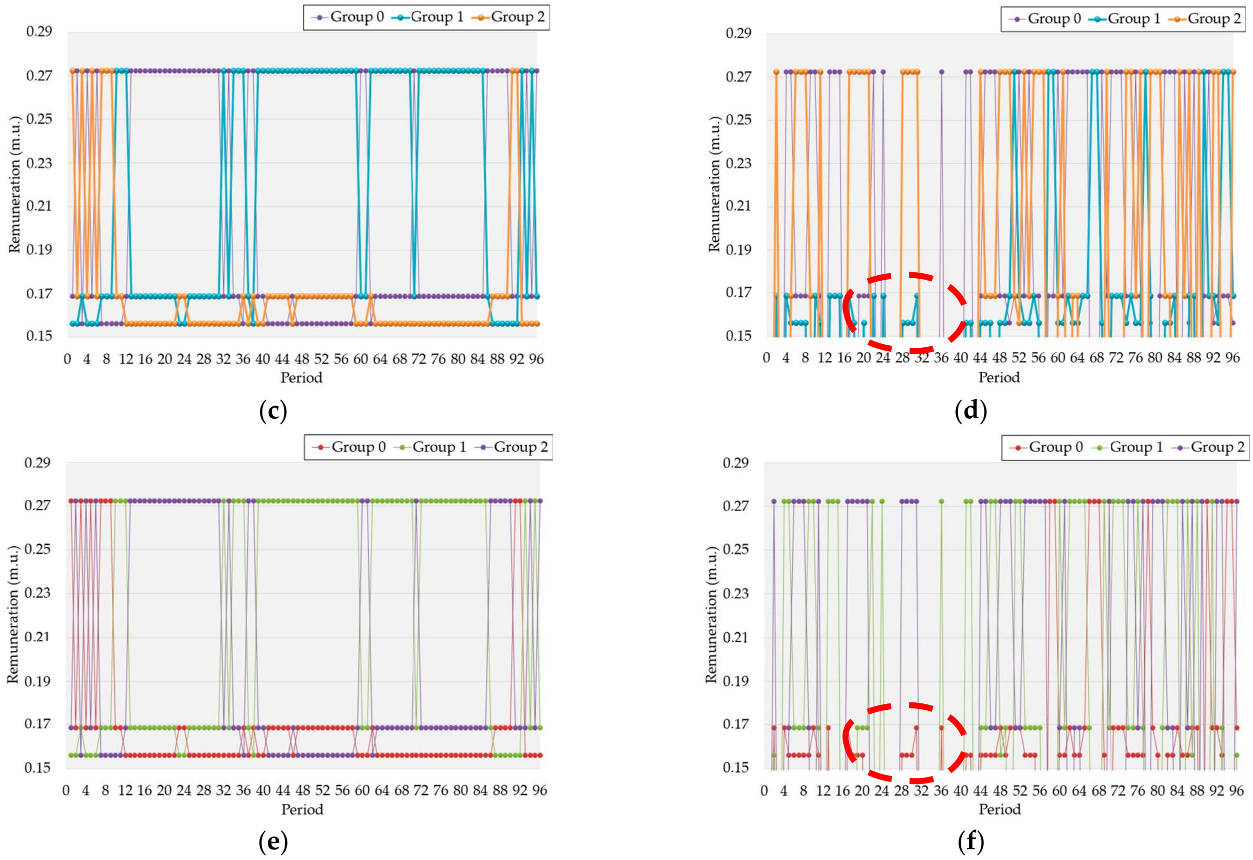


Figure 7. Contextual tariffs for case study 1 according to clustering results: (**a**) prosumers' load flexibility remuneration per period for case study 1, (**b**) prosumers' BES discharging remuneration per period for case study 1, (**c**) prosumers' load flexibility remuneration per period for case study 2, (**d**) prosumers' BES discharging remuneration per period for case study 2, (**e**) prosumers' load flexibility remuneration per period for case study 3, (**f**) prosumers' BES discharging remuneration per period for case study 3. The red circles highlight the same periods of Figure 5.

As expected from the previous results, the remuneration from the actual flexibility of participants is the same for all the groups in the different case studies. However, the BES discharging results are different, demonstrating a higher gap between case study 3 and the remaining. Group 0 achieved a 2.75 m.u. for case study 1 and case study 2. Group 1 from case study 1 and Group 2 from case study 2 had similar remuneration of around 2.20 m.u. Group 2 from case study 3 received 2.22 m.u. The lowest remuneration was attributed to Group 2 from case study 1 (with 0.84 m.u.), Group 1 from case study 2 (with 0.87 m.u.), and Group 0 from case study 3 (with 1.08 m.u.). Regarding these results, from an overall perspective, opting for case study 3 can benefit the aggregator. These results indicate that adding more contextual information may reduce the total remuneration and still be fair with the participation compensation.

Furthermore, the authors used three different classification methods to create the proper tool to attribute the remuneration group to each participant, resorting to the results obtained from the clustering results. The classification method's performance, using the selected indexes (accuracy and MAE), can be seen in Table 6. The results were obtained using Python libraries created for this goal. In examining the results and regarding the actual flexibility, the lowest accuracy value was achieved when the decision tree was performed—10.59%, with the 83.33% achieved with KNN. This method obtained better results from both accuracy and MAE for both datasets.

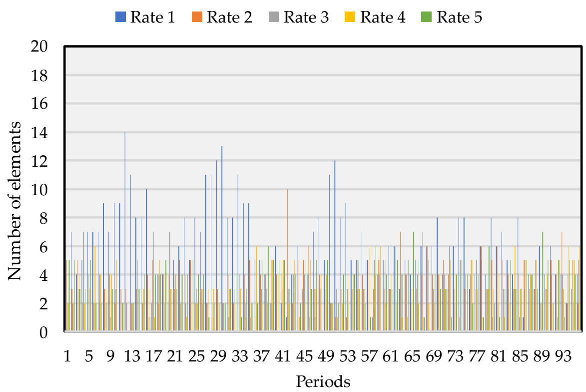
Table 6. Performance results from the classification methods.

Classification Methods	Actual Flexibility		BES Discharging	
	Accuracy	MAE	Accuracy	MAE
Decision Tree	0.10588	0.42105	0.41651	0.50877
K-nearest neighbors	0.83333	0.33333	0.41666	0.50877
Artificial Neural Networks	0.57780	-	0.37780	-

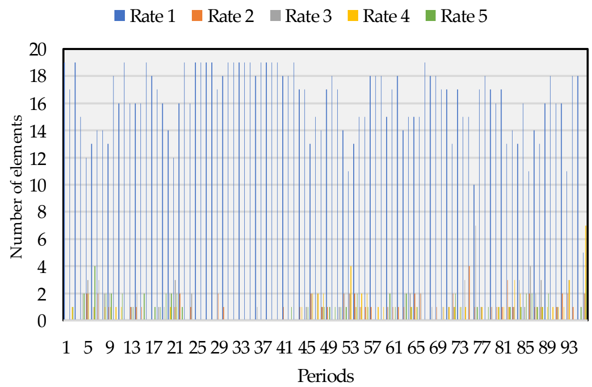
Finally, the last remuneration method, considering the rate created by the authors, is the CTR. Table 7 shows the total obtained per rate throughout the day according to the participants' performance—the actual distribution can be seen in Figure 8. For both cases, rate 1 is the one with more prosumers—mainly on BES discharging, as seen in the blue columns in Figure 8b. Throughout the 96 periods, 584 lower rates were attributed to the load flexibility and 1554 regarding BESS discharging.

Table 7. The number of participants per rate throughout the day.

	Actual Flexibility (m.u.)					BES Discharging (m.u.)				
Rate	1	2	3	4	5	1	2	3	4	5
Participants	584	334	302	290	314	1554	65	83	60	62



(**a**)



(**b**)

Figure 8. CTR from (**a**) prosumers' load flexibility per period and (**b**) prosumers' BES discharging.

The remuneration obtained with this approach can be seen in Table 8. Focusing on the actual flexibility from the participants' load reduction, as already shown previously, the results are around 160 m.u. for the three case studies. However, when comparing with the results from Table 5, the overall remuneration decreased near 20.27 m.u. Although the ones with better performance receive better compensation, mainly during peak hours, the number of participants with a rate of 5 is still low.

Table 8. Total remuneration according to the CTR method.

Case Study	Actual Flexibility (m.u.)					Total	BES Discharging (m.u.)					Total
	1	2	3	4	5		1	2	3	4	5	
1	28.56	34.67	30.01	30.80	36.14	160.16	0.85	0.79	1.09	0.84	0.88	4.45
2	28.56	34.67	30.01	30.80	36.14	160.16	0.91	0.77	1.09	0.84	0.87	4.49
3	28.56	34.67	30.01	30.80	36.14	159.63	0.91	0.77	1.09	0.84	0.87	4.49

To validate the proposed methodology and support the claim that resources from DR participation in market transactions can bring economic benefits to both players and aggregators, an individual perspective comparing two prosumers with similar behaviors will be analyzed. Although remuneration approach 1 provided low values of total remuneration, which is better from the aggregator perspective, the CTR fair remuneration had a close result to the single fair remuneration and has the advantage of increasing the remuneration by increasing the rate. In the end, this is advantageous for both sides—increasing trustworthiness and giving the proper knowledge regarding community members. With this, the chosen program for this comparison was remuneration approach 4, case study 3.

Figures 9 and 10 show the comparison-resulting load diagram and generation for prosumer ID2 and prosumer ID6, respectively. It can be seen that the load peak for both prosumers is in a different period from the generation. Participating in the DR event can move their consumption where self-consumption can be applied through their PV generation and saving money, mainly prosumer ID6 from period 36 to 46. Furthermore, prosumer ID 2, from participating in DR events, received a total of 7.58 m.u., and prosumer ID 6 received 8.69 m.u.

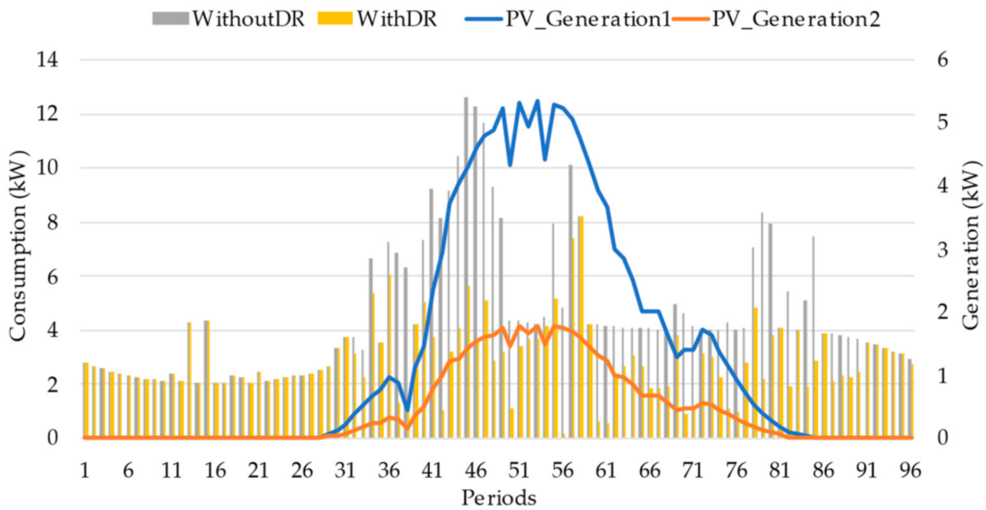


Figure 9. Prosumer ID2 consumption and generation profiles.

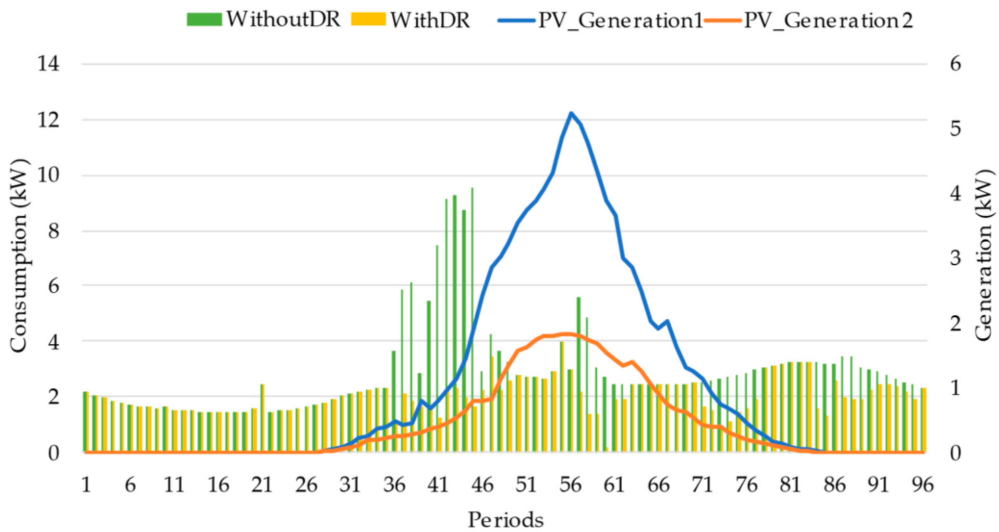


Figure 10. Prosumer ID6 consumption and generation profiles.

5. Conclusions

The consumer's role is changing in the power and energy market. With the smart grid concept being implemented in the real market, their market influence will increase, not only by providing load flexibility, but also by upgrading their portfolio with distributed generation resources, such as renewable bases like photovoltaic panels and battery energy storage systems. For the present paper's case studies, the authors aim to better understand the influence of the power and energy price on community resource scheduling and their willingness to move their load consumption by participating in demand response events.

From the results obtained in the study presented in this paper, the prosumers' flexibility to participate was not impacted by the energy price fluctuation for different schedules. The residential prosumers and their reluctance to change their behavior to avoid jeopardizing their comfort are still a complex problem. Although flexibility was provided, it was expected to have a higher level of demand response participation, since the energy prices increased for several periods. Nevertheless, the authors know that higher participation levels will move load consumption to other periods. This fact must be well managed to avoid a rebound effect after the demand response event, considering that prosumers will also reduce the load requested to the grid and, sometimes, help to balance the generation resources associated by selling their excess, namely from battery energy storage. Regarding battery energy storage discharging flexibility, the response to energy price changes in the scheduling phase was observed for this case. Although photovoltaic generation was also considered in these case studies, battery energy storage is much more predictable and controllable, which is useful for load consumption satisfaction for both the owner and the community-associated.

Regarding the perspective of remuneration, although the single approach had the lower values of remuneration, the authors believe that the approach with a rate that classifies the performance from the demand response participants can benefit from the aggregator perspective without jeopardizing the fairness—the ones with a higher level of trustworthiness will still have higher values of compensation. Furthermore, this approach will also motivate continuous participation to increase the rate assigned and have better benefits, sometimes not paying for the energy prices, since their compensation from the flexibility provided may be higher.

To conclude, the authors summarize the results found in this study and compare them with the current state of the art reviewed previously (Table 1):

- On the simulated scheduling results, the contextual energy price did not much change the behavior from the prosumer load flexibility. However, BES was used several times when PV generation was low, as mentioned [16,17].
- Single fair remuneration was the one with the lowest total value of remuneration. From the community manager's perspective, fair remuneration can still be applied, since the participants will receive higher compensation values for DR participation. In [20], single fair remuneration was also considered in the case studies, but not for prosumers.
- Clustering fair remuneration was the one with the higher total value of remuneration. From the prosumer perspective, aggregating the participants into three groups might be interesting, as providing higher flexibility can help them join different groups. This approach was also considered in [21] but might be highly costly for the community manager.
- CTR fair remuneration had results close to the single fair remuneration plus and has the advantage of increasing the remuneration by increasing the rate. This is advantageous for both sides, increasing trustworthiness and giving the proper knowledge regarding community, as in [19].

In future works, the authors will add electric vehicles as prosumer resources for other types of consumers, such as office buildings. Furthermore, one factor that might impact the results and was not considered was the ramp period and the number of cycles of charge and discharge, which can be considered a disadvantage of the proposed methodology.

Author Contributions: Conceptualization, P.F., L.G., and Z.V.; methodology, C.S., P.F., L.G., and Z.V.; software, C.S., B.R., and L.G.; validation, C.S., P.F., L.G., and Z.V.; formal analysis, P.F., and L.G.; investigation, C.S., P.F., and L.G.; resources, P.F., L.G., and Z.V.; data curation, C.S., P.F., and L.G.; writing—original draft preparation, C.S., and P.F.; writing—review and editing, C.S., P.F., L.G., and Z.V.; visualization, C.S., and P.F.; supervision, P.F., L.G., and Z.V.; project administration, P.F., L.G., and Z.V.; funding acquisition, P.F., L.G., and Z.V. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by FEDER Funds through COMPETE program and by National Funds through FCT under projects UIDP/00760/2020, UIDB/00760/2020, and CEECIND/01423/2021. Cátia Silva is supported by national funds through Fundação para a Ciência e a Tecnologia (FCT) with Ph.D. grant reference SFRH/BD/144200/2019.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: https://zenodo.org/record/7277686#.Y3Tj2uzP23I (accessed on 3 November 2022).

Conflicts of Interest: The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

Nomenclature

$C_{(t)}^{grid_{in}}$	Cost of selling on period t (m.u./kW)
$C_{(t)}^{grid_{out}}$	Cost of buying on period t (m.u./kW)
$E_{(s,t)}^{stor}$	State of charge from energy storage s on period t (kW)
$E_{(s,t)}^{stormax}$	Maximum state of charge from energy storage s on period t (kW)
$E_{(s,t)}^{stormin}$	Minimum state of charge from energy storage s on period t (kW)
$P_{(c,t)}^{DR}$	Flexibility provided by prosumer c on period t (kW)
$P_{(c,t)}^{DRmax}$	Maximum flexibility provided by prosumer c on period t (kW)
$P_{(t)}^{grid_{in}}$	Power sold from External Supplier on period t (m.u./kW)
$P_{(t)}^{grid_{out}}$	Power bought to External Supplier on period t (m.u./kW)
$P_{(t)}^{gridmax_{in}}$	Maximum power that can be bought from External Supplier on period t (m.u./kW)
$P_{(t)}^{gridmax_{out}}$	Maximum power that can be bought from External Supplier on period t (m.u./kW)
$P_{(c,t)}^{DR}$	Power from Demand Response active consumer c on period t (kW)
$P_{(p,t)}^{PV}$	Power from Distributed Generation p on period t (kW)
$P_{(s,t)}^{ch}$	Power from charging Energy Storage System b on period t (kW)
$P_{(s,t)}^{dch}$	Power from discharging Energy Storage System b on period t (kW)
$P_{(t)}^{grid}$	Power from External Supplier on period t (kW)
$P_{(t)}^{load}$	Initial Load on period t (kW)
$W_{(c,t)}^{DR}$	Flexibility weight from prosumer c on period t
$X_{(c,t)}^{DR}$	Availability from prosumer c on period t
$X_{(s,t)}^{ch}$	Charging status from Energy Storage System b on period t
$X_{(s,t)}^{dch}$	Discharging status from Energy Storage System b on period t

Appendix A

The dataset used in the present paper was published on Zenodo (https://zenodo.org/record/7277686, accessed on 3 November 2022).

References

1. Ramos, D.; Faria, P.; Vale, Z.; Correia, R. Short Time Electricity Consumption Forecast in an Industry Facility. *IEEE Trans. Ind. Appl.* **2022**, *58*, 123–130. [CrossRef]
2. Fei, L.; Shahzad, M.; Abbas, F.; Muqeet, H.A.; Hussain, M.M.; Bin, L. Optimal Energy Management System of IoT-Enabled Large Building Considering Electric Vehicle Scheduling, Distributed Resources, and Demand Response Schemes. *Sensors* **2022**, *22*, 7448. [CrossRef] [PubMed]
3. Bhattacharya, S.; Chengoden, R.; Srivastava, G.; Alazab, M.; Javed, A.R.; Victor, N.; Maddikunta, P.K.R.; Gadekallu, T.R. Incentive Mechanisms for Smart Grid: State of the Art, Challenges, Open Issues, Future Directions. *Big Data Cogn. Comput.* **2022**, *6*, 47. [CrossRef]
4. Cheng, L.; Yin, L.; Wang, J.; Shen, T.; Chen, Y.; Liu, G.; Yu, T. Behavioral decision-making in power demand-side response management: A multi-population evolutionary game dynamics perspective. *Int. J. Electr. Power Energy Syst.* **2021**, *129*, 106743. [CrossRef]
5. Muqeet, H.A.; Javed, H.; Akhter, M.N.; Shahzad, M.; Munir, H.M.; Nadeem, M.U.; Bukhari, S.S.H.; Huba, M. Sustainable Solutions for Advanced Energy Management System of Campus Microgrids: Model Opportunities and Future Challenges. *Sensors* **2022**, *22*, 2345. [CrossRef] [PubMed]
6. Halbe, S.; Chowdhury, B.; Abbas, A. Mitigating Rebound Effect of Demand Response using Battery Energy Storage and Electric Water Heaters. In Proceedings of the 2019 IEEE 16th International Conference on Smart Cities: Improving Quality of Life Using ICT & IoT and AI (HONET-ICT), Charlotte, NC, USA, 6–9 October 2019; pp. 095–099. [CrossRef]
7. Barik, A.K.; Das, D.C. Integrated resource planning in sustainable energy-based distributed microgrids. *Sustain. Energy Technol. Assessments* **2021**, *48*, 101622. [CrossRef]
8. Estebsari, A.; Mazzarino, P.R.; Bottaccioli, L.; Patti, E. IoT-Enabled Real-Time Management of Smart Grids With Demand Response Aggregators. *IEEE Trans. Ind. Appl.* **2022**, *58*, 102–112. [CrossRef]
9. Zhu, N.; Gao, C.; Lu, T.; Liu, F.; Han, Y.; Zhang, J. Assistant analyzer for the characteristics of electricity behavior based on big data technology. In Proceedings of the 5th IEEE International Conference on Electric Utility Deregulation, Restructuring and Power Technologies, DRPT 2015, Changsha, China, 26–29 November 2015; pp. 704–711. [CrossRef]
10. Oprea, S.-V.; Bâra, A.; Tudorică, B.G.; Călinoiu, M.I.; Botezatu, M.A. Insights into demand-side management with big data analytics in electricity consumers' behaviour. *Comput. Electr. Eng.* **2021**, *89*, 106902. [CrossRef]
11. Pham, Q.-V.; Liyanage, M.; Deepa, N.; VVSS, M.; Reddy, S.; Maddikunta, P.K.R.; Khare, N.; Gadekallu, T.R.; Hwang, W.-J. Deep Learning for Intelligent Demand Response and Smart Grids: A Comprehensive Survey. *arXiv* **2021**, arXiv:2101.08013. [CrossRef]
12. Khojasteh, M.; Faria, P.; Vale, Z. Scheduling of battery energy storages in the joint energy and reserve markets based on the static frequency of power system. *J. Energy Storage* **2022**, *49*, 104115. [CrossRef]
13. Khojasteh, M.; Faria, P.; Vale, Z. A robust model for aggregated bidding of energy storages and wind resources in the joint energy and reserve markets. *Energy* **2022**, *238*, 121735. [CrossRef]
14. Yao, J.; Venkitasubramaniam, P. Stochastic games of end-user energy storage sharing. In Proceedings of the 2016 IEEE 55th Conference on Decision and Control (CDC), Las Vegas, NV, USA, 12–14 December 2016; pp. 4965–4972. [CrossRef]
15. Pandey, A.K.; Jadoun, V.K.; Sabhahit, J.N. Real-Time Peak Valley Pricing Based Multi-Objective Optimal Scheduling of a Virtual Power Plant Considering Renewable Resources. *Energies* **2022**, *15*, 5970. [CrossRef]
16. Sijakovic, N.; Terzic, A.; Fotis, G.; Mentis, I.; Zafeiropoulou, M.; Maris, T.I.; Zoulias, E.; Elias, C.; Ristic, V.; Vita, V. Active System Management Approach for Flexibility Services to the Greek Transmission and Distribution System. *Energies* **2022**, *15*, 6134. [CrossRef]
17. Calearo, L.; Ziras, C.; Sevdari, K.; Marinelli, M. Comparison of Smart Charging and Battery Energy Storage System for a PV Prosumer with an EV. In Proceedings of the 2021 IEEE PES Innovative Smart Grid Technologies Europe: Smart Grids: Toward a Carbon-Free Future, ISGT Europe 2021, Espoo, Finland, 18–21 October 2021.
18. Arasteh, F.; Riahy, G.H. MPC-based approach for online demand side and storage system management in market based wind integrated power systems. *Int. J. Electr. Power Energy Syst.* **2019**, *106*, 124–137. [CrossRef]
19. Silva, C.; Faria, P.; Vale, Z.; Terras, J.M.; Albuquerque, S. Rating the participation in Demand Response events with a contextual approach to improve accuracy of aggregated schedule. *Energy Rep.* **2022**, *8*, 8282–8300. [CrossRef]
20. Silva, C.; Faria, P.; Vale, Z. Aggregation of Prosumers in the Context of Demand Response and Distributed Generation Remuneration and Scheduling. In Proceedings of the 2020 IEEE/PES Transmission and Distribution Conference and Exposition (T&D), Chicago, IL, USA, 12–15 October 2020; pp. 1–5. [CrossRef]
21. Faria, P.; Spinola, J.; Vale, Z. Aggregation and Remuneration of Electricity Consumers and Producers for the Definition of Demand-Response Programs. *IEEE Trans. Ind. Inform.* **2016**, *12*, 952–961. [CrossRef]
22. Silva, C.; Faria, P.; Vale, Z.; Corchado, J. Demand response performance and uncertainty: A systematic literature review. *Energy Strat. Rev.* **2022**, *41*, 100857. [CrossRef]
23. Silva, C.; Faria, P.; Vale, Z. Multi-Period Observation Clustering for Tariff Definition in a Weekly Basis Remuneration of Demand Response. *Energies* **2019**, *12*, 1248. [CrossRef]

24. Silva, C.; Faria, P.; Vale, Z. DR Participants' Actual Response Prediction Using Artificial Neural Networks. In Proceedings of the 17th International Conference on Soft Computing Models in Industrial and Environmental Applications (SOCO 2022), Salamanca, Spain, 5–7 September 2022; García Bringas, P., Pérez García, H., Martinez-de-Pison, F.J., Villar Flecha, J.R., Troncoso Lora, A., de la Cal, E.A., Herrero, Á., Martínez Álvarez, F., Psaila, G., Quintián, H., et al., Eds.; Springer Nature: Cham, Switzerland, 2023; pp. 176–185.
25. Ribeiro, B.; Pereira, H.; Gomes, L.; Vale, Z. Python-Based Ecosystem for Agent Communities Simulation. In Proceedings of the 17th International Conference on Soft Computing Models in Industrial and Environmental Applications ({SOCO} 2022), Salamanca, Spain, 5–7 September 2022; Bringas, P.G., Garc'ia, H.P., de Pisón, F.J.M., Flecha, J.R.V., Lora, A.T., de la Cal, E.A., Herrero, Á., Mart'inez-Álvarez, F., Psaila, G., Quintián, H., et al., Eds.; Springer: Cham, Switzerland, 2022; pp. 62–71. [CrossRef]
26. Yang, Y.; Bremner, S.; Menictas, C.; Kay, M. Modelling and optimal energy management for battery energy storage systems in renewable energy systems: A review. *Renew. Sustain. Energy Rev.* **2022**, *167*, 112671. [CrossRef]

Appendix B. Other Publications

Publication I

C. Silva, P. Faria, J.M. Corchado, and Z. Vale, "Clustering Methods for the Profiling of Electricity Consumers Owning Energy Storage System," In Intelligent Data Mining and Analysis in Power and Energy Systems (eds Z. Vale, T. Pinto, M. Negnevitsky and G.K. Venayagamoorthy)

Resumen

Los consumidores activos, como nuevos actores que pueden contribuir a las transacciones del mercado, proporcionarán flexibilidad a través de eventos de respuesta a la demanda para hacer frente al comportamiento volátil de los recursos de generación distribuida, como la energía solar y eólica. Sin embargo, su falta de conocimiento y comportamiento incierto añadirán un nuevo nivel de complejidad a la gestión de la comunidad. En este sentido, los autores proponen una metodología capaz de lidiar con estos recursos y promover la equidad entre todos los participantes. En el presente estudio, para agregar más características y enriquecer los diversos pasos metodológicos de trabajos anteriores, se compararon varios métodos de agrupamiento para encontrar patrones entre los participantes en los eventos de respuesta a la demanda desencadenados. Dado que algunos métodos de agrupamiento son sensibles al número inicial de grupos, se debe encontrar un número óptimo para el conjunto de datos. Los autores también realizaron una comparación entre algoritmos y descubrieron que un bajo número de grupos puede ser reduccionista, ya que hay diferentes comportamientos de los consumidores en diferentes contextos en cada evento de respuesta a la demanda.

Clustering Methods for the Profiling of Electricity Consumers Owning Energy Storage System[1]

Cátia Silva,[1] Pedro Faria,[1*] Zita Vale,[1] and, Juan Manuel Corchado[2]

[1] *GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, Porto, Portugal*
[2] *II Author Organization Division Name, Organization Name, Postal Code, Part of the Country, City Name, Street Name, Country*

*Corresponding Author: Author; pnf@isep.ipp.pt

Abstract: Active consumers will provide flexibility through Demand Response events to deal with the volatile behavior from the Distributed Generation resources such as solar and wind. However, their lack of knowledge and uncertain behavior will add a new level of complexity to the community management. In this way, the authors propose a methodology capable of dealing with these resources and promoting fairness between all players. Several clustering methods were compared to find patterns between the participants in the triggered events in the study present. Since some clustering methods are sensitive to the initial number of clusters, an optimal must be found for the dataset. The authors also made a comparison between algorithms designed for this purpose.

Keywords: Clustering, Demand Response, Energy Storage Systems, Consumer Profiling, Smart Grids

[1] This is a sample for chapter footnote.

1.1 Introduction

In the current paradigm, small consumers have indirect influence regarding the transactions in the energy market. With the Smart Grids concept, namely, to avoid the usage of non-renewable generation, new players and resources will be added to the energy system (Osório et al. 2019). Distributed Generation technologies, such as wind and solar, will be the main source in the future. However, their volatile behavior will impact the system's reliability and security (Silva, Faria, and Vale 2019a). To avoid this problem, the consumers must provide flexibility, introducing a new paradigm where the generation no longer follows demand (de São José, Faria, and Vale 2021).

The Demand Response concept brings the empowerment of the consumers and increases their influence in the operations (Faria and Vale 2021). DR allows active players to receive and react to signals and change their consumption accordingly. These signals can be price-based or incentive-based and are triggered considering the system balance achievement. For instance, at peak hours, DR event participants receive a signal to reduce their consumption when the generation is low. Those who comply are rewarded, and continuous participation is remunerated (Vale et al. 2011; Morais, Faria, and Vale 2014; Gomes, Vale, and Corchado 2020).

However, the implementation of these programs in the real market is still very scarce. Efforts are being made to provide all the means necessary to be successful. In Europe, for instance, regarding policy and rule creation, Directive 2019/944 was created (European Parliament and Council of the EU 2019). The importance of active consumers and their core role is well referenced throughout this Directive. Moreover, to achieve the targets with effectiveness, innovation must be encouraged, and the flexibility from the consumers well compensated. After implementing the DR and fully functional energy market, the possibility of adding renewable energy to the actual grid can become a reality taking a new step to decarbonize the system (Abrishambaf et al. 2019).

The lack of knowledge from these new players adds complexity to the system management (Zheng et al. 2021). Therefore, to supervise the new communities created, a new entity was designed – the Aggregators. By becoming responsible for coordinating all the small resources associated with the community, the Aggregator will participate in wholesale electricity markets as an intermediary in the transactions with the Independent System Operator (Okur et al., 2019). With this approach, the active consumers will take a step closer to the energy market without jeopardizing the system's functioning.

The authors propose a methodology to ease the complex task of managing such uncertain resources in the current chapter. The methodology comprises several steps: Scenario Definition, Optimal Scheduling, Aggregation, Remuneration, and Classification. The method may serve as a planning approach with all the aggregate resources, being capable of dealing with Distributed Generation (DG), prosumers, Energy Storage Systems (ESS), and participants in Demand Response (DR) events. But it can also be used in the case of real-time operation, resorting to the last phase, Classification. With this, the authors worked to find a solution that contemplates the same phases, but quickly.

The study performed will be crucial for the Aggregation phase, where a clustering method is used to find patterns in the consumers' resources profiles. The core idea is to gather similar ones and recompense them according to their actual performance - incentivizing fairness between all players. This way, four different clustering methods were tested and evaluated according to this context. Some of them are sensitive to the number of clusters used as input, so three different methods used to find the optimal one will also be compared.

The chapter is organized into five sections. Section 1 serves as an introduction to the topic addressed. Section 2 details the methodology proposed by the authors. Section 4 presents the case study chosen to prove the feasibility of the methodology which the results are further presented in Section 5. Finally, Section 6 presents the conclusions from the present study.

1.2 Methodology Definition

To better define an effective business model, able to adapt to the future changes in the energy market the authors consider that there is an important question that should be analyzed: since the active consumers are now such an important player in the future market, providing flexibility when generation is not able to suppress all the demand requests, how can the entity manager motivate their participation? Also, predict and reduce the uncertainty of their behaviors and the resources associated? Because it is already known that these volatile resources will impact the system's reliability and security if not well managed.

In this way, the authors proposed a multifaceted methodology for different approaches (both planning and operation) that support the decisions from the Aggregator perspective. The previous works developed by the authors were able to gather several steps considered crucial to define the proper methodology to manage an active community with different types of resources. Figure 1.1 specifies the five main phases, further explored after Scenario Definition, Optimal Scheduling, Aggregation, Remuneration, and Classification. One of the key factors introduced, highly important for the continuous participation in the authors' opinion, is the fair compensation of the participants in DR events wherever requested. Although the DR contract cannot always imply a guaranteed reduction from the demand side – the participation is voluntary. Even with the appliance control, the active consumer can withdraw this permission at any time.

Being a continuity from previous works (Silva, Faria, and Vale 2019b), The authors define the model according to a real scenario. Starting with Distributed System Operator (DSO) performing the load forecast for the community – in a higher or lower time range, meaning, weekly or real-time approach. After, DSO performs a Power Flow (PF) and the respective analysis, using the PF service and looking for any issues in the considered network. If none is detected, the scheduling is performed normally. On the other hand, if any violation is detected, the DSO must request a load reduction to each community manager, the Aggregators. This entity will then trigger a DR event using the proposed methodology. It must be highlighted that Aggregator may or may not have the load forecast information, so both operation and planning approaches can be useful.

Firstly, as entity manager from the active community, the Aggregator must gather all the essential information to serve as input for the proposed methodology and do a pre-treatment. This solution has already proved to be robust since it can easily be used for a small database and one that reaches thousands of resources (Silva, Faria, and Vale 2019a). Remember, however, that there may be a hardware limitation when applying in these cases. Furthermore, regarding the time to process the information, the authors advise gathering all the information in the planning case to ease a day-ahead or hour-ahead configuration. So, the input database must collect useful contextual knowledge from the External Supplier, the participants in the DR events and the resources associated with them, such as the DG found in the active community or ESS installed.

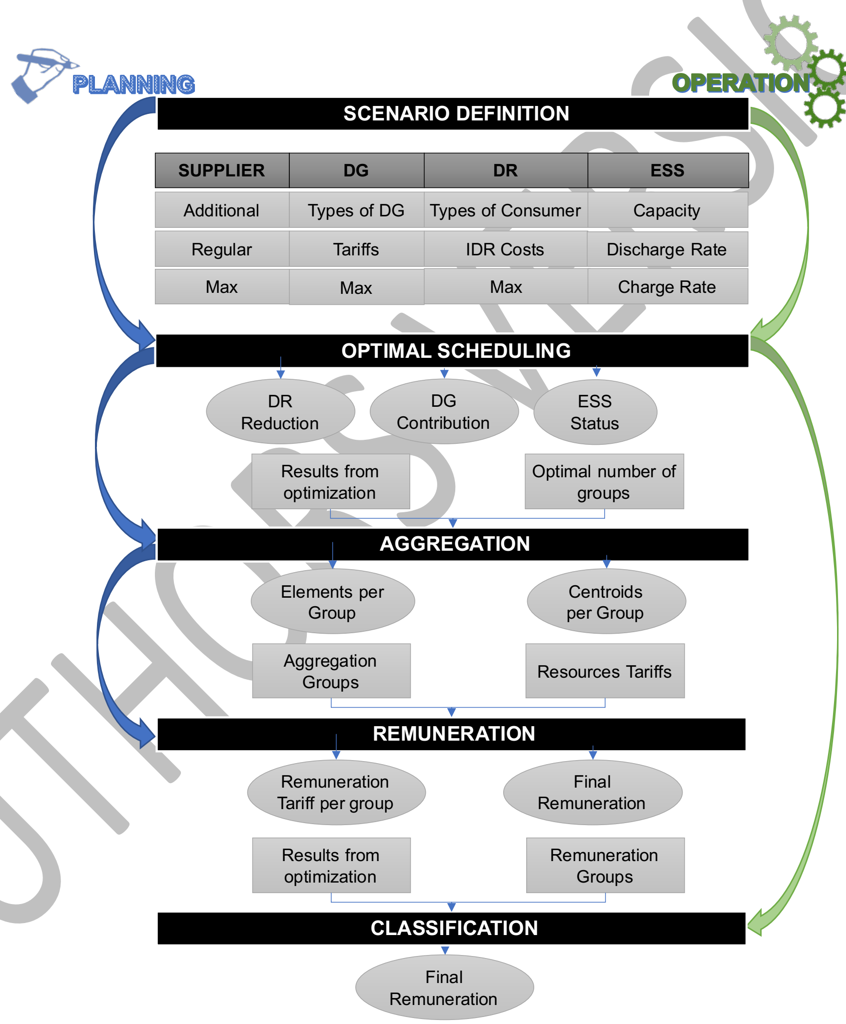


Figure 1.1: Proposed methodology.

Having the database ready for the next phase, Optimal Scheduling, the Aggregator collects the current information for the DR participants, the DG contribution, and the ESS status. The active consumers must provide information on the available demand flexibility and the willingness to participate in this context.

External Suppliers are only introduced if the resources in the active community cannot suppress the demand. However, the optimization objective function must minimize the operation costs, so the priority must be given to the resources within the community, always considering the fair remuneration. A linear approach is employed and defined in Equation (1.1). Let c be the number of consumers, t be the period, g the DG unit, s be the external supplier, and b be the number of Energy Storage Systems (ESS).

$$Min.OF = \sum_{p=1}^{P}\left[P_{RES(g,t)}C_{RES(g,t)}\right] + \sum_{c=1}^{C}\left[P_{DR(c,t)}C_{DR(c,t)}\right] + P_{NSP(t)}C_{NSP(t)} + \sum_{s=1}^{S}\left[P_{Supplier(s,t)}C_{Supplier(s,t)}\right] + \sum_{b=1}^{B}\left[P_{ESSd(b,t)}C_{ESSd(b,t)}\right] \quad (1.1)$$

$$c,t,g,s,b \in \mathbb{Z} : \; c,t,g,s,b > 0$$

The objective function (OF) represented in Equation (1.1) is subjected to several constraints. To maintain the system reliability and achieve the network power balance – stability between consumption and generation, Equation (1.2) was defined. The sum of the difference between the initial load, the ESS charge, and the requested reduction should match the value from the total generation within DG units, external suppliers, and ESS discharge.

$$\sum_{c=1}^{C}\left[P_{(c,t)}^{initial} + P_{EVc(v,t)} + P_{ESSc(b,t)} - P_{DR(c,t)}\right] = \sum_{g=1}^{G}\left[P_{RES(g,t)}\right] + \sum_{s=1}^{S}\left[P_{Supplier(s,t)}\right] + \sum_{v=1}^{V}\left[P_{EVd(v,t)}\right] + \sum_{b=1}^{B}\left[P_{ESSd(b,t)}\right] + P_{NSP(t)} \quad (1.2)$$

$$c,t,g,s \in \mathbb{Z} : \; c,t,g,s > 0$$

The OF is restricted by the maximum contribution requested from each active consumer to a DR event ($P_{DR\,(c,t)}^{Max}$), according to the context in which the event is triggered. To define boundaries for the DG units' contribution, the Aggregator to control the upper ($P_{RES\,(g,t)}^{Max}$) and lower limits ($P_{RES\,(g,t)}^{Min}$) and the total value of generation provided from each different technology found in the active community ($P_{RES\,(t)}^{Total}$). In the case where the ESS and DG units cannot suppress the demand, other constraints are introduced and represent the external suppliers' constraints, restricting the maximum capacity ($P_{Supplier\,(s,t)}^{Max}$) and the total amount of generation provided from this source ($P_{Supplier\,(t)}^{Total}$).

Regarding ESS, firstly the limits and(?) the operation capacity are added, both max ($E^{stormax}_{(s,t)}$) and ($E^{stormin}_{(s,t)}$). After, the ESS charge ($P^{chmax}_{(s,t)}.X^{essch}_{(s,t)}, X^{essch}_{(s,t)}$) and ESS discharge ($P^{dchmax}_{(s,t)}.X^{essdch}_{(s,t)}, X^{essdch}_{(s,t)}$), respectively. Each of these equations includes one binary variable, which guarantees the impossibility of charging and discharging during the same period t ($X^{essdch}_{(s,t)} + X^{essch}_{(s,t)}$). Finally, to maintain the power balance within the ESS – the previous state of what was charged and discharged.

In the meantime, the optimal number of clusters to be used in the Clustering method is also defined to serve as input to the third phase of the methodology: Aggregation, along with the optimization results, as shown in Figure 1.1. The mentioned phase may be used with several intermediate goals and for different resources (load consumption or ESS status to find similar profiles, load reduction to understand the behavior in a certain context, and many more), but the main goal is to always achieve the fairness between participating resources – granting that they are compensated according to their contribution. The Aggregator will be more confident in other decisions by finding resource groups with similar characteristics.

The following phase is one of the most important ones in the author's opinion. All the work done in the previous phases culminate in this final step, guarantying the active community's continuous participation in the management: the Remuneration phase. The compensation tariff must be well defined to serve as a good incentive and always according to the context and the active consumer characteristics.

A new phase is added for the operation stage concerning the planning approach – the Classification phase. As already mentioned earlier, it will be necessary to find a feasible solution promptly. Thus, it is proposed to use classification methods to assist this task. With the output from the Optimal Scheduling phase, as shown in Figure 1.1, the Aggregator can use any classification method to predict, for instance, which remuneration group should assign each resource skipping tasks from other phases.

This proposal presents several contributions to successfully implement DR in real market, aiding the Aggregator in the complex task of managing this active communities. In this way, the proposed methodology highlights:

- Active consumers will be the future center of the energy market. Therefore, the new business models should study their behavior, the associated resources (prosumers), and ways to motivate their participation to maintain the system reliable and secure. In addition, the authors believe that unique characteristics should be further studied to develop better solutions.

- Definition of resource groups according to their similarity. For example, for both participation selection and remuneration definition, the individual approach may not be the quickest one in a real-time approach. In this way, assembly resources with similar behaviors in the same group may lead to more precise and fair decisions.
- When aggregating the active consumers, and since some clustering methods may be input sensitive, the introduction of methods to find the optimal number of clusters is discussed so the Aggregator can determine the best number of groups to be implemented.
- A contextual approach aids the reduction prediction of trustworthy consumers. Furthermore, it introduced information from different contexts in the model definition, for instance, period, day or even season, and historical. Finally, performances add variability to the methodology, thus increasing its interest in dealing with the new and complex players in the energy market.

The present study's focus will be the Aggregation phase detailing all the steps and comparing well-known methods to find the optimal number of clusters and several Clustering algorithms.

Twenty prosumers in an active community can participate in DR events following a Time-of-use (TOU) tariff as incentive signals for DR events by the Aggregator. This DR program is the most widely used strategy in academic research and practical projects (Jin et al. 2019). The case study presented TOU tariff is divided into three different periods: peak, intermediate, and off-peak, as can be seen in Table 1.1 and according to the Portuguese legislation. The table also presents the parameter W, representing the DR weight according to the periods.

Table 1.1: Active community characterization.

Transactions	Peak	Intermediate	Off-Peak
Sell (m.u./kWh)		0.1659	
Buy (m.u./kWh)	0.3326	0.1681	0.0930
Periods	10 AM – 1 PM 7 PM – 9 PM	8 AM – 10 AM 1 PM – 7 PM 9 PM – 10 PM	10 PM – 8 AM
DR weight	0.000	0.2000	0.4000

The preferred DG technologies used are the Photovoltaic panels. Still, all of them also have Energy Storage Systems (ESS) installed, and the main appliances used for DR events are the dishwasher, air conditioning, and the water heater. The information gathered regarding the mentioned community resources is on a 15-minute interval, resulting in 96 periods throughout the day. Figure 1.2 was then created to visualize better the expected community resource consumption, production, and DR flexibility from each main type of appliance.

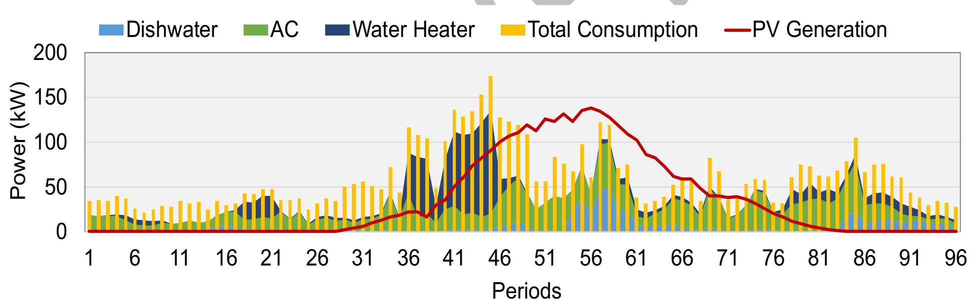


Figure 1.2: Discriminated Consumption for the active community: DR flexibility, total consumption, and PV Generation**.**

Since the ESS focus on the present study, the idea is to optimize their behavior according to the remaining resources. With the results, such as their status throughout the day, the charge and discharge curve are withdrawn from the Optimal Scheduling step for further analysis and discussion. After only the status will be analyzed in the Aggregation phase.

1.3 Clustering of Consumers with ESS

A comparison between several methods results will be analyzed and discussed in a planning perspective further to improve the Aggregation phase from the proposed methodology. The results from using the problem database described previously applied to the proposed methodology will be used as input for this phase, namely the ESS dataset. The focus is on ESS status to find similar profiles between these resources. The dataset to be used is represented in Figure 1.3. There was an assumption that the minimum should be 1,5kW to all the ESS in the active community.

The authors use this type of study to answer questions like: which ones should be activated in a certain context, according to previous experiences? Instead of calling all the resources in the community, by knowing their expected behavior, there may be some more trustworthy than others for the DR event.

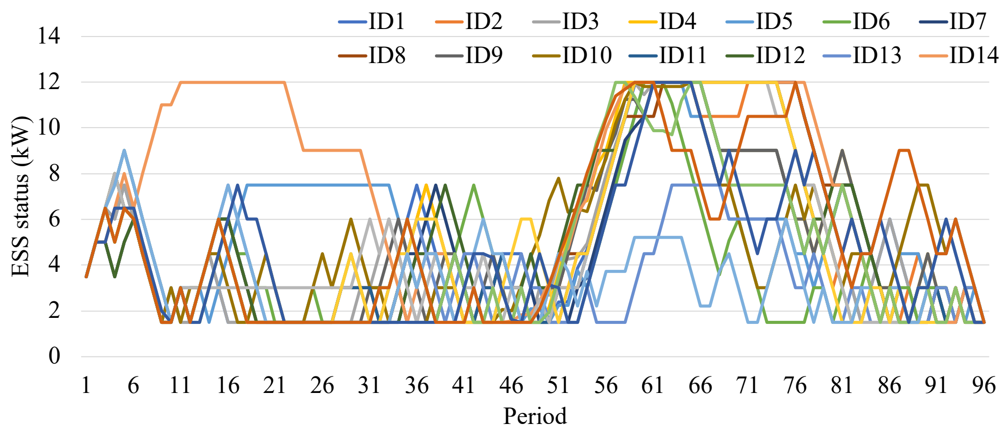


Figure 1.3: Optimal Scheduling results: State of Charge.

In this way, the current section will be divided into two main topics: discovering the optimal number of clusters and the group definition according to several clustering methods for the value found.

1.3.1 Optimal Number of Clusters

Three different methods will be compared: average silhouette, elbow, and gap statistic methods. The first two are direct methods, and the last one is statistical testing.

Average Silhouette Method

Kaufman and Rousseeuw proposed the first method in 1990 (Subbalakshmi et al., 2015), and it is a direct method. The criterion used for this method, the average silhouette, determine the clustering quality. In other words, the k with higher Average

Silhouette Width (ASW) is considered the optimal cluster in a certain range, as can be seen in Equation (1.14).

$$\bar{S}(C,d) = \frac{1}{n}\sum_{i=1}^{n}\frac{b(i)-a(i)}{max\{a(i),b(i)\}} \tag{1.14}$$

Let *a (i)* be the average distance between the points in the cluster to which it was assigned, and *b(i)* be the average distance of the nearest cluster to which it was not assigned. Considering that clusters are meant to be homogeneous and well separated, the larger the silhouette score and of ASW, the better the clustering quality is. Unfortunately, t ASW cannot be calculated for *k=1* because this method cannot directly be used to decide whether the dataset is homogeneous and whether there should be any clustering at all (Batool and Hennig 2021). The results from the selected dataset can be seen in Figure 1.4. All ASW curves were drawn to ease the visualization of the optimal number of clusters found, resorting to this method. Data treatment was done previously, and all the data was standardized.

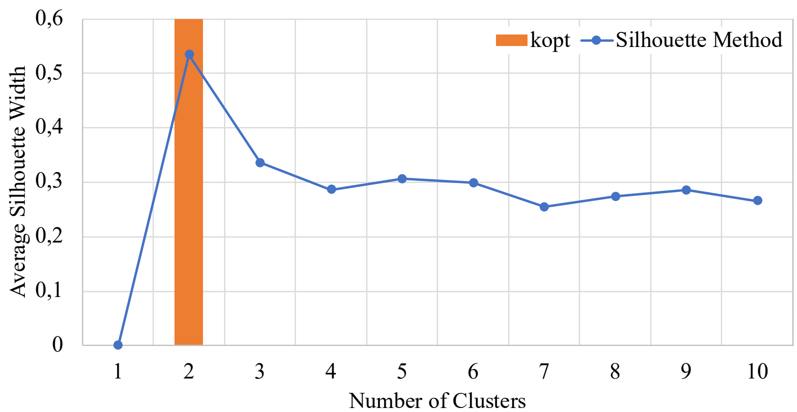


Figure 1.4: Average Silhouette method results for the dataset selected – ESS status.

In the selected range, from *k=2* to *k=10*, the maximum value of ASW can be found in *k=2*. In this way, according to the Silhouette method, dividing the ESS into two different groups is the best approach. It should be highlighted that all the following clustering methods tested obtained the same value for an optimal number of clusters regarding the silhouette method and the remaining.

Elbow Method

The following method is one of the oldest ones since it traced to Robert L. Thorndike in 1953 (Subbalakshmi et al. 2015) and, like Silhouette Method, it is a direct method. So, starting the number of clusters at 2 and incrementing this value with step 1, the total Within-cluster Sum of Square (WSS) is calculated for each of them according to Equation (1.15) (Kashani and Graettinger 2015).

$$WSS = \sum_{i=1}^{k} \sum_{xj \in Si} \left\| x_j - \mu_i \right\|^2 \tag{1.15}$$

Let x be the observations, S be the clusters, and μi be the mean of observations in cluster Si. Since the sum of squares is the squared Euclidean distance, the minimum wss will be generated by choosing the nearest mean. In this way, Figure 1.5 represents the results found. For better visualization, these results are plotted by the analyst. The value where the cost drastically reduces and then hits the plateau is where the optimal number of clusters was found.

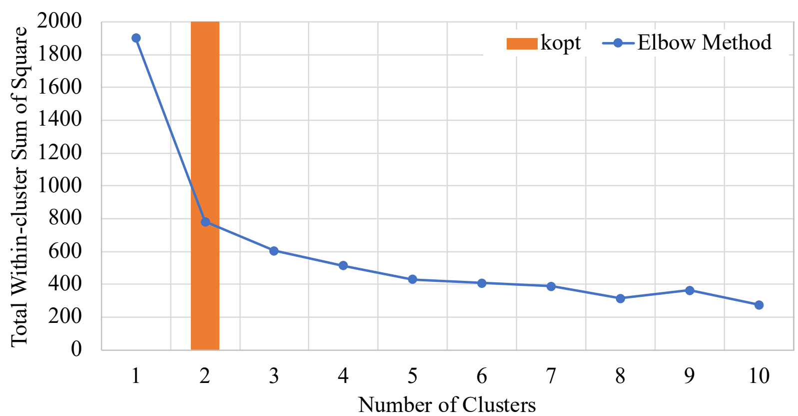


Figure 1.5: Elbow method results for the dataset selected – ESS status.

In other words, by plotting the results of the study set, it will be possible to find an "elbow" considered an indicator of the appropriate number of clusters – but it can lead to misreading. In this case, for the same range as in the Average Silhouette method, the optimal number of clusters is $k=2$.

Gap Statistic Method

Finally, the Statistical Testing Method chosen was Gap statistic published by R. Tibshirani, G. Walther, and T. Hastie in 2001 (Subbalakshmi et al., 2015). The algorithm steps in this method intend to compare the total intra-cluster variation for a range of k clusters with their expected values under null reference distribution of the data – in other words, with no apparent grouping. So, to find the optimal number of clusters, the gap statistic value must be maximum. Figure 1.6 shows the results from this method applied to the selected dataset in the case study. The results show a different optimal number of clusters. In the following sub-section, the values will be compared.

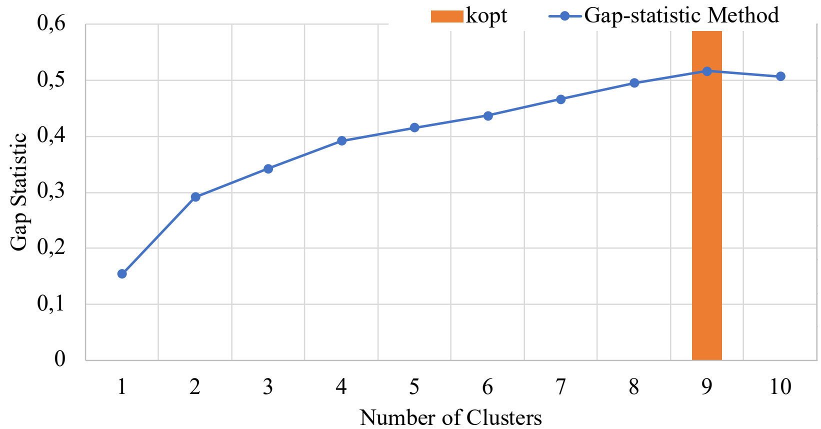


Figure 1.6: Gap Statistic method results for the dataset selected – ESS status.

1.3.2 Clustering methods

Many authors use clustering methods within the current literature on consumer profiling modeling (Granell, Axon, and Wallom 2015b, 2015a; Sun, Zhou, and Yang 2020). Being an unsupervised learning method, from the machine learning perspective, this technique of dividing data into different object groups with similar characteristics – the so-called clusters- can find hidden patterns in the same information. In other words, this algorithm can be used to explore existing relations in the patterns set and organize the objects into homogeneous groups. So, unlike the supervised learning methods, such as Classification, no data labeling is provided for a-priori differentiation.

In this way, to measure the density of connection between the objects within each cluster, intra-connectivity must be used so that the higher the value, the more certainty the analyst can have. On the other hand, the concept of inter-connectivity measures the degree of connectivity between different clusters. Therefore, this value will be important to be low, meaning that each cluster is individually disparate from the rest. To further understand the several types of clustering methods, a comparison is made in this section and a detailed explanation of each one. For this study were selected four of the most-well know methods.

Partitional Clustering

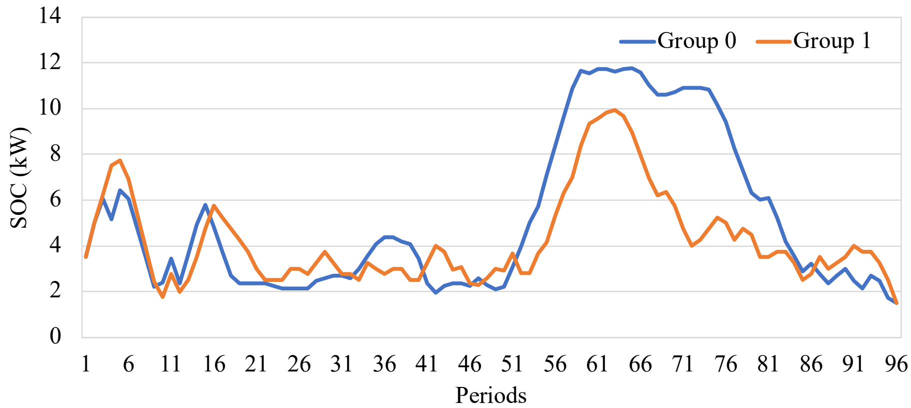
Firstly, the following methods distribute the data into non-overlapping subsets, guaranteeing that all data belongs to a cluster. As mentioned, the number of k clusters to be generated must first be defined by the analyst – as done before. Partitioning clustering includes several known methods, such as k-means or k-medoids clustering.

K-means is the most common unsupervised machine learning algorithm for partitioning (Singh, Yadav, and Rana 2013). Between many adaptations done throughout the years, the one defined by Hartigan-Wong in 1979 (Hartigan and Wong 1979) treats the total variation within a cluster as the sum of the squares of Euclidean distance between a point and the center of the cluster, assigning the point to the nearest k cluster. Iteratively, each cluster is represented by a new centroid, which corresponds to the average of the points assigned to the k cluster in question. However, the main problems from this method are the sensitivity to noise and outliers, so the previous data treatment is crucial to the successful implementation (Sinaga and Yang 2020).

Resorting to the ESS dataset, regarding the status throughout the day from each ESS in the active community, Figure 1.7 represents the comparison between the optimal numbers found with the three methods used in the previous sub-section.

In Figure 1.7 (a), the centroid values to all the periods are represented and can be seen for Group 0 and Group 1. The first one gathered 14 ESS profiles, and the remaining were assigned to Group 1. From around period 51, Group 0 gathered the ESS with power higher value, achieving almost 12kW – the maximum capacity from these resources. On the other hand, group 1 consumers did not achieve the 10kW. These consumers were probably the ones called to participate, being unable to charge until the maximum level.

(a)



(b)

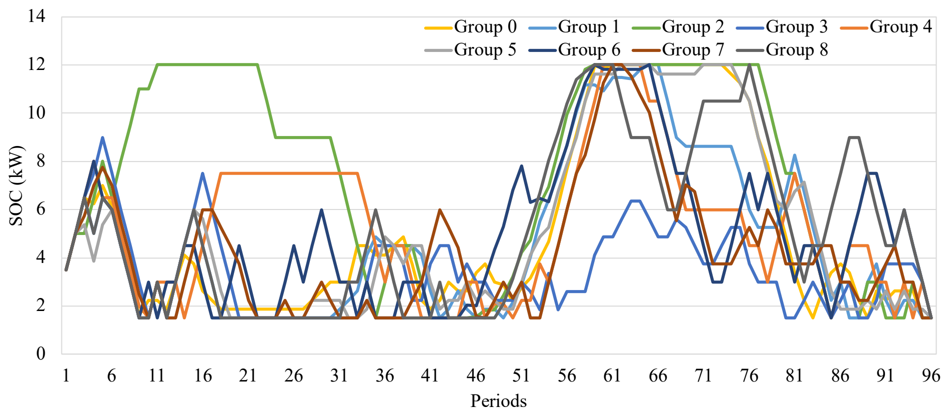


Figure 1.7: Partitional Clustering: k-means results for the dataset selected for (a) kopt=2; (b) kopt =9.

Moving to Figure 1.7 (b), it became harder to visually understand a pattern between groups and why the algorithm gathered these consumers. Table 1.2 is introduced to aid with more information regarding the results obtained.

Table 1.2: Partitional Clustering - Number of ESS per group (k-means).

Group	0	1	2	3	4	5	6	7	8
Number of ESS	4	4	1	2	1	4	1	2	1

By analyzing this table, Group 0, Group 1, and Group 5 gather more ESS within a cluster. These follow a similar pattern to the groups in Figure 1.7 (a). Furthermore, it can also be observed that Group 2, Group 4, Group 6, and Group 8 are composed of only one object. Taking a closer look, these ESS profiles are very different from the remaining, for instance, from period 6 to period 36. Their dissimilarity from the other objects can impact the motivation from the active community due to the fairness matter. For example, suppose the Aggregator opt with the Figure 1.7 (a) solution. In that case, the remaining groups contributed to the market's electricity transactions. In contrast, these groups – for instance, the ESS assigned on Group 2, Group 4 in the mentioned period in Figure 1.7 (b), these resources were able to charge until they reached max capacity and received the same remuneration as if they contributed.

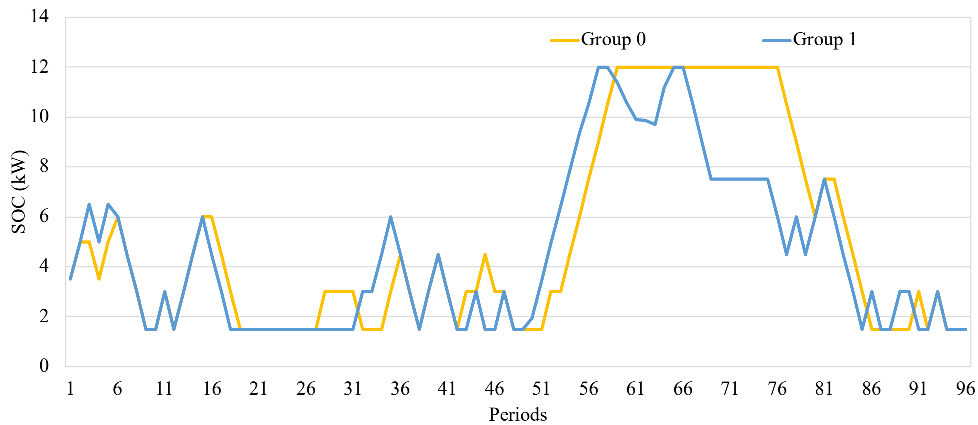
Moving on to k-medoids, two algorithms can be identified: Partitioning around medoids (PAM) and Clustering Large Applications (CLARA). The second is an extension of the first to deal with datasets with thousands of observations, where typically PAM is unsuccessful. This algorithm is search-based for objects, medoids, representing a cluster. After each medoid exchange with each non-medoid and only if there is an improvement over a criterion (minimization of the sum of the dissimilarities of all objects relative to the nearest medoid), this non-medoid will represent the group. Iteratively, all the non-medoids are tested until found achieve the criterion value.

The PAM method was also tested, and the results can be seen in Figure 1.8. In Figure 1.8 (a), both groups have a similar behavior overall. However, differences can be seen around period 67 until period 80 – Group 1 objects may have participated in the market transactions since the ESS status reduces almost 1/3 of their capacity in certain periods. Similar behavior was seen in Figure 1.7 (a) for the same group.

Also, the difference between these curves in the PAM method results and those shown in Figure 1.7 (a), where the lines are curvy.

In Figure 1.7 (a), k-means assigned to Group 0 a total of 14 objects, while in Figure 1.8 (a), the dataset was divided more evenly: Group 0 with 11 elements and Group 1 with nine elements. In this way, the centroids found within these groups result in a distinct curve in Figure 1.7 (a) – remembering that k-means centers are created resorting to the mean. However, the PAM method to find the cluster centers, medoids, is different, so the curves are more like those seen in Figure 1.3.

(a)



(b)

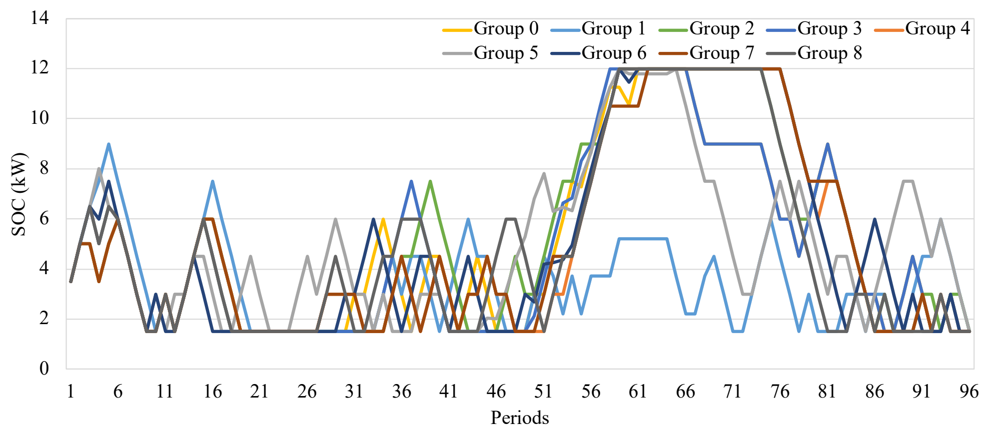


Figure 1.8: Partitional Clustering: PAM results for the dataset selected for (a) kopt=2; (b) kopt =9.

Moving to Figure 1.8 (b), the first highlight when compared with Figure 1.7 (b) are the periods mentioned earlier (period 6 to period 36). There are no longer the two groups with values closer to the maximum capacity. However, with the help from **Table 1.3**, there are still two groups with only one object. By taking a closer look and analyzing the Groups in Figure 1.8 (b), Group 2 was assigned consumer ID 12, and Group 4 was assigned consumer ID 11.

Table 1.3: Partitional Clustering - Number of ESS per group (PAM).

Group	0	1	2	3	4	5	6	7	8
Number of ESS	3	3	1	2	1	2	4	2	2

Regarding the results from k-means in Figure 1.7 (b), Group 2 was assigned consumer ID 14, and Group 4 was assigned consumer ID 5. Compared with Figure

1.3., these were the ones with higher values in the mentioned periods – so their group should be different from those with a higher contribution in the market transactions.

Fuzzy Clustering

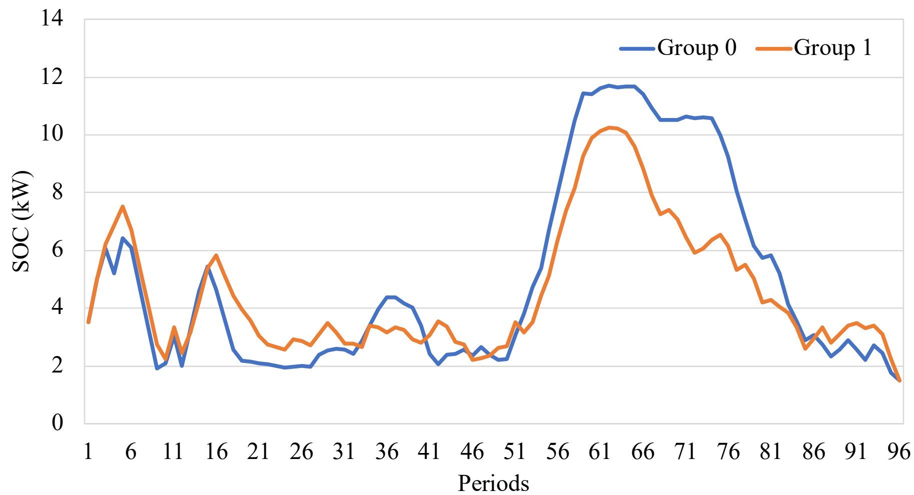
This algorithm has been used in many areas: cluster analysis, pattern recognition, image processing, and so forth. C-means is the most used within fuzzy clustering methods. Using fuzzy theory divides data points into a set of fuzzy clusters according to a certain partitioning criterion.

The core idea behind this concept is that objects within the same cluster have high values of similarity and minimal values of similarity among the different clusters (Wan et al., 2019). To do this, it is considered a membership degree to which an element can belong to a given cluster, being this degree between 0 and 1. With this, objects near the center of the cluster may have a degree greater than the points at the cluster's edges. Furthermore, due to this membership degree, the final center coordinates will always be affected by choice of initial center coordinates – stochastic algorithm. In this way, selecting the right center will have a high impact on the results (Wu et al., 2018).

The results for *k=2* and *k=9* using the ESS status dataset can be seen in Figure 1.9. Starting with Figure 1.9 (a) and comparing with the outcomes from the Partitional Clustering methods, the results from c-means were more like the k-means method in Figure 1.7 (a). Again, the calculation method uses the mean. Here, Group 0 also had 14 elements and assigned six elements to Group 1. The most notorious difference, although small, can be seen between period 50 and period 60, where the curve from Group 1 is closer to Group 0.

Regarding Figure 1.9 (b), the groups can again be well spotted when confronting the previous results, but the consumer ID 14 from Figure 1.3. has not a single group assigned to him like Figure 1.7 (a).

(a)



(b)

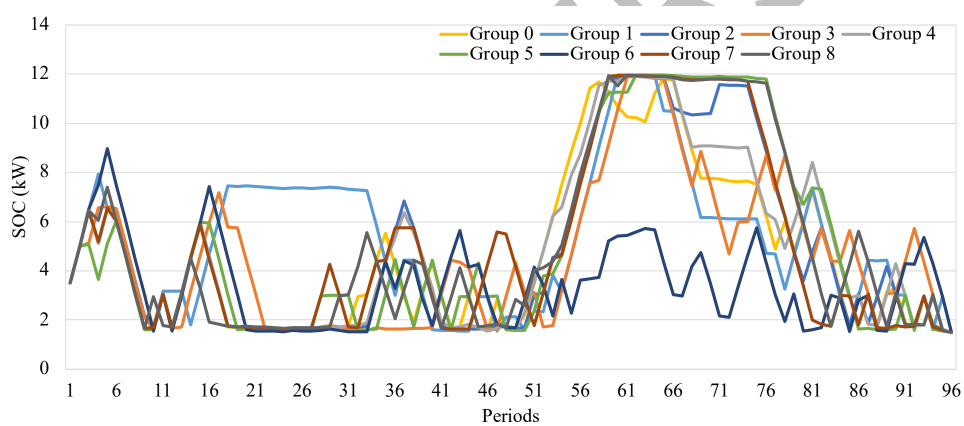


Figure 1.9: Fuzzy Clustering: c-means results for the dataset selected for (a) kopt=2; (b) kopt =9.

In this way, Table 1.4 is added to understand how many elements each group has. According to the values shown, the groups with a single element are Group 2, Group 3, and Group 7.

Table 1.4: Fuzzy Clustering - Number of ESS per group (c-means).

Groups	0	1	2	3	4	5	6	7	8
Number of ESS	2	2	1	1	3	3	3	1	4

In this way, Group 2 was assigned consumer ID 2, Group 3 was assigned consumer ID 19, and Group 7 was assigned consumer ID 16. None of the consumers previously mentioned in the single groups were also attributed in this method. It is important to highlight that consumer IDs 5 and 14 were assigned to the same group in this method – Group 1.

Hierarchical Clustering

Unlike other algorithms, the number of groups to be defined is not required a priori. As the name suggests, this method defines a hierarchical structure according to a proximity matrix. This structure is usually presented in dendrograms or binary trees. Consequently, if the analyst wants any other specific number of clusters, just cut the dendrogram at the desired level. Hierarchical clustering is subdivided into two main groups: Agglomerative Clustering and Divisive Clustering.

Firstly, Agglomerative Clustering starts by gathering all objects in the database as a singleton cluster or a "leaf." After, clusters are successfully created until each object is in a single cluster, or "root." For Divisive Clustering, the opposite logic applies – as a top-down approach. In this way, it is considered that Agglomerative Clustering is a good option to identify smaller clusters. On the other hand, Divisive Clustering is the preferred choice for recognizing larger clusters.

Considering this assumption, Figure 1.10 represents the results from applying the Hierarchical Clustering method chosen to the dataset selected. Both values of the optimal number of clusters can be seen in the figure by cutting the dendrogram in *k=2* and *k=9*.

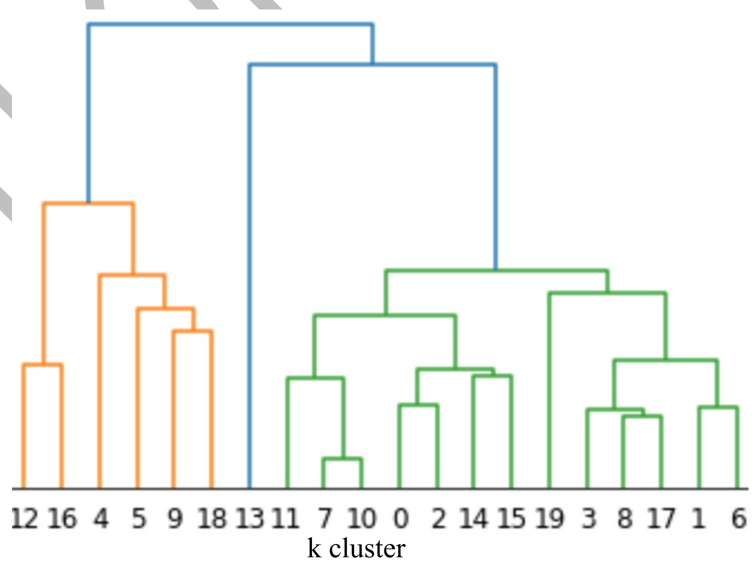


Figure 1.10: Hierarchical Clustering: Agglomerative results for the dataset selected.

However, to ease the understanding of the results, Table 1.5 was added to indicate the group for each consumer, in *k=2* and *k=9*.

For the first scenario, where *k=2*, there were 14 elements in Group 0 and 6 elements in Group 1, the same result as in s 1.7 (a) and (a). Regarding the scenario where *k=9*, Group 0 gathered consumer ID 10 and consumer ID 19; to Group 1 was assigned consumer ID 2, consumer ID 4, consumer ID 7, consumer ID 9, and consumer ID 18; Group 2 has a single element (consumer ID 20); Group 3 has two elements, consumer ID 13 and consumer ID 17; Group 4 has four elements being consumer ID 1, consumer ID 3, consumer ID 15 and consumer ID 16; Group 5, Group 6 and Group 7 are single elements groups gathering consumer ID 5, consumer ID 14, and consumer ID 6 respectively; finally, Group 8 has the remaining consumers. Again, consumer IDs 5 and 14 are highlighted with a single group.

Table 1.5: Hierarchical Clustering: Group attribution.

Consumer ID	k=2	k=9
1	0	4
2	0	1
3	0	4
4	0	1
5	1	5
6	1	7
7	0	1
8	0	8
9	0	1
10	1	0
11	0	8
12	0	8
13	1	3
14	0	6
15	0	4
16	0	4
17	1	3
18	0	1
19	1	0
20	0	2

1.4 Conclusion

A methodology to optimally manage an active community from the Aggregator perspective was presented throughout this chapter. In the future, in Smart Grids, the consumers will become the core player due to the load flexibility provided to suppress the volatile behavior from the distributed generation resources. However, their knowledge regarding this matter is still very scarce, and to depend on their behavior to guarantee the reliability and security of the entire system can be faulty. In this way, the authors believe in understanding the consumers, how they react in the event context, their behaviors, and new ways to motivate their participation in the market transactions to reduce the uncertainty.

Clustering methods are widely used in different areas such as cluster analysis, pattern recognition, image processing, among others. In the present chapter, the authors intend to use these algorithms to find patterns and use consumer profiling to find the proper motivation for Demand Response events, with information not only from the load consumption but also the remaining resources that can be associated with this new player, for instance, Distributed Generation or Energy Storage Systems. The core idea is to find, within the dataset, objects with similar characteristics. So, the number of groups to be formed is crucial for the method's success.

Three of the most well-known methods were compared: Elbow, Silhouette, and Gap-statistic. The direct methods obtain a different value from the statistical method from the study. So, the authors went further and tested both approaches in the second comparison: different types of clustering methods. Partitional, Fuzzy, and Hierarchical Clustering methods were confronted for both "optimal" numbers of clusters found. From the authors' perspective and after the analysis of all the methods performed, the solution $k=2$ might be very reductive for a 96 periods perspective. Consumers with different behaviors were assigned to the same group to receive remuneration. So, fairness, in this case, may have been jeopardized. Although the perspective presented was on a planning approach, the Aggregator might benefit from performing the aggregation phase each period and understanding the complex behavior in a deeper form of contextualization. To ease the task, the authors suggest using Hierarchical clustering since several k can be visualized.

Acknowledgements

This work has received funding from the European Union's Horizon 2020 research and innovation program under project DOMINOES (grant agreement No 771066), from FEDER Funds through COMPETE program, and from National Funds through (FCT) under the projects UIDB/00760/2020, MAS-SOCIETY (PTDC/EEI-EEE/28954/2017), CEECIND/02887/2017, and SFRH/BD/144200/2019.

Bibliography

Abrishambaf, Omid, Fernando Lezama, Pedro Faria, and Zita Vale. 2019. “Towards Transactive Energy Systems: An Analysis on Current Trends.” Energy Strategy Reviews 26 (November): 100418. doi:10.1016/j.esr.2019.100418.

Batool, Fatima, and Christian Hennig. 2021. “Clustering with the Average Silhouette Width.” Computational Statistics & Data Analysis 158 (June): 107190. doi:10.1016/j.csda.2021.107190.

European Parliament, and Council of the EU. 2019. “Directive (EU) 2019/944 on Common Rules for the Internal Market for Electricity and Amending Directive 2012/27/EU.” Official Journal of the European Union, no. 158: 18. doi:http://eur-lex.europa.eu/pri/en/oj/dat/2003/l_285/l_28520031101en00330037.pdf.

Faria, Pedro, and Zita Vale. 2021. “Distributed Energy Resource Scheduling with Focus on Demand Response Complex Contracts.” Journal of Modern Power Systems and Clean Energy 9 (5): 1172–82. doi:10.35833/MPCE.2020.000317.

Gomes, Luis, Zita A. Vale, and Juan Manuel Corchado. 2020. “Multi-Agent Microgrid Management System for Single-Board Computers: A Case Study on Peer-to-Peer Energy Trading.” IEEE Access 8: 64169–83. doi:10.1109/ACCESS.2020.2985254.

Granell, Ramon, Colin J. Axon, and David C. H. Wallom. 2015a. "Impacts of Raw Data Temporal Resolution Using Selected Clustering Methods on Residential Electricity Load Profiles." IEEE Transactions on Power Systems 30 (6): 3217–24. doi:10.1109/TPWRS.2014.2377213.

Granell, Ramon, Colin J. Axon, and David C.H. Wallom. 2015b. "Clustering Disaggregated Load Profiles Using a Dirichlet Process Mixture Model." Energy Conversion and Management 92 (March): 507–16. doi:10.1016/j.enconman.2014.12.080.

Hartigan, J. A., and M. A. Wong. 1979. "Algorithm AS 136: A K-Means Clustering Algorithm." Applied Statistics 28 (1): 100. doi:10.2307/2346830.

Jin, Hongyang, Zhengshuo Li, Hongbin Sun, Qinglai Guo, and Bin Wang. 2019. "Coordination on Industrial Load Control and Climate Control in Manufacturing Industry under TOU Prices." IEEE Transactions on Smart Grid 10 (1). IEEE: 139–52. doi:10.1109/TSG.2017.2733578.

Kashani, Alireza G., and Andrew J. Graettinger. 2015. "Cluster-Based Roof Covering Damage Detection in Ground-Based Lidar Data." Automation in Construction 58 (October): 19–27. doi:10.1016/j.autcon.2015.07.007.

Morais, Hugo, Pedro Faria, and Zita Vale. 2014. "Demand Response Design and Use Based on Network Locational Marginal Prices." International Journal of Electrical Power & Energy Systems 61 (October): 180–91. doi:10.1016/j.ijepes.2014.03.024.

Okur, Özge, Nina Voulis, Petra Heijnen, and Zofia Lukszo. 2019. "Aggregator-Mediated Demand Response: Minimizing Imbalances Caused by Uncertainty of Solar Generation." Applied Energy 247 (October 2018). Elsevier: 426–37. doi:10.1016/j.apenergy.2019.04.035.

Osório, Gerardo J., Miadreza Shafie-khah, Mohamed Lotfi, Bernardo J. M. Ferreira-Silva, and João P. S. Catalão. 2019. "Demand-Side Management of Smart Distribution Grids Incorporating Renewable Energy Sources." Energies 12 (1): 143. doi:10.3390/en12010143.

Silva, Cátia, Pedro Faria, and Zita Vale. 2019a. “Demand Response and Distributed Generation Remuneration Approach Considering Planning and Operation Stages.” Energies 12 (14): 2721. doi:10.3390/en12142722.

———. 2019b. “Multi-Period Observation Clustering for Tariff Definition in a Weekly Basis Remuneration of Demand Response.” Energies 12 (7): 1248. doi:10.3390/en12071248.

Sinaga, Kristina P., and Miin-Shen Yang. 2020. “Unsupervised K-Means Clustering Algorithm.” IEEE Access 8: 80716–27. doi:10.1109/ACCESS.2020.2988796.

Singh, Archana, Avantika Yadav, and Ajay Rana. 2013. “K-Means with Three Different Distance Metrics.” International Journal of Computer Applications 67 (10). Citeseer.

Subbalakshmi, Chatti, G. Rama Krishna, S. Krishna Mohan Rao, and P. Venketeswa Rao. 2015. “A Method to Find Optimum Number of Clusters Based on Fuzzy Silhouette on Dynamic Data Set.” Procedia Computer Science 46: 346–53. doi:10.1016/j.procs.2015.02.030.

Sun, Li, Kaile Zhou, and Shanlin Yang. 2020. “An Ensemble Clustering Based Framework for Household Load Profiling and Driven Factors Identification.” Sustainable Cities and Society 53 (February): 101958. doi:10.1016/j.scs.2019.101958.

Vale, Z., H. Morais, S. Ramos, J. Soares, and P. Faria. 2011. “Using Data Mining Techniques to Support DR Programs Definition in Smart Grids.” In 2011 IEEE Power and Energy Society General Meeting, 1–8. IEEE. doi:10.1109/PES.2011.6039081.

Wan, Runze, Naixue Xiong, Qinghui Hu, Haijun Wang, and Jun Shang. 2019. “Similarity-Aware Data Aggregation Using Fuzzy c-Means Approach for Wireless Sensor Networks.” EURASIP Journal on Wireless Communications and Networking 2019 (1): 59. doi:10.1186/s13638-019-1374-8.

Wu, Shaochun, Yijie Pang, Sen Shao, and Keyuan Jiang. 2018. "Advanced Fuzzy C-Means Algorithm Based on Local Density and Distance." Journal of Shanghai Jiaotong University (Science) 23 (5): 636–42. doi:10.1007/s12204-018-1993-y.

Zheng, Shunlin, Yi Sun, Bin Li, Bing Qi, Xudong Zhang, and Fei Li. 2021. "Incentive-Based Integrated Demand Response for Multiple Energy Carriers under Complex Uncertainties and Double Coupling Effects." Applied Energy 283 (June 2020). Elsevier Ltd: 116254. doi:10.1016/j.apenergy.2020.116254.

Publication II

C. Silva, P. Faria, and Z. Vale, “Rating consumers participation in demand response programs according to previous events,” Energy Reports, vol. 6, pp. 195–200, Dec. 2020

Resumen

El sector energético, al igual que muchos otros, se está adaptando para satisfacer las preocupaciones ambientales y evitar los combustibles fósiles. Por ello, se promueve el concepto de Smart Grids, que incorpora la Generación Distribuida en la red, especialmente energía basada en fuentes renovables, como una alternativa respetuosa con el medio ambiente. Además, se empodera el papel de los consumidores a través de la Respuesta a la Demanda (DR, por sus siglas en inglés). Los consumidores reciben incentivos para modificar activamente su comportamiento de consumo y recibir una remuneración adecuada. Con esto, el sistema eléctrico reduce los costos de operación y la DR se puede utilizar como una alternativa a la generación. Sin embargo, gestionar estos nuevos recursos activos y sus transacciones en el mercado energético es una tarea compleja debido a la incertidumbre asociada. Muchos factores pueden provocar una falta de respuesta y el Agregador debe ser capaz de gestionar estas situaciones, especialmente cuando se requiere una cierta reducción objetivo del mercado mayorista. Los autores propusieron un enfoque que incluye una clasificación confiable para seleccionar a los consumidores en eventos de DR: los consumidores participan teniendo en cuenta su confiabilidad. En el presente artículo, se compararán los efectos del enfoque entre dos estaciones, demostrando la viabilidad de proporcionar la información correcta al administrador de la comunidad y comprendiendo qué tan variable es el comportamiento de esta clasificación en diferentes momentos del año.

.

Available online at www.sciencedirect.com
ScienceDirect
Energy Reports 6 (2020) 195–200
www.elsevier.com/locate/egyr

7th International Conference on Energy and Environment Research, ICEER 2020, 14–18 September, ISEP, Porto, Portugal

Rating consumers participation in demand response programs according to previous events

Cátia Silva[a,b,*], Pedro Faria[a,b], Zita Vale[b]

[a] GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, Portugal
[b] Polytechnic of Porto, Portugal

Received 23 October 2020; accepted 11 November 2020

Abstract

The energy sector, as many, is being adapted to meet environmental concerns and avoid fossil fuels. So, Smart Grids concept is promoted, penetrating Distributed Generation into the grid, namely renewable-based energy, providing an environmentally friendly alternative. Also, the consumers' role is empowered through Demand Response (DR). The consumers are incentivized to actively modify their consumption behavior receiving the proper remuneration. With this, the power system will decrease operation costs and DR can be used as an alternative to generation. However, manage these new and active resources as well as their transactions in the energy market is a complex task due to the uncertainty associated. Many factors can cause a non-response and the Aggregator must be able to manage these situations mainly when a certain target of reduction is required from the wholesale market. The authors proposed an approach including a Trustworthy Rank to select consumers for on DR events: consumers participate considering their reliability. In the present paper, the effects of the approach will be compared between two seasons, proving the viability on giving the correct information to the community manager and understanding how variable is the behavior of this rank at different times of the year.

Peer-review under responsibility of the scientific committee of the 7th International Conference Energy and Environment Research, ICEER, 2020.

Keywords: Demand response; Energy market; Trustworthiness; Smart grids

1. Introduction

Currently, the energy sector is facing changes that will drive towards a more sustainable and efficient energy usage. The growing concern motivates all the intervenient on working in ways to preserve the environment to not compromise the natural resources of upcoming generations. For the energy sector, it is believed that Smart Grids concept is the future and can find the balance between social, energy, economic and environmental issues. The concept guarantees a more reliable and efficient market, empower the small players introducing Demand

* Corresponding author at: GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, Portugal.

E-mail addresses: cvcds@isep.ipp.pt (C. Silva), pnf@isep.ipp.pt (P. Faria), zav@isep.ipp.pt (Z. Vale).

https://doi.org/10.1016/j.egyr.2020.11.101

Peer-review under responsibility of the scientific committee of the 7th International Conference Energy and Environment Research, ICEER, 2020.

Response (DR), enabling bidirectional communication and penetrate Distributed Generation (DG) resources, namely renewable-based such as wind and solar, fighting the intensification of the greenhouse effect and air pollution. Although slow, the implementation of Smart Grids in real markets is starting and political efforts are being made to introduce DR and empower consumers, such as Directive 2019/944 providing common rules for the internal market [1]. The role from consumers in the energy market and their potential is crucial to take the step forward to a sustainable future. The definition of consumer is changing. Now, being able to participate in the transactions in the market, understand their consumption and find ways to improve and reduce their costs, even produce their energy as prosumers, it creates a new player in the energy sector, a more active and conscious one. Yet, it will take time, education, and resources until taking rational decisions. Still, Ilieva et al. [2] highlight the impact of millennials actions and how there are different from previous generations. Their sensitivity to environmental aspects makes them more ready to embrace "green initiatives". Considered as the type of users that will be responding to energy flexibility signals, promote local and sustainable energy production as well as consumption. However, the actual business models do not include or can deal with the uncertainty associated with these new resources. The unpredictable behavior, from both consumers and DG units, increase the complexity of managing the network. An entity was created to be responsible for the transactions in local communities with active players — the Aggregator. Many models in the literature were created finding solutions to optimally manage and to aid and decrease the difficulty of the [3–5]. However, the authors found the necessity to search for a way to increase reliability in the network namely when DR events are triggered, considering the uncertainty associated with the small consumers' behavior. As Good [6] reminds, most of the studies are shaped given end-users as always rational and economic agents, and the uncertainty behind their random behavior must be considered. Taking a step forward from previous works [7], the methodology proposed in the present paper was designed to select trustworthy consumers to be selected for a DR event. Considering a DR target required from the wholesale market, the Aggregator must rely on the active consumers in the community to achieve the goal. The idea is assigning a trustworthiness rank considering previous experiences and, for the case of none, the low rank is attributed and continuous participation with good results will rise their reputation. Having this information, the Aggregator will opt for the more "reliable" for this task. The proposed methodology can optimally manage several resources: the mentioned DR program participants, DG units and the joint from those concepts. A more detailed explanation of the process is present in Section 2.

The present paper is divided into five sections. Section 1 is an introduction to the theme approached. Section 2 details the proposed method. The case study, the results, and the discussion are presented in Sections 3 and 4. Finally, the conclusions from the study are summarized in Section 5.

2. Materials and methods

The authors proposed a method including a trustworthy rank (TR) considering past experiences from the active consumers with DR events through time: Current Reduction (CR) being the actual reduction in the present event, Last event Day (LD) being the performance from the last event in the same period and Historical Rank (HR) is the average from previous performances within the same context, explained on Fig. 1.

The innovation from previous works is the influence from different contexts, namely different seasons, as the consumers' behaviors change through the year. The higher the rank, the more trustworthy is considered the active consumer giving useful information to the Aggregator for the following DR events on the same context. The lowest rank is attributed to the first participation, and consumers must continuously contribute to obtaining an improve. At the beginning of the DR event, the Aggregator selects the consumers with TR higher than a denominated minimum to participate and schedules them with the remaining resources.

The objective function aims to minimize operational costs from the perspective of the aggregator and fairly remunerate active consumers (Eq. (1)). Let PDG be the power for each p DG resources; PDR is the flexibility from each c consumers; PSUP is the power from each s external suppliers and PNSP be the non-supplied Power. Each of these variables has an associated cost. To achieve the balance between consumption (Pinitial) and generation, the Eq. (2) is added. The remaining constraints introduce inequations used to bound to all resources involved. From Eq. (3) to Eq. (6), control the DR event targets and the amount of reduction from each active consumer.

Eqs. (7) and (8) constrain DG units on upper and lower bounds. Eq. (9) restrict the amount of DG used. Eq. (10) provides an upper limit for external suppliers and Eq. (11) restrict the total amount of generation from this source.

$$Min\ OF = \sum \left[P_{DG}(p,\ t)\, C_{DG}(p,\ t) \right] + \sum \left[P_{DR}(c,\ t)\, C_{DR}(c,\ t) \right]$$

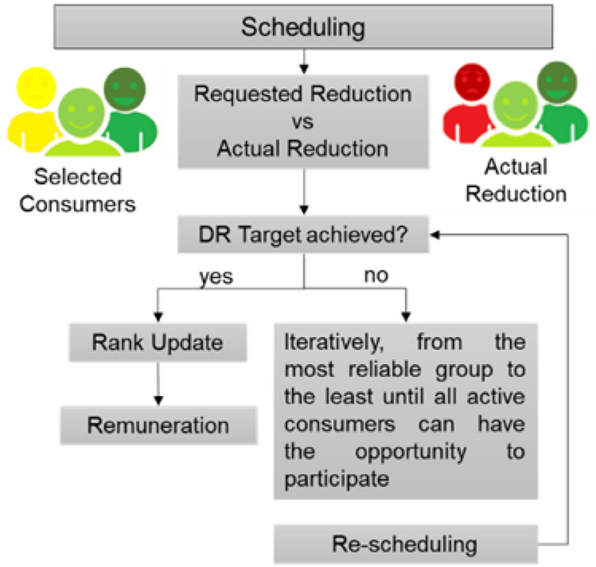


Fig. 1. Proposed methodology.

$$+ \sum [P_{SUP}(s,\ t)\, C_{SUP}(s,\ t)] + P_{NSP}(t)\, C_{NSP}(t) \tag{1}$$

$$\sum[P_{\text{initial}}(c,\ t) - P_{\text{DR}}(c,\ t)] = \sum[P_{\text{DG}}(p,\ t)] + \sum[P_{SUP}(s,\ t)] + P_{NSP}(t) \tag{2}$$

$$P_{\text{DR}}(c,\ t) \le P_{\text{DR}}^{\text{Max}}(c,\ t) \tag{3}$$

$$P_{\text{DR}}(c,\ t) \ge P_{\text{DR}}^{\text{Min}}(c,\ t) \tag{4}$$

$$\sum[P_{\text{DR}}(c,\ t)] \le DR_{\text{target}}^{\text{Max}}(c,\ t) \tag{5}$$

$$\sum[P_{\text{DR}}(c,\ t)] \ge DR_{\text{target}}^{\text{Min}}(c,\ t) \tag{6}$$

$$P_{\text{DG}}(p,\ t) \le\ P_{\text{DG}}^{\text{Max}}(p,\ t) \tag{7}$$

$$P_{\text{DG}}(p,\ t) \ge P_{\text{DG}}^{\text{Min}}(p,\ t) \tag{8}$$

$$\sum[P_{\text{DG}}(p,\ t)] \le P_{\text{DG}}^{\text{Total}}(t) \tag{9}$$

$$P_{SUP}(s,\ t) \le P_{SUP}^{\text{Max}}(s,\ t) \tag{10}$$

$$\sum[P_{SUP}(s,\ t)] \le P_{SUP}^{\text{Total}}(t) \tag{11}$$

Performed the scheduling phase, the requested reduction is compared with the actual response. If DR target is not achieved, the remaining consumers are called, iteratively, allowing increasing their rank. After achieving the goal, proceeds the following stage where the rank is updated. Compensation for the response plays as an incentive to motivate a continuous contribution to DR events and it is done after the update. For the present paper, the purpose is to investigate the performance of the proposed methodology for distinct seasons. It is known that consumers behaviors and willingness to participate in DR events can be different throughout the year. The innovative element from previous works done by the authors is the addition of uncertainty regarding context. The following section will detail each assumption considered in the case study developed.

3. Case study

To prove the viability of the proposed approach, the authors wanted to simulate the current implementation of DR in the real world. A database with 20,310 consumers between ten communities was considered, and the main characteristics can be seen in Table 1.

The one with a higher average of trustworthiness from previous events was considered (406 consumers where 263 are active elements). Is composed mainly by households where, usually, the approach is reducing the impact of

Table 1. Characterization of consumers in the ten communities.

Type	Domestic	Small commerce	Medium commerce	Large commerce	Industrial
# elements	10,168	9828	82	85	147
Energy [kWh]	9369.35	7983.35	11,254.75	10,880.48	23,142.48
Max Load Reduction [kW]	4684.7	3991.7	15,756.7	9792.4	20,828.2

DR events in their comfort and wellbeing. For example, one of the age range to likely have a lower response or not willing to participate are the elderly. Ilieva et al. [2] wrote about how the elderly may have problems or be inhibited from using certain technologies. Alexander [8] refers to a more critical matter and presents evidence that elderly consumers, being more fragile, will not seek out or apply for "low income" programs due to their necessities. Information extracted from official entities affirms that almost 35% of the population with private households is composed of people above 65. In this scenario, the same percentage of the dataset will not participate in DR events (35%) and the remaining established DR contracts, being some of them not willing to participate at the weekend. Spring and Autumn were the chosen seasons considering April and October. Two different event types were considered: Event Type 1 (ET1) occurs between 1 pm–3 pm represented by 13 to 15 and Event Type 2 (ET2) occurs between 6 pm–8 pm represented by 18 to 20. A wide range was studied to see the variety of responses in the selected periods. It is also considered a DR target of 100kW per period of the event (each divided into periods of 15 min). The risk of not achieving the goal is high, considering the uncertainty of behaviors from users, however, the limit from the model is tested to include all the active members and understand if the information obtain is useful for the Aggregator. TR goes between 1 and 5 and rank 3 is the minimum in the first active consumers' selection.

4. Results and discussion

Fig. 2 presents the comparison between the selected and the actual participants as well as the actual and requested reduction for DR events. The darker color charts represent the which was trigged on Monday (a), Tuesday (c), Thursday (e), and Sunday (g). The lighter color chart represented ET2 and was tested for the remaining weekdays. The proposed approach was able to always reach the DR target in events from April by calling the remaining active consumers, the value of 100 kW in every 15 min from the DR event was achieved by the optimization (Requested line on Fig. 2). Ideally, this would happen in the actual line as well, and the target of reduction would be accomplished. However, in the simulation, not all the selected users responded as expected. The authors considered them has not always rational and active agents, and that assumption had an impact as can be seen in the Actual curve from Fig. 2. The group with a higher percentage of non-responses was rank 1. Taking as an example Fig. 2(a) at 13:30, from the rank 1 elements was requested 13,62 kW and the actual value was 2,12 kW.

These achievements highlight the necessity and the importance of focusing on consumers and ways to increase their willingness to participate in DR events but also find models to avoid high risks on the management side perspective. Fig. 3 presents the results from October.

The darker color charts represent the ET1 which was trigged on Tuesday (a), Wednesday (c), Friday (e), and Monday (g). The lighter color chart represents ET2 and the remaining weekdays. Once again, the DR target could be achieved by the active consumers, but their actual responses were different from the requested. The elements on lower TR groups were again essential to achieve the goal. However, a distinct month did have a greater impact on the overall reduction since the value was always between 80 kW and 100 kW as in April. The authors prove the viability of the model on finding useful information from the community behavior. Also add a step forward on design solutions to deal with consumers, an important role in the future energy market.

5. Conclusions

Empowering the consumer's role in the energy market is one of the main topics on the Smart Grid approach. However, introducing DR programs on the management can be a complex task considering the uncertainty. The authors proposed a model where a Trustworthy Rank was created to provide the Aggregator with valuable information from active consumers. Two different events were created and triggered throughout April and October to compare the impact of the seasons on the model. Also, on the contrary of several models on the literature, the consumers were assumed as not always rational and economic agents, so their response was difficult to predict, and the target was not achieved. Regarding the season impact on the ranks, being a studied as group, the effects were not noticed. For future works, find ways to motivate positive responses on DR events and penalize for non-responses.

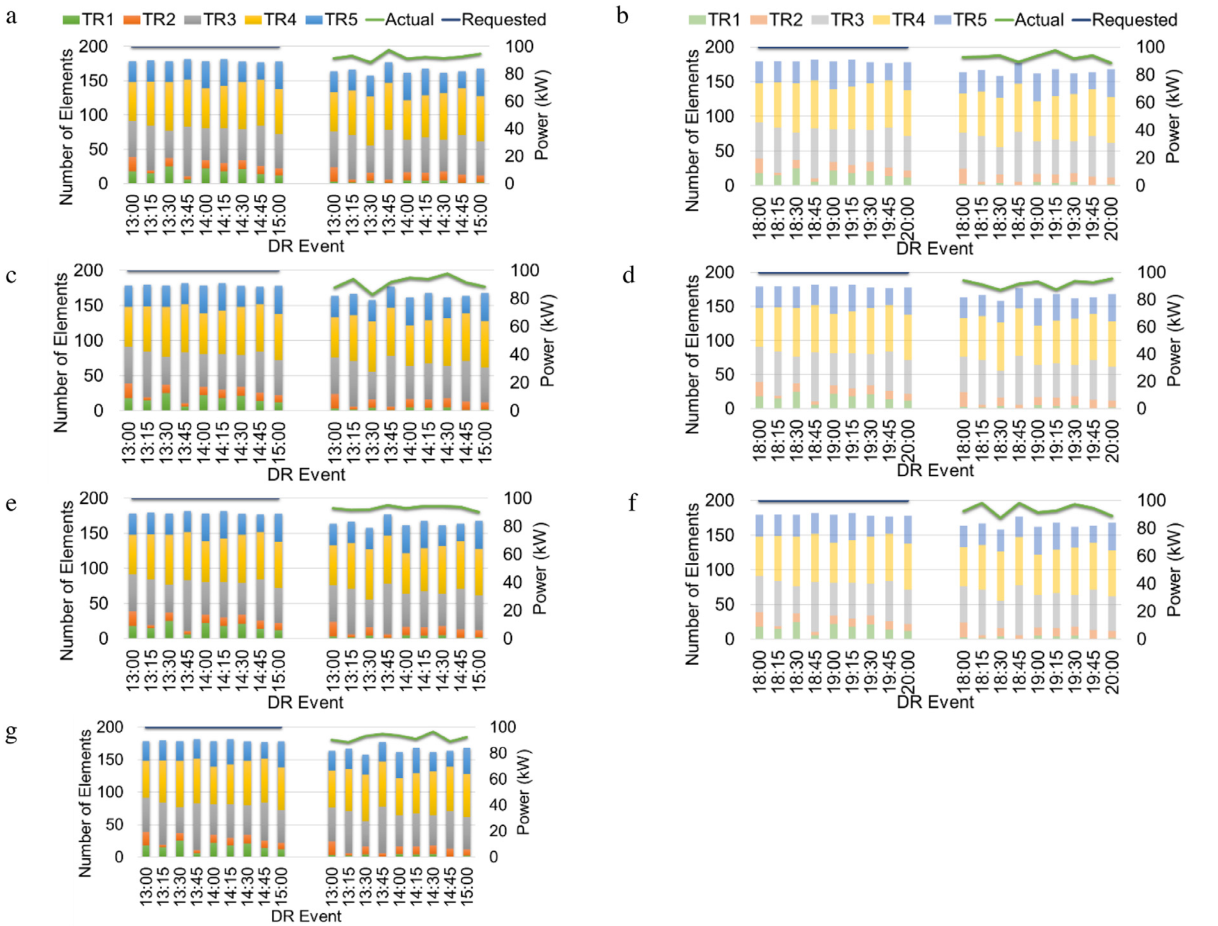


Fig. 2. Participants and Average Rank in DR events from April: ET1 (a), (c), (e) and (g). ET2 (b), (d), (f).. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

CRediT authorship contribution statement

Cátia Silva: Data curation, Formal analysis, Investigation, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Pedro Faria:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Zita Vale:** Conceptualization, Data curation, Funding acquisition, Methodology, Project administration, Resources, Supervision, Validation, Writing - original draft, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work has received funding from the European Union's Horizon 2020 research and innovation programme under project DOMINOES (grant agreement No 771066), from FEDER Funds, Portugal through COMPETE program and from National Funds through (FCT) under the projects UIDB/00760/2020, CEECIND/02887/2017, and SFRH/BD/144200/2019, and from ANI (project GREEDi).

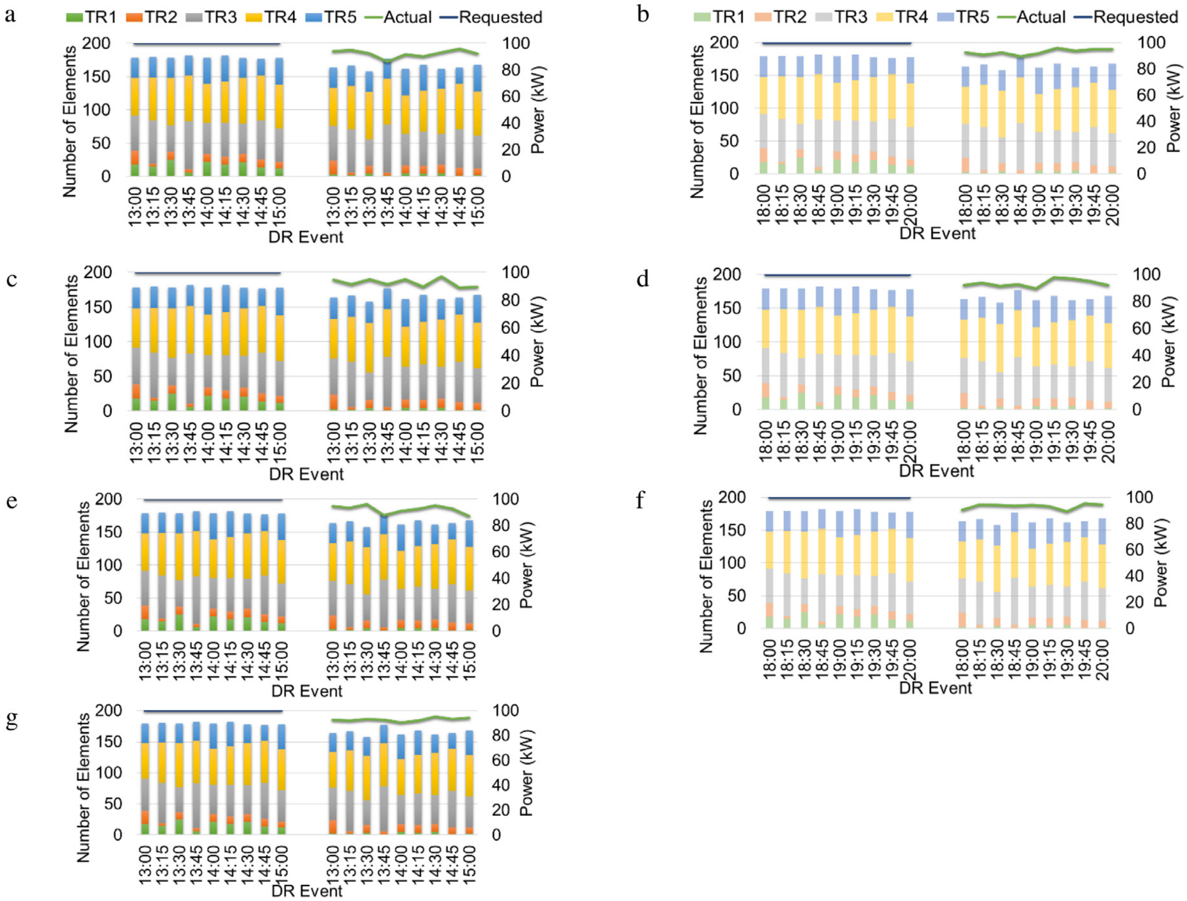


Fig. 3. Participants and Average Rank in DR events from October: ET1 (a), (c), (e) and (g). ET2 (b), (d), (f).. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

References

[1] European Parliament, Council of the EU. Directive (EU) 2019/944 on common rules for the internal market for electricity and amending directive 2012/27/eu. Off J Eur Union 2019;18. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32019L0944.

[2] Ilieva I, Bremdal B, Puranik S. Bringing business and societal impact together in an evolving energy sector. J Clean Energy Technol 2019;7:42–8. http://dx.doi.org/10.18178/JOCET.2019.7.3.508.

[3] Carreiro AM, Antunes CH, Jorge H. Assessing the robustness of solutions to a multi-objective model of an energy management system aggregator. In: 2016 IEEE symposium series on computational intelligence. IEEE; 2016, p. 1–6. http://dx.doi.org/10.1109/SSCI.2016.7849845.

[4] Chen S, Cheng RS. Operating reserves provision from residential users through load aggregators in smart grid: A game theoretic approach. IEEE Trans Smart Grid 2019;10:1588–98. http://dx.doi.org/10.1109/TSG.2017.2773145.

[5] Luo F, Ranzi G, Dong Z. Rolling horizon optimization for real-time operation of thermostatically controlled load aggregator. J Mod Power Syst Clean Energy 2017;5:947–58. http://dx.doi.org/10.1007/s40565-017-0329-5.

[6] Good N. Using behavioural economic theory in modelling of demand response. Appl Energy 2019;239:107–16. http://dx.doi.org/10.1016/j.apenergy.2019.01.158.

[7] Silva C, Faria P, Vale Z. Combining real-time and fixed tariffs in the demand response aggregation and remuneration. Energy Rep 2020;6:114–9. http://dx.doi.org/10.1016/j.egyr.2019.08.028.

[8] Alexander BR. Dynamic pricing? Not so fast! a residential consumer perspective. Electr J 2010;23:39–49. http://dx.doi.org/10.1016/j.tej.2010.05.014.

Publication III

O. Abrishambaf, C. Silva, P. Faria, and Z. Vale, "An Optimization Based Community Model of Consumers and Prosumers: A Real-Time Simulation and Emulation Approach", International Conference on Renewable Energy (ICREN), 2021

Resumen

El patrón de consumo de electricidad está aumentando día a día. Actualmente, los operadores de redes se están moviendo hacia recursos de energía renovable y aplicando programas de respuesta a la demanda. Sin embargo, es necesario aglutinar a los consumidores y productores de pequeña y mediana escala para que participen en los mercados eléctricos como un recurso único. En este documento se propone un modelo de comunidad basado en optimización para aglutinar a los consumidores y productores de pequeña escala. El modelo incluye un controlador central, que se considera un agregador, y varios administradores de comunidades locales para mantener el equilibrio de la red a nivel local. Además, se utiliza un enfoque de simulación en tiempo real y varios dispositivos reales como hardware-in-the-loop para validar el sistema frente a desafíos prácticos. Los resultados del artículo revelan una brecha entre los resultados de la simulación y los experimentales, y demuestran el rendimiento del sistema en modo en tiempo real utilizando dispositivos reales.

An Optimization Based Community Model of Consumers and Prosumers: A Real-Time Simulation and Emulation Approach

Omid Abrishambaf [1] , *Cátia* Silva [1] , *Pedro* Faria [1,*], and *Zita* Vale [1]

[1] IPP—Polytechnic Institute of Porto, Porto, Portugal

Abstract. The electricity consumption pattern is being increased day by day. Currently, network operators are moving towards renewable energy resources and applying demand response programs. However, the small and medium scale consumers and producers are needed to be aggregated and participate in the electricity markets as a unique resource. This paper proposes an optimization-based community model for aggregating the small scales consumers and producers. The model includes a central controller, which is considered as an aggregator, and several local community managers to keep the network balanced locally. Furthermore. real-time simulation approach and several real devices as hardware-in-the-loop are used to validate the system under practical challenges. The results of the paper reveal a gap between the simulation and experimental results and prove the performance of system in real-time mode using actual devices.

1 Introduction

The actual trend of power systems operation and continued growth of consumption forced the network operators all around the world to consider Distributed Renewable Energy Resources (DRERs), such as Photovoltaic (PV) and wind turbine [1]. In order to effectively merge the large scale of DRERs in the network, further tactical services are needed, such as Demand Response (DR) program [2]. In fact, DR brings flexibility in the current trend of power systems, enabling the network operator to relieve congestion of the grid and reduce the peak periods [3][4]. DR program is defined as the modification in the consumption patterns of the end-users in order to respond to the incentives paid by DR entity [5]. Based on the information provided by [6], there is a limitation for minimum reduction capacity by consumers and prosumers (consumers who can also produce electricity) in order to participate in the DR programs (i.e. 100 kW [7]). This limitation makes the small and medium electricity customers almost incapable to participate in these kinds of management programs [8]. Therefore, the need of a third-party entity is evident in this context (i.e. aggregator), in order to aggregate all small and medium consumers and prosumers and participate them as a unique resource in the electricity markets [9].

* Corresponding author: pnf@isep.ipp.pt

This paper presents an optimization-based community model for electricity consumers and producers. The model contains a central controller unit (i.e. aggregator), and several local community managers to control the electricity network locally, as Fig. 1 shows. An optimization algorithm is also used for the community model to optimally schedule the resources and apply DR programs [10]. Furthermore, real-time simulation and several laboratory resources are employed using Hardware-In-the-Loop (HIL) method, to survey the performance of the model by actual consumers and producers.

There are plenty of related works in this context. In [11], the authors presented a smart community model to control the energy resources of its member by establishing contract. Also, a single period optimization algorithm was used in the same work to minimize the operational cost of the community by applying different types of DR programs. In [12], a real-time simulation model has been presented for a curtailment service provider, and an optimization problem was used to perform energy scheduling and applying DR programs. In [13], a real-time commercial aggregator model has been presented that utilized flexibilities offered by its customers to participate in the market bids and negotiations. The emulation results of the same work showed the effect of participating DRERs and microgrids for minimizing the congestion management of the network. However, the contribution of this paper is centered on two levels: (i) Real-Time Simulation: to develop a Simulink model for the community model, running in real-time and obtaining the simulation results; (ii) Laboratory Emulation: to test the model with actual and laboratory resources under practical challenges and technical issues.

After this introductory section, the real-time simulation model for community is described in Section 2. The components modelling used for system are shown in Section 3, and the proposed optimization method is described in Section 4. A case study in Section 5 is set to validate the system, and its results are presented in Section 6. Finally, Section 7 explains the main conclusions of the work.

2 Real-Time Simulation Approach for Community

This section describes the theory of the proposed community model. As Fig. 1 illustrates, there is a central management entity in the model, which is an aggregator. Also, there are several local managers that are responsible for local communities of consumers and prosumers. In fact, the aggregator is accountable for communicating with each local community manager to keep the network balanced and perform other tactical services, such as DR programs. The main purpose of using local community managers behind of aggregator is that the energy balance being performed locally in several small communities, which then can be employed in the local transactive systems and peer-to-peer electricity markets. Moreover, the aggregator in this model is an entity between the upstream level and demand-side level of the power system. In the upstream level, it negotiates with the market operators, and in demand-side, it deals with local community managers for defining the DR programs, and purchase or sell energy to them. The main focus of this paper is given to the downstream level of the aggregator and technically validating the performance of the community model.

In this community model, the main intention of the aggregator is to supply the electricity demand from the local energy resources and prevent purchasing energy from the electricity markets. In fact, the aggregator is not owning any resources, and it only controls and manages the rate of consumption by applying for DR programs and paying remunerations to the consumers and purchase the surplus of the generated power by the prosumers. Therefore, aggregator in this model is not accountable for the technical validation of the network, such as voltage or frequency control. These technical management of the network in this model is considered as the responsibilities of the grid operators, such as Distribution network operators (DSO).

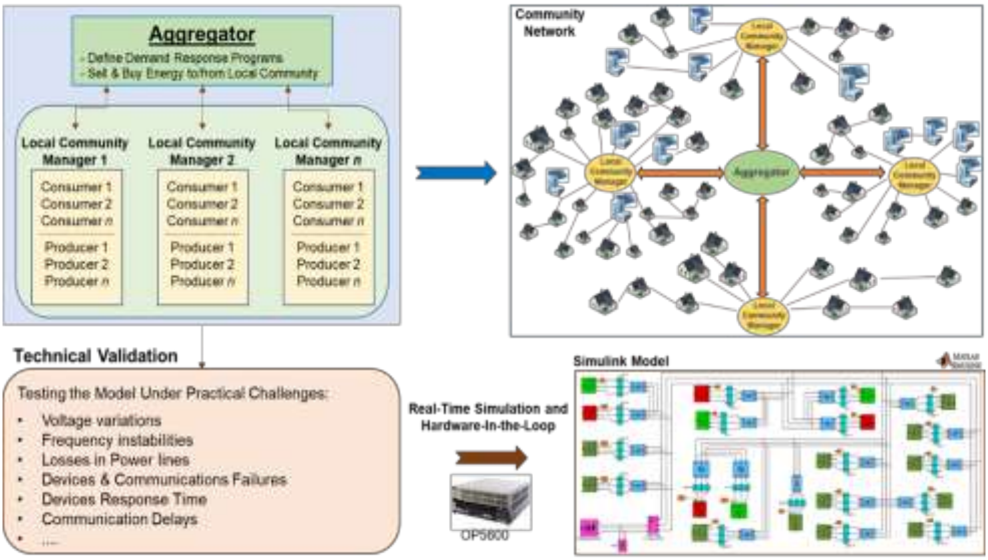


Fig. 1. The architecture of the proposed community model for real-time simulation.

Furthermore, the aggregator is able to perform energy transaction between the local communities to keep the network balance without buying energy from the electricity markets. Also, the aggregator is able to perform scheduling of the resources by relying on the external supplier (electricity markets), RERs available in the community, and DR programs. While the aggregator keeps the network balance between all local communities, it can negotiate in the electricity markets with the flexibilities provided by each local community. In fact, the aggregator can present several bids in the market with the available energy from the local communities and a certain price that has been obtained based on the financial profits of the customers.

3 Components Modelling

This section presents the real-time simulation architecture, and proposed model for the HIL methodology. The main player of this model is OP5600 (www.opal-rt.com). In fact, OP5600 is capable to run the MATLABTM/Simulink models in real-time that enables the operator to integrate the real data in the Simulink environment via HIL methodology.

In other words, OP5600 integrates the emulation and simulation results in a unique model that can be used for the management and control scenarios, such as optimization algorithms and resources scheduling. This integration enables the system to have more reliable results to verify and validate the performance of the model under practical challenges namely voltage variations, frequency instabilities, devices response time, etc.

Fig. 2 shows the Simulink model concerning a part of the community electricity network placed. As Fig. 2 demonstrates, all consumers are modelled by a three-phase dynamic load model, where all of them are connected and supplied by a three-phase source model. Furthermore, there are several three-phase series RLC branch blocks to simulate the impedance of each line in the network. By this way, the model can provide the most accurate and near to real results.

In Fig. 2, the colour of each block indicates its role in the community model. Dark green and red blocks are showing the consumers of the community (e.g., residential and commercial buildings), and light green blocks are the RERs (e.g., PV units). As it was mentioned, real laboratory devices are integrated into the proposed Simulink model via HIL methodology.

For this purpose, three network players of the community model are dedicated for the HIL devices and considered these three players are real consumers and producers, as Fig.2 shows.

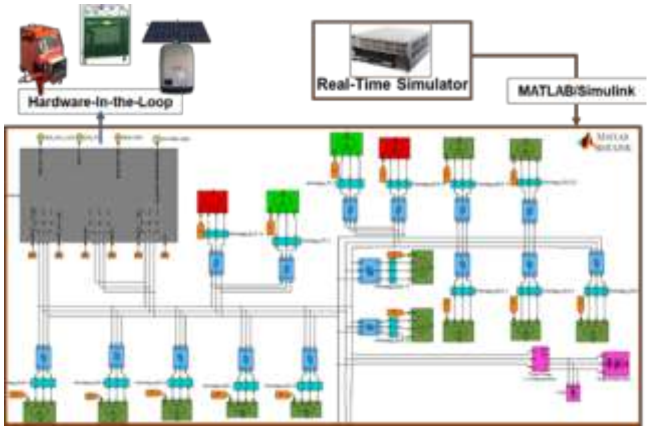


Fig. 2. Simulink model of the community electricity network including laboratory HIL devices.

The HIL devices are two laboratory load banks and a real top roof PV installation. The two load banks are a 30 kW and a 4 kVA loads considered as two HIL consumers in the model. In the 30 kW load, there are four relays that increase or decrease the desire rate of consumption, and in 4 kVA load, there is an Arduino® (www.arduino.cc), which manages the amount of consumption.

In the top roof PV, the model only acquires the real-time generation data and integrates them in the Simulink. The nominal generation rate of this PV installation is 10 kW. The hardware installation and configuration of the HIL devices have been developed by the authors in the scope of their previous works, and more detailed information is available on [14].

To sum up, by using the Simulink models shown in this section, the user can specify any rate of consumption and generation to be simulated and emulated through the full simulation models as well as the HIL devices. Also, it is possible to compare the results obtained from real equipment with the gained results from the full simulation models.

4 Optimization Methodology

This section discusses the proposed optimization method for the community model. The objective is to find a balance locally to minimize the operational costs. For this purpose, the proposed optimization algorithm considers a linear cost for each resource and performs the optimization in line with the costs in each single period.

In this way, the following optimization algorithm has been developed where all consumers participate in DR programs (P_{DR}). Distributed Generation (P_{DG}) units and External Supplier ($P_{Supplier}$) are the energy providers in this model. All the consumers from DR programs should have a pre-contracted reduction limit as well as the remuneration tariffs associated with each one. Equation (1) presents the objective function of the problem. In (1), C is the associated cost for each resource.

$$MinOF = \sum_{p=1}^{P} P_{DG(p)} C_{DG(p)} + \sum_{c=1}^{C} P_{DR(c)} C_{DR(c)} + \sum_{s=1}^{S} P_{Supplier(s)} C_{Supplier(s)} \tag{1}$$

This function is from the local community managers standpoint and considers all the different participants and their associated costs. The goal is to guarantee the balance in the local communities, as shown in (2). In the hypothesis of the local communities, the manager won't be able to find the equilibrium locally with only production from DG units, an external supplier is applied. The idea is to only use external suppliers in extreme case, giving always priority to the DG units in the local community network.

$$\sum_{c=1}^{C}[P_{Load(c)}^{Initial} - P_{DR(c)}] = \sum_{p=1}^{P} P_{DG(p)} + \sum_{s=1}^{S} P_{Supplier(s)} \tag{2}$$

Equation 2 shows that sum of consumption (should be the possible reduction from DR program for each consumer to its initial load – $P_{InitialLoad}$) equals the sum of production (all DG units and Suppliers) to find the network balance. In this objective function, there are other constraints that should be considered. Firstly, the restriction associated with the consumers belonging to DR programs, and the maximum reduction capacity ($P^{Max}{}_{DR}$) is presented in (3).

$$P_{DR(c)} \leq P_{DR(c)}^{Max}, \ \forall c \in \{1, \dots, C\} \tag{3}$$

For distributed resources, the DG units are limited by (4) and (5) being the upper bound and the total amount that can be used from DG units, respectively. In the case of PV production, (4) and (5) would come as equality equations, so all the PV production should be used.

$$P_{DG(p)} \leq P_{DG(p)}^{Max}, \ \forall p \in \{1, \dots, P\} \tag{4}$$

$$\sum_{p=1}^{P} P_{DG(p)} \leq P_{DG}^{TotalMax} \tag{5}$$

In the case that external suppliers are needed, (6) - (9) are introduced. The upper bound and the total available amount helps the local community managers to restrict the use of this option.

$$P_{Supplier(sr)}^{reg} \leq P_{Supplier(sr)}^{regMAX}, \forall \in \{1, \dots, Sr\} \tag{6}$$

$$\sum_{sr=1}^{Sr} P_{Supplier(sr)}^{reg} \leq P_{Supplier(sr)}^{regTOTAL} \tag{7}$$

$$P_{Supplier(sa)}^{add} \leq P_{Supplier(sa)}^{addMAX}, \forall \in \{1, \dots, Sa\} \tag{8}$$

$$\sum_{sa=1}^{Sa} P_{Supplier(sa)}^{add} \leq P_{Supplier(sa)}^{addTOTAL} \tag{9}$$

In fact, in this optimization two types of external suppliers are considered: Regular ($P_{regsupplier}$); and Additional ($P_{addsupplier}$). The additional supplier is considered as an auxiliary supplier that would be used while the regular supplier is not able to provide the committed amount of energy. Also, additional supplier is considered as a more expensive resource comparing to the regular supplier.

In this way, $P^{regMax}{}_{supplier}$ and $P^{addMax}{}_{supplier}$ are maximum power from a regular or additional supplier respectively. Also, $P^{regTotal}{}_{supplier}$ and $P^{addTotal}{}_{supplier}$ are total power allowed from all the regular and additional suppliers respectively. Therefore, the use of external supplier is being optimized by the proposed algorithm to minimize the costs, while network balance has been respected in all communities.

The output of optimization algorithm proposed in this section is a requested amount of power for each consumer to reduce its demand in a certain period. The actual implementation of this demand reduction request in a real load will depend on the electrical grid conditions. This is in fact one of the advantages of using real-time simulation (in this paper OP5600) and laboratorial equipment for consumption modelling. In this way, the actual demand reduction will be validated to be included in the simulation results, namely for remuneration purposes.

5 Case Study

This section focuses on a case study in order to test and validate the functionalities of the developed community model. For this purpose, it is considered there are four villages in the proposed community network that each is being controlled by local community manager. The number of consumers and producers in this community network is shown in Table 1.

Table 1. Quantity and type of consumers and producers in the case study for the community network.

	Consumers		**Producers**
	Residential Building	***Public Building***	***PV***
Village 1	93	7	100
Village 2	23	4	4
Village 3	12	4	4
Village 4	13	-	-

Therefore, there are 156 consumers and 108 PV units in the community in total. The consumption and generation profile of the entire community network considered for day-ahead scheduling are illustrated in Fig. 3.

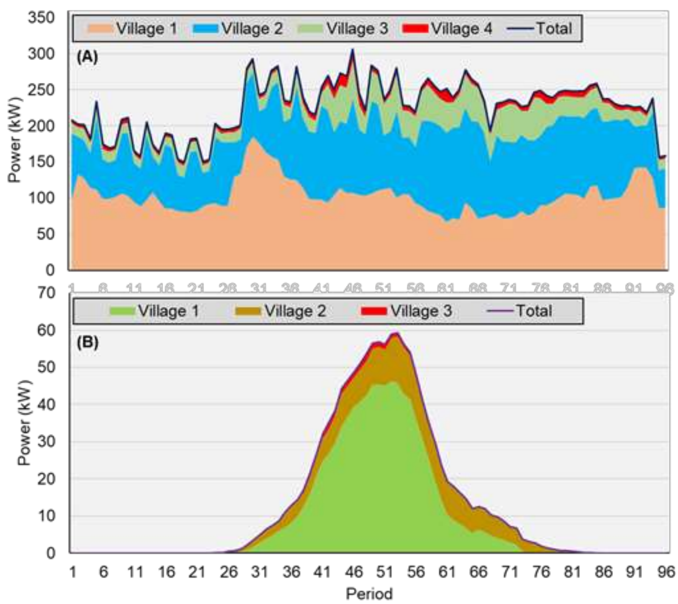


Fig. 3. Day-ahead profiles of the community network considered for the case study: (A) Consumption, (B) PV Generation.

As it is clear in Fig. 3, a huge part of consumption and generation of the community is dedicated to the Village 1. The profiles shown in Fig. 3 – B has been created by aggregating several real generation data from GECAD research center database, Porto, Portugal. As it was mentioned in Section 4, the priority of the system is to supply the electricity demand from the local generation resources (i.e. PV units). In the periods that the local resources are not adequate to supply the demand, the system decides to purchase energy from an external supplier or apply DR programs to reduce the consumption. This is dependent on the market prices and the incentives that are being paid to the customers for applying DR. There are two types of electricity prices considered in this case study, as Fig. 4 shows. In fact, the market price belongs to the energy that aggregator purchases from the electricity markets and

External Supplier price is for the energy that aggregator sells to the local community managers.

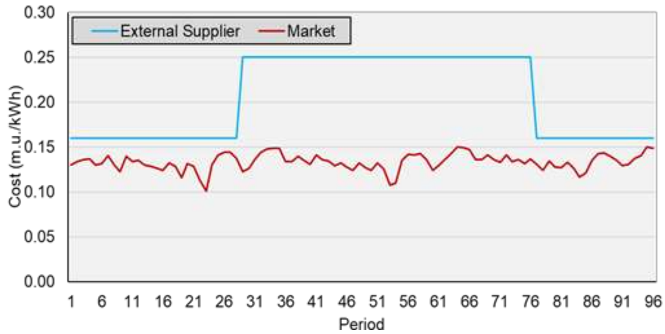


Fig. 4. Electricity prices during the case study.

The electricity market price shown in Fig. 4 have been adapted from Portuguese sector of Iberian Electricity Markets (MIBEL – www.omie.es). Also, the External Supplier price is based on Time-Of-Use (TOU) scheme according to the tariffs provided by incumbent Portuguese electricity retailer in the liberalized market (EDP Commercial – www.edp.pt). Furthermore, a linear cost considered for the energy resources of the community. Also, Table 2 shows the linear remuneration costs regarding DR programs considered for each consumer based on its type. These costs are for load reduction, and in this case, study it is considered that 7% of initial consumption belongs to the maximum load reduction capacity of customers.

Table 2. Remuneration costs of DR programs for community consumers.

Residential Buildings	Period	[1-20], [37-57], [74-96]	[21-36], [58-73]
	Incentive	0.7 (m.u./kWh)	0.12 (m.u./kWh)
Public Buildings	Period	[1-28], [70-96]	[29-69]
	Incentive	0.04 (m.u./kWh)	0.1 (m.u./kWh)

6 Results

In this section, the optimization methodology is being solved by RStudio ® tools (www.rstudio.com) using the presented case study data, and the results are shown. The algorithm is solved on a personal computer with Intel® Xeon® CPU @2.10 GHz, and 16 GB RAM. The total solving time of the optimization problem was 6.92 seconds, which the average time per iteration was 0.04 seconds, and 51.3 MB was used during the problem solving. While the optimization results have been adapted, they will be provided to OP5600 to validate the system using real devices. Considering the accumulated results from all villages, Fig. 5 presents the difference between the initial load profile of all communities and DR reduction results while applying the optimization methodology. The highest reduction value from DR programs is reached around the period of 46, reducing the initial load from 305.98 kW to 284.56 kW. Fig. 6 shows the optimization results for all the resources, from aggregator point of view.

According to Fig. 6, the highest supply from PV units in this case study is 24% of the total production needed to satisfy the demand of the community. In village 1, the total remuneration cost during the case study is 52.57 m.u./kWh, and in village 2, the total remuneration equals to 44.39 m.u./kWh. Also, in village 3 and 4, the total remuneration cost is respectively 14.09 and 0.16 m.u./kWh.

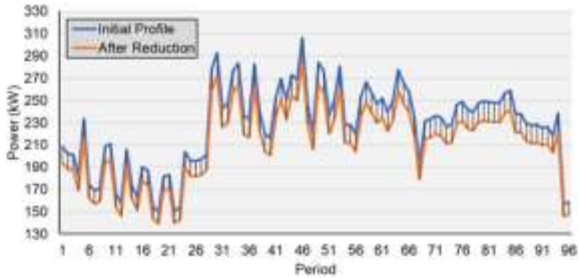


Fig. 5. Optimization results after applying DR programs (Power axis zoomed in the corresponding values).

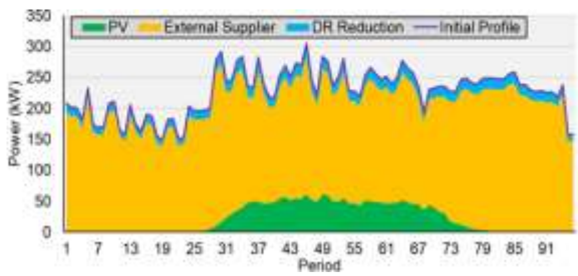


Fig. 6. Scheduling results for all the resources of the community.

Moreover, since there are a lot of consumers and producers in the model, only some sample results are demonstrated. Fig. 7 – (A) shows the consumption profile of a residential building that has been fully simulated by community Simulink model. Also, Fig. 7 – (B) shows the consumption profile of a public building in community network emulated by the HIL devices. The results shown in Fig. 7 is for 96 periods of 7 seconds (672 seconds in total).

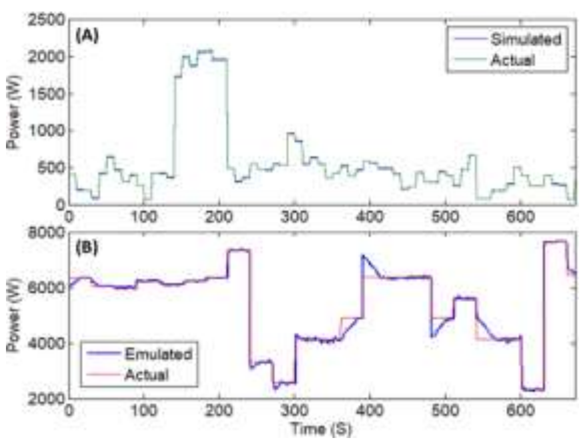


Fig. 7. Real-Time simulation results of consumption in: (A) a residential building in simulation phase, (B) a public building in emulation phase.

As Fig. 7 – (B) shows, while the consumption rates are being changed, the laboratory devices need some time to reach the favourable rate of consumption. In fact, this is the main differences between the laboratory experiments and simulation models; in the simulation environment the consumption rates change instantly (Fig. 7 – (A)), although, the consumption profile emulated by the HIL devices used in this model require some times to reach the favourable rates since several technical challenges and practical conditions are involved, such as voltage and frequency variations.

7 Conclusions

An optimization-based community model was proposed in this paper. The model contained an aggregator and several local community managers to optimally schedule resources and apply for demand response programs. Also, a real-time simulation model was shown to validate the proposed community model. The actual implementation of demand reduction and consumption profiles were shown as well.

This implementation of some resources in practice validated the performance of the model under practical challenges and electrical grid conditions. In fact, this is the advantage of using real-time simulation and laboratory equipment, since the actual demand reduction is being integrated with a full simulation model. So, the system is able to provide more reliable results, which can be useful in network management scenarios, such as remuneration and scheduling purposes.

Acknowledgement

This work has received funding from FEDER Funds through COMPETE program and from National Funds through FCT under the project UID/EEA/00760/2019.

References

[1] I. Worighi, A. Maach, A. Hafid, O. Hegazy, J. Van Mierlo, Integrating renewable energy in smart grid system: Architecture, virtualization and analysis, Sustain. Energy, Grids Networks. **18** (2019) 100226. https://doi.org/10.1016/j.segan.2019.100226.

[2] F. Salah, R. Henriquez, G. Wenzel, D.E. Olivares, M. Negrete-Pincetic, C. Weinhardt, Portfolio Design of a Demand Response Aggregator With Satisficing Consumers, IEEE Trans. Smart Grid. **10** (2019) 2475–2484. https://doi.org/10.1109/TSG.2018.2799822.

[3] C. Silva, P. Faria, Z. Vale, Demand Response and Distributed Generation Remuneration Approach Considering Planning and Operation Stages, Energies. **12** (2019) 2721. https://doi.org/10.3390/en12142721.

[4] N. Good, K.A. Ellis, P. Mancarella, Review and classification of barriers and enablers of demand response in the smart grid, Renew. Sustain. Energy Rev. **72** (2017) 57–72. https://doi.org/10.1016/j.rser.2017.01.043.

[5] L. Gkatzikis, I. Koutsopoulos, T. Salonidis, The Role of Aggregators in Smart Grid Demand Response Markets, IEEE J. Sel. Areas Commun. **31** (2013) 1247–1257. https://doi.org/10.1109/JSAC.2013.130708.

[6] O. Abrishambaf, P. Faria, Z. Vale, J.M. Corchado, Real-Time Simulation of a Curtailment Service Provider for Demand Response Participation, in: 2018 IEEE/PES Transm. Distrib. Conf. Expo., IEEE, 2018: pp. 1–9. https://doi.org/10.1109/TDC.2018.8440492.

[7] N.G. Paterakis, O. Erdinç, J.P.S. Catalão, An overview of Demand Response: Key-elements and international experience, Renew. Sustain. Energy Rev. **69** (2017) 871–891. https://doi.org/10.1016/j.rser.2016.11.167.

[8] E.A. Martínez Ceseña, N. Good, P. Mancarella, Electrical network capacity support from demand side response: Techno-economic assessment of potential business cases for small commercial and residential end-users, Energy Policy. **82** (2015) 222–232. https://doi.org/10.1016/j.enpol.2015.03.012.

[9] R. Alasseri, T.J. Rao, K.J. Sreekanth, Conceptual framework for introducing incentive-based demand response programs for retail electricity markets, Energy Strateg. Rev. **19**

(2018) 44–62. https://doi.org/10.1016/j.esr.2017.12.001.

[10] C. Silva, P. Faria, Z. Vale, Multi-Period Observation Clustering for Tariff Definition in a Weekly Basis Remuneration of Demand Response, Energies. **12** (2019) 1248. https://doi.org/10.3390/en12071248.

[11] O. Abrishambaf, P. Faria, Z. Vale, Participation of a Smart Community of Consumers in Demand Response Programs, in: 2018 Clemson Univ. Power Syst. Conf., IEEE, 2018: pp. 1–5. https://doi.org/10.1109/PSC.2018.8664007.

[12] O. Abrishambaf, P. Faria, Z. Vale, Application of an optimization-based curtailment service provider in real-time simulation, Energy Informatics. **1** (2018) 3. https://doi.org/10.1186/s42162-018-0006-6.

[13] G. Lipari, G. Del Rosario, C. Corchero, F. Ponci, A. Monti, A real-time commercial aggregator for distributed energy resources flexibility management, Sustain. Energy, Grids Networks. **15** (2018) 63–75. https://doi.org/10.1016/j.segan.2017.07.002.

[14] O. Abrishambaf, L. Gomes, P. Faria, J.L. Afonso, Z. Vale, Real-time simulation of renewable energy transactions in microgrid context using real hardware resources, in: 2016 IEEE/PES Transm. Distrib. Conf. Expo., IEEE, 2016: pp. 1–5. https://doi.org/10.1109/TDC.2016.7520009.

Publication IV

C. Silva, P. Faria, Z. Vale, "Classification of New Active Consumers Performance According to Previous Events Using Decision Trees", International Federation of Automatic Control (IFAC), vol. 55, no. 9, 2022, p. 297-302

Resumen

Con la creciente preocupación sobre el cambio climático, soluciones como la generación distribuida, especialmente basada en fuentes renovables, han aumentado en el sistema energético. Sin embargo, su comportamiento volátil requiere una mayor flexibilidad por parte de la demanda para equilibrar el sistema, recurriendo a programas de respuesta a la demanda. Los consumidores activos desempeñan un papel fundamental en este nuevo paradigma. De esta manera, la incertidumbre de su respuesta a eventos desencadenados debe ser modelada. Los autores han desarrollado una tasa contextual del consumidor para seleccionar adecuadamente a los participantes en un evento de respuesta a la demanda según sus eventos anteriores en contextos similares. La innovación en el presente artículo radica en la clasificación de nuevos consumidores activos sin experiencia previa. Luego, se utilizó un método de árbol de decisiones para atribuir una tasa de confiabilidad. Se exploró un estudio de sensibilidad sobre el número de nodos hoja utilizados. Los resultados demuestran que el uso de información privada relacionada con los consumidores activos mejora el rendimiento del algoritmo.

Classification of New Active Consumers Performance According to Previous Events Using Decision Trees

Cátia Silva*, Pedro Faria*, and Zita Vale**

** GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, 4249-015, Porto, Portugal*

*** Polytechnic of Porto, 4249-015, Porto, Portugal*

Abstract: With the growing concern regarding climate change, solutions such as distributed generation, namely renewable-based, increased in the energy system. However, their volatile behavior needed more flexibility from the demand side to balance – resorting to demand response programs. Active consumers play a critical role in this new paradigm. In this way, the uncertainty of their response to triggered events should be modeled. The authors developed a contextual consumer rate to properly select the participants in a demand response event according to their previous events in similar contexts. The innovation in the present paper lies in the classification of new active consumers with no prior experience. A decision tree method was then used to attribute a trustworthy rate. A sensitivity study on the number of leaf nodes used is explored. The results prove that the use of private information related to active consumer increase the performance of the algorithm.

Keywords: Active consumer, Behavior, Decision Trees, Demand Response, Uncertainty.

1. INTRODUCTION

As an alternative for the fossil fuels in the power and energy systems, the Smart Grid concept focuses mainly on Distributed Generation (DG), particularly the renewable-based technologies, and the inclusion of the Demand Side in the market transactions. However, both have an uncertain behavior, which adds high values for the control and management of the network (Yang et al., 2019). First, the sources from DG are highly volatile. With this new paradigm, it is expected from the end-users to adapt their consumption and offer more flexibility, becoming a crucial part of the energy market for periods with low generation values.

Nevertheless, and until this point, the end-users have little or no knowledge of what was happening in the energy market since their contribution was always in an indirect way. The Demand Response (DR) concept brings the empowerment of the consumers. It increases their influence in the operations being able to react to signals and modify their consumption (Scott and Thiebaux, 2019). However, having a role in the market, it is not yet possible to transact by themselves. It is risky to give so much control to such an uncertain player with such a reduced experience. It takes time, education, and resources until they can make rational decisions. There are successful DR cases in the industrial sector since this consumer is more reliable and predictable (Vale et al., 2010). But smaller consumers represent a more complex problem and have a higher percentage in the total load consumption of the system. Human behavior depends on distinct factors, and the accurate response prediction in a certain situation can be extremely complex. From the perspective of the small consumers, comfort can be a very important topic, and to be willing to surrender would require a good motive or a good incentive (Yang et al., 2018). The authors believe that context is a crucial topic to find more acceptable assumptions. In this way, a new entity was created for the management of participants in DR events – Aggregator. It must acquire the right tools to deal with the uncertainties associated with the consumers' response (Faria and Vale, 2021). As mentioned earlier, each active consumer has a singular behavior and depends on their inserted context. For instance, information such as the time of day, the day of the week, or even the temperature that has been recorded will impact the availability modify their consumption. According to a given context, an approach gives the Aggregator confidence of the most trustworthy participants in the work developed by the authors.

The proposed methodology, presented in Figure 1, includes a Contextual Consumer Rate (CCR), which classifies each consumer according to their performance on previous events in the same context. So, suppose they have a good rate value. In that case, they can be selected to participate in the current event – giving the aggregator a higher level of confidence in the selection process. However, some of them may not have previous experience on DR events – new DR event players. The innovation from previous works by the authors is the "Rate Prediction" phase. Resorting to a machine learning algorithm, the authors intend to attribute a trustworthy rate to these new players, with only information regarding the actual context, by training the model with information for the current community. Another approach is also introduced regarding the privacy-awareness matters raised in (Silva et al., 2020) since players are hesitant on granting access and sharing private information. Different scenarios were created and compared. The rate definition is important to select trustworthy consumers from the aggregator perspective. Although the aggregator and the active consumers have a DR contract, the latter has control over the appliances. Penalties should be applied but the system was already jeopardized. This is the role of our research question: understanding the type of consumers and classifying them to decide the proper participants for each context.

The present paper is organized according to five different sections. The first one is an introduction to the topic with the motivations of the study and innovations from previous works. The following sections present a detailed explanation of the proposed methodology, a case study section, and the results found are analyzed and discussed. Finally, the conclusions withdrawn will be reviewed.

2. MATERIALS AND METHODS

Managing the flexibility provided by the active consumers in a local community can be a complex task – the right methods and tools must be applied by the aggregator – entity behind the community's supervision. In this way, the authors proposed a method to successfully operate the network in a real-time perspective – as shown in Figure 1. The focus of the present methodology is reducing the uncertainty in the response from the active consumers. However, the authors will focus on new participants with no information regarding DR events in this paper. So, the authors intend to predict their behavior according to a certain context to attribute a CCR.

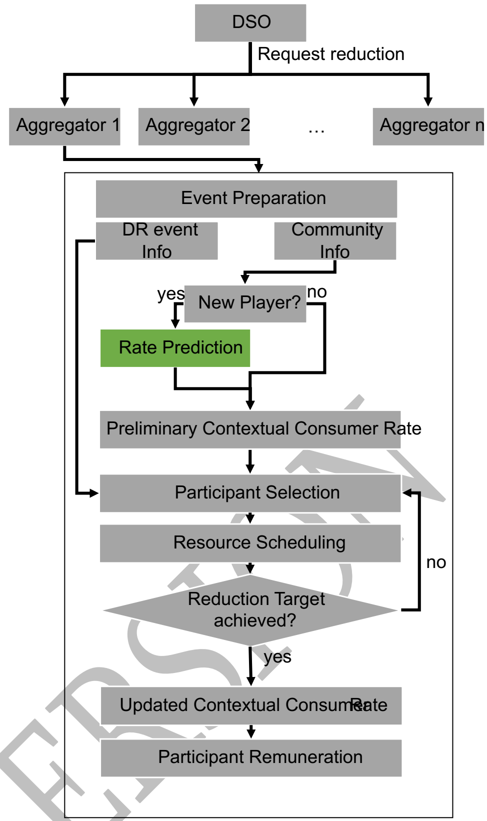


Figure 1. The proposed methodology, focusing on paper innovation.

The basis of the proposed methodology considers a setting where the Distributed System Operator (DSO) performs the load forecast for the community followed by an Optimal Power Flow and the respective analysis, looking for voltage limit violations for upper and lower bounds. If none is detected, the scheduling is performed normally. On the other hand, if any violation is detected, the DSO must request a load reduction to each community manager, the aggregators. Many other alternative solutions could be applied in this case, such as adjusting upstream transformer tap settings. However, the authors believe that active consumers should be further studied since they are becoming the center of the Smart Grid paradigm. Studying and finding solutions to deal with their uncertainty is the focus of this study.

The aggregator will then trigger a DR event – The event Preparation phase. The active consumers, with a contract, must provide demand flexibility, their availability, and the willingness to participate in this context – community info step. In previous works, the author created a trustworthy rate useful for selecting the participants of DR events, according to their performance on previous ones – the mentioned CCR. The definition and the difference between Preliminary and Updated CCR presented in Figure 1 can be seen in detail in Figure 2.

Figure 2. Contextual Consumer Rate formulation.

Consumer Historical Rate (CHR) represents the historical performance of each consumer in previous events, in similar contexts – as the average. Consumer Context Rate (CCtR) considers two viewpoints and changes according to the daily availability of the consumer – which can be different for a certain day of the week and period of the day. Consumer Last Event Rate (CLER) shows the performance of the active consumer in the last event of the same context (weekday, period, and temperature). The addition of this performance rate is important to understand and update the consumer's behavior. Consumer Location Rate (CLR) introduces the spatial flexibility concept, considering that the aggregator can access the grid bus where the violation was detected. The small consumers near this location must prioritize participation since they can be crucial to solving the problem. Equation (1) adds CLR along with CHR and CLER for this initial trustworthy rate.

$$PR = \omega_{P\_CHR} CHR + \omega_{P\_CLER}\, CLER + \omega_{P\_CLR}\, CLR + \omega_{P\_CCtR} CCtR \quad (1)$$

But a consumer with none of this information, a CCR cannot be attributed. The innovation from the present study focuses on this situation with the "Rate Prediction" step, resorting to a machine learning algorithm. The authors opted for the Decision tree (DT) method. This technique is the hierarchical exemplification of knowledge relationships that contain nodes and connections and is mainly used for grouping purposes. Like a tree, DT has a root, branches, nodes, and leaves (Charbuty and Abdulazeez, 2021). The path begins from the root, and the data is separated in sequence until a Boolean outcome at the leaf node is achieved. Decision trees have found many implementation fields because of their simple analysis and precision on multiple data forms (Zhou et al., 2021). The training database will be composed of the remaining members of the community, whereas the test database will gather contextual information regarding the current event and the new participants. Mean absolute error (MAE) measures the accuracy of continuous variables. It was used to evaluate the model, defined in (2) (Jumin et al., 2021), as CCR was considered a continuous variable.

$$MAE = \frac{1}{n}\sum_{n=1}^{N} |y_i - y_i| \quad (3)$$

With all the consumers with a CCR, the participation selection phase moves on to the next step. A linear approach is employed in the resource scheduling, and the objective function aims to minimize operational costs from the Aggregator perspective. The detailed formulation from this optimization can be seen in (Silva et al., 2021). If the reduction target is achieved, the CCR must be updated according to (4).

$$UR = \omega_{U\_CHR}\, CHR + \omega_{U\_CLER}\, CLER + \omega_{U\_CSR}\, CSR + \omega_{U\_CCtR}\, CCtR + \omega_{U\_CCER}\, CCER \quad (4)$$

The difference from the preliminary one is the Consumer Current Event Rate (CCER). Defines the rate according to the actual response of the consumer to the event: if responded as requested, the resulting rate is high. The opposite applies, and the active consumer is penalized with a lowered value of RR. The UR is highly important for the Participant Remuneration Phase because the compensation value is defined according to the performance.

3. CASE STUDY

The current section presents the detail regarding the case study and the scenarios created to prove the viability of the proposed methodology. Figure 3 shows the low voltage distribution network used, based on a real distributed grid with 236 buses. Several zones are defined according to the buses where a voltage limit violation was detected – triggering a DR event. Considering real events, the DSO detected a total of 13 voltage limit violations throughout one week. This information was used for defining the CCR but being able to attribute the proper rate to each participant is highly difficult. The authors believe that context is important, so, it should be necessary for consumers to participate several times in the same context, for different contexts. In this way, to define this dataset, the authors use information from several consumers and the different contexts they participate.

The personal availability from the consumers is provided prior when the DR contract with the aggregator is done – several schedules are agreed between both parties.

These zones were useful to define the CLR. However, the model created in the present paper is only valid for the violation detected in this zone since the CLR changes accordingly. The DR program applied was load shifting. Participating consumers, with a previous contract, allows the aggregator to shift the appliances schedule to different times. Must be highlighted that both players agreed on a schedule to control this load, to avoid causing major inconvenience to the participants. Still, an uncertainty factor exists since the consumer can switch on the appliance without further notice – penalties should be applied.

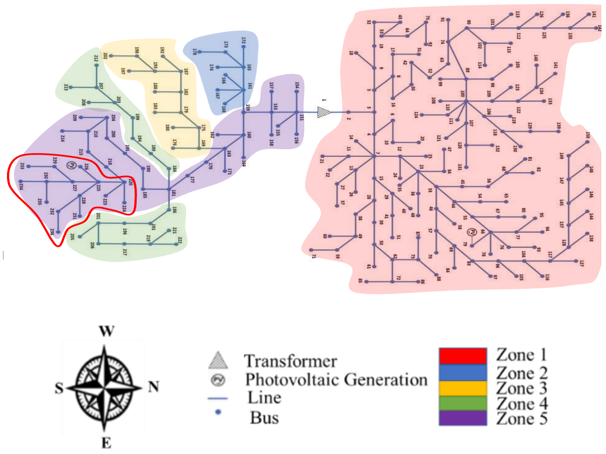


Figure 3. Zone Definition for according to the limit violation detected.

For the test dataset, it is crucial to have information regarding the new participants and the context in which the DR event was triggered. For example, figure 4 has the temperature registered in a period where a limit violation could be detected.

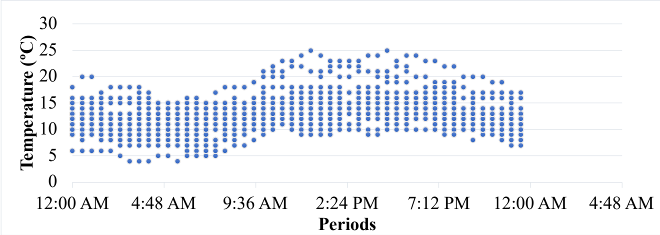


Figure 4. The temperature is registered to define the CCtR.

The dataset used to train the DT algorithm has information regarding 406 participants in DR events for several contexts. This study attributes a CCR to new players with no previous information regarding their DR event performances. Table 1 defines the scenarios created regarding the target, features, and the type of variables included in the algorithm. The authors opt for contextual information such as period, temperature, day of the week, day of the month, and if it is a holiday or not. A data preparation step was performed, where all the missing values and categorical data were dealt with. In the "Day of the week" feature, the first day is Sunday, classified as 1. The "Period" feature regards the data gathered every 15-minutes, where the first period was at 12 PM, and the dataset has information regarding one month of events.

It was also included personal information regarding the participant – their expected availability for the context in which the DR event was triggered. However, as mentioned before, privacy matters could be raised. Therefore, the authors wanted to distinguish between both perspectives: with and without any information that could probably identify the active consumer.

Table 1. Scenario Definition

Scenario		Type	1	2	3	4
Features	Period	Integer	x	x	x	x
	Temperature	Decimal	x	x	x	x
	Day of Week	Integer	x	x	x	x
	Day of Month	Integer	x	x	x	x
	Holiday	Binary	x	x	x	x
	Availability	Binary		x		x
Includes all rates?		-	No	No	Yes	Yes

The difference between scenarios lies in both availability features as well as the inclusion of all rates. For example, in the database used as training, the number of samples for rates 1 and 5 was far less than the remaining. By creating these unique scenarios, the authors want to understand the real impact of these variables in the result.

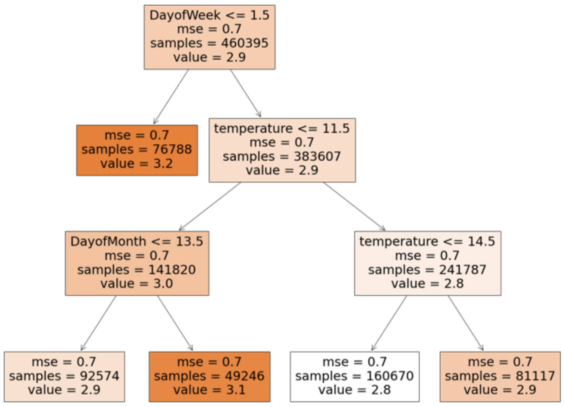
4. RESULTS AND DISCUSSION

Throughout the present section, the authors analyze and discuss the results presenting the distinct DT for each scenario and their performance when predicting the CCR. For better understanding, Figure 5 presents the DT with only five nodes. This decision tree structure was created to predict the CCR in an easy and quick way. The authors' goals are to develop a tool to be used in both planning situations (maybe weekly plan) as well as in real-time approaches. Analyzing a decision tree with several nodes takes time that sometimes the Aggregator does not have and increases the computational cost. The authors picked, in their opinion, some crucial factors that can impact consumer behavior and provoke a non-response, which will affect their CCR.

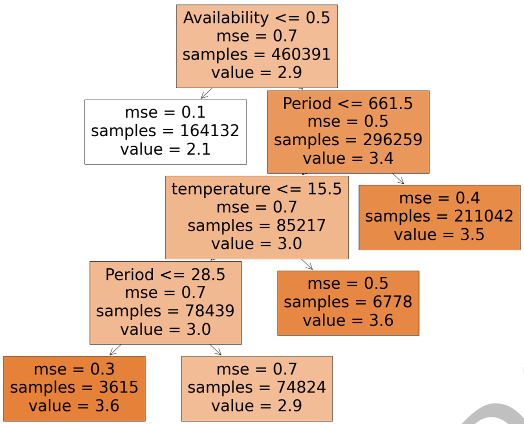
However, a sensitivity analysis was done regarding the number of nodes and the corresponding performance to understand which scenario is more reliable. The color scale in the decision trees (from white to orange) is regarding the CCR range – the higher, the darker is the color.

Analyzing the results found in Figure 5, the first scenario starts with the feature "Day of the Week." If before a Monday, the initial CCR was 3.2. On the other hand, if the "Temperature" was less than 11.5 ºC and the "Day of the Month" was less than 14, the CCR value was 2.9.

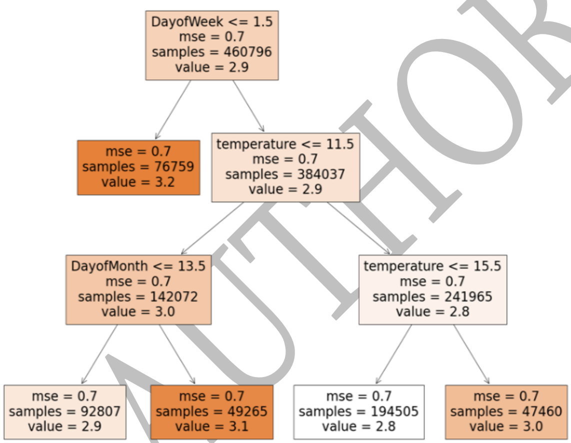
Otherwise, 3.1. However, if the "Temperature" was more than 11.5 ºC and less than 14.5ºC, the CCR value was 2.8. Otherwise, 2.9.



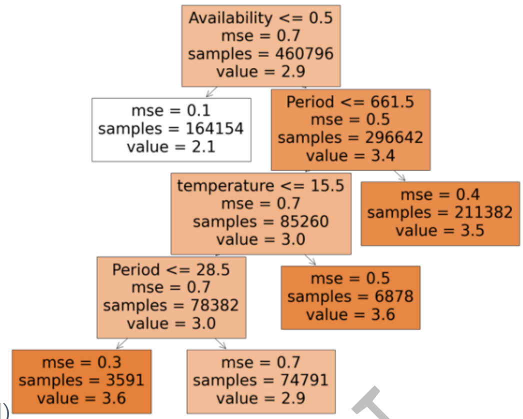
a)



b)



c)



d)

Figure 5. Decision trees a) Scenario 1, b) Scenario 2, c) Scenario 3, and d) Scenario 4.

In this perspective, "Holiday" and "Period" features were not used. Moving to Scenario 2 in Figure 5 b), if the consumer has no availability at the event, the CCR is 2.1. Else, if the "Period" is higher than 662, the CCR is 3.5. Otherwise, if the "Temperature" is higher than 15.5 ºC, the CCR is 3.6. But if the "Temperature" is less than 15.5ºC and the "Period" is lower than 29, the CCR value is 3.6 else, 2.9. In this case, "Day of the Month," "Day of the Week," and "Holiday" features were not used. In Scenario 3 (Figure 5 c)), if the "Day of the Week" is before a Monday, the initial CCR was 3.2. On the other hand, if the "Temperature" was less than 11.5 ºC and the "Day of the Month" was less than 14, the CCR value was 2.9. Otherwise, 3.1. However, if the "Temperature" was more than 11.5 ºC and less than 14.5ºC, the CCR value was 2.8. Otherwise, 3.0. In this perspective, "Holiday" and "Period" features were not used in Scenario 1. Finally, Scenario 4 in Figure 5 d) has a resulting DT with five nodes equal to Scenario 2 in Figure 5b). However, as shown in Table 2, their mean absolute error is different for the same number of nodes.

This approach is used because the sensitivity test was done for eight different experiments: 5, 20, 35, 50, 100, 500, 5000, and 10.000. Therefore, the lower the MAE, the better is the result. By analyzing the prior results, Scenario 1, the MAE reduced from 5 to 35 leaf nodes from 0.75 to 0.70. When the DT has 100 nodes, the MAE is 0.64, and only 5.000 leaf nodes reduce to 0.57. There is no value difference between the 5.000 and 10.000 leaf nodes for the first five decimals' digits: 0.57179.

Scenario 2 includes the availability for the DR event in both tests (new participants) and training databases. Compared with the previous scenario, the performance was much better since the higher value of nodes in Scenario 1 has a lower performance than the five-leaf nodes resulting in Scenario 2: 0.57 vs. 0.47. However, the difference between the several experiences is lower than in Scenario 1. For example, between 5 leaf nodes and 10.000 leaf nodes in

Scenario 1, the MAE difference is 0.17633. For this case, with five leaf nodes and 10.000 leaf nodes, the MAE difference is 0.10346. The results of Scenario 3 are like Scenario 1 regarding MAE since, with five leaf nodes, the MAE value was 0.75 and with 10.000 nodes was 0.57. The differences are only noticed on the third decimal digit. Since the availability is also used, the results are better than the previous scenario regarding the last scenario results. The better MAE was found here, being 0.36181 with 5.000 or 10.000 leaf nodes.

Table 3 presents the sensitivity test results with a different perspective: the number of actual right predictions regarding the number of samples in the total number of samples. The authors believe that an acceptable and useful accuracy, from the Aggregator perspective, is above 60%, for lower nodes. If the accuracy is low can attribute wrong CCR to the consumers, leading to loss of fairness.

Like the sensitivity test with MAE, the results for 5.000 leaf nodes and 10000 leaf nodes are similar, having the same value within scenarios. The performance of the dataset from Scenario 1 with five leaf nodes was 26.56%, and on the 50-leaf node, experience achieved the 32.57%. The higher value from this scenario was achieved in the prior experience with 47.47%, not achieving a 50% correct prediction from the total dataset.

Table 2. Sensitivity study – MAE

Max leaf nodes	Mean absolute error			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4
5	0.748	0.466	0.745	0.464
20	0.721	0.445	0.727	0.443
35	0.703	0.435	0.708	0.433
50	0.693	0.428	0.690	0.426
100	0.643	0.412	0.647	0.411
500	0.574	0.372	0.574	0.370
5,000	0.571	0.362	0.571	0.361
10,000	0.571	0.362	0.571	0.361

Table 3. Sensitivity study – Accuracy

Max leaf nodes	Accuracy			
	Scenario 1	Scenario 2	Scenario 3	Scenario 4
5	26,56%	64,03%	26,90%	63,95%
20	28,84%	62,06%	29,67%	62,04%
35	31,53%	65,76%	30,68%	65,86%
50	32,57%	66,84%	33,47%	67,03%
100	41,59%	68,11%	39,01%	68,19%
500	46,94%	66,84%	47,24%	70,19%
5,000	47,47%	70,55%	47,81%	70,59%
10,000	47,47%	70,55%	47,81%	70,59%

Regarding Scenario 2, considering the availability from all the consumers in the training dataset and the new ones, the performance from 5 leaf nodes was way superior achieving 64.03% of correct answers – almost 40% higher than the previous scenario in the same experience. Like the previous table results, the difference between leaf nodes test for the several experiences is lower than in Scenario 1. For example, between 5 leaf nodes and 10.000 leaf nodes in Scenario 1, the percentage difference is 20.91%. For this case, with five leaf nodes and 10.000 leaf nodes, the percentage difference is 6,52%.

Moving on to Scenario 3, the resulting percentages are like Scenario 1 – starting with 26.90% in 5 leaf nodes. However, on 10.000 leaf nodes, the percentage was 47.81% (only 0.34% better than the same experience on Scenario 1). Although the number of samples from rates 1 and 5 was lower, it is important to include them in the training dataset. Lastly, the first two experiences of Scenario 4 had a lower percentage than Scenario 2. Also, the difference of performance between the max-leaf nodes in this sensitivity was 0.04%. In Figure 6, the authors compare both Scenario 2 and Scenario 4, choosing a consumer in a certain context to understand and further discuss the results in a more detailed perspective.

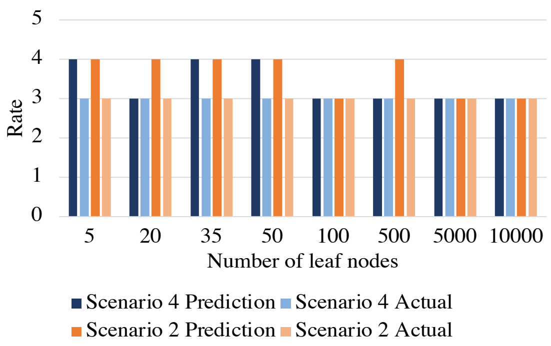


Figure 6. Comparison between Scenario 2 and Scenario 4 for a selected consumer in a certain context.

For 5 leaf nodes, both Scenario 2 and Scenario 4 models could not attribute the right rate to this consumer – predictions indicate a rate 4, but the actual one was 3. Moving to 20 leaf nodes, Scenario 4 made the right prediction while Scenario 2 maintained the previous result. In the following leaf nodes studies (35 and 50), both scenarios fail to attribute the right rate to this consumer. However, after these two studies, Scenario 4 was always able to attribute the actual rate to the consumer, unlike Scenario 2, which managed to fail again on the 500 leaf node study.

When the aggregator has no private information regarding the new participant, it is worth increasing the number of leaf nodes. Otherwise, although the results are better, the percentage difference between fewer leaf nodes and 10000 leaf nodes may not be worth visual analysis.

5. CONCLUSION

To suppress the impacts of the non-renewable resources regarding climate changes, the demand side must provide flexibility to achieve system balance when the renewable resources may not be sufficient. However, the uncertain behavior from the active consumers increases the complexity of managing an active community. The authors propose a tool to aid the aggregator in choosing the proper participants for a DR event. This rate classifies the participants according to their performance on DR events. In the case study, the idea is to give a trustworthy rate to a new player with no performance information. To achieve this, a decision tree was developed considering different context information at the DR event time. From Aggregator's perspective, the availability from active consumers can be useful, but privacy matters could be raised. The scenarios were divided: with and without private information. A sensitivity test was done regarding the leaf nodes used in the decision tree. Results show that scenarios with private information have better performance results – 71% accuracy. When no data is given, the higher the number of leaf nodes, the better the algorithm's performance.

REFERENCES

Charbuty, B., Abdulazeez, A., 2021. Classification based on decision tree algorithm for machine learning, in: Journal of Applied Science and Technology Trends 2, 20–28.

Faria, P., Vale, Z., 2021. Distributed Energy Resource Scheduling with Focus on Demand Response Complex Contracts, in: Journal of Modern Power Systems and Clean Energy 9, 1172–1182. https://doi.org/10.35833/MPCE.2020.000317

Jumin, E., Basaruddin, F.B., Yusoff, Y.Bte.M., Latif, S.D., Ahmed, A.N., 2021. Solar radiation prediction using boosted decision tree regression model: A case study in Malaysia, in: Environmental Science and Pollution Research 28, 26571–26583. https://doi.org/10.1007/s11356-021-12435-6

Scott, P., Thiebaux, S., 2019. Identification of Manipulation in Receding Horizon Electricity Markets, in: IEEE Transactions on Smart Grid 10, 1046–1057. https://doi.org/10.1109/TSG.2017.2758394

Silva, B.N., Khan, M., Han, K., 2020. Futuristic Sustainable Energy Management in Smart Environments: A Review of Peak Load Shaving and Demand Response Strategies, in: Challenges, and Opportunities. Sustainability 12, 5561. https://doi.org/10.3390/su12145561

Silva, C., Faria, P., Vale, Z., 2021. Managing Smart City Power Network by Shifting Electricity Consumers Demand, in: Sustainable Smart Cities and Territories International Conference 253, 81–91. https://doi.org/10.1007/978-3-030-78901-5_8

Vale, Z., Morais, H., Faria, P., Khodr, H., Ferreira, J., Kadar, P., 2010. Distributed energy resources management with cyber-physical SCADA in the context of future smart grids, in: Proceedings of the Mediterranean Electrotechnical Conference - MELECON. IEEE, pp. 431–436. https://doi.org/10.1109/MELCON.2010.5476239

Yang, J., Huang, G., Wei, C., 2018. Privacy-aware electricity scheduling for home energy management system, in: Peer-to-Peer Networking and Applications. pp. 309–317. https://doi.org/10.1007/s12083-016-0492-x

Yang, X., Zhang, Y., He, H., Ren, S., Weng, G., 2019. Real-Time Demand Side Management for a Microgrid Considering Uncertainties, in: IEEE Transactions on

Smart Grid. pp. 3401–3414. https://doi.org/10.1109/TSG.2018.2825388

Zhou, H., Zhang, J., Zhou, Y., Guo, X., Ma, Y., 2021. A feature selection algorithm of decision tree based on feature weight, in: Expert Systems with Applications 164, 113842.

Publication V

C. Silva, P. Faria, and Z. Vale, "DR Participants' Actual Response Prediction Using Artificial Neural Networks," 17th International Conference on Soft Computing Models in Industrial and Environmental Applications (SOCO) p. 176–185, 2023

Resumen

Empoderar a los consumidores aumentará la complejidad en la gestión de las comunidades locales. Habilitar la comunicación bidireccional y hacer que los electrodomésticos sean más inteligentes puede ser un gran avance hacia la implementación de la respuesta a la demanda. Sin embargo, es necesario desarrollar una solución capaz de proporcionar el conocimiento y las herramientas adecuadas. Los autores proponen una metodología para gestionar de manera óptima a los consumidores activos en eventos de respuesta a la demanda, teniendo en cuenta el contexto en el que se desencadenan. El operador del sistema de distribución detecta una violación de voltaje y solicita una reducción de carga a los agregadores. En este estudio, para probar una tasa de rendimiento diseñada por los autores para lidiar con la incertidumbre de la respuesta, se realiza una comparación entre la reducción solicitada y la reducción real. La metodología propuesta se aplicó a tres escenarios donde el objetivo es predecir la respuesta de los consumidores utilizando redes neuronales artificiales, modificando las características utilizadas en la entrada.

DR participants' actual response prediction using Artificial Neural Networks

Cátia Silva[1], Pedro Faria[1], and Zita Vale[1]

[1] GECAD - Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development; LASI - Intelligent Systems Associate LAboratory
Polytechnic of Porto, Portugal
cvcds@isep.ipp.pt,pnf@isep.ipp.pt,zav@isep.ipp.pt

Abstract. Empowering the consumers will increase the complexity of local communities' management. Enabling bidirectional communication and appliances to become smarter can be a huge step toward implementing demand response. However, a solution capable of providing the right knowledge and tools must be developed. The authors thereby propose a methodology to manage the active consumers on Demand Response (DR) events optimally, considering the context in which it is triggered. The distribution system operator detects a voltage violation and requests a load reduction to the aggregators. In this study, to test a performance rate designed by the authors to deal with response uncertainty, a comparison between requested and actual reduction is done. The proposed methodology was applied to three scenarios where the goal is predicting the response from the consumers using artificial neural networks, by changing the features used in the input.

Keywords: Active consumers, Artificial Neural Networks, Demand response, Machine Learning, Smart grids

1 Introduction

The energy sector is facing changes that will drive toward a more sustainable power and energy use. The growing concern, regarding climate change, introduce distributed generation solutions to deal with the greenhouse effects and air pollution. However, the volatile behavior of these resources requires more flexibility from the demand side. So, the active consumers are empowered and their role in the market is changing. The authors in [1] reinforce the importance of flexibility in the system to enable and promote renewable consumption and reduce the consumers' energy costs while maintaining comfort. Their study presents a Stackelberg game optimization framework for integrated energy systems scheduling by coordinating renewable generations and demand response. However, only the uncertainty from renewable generations is included. The authors in [2] refers those small consumers such as domestic will play a more active role in managing the system and becoming producers of their energy. The simulation results from their study showed that promoting cooperation between the power supplier and the prosumer could lead to significant cost reductions and energy savings. É. Mata et al. [3] also refer that including flexible behavior can bring several benefits for all the parties: providing service toward energy system stability, security, and cost-effectiveness as well as growing energy awareness for active consumers who participate and provide load reduction.

With this, solutions must be developed to aid the aggregator in the complex task of managing the active communities to be able to send the proper signals to the most trustworthy players. The complexity comes from the different behavior of each resource for each context, increasing the uncertainty of the response. The authors believe that attributing a Contextual Consumer Rate (CCR) will be useful to select the right participants for a DR event since avoiding discomfort from the consumer side and reducing costs from the aggregator perspective. CCR's goal is to characterize the performance of each resource in a DR event, for each context. The present study is a continuation of previous works [4]–[6], where the goal is to find ways to deal with the DR response uncertainty

The present paper is organized according to five different sections. The first one is an introduction to the topic with the motivations of the study and innovations from previous works. The following sections present a detailed explanation of the proposed methodology, a case study section, and the results found are analyzed and discussed. Finally, the conclusions withdrawn will be reviewed.

2 Proposed Methodology

To further apply the smart grid concept in the real market, it will be crucial to give active consumers the proper information regarding the market transactions to provide the flexibility to achieve reduction goals. Figure 1 shows the algorithm for the proposed methodology. Considering that Distribution System Operator (DSO), after a power flow analysis where a voltage violation was found, requires a load reduction to all the aggregators associated. With this signal, all of them must trigger a DR event.

With this, it will be possible to identify the proper participants, the ones with higher levels of trust for the context, dealing with the uncertainty. For instance, are all active consumers prepared to participate in the same way and give up their comfort to assure their position in the market? Currently, probably not. Most of them, being new players in the market, have no or insufficient knowledge regarding the actual transactions. Many works in the literature are expecting them to be as always rational and economic players and, in the authors' opinion, this approach may lead to inaccuracies. So, understanding previous behaviors in the same context, and contemplating their availability at the time of the event, can avoid misleading the aggregator perspective when performing the scheduling of the small resources in the community.

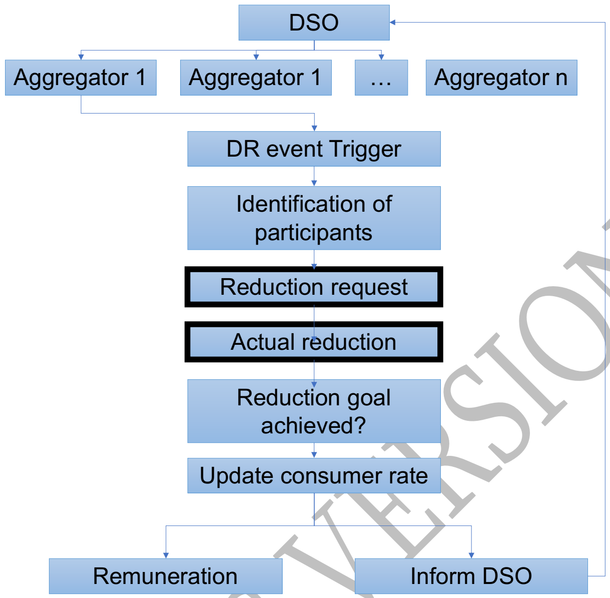


Fig 1. The proposed methodology, focusing on consumer response.

CR depends on several factors regarding consumer characteristics: Context Rate (CR), Historic Rate (HR), Last Event Rate (LER), Spatial Rate (SR), and Response Rate (RR). This rate has two phases: the preliminary (PR) - for the selection purposes, and the updated (UR) - for remuneration purposes. The first one is formulated by the sum of CR, HR, SR, and LER, each one with an attributed weight. If a consumer does not have any previous information, for instance, when it is the first time with DR programs, the lowest rate is assigned and must improve the CCR.

Understanding each one, CR depends on the availability and the willingness to participate according to the time (ω_{CRP} CRP) and weather (ω_{CRW} CRW) recorded during the period of the event – both have a major influence on consumer response, particularly when distinguishing working days from the weekend or days with extreme temperatures. The formulation can be seen on Equation 1.

$$CR = \omega_{CRP}\, CRP + \omega_{CRW}\, CRW \tag{1}$$

Using HR, the Aggregator learns from historical information collected from active consumer and their performance in previous events in similar contexts, according to Equation 2.

$$HR = \text{average (previous performances same context)} \tag{2}$$

LER is used to update CCR according to only previous event performance. For instance, a consumer with a higher rate on HR can have a poor LER, which will be important for updating issues.

$$LER = UR \text{ last event in the same context} \tag{3}$$

In the case of SR, for the case where the aggregator has information regarding a voltage violation in a network bus, it will be important to give priority to the ones closer to the local.

The preliminary CCR is formulated according to Equation 5.

$$PR = \omega_{HR} * HR + \omega_{LER} * LER + \omega_{CR} * CR + \omega_{SR} * SR \tag{5}$$

Moving on to the reduction request phase, a linear optimization of the resources scheduling is done. The objective function aims to minimize operational costs from the Aggregator perspective [7], [8]. Performed the scheduling phase, the reduction is requested to the active consumers. In this step, the innovation from the present paper is presented. Here, the authors intend to predict the actual response from the selected participants as an evaluation of the CCR methodology. The authors opted for the Artificial Neural Networks method. The training database will be composed of the members of the community that already participated in the event, whereas the test database will gather contextual information regarding the current event and will try to predict the response from the active consumers for the event. Should be highlighted that the load requested to be reduced is shifted to another period according to the consumers' preferences.

After, as soon as the reduction request and the actual reduction is compared, the CCR is updated, as mentioned earlier. This updated version is formulated by the sum of CR, HR, SR, LER, and RR, each one with an attributed weight, according to Equation 6.

$$UR = \omega_{HR}\, HR + \omega_{LER}\, LER + \omega_{SR}\, SR + \omega_{CR}\, CR + \omega_{RR}\, RR \tag{6}$$

RR represents the performance according to the actual response of the consumer in the current event: if the active consumer responded as requested, the rate would be high, the opposite will also apply, and the active consumer will be penalized with a reduced value. Once the CCR is updated, the remuneration is attributed to the participants, and the DSO is informed of the DR reduction obtained.

3 Case Study

For the present section, the authors intend to test the proposed innovation in the case study, creating different scenarios. For this case, Figure 2 represents the low voltage distribution network used for the case study, based on a real distributed grid with 236 buses.

The authors believe that context is important, so, it should be necessary for consumers to participate several times in the same context, for different contexts. In this way, to define this dataset, the authors use information from several consumers and the different contexts they participate.

The active consumer availability must be also provided in the input since it is essential to predict the actual response from the participants – several schedules are agreed upon in the DR contract between both parties. As mentioned in the previous section, the DR program applied is load shifting. The selected consumers allow shifting the appliances' schedule – both players agreed on a schedule to control this load, to avoid causing major inconvenience to the participants. Still, an uncertainty factor exists since the consumer can switch on the appliance without further notice – penalties should be applied.

To the ANN algorithm training step, a total of 406 participants in the DR events were used, considering several contexts – both temperature and time factors. Also, to evaluate the importance of the personal data, the authors added two new features and simulated according to the percentages presented in the study done in [9], performing the extrapolation for this case.

The goal of the ANN is to try to predict the actual response from the active consumer, as their expected availability for the context in which the DR event was triggered. The authors wanted to distinguish between both perspectives: with (Scenario 2 and 3) and without (Scenario 1) any information that could probably identify the active consumer. With this, the authors intent to understand if the personal data can lead to better results, since can better identify each consumer.

4 Results and Discussion

Table I defines several scenarios where the features are DR period, temperature, day of the week, day of the month, the CCR, age and gender of the participants. The independent rates such as CR, HR, SR and LER were not included as input feature since are already represented by the CCR. To express the age interval and gender with integers, the authors used a label, and their distribution can be seen in Table II and Table III. Also, reference [9] was used to extrapolate the percentage of participants within the age interval and gender features.

Table I. Scenarios defined for the proposed study.

Scenario		Type	1	2	3
Features	Period	Integer	x	x	x
	Temperature	Decimal	x	x	x
	Day of Week	Integer	x	x	x
	Day of Month	Integer	x	x	x
	CCR	Integer		x	x
	Age	Integer			x
	Gender	Integer			x

Table II. Age interval input definition

Age Interval	[9]	Participants	Label
[20,29]	3.00%	11	1
[30,39]	25.80%	105	2
[40,49]	38.70%	158	3
[50,59]	23.8%	97	4
[60,69]	8.60%	35	5
[70,79]	0.10%	0	6

Table III. Gender input definition

Gender	[9]	Participants	Label
Female	49.80%	202	0
Male	50.2%	203	1

The three defined scenarios are increasing the level of information since more features are added. The first one does not include any knowledge that could lead to the identification of the active consumer, since privacy problems can be raised – namely since CCR includes the SR. A data preparation step was performed, where all the missing values and categorical data were dealt with. In the "Day of the week" feature, the first day is Sunday, classified as 1. The "Period" feature regards the data gathered on a 15-minute basis, where the first period was at 12 PM, and the input dataset has information regarding one month of events.

The implementation of ANN for the present case study was performed using python language and resorting to Google Colab. The libraries for this purpose were pandas, numpy, tensorflow and scikit-learn. As input, the dataset with more features has 6 dimensions and a total of 1.169.274 records per dimension and was withdrawn from previous works by the authors [7], diving the test and train datasets in a 20 to 80 percentage. The authors main goal is to create an ANN capable of predict the active consumer availability to respond to a DR event in a certain context. There was a total of two hidden layers, the batch size was 32 and the number of epochs was 100. For the target value, it was considered that 0 represents a non-response and 1 represents a response.

When importing the dataset, and since the categorical variable were already dealt with, it was time to split into training and testing dataset. Firstly, the authors used the train_test_split function from the scikit-learn library, using a configuration such that 80 percent of data will be there in the training phase and 20 percent of data will be in the testing phase. Also, the feature scaling was performed.

Initializing the ANN by creating an object by using a Sequential class – the input layer. After, the first test is initialized, modifying the number of hidden layers comparing one and two. It is believed that one hidden layer might be enough by many authors in the literature in the Dense class: units and activation. Units stands for the number of neurons that will be presented in the layer and activation specifies. For the present study, rectified linear unit was used as an activation function. Finally, the output layer is created. Should be highlighted that, since this is a binary classification problem – 0 represents a non-response and 1 represents a response, only one neuron it is allocated to the output. So, unit is equal to one. For this final layer, the activation function was sigmoid. With this, it is possible to compile the ANN, where the optimizer used was adam, the loss function was binary_crossentropy, and the performance metrics used was accuracy. As the last step, the fitting process introduces the number of epochs. For this case, one hundred epochs were studied.

So, the results from the case study one, as a training dataset with 80 percent, number of hidden layers equal to one and number of epochs equal to 100 and can be seen in Figure 2.

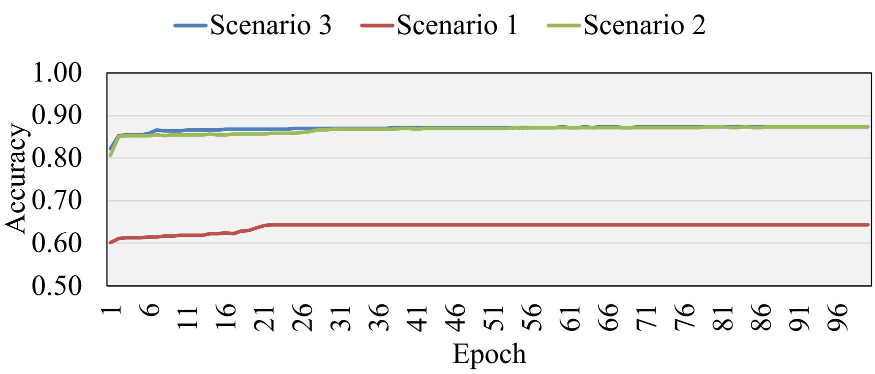


Fig 2. Case Study 1 – Scenario accuracy comparison

The time per epoch was rather small for all the data considered, around 20s, taking a maximum of 34 minutes per scenario. Regarding the values of accuracy, scenario 1 was the one with a lower value. The remaining had similar behaviour, achieving 87.32% and 87.41%, respectively. Regarding the prediction results, Table IV, presents the comparison for this case study

Table IV. Case Study 1 – Prediction vs Actual results from ANN

Scenario	Prediction		Actual	
	Responses	Non-responses	Responses	Non-responses
1	115199	0	74.065	41.134
2	78939	36260		
3	71080	44119		

The ANN in scenario 1 predicted that all the participants responded for the contexts in the test. Although only 74.065 actually participated. Regarding scenario 2, the error on the prediction was a total of 4874 records while scenario 3 deviation was around 2985 records.

Moving for the case study 2, where the dataset was divided into 80 percent for training, the number of hidden layers equals to two and number of epochs equals to 100. So, the ANN accuracy for the three different scenarios can be seen in Figure 3. Again, the time per epoch was rather small for all the data considered, around 20s, taking a maximum of 36 minutes per scenario.

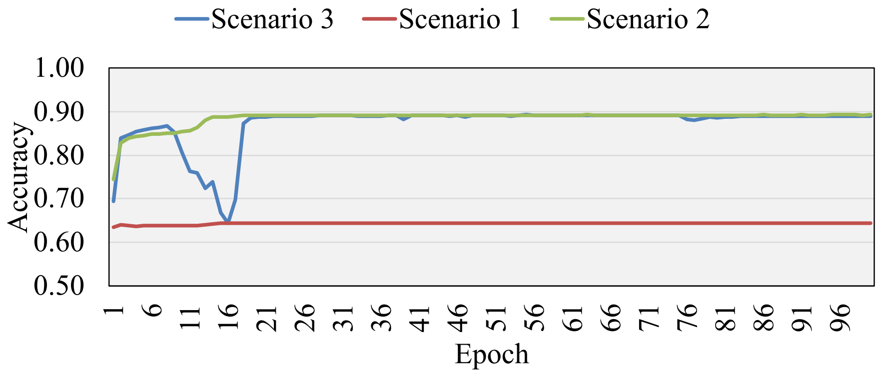


Fig 3. Case Study 2 – Scenario accuracy comparison

The scenario 1 was the one with the lowest accuracy. Considering only the outside contexts do not lead to a high value of accuracy since the maximum value (64.35%) was found on epoch 16 and maintained this value until epoch 100. Regarding scenario 2, remembering that the different between the last is the CCR, the accuracy increased around 24.95% for the maximum value. However, this value was only achieved in the epoch 86. For the last scenario, the maximum accuracy value was close to scenario 2 (89.29%), yet, it was reached sooner, on epoch 55.

So, in terms of practical numbers, Table V presents the comparison between the predicted and the actual values for the trained ANNs.

Table V. Case Study 2 – Prediction vs Actual results from ANN

Scenario	Prediction		Actual	
	Responses	Non-responses	Responses	Non-responses
1	115.199	0	74.065	41.134
2	80.217	34.982		
3	78.944	36.255		

The test dataset had a total of 115.199 records and, that was the number of responses that scenario 1 predicted – although the number of actual responses was 74.065. For scenario 2, the number of predicted responses was 6.152 above the actual value. While for scenario 3, the predicted responses were below, 4.879 records closer to the actual value. Indeed, having more information regarding the active consumers helped reduce the number of responses that were non-responses. Regarding the number of hidden layers, for scenario 1 there was no difference. For both scenario 2 and scenario 3, two layers had a higher value of accuracy but in the comparison of predicted records, one layer had lower errors.

5 Conclusion

Nowadays, to deal with the impacts of the non-renewable resources regarding climate change, the active consumers must provide flexibility to achieve system balance when the renewable resources do not. Yet, it will take time, education, and resource to make rational decisions as economic players. In this way, the authors propose a Contextual Consumer Rate as a tool to aid the aggregator in choosing the proper participants for a DR event. This rate classifies the participants according to their performance at DR events.

In the case study presented, the idea was to design an ANN capable of predicting the actual response of a participant in a DR event using features such as DR period, temperature, day of the week, day of the month, the CCR, age, and gender of the participants. However, privacy concerns were raised so, three different scenarios were created to understand the need for personal information for the proposed methodology. Also, a comparison between the number of hidden layers in ANN was performed. The scenario, where besides outside context information, the CCR was included had high values of accuracy. Although CCR can provide personal information, regarding to the location of the active consumer, can also give to the aggregator proper knowledge to predict the actual response from the active consumers in the local community with only one feature. Also, according to the results section, after epoch 30 nothing significant happens but, to take this conclusion was needed to test with a higher number of epochs.

Acknowledgments

This article is a result of the project RETINA (NORTE-01-0145-FEDER-000062), supported by Norte Portugal Regional Operational Programme (NORTE 2020), under the PORTUGAL 2020 Partnership Agreement, through the European

Regional Development Fund (ERDF). Cátia Silva is supported by national funds through Fundação para a Ciência e a Tecnologia (FCT) with PhD grant reference SFRH/BD/144200/2019. Pedro Faria is supported by FCT with grant CEECIND/01423/2021. The authors acknowledge the work facilities and equipment provided by GECAD research center (UIDB/00760/2020) to the project team.

References

1. Y. Li, C. Wang, G. Li, and C. Chen, "Optimal scheduling of integrated demand response-enabled integrated energy systems with uncertain renewable generations: A Stackelberg game approach," Energy Conversion and Management, vol. 235, p. 113996, May 2021, doi: 10.1016/j.enconman.2021.113996.
2. V. Stavrakas and A. Flamos, "A modular high-resolution demand-side management model to quantify benefits of demand-flexibility in the residential sector," Energy Conversion and Management, vol. 205, p. 112339, Feb. 2020, doi: 10.1016/j.enconman.2019.112339.
3. É. Mata et al., "Non-technological and behavioral options for decarbonizing buildings – A review of global topics, trends, gaps, and potentials," Sustainable Production and Consumption, vol. 29, pp. 529–545, Jan. 2022, doi: 10.1016/j.spc.2021.10.013.
4. C. Silva, P. Faria, and Z. Vale, "Finding the Trustworthy Consumers for Demand Response Events by Dealing with Uncertainty," 21st IEEE International Conference on Environment and Electrical Engineering and 2021 5th IEEE Industrial and Commercial Power System Europe, EEEIC / I and CPS Europe 2021 - Proceedings, 2021, doi: 10.1109/EEEIC/ICPSEUROPE51590.2021.9584667.
5. C. Silva, P. Faria, and Z. Vale, "Rating the Participation of Electricity Consumers in Demand Response Events," International Conference on the European Energy Market, EEM, vol. 2020-September, Sep. 2020, doi: 10.1109/EEM49802.2020.9221907.
6. C. Silva, P. Faria, and Z. Vale, "A Consumer Trustworthiness Rate for Participation in Demand Response Programs," IFAC-PapersOnLine, vol. 53, no. 2, pp. 12596–12601, Jan. 2020, doi: 10.1016/J.IFACOL.2020.12.1825.
7. C. Silva, P. Faria, and Z. Vale, "Rating the Participation in Demand Response Programs for a More Accurate Aggregated Schedule of Consumers after Enrolment Period," Electronics (Basel), vol. 9, no. 2, p. 349, Feb. 2020, doi: 10.3390/electronics9020349.
8. C. Silva, P. Faria, Z. Vale, J. M. Terras, and S. Albuquerque, "Rating the participation in Demand Response events with a contextual approach to improve accuracy of aggregated schedule," Energy Reports, vol. 8, pp. 8282–8300, Nov. 2022, doi: 10.1016/j.egyr.2022.06.060.
9. S. Yoo, J. Eom, and I. Han, "Factors driving consumer involvement in energy consumption and energy-efficient purchasing behavior: Evidence from Korean residential buildings," Sustainability (Switzerland), vol. 12, no. 14, pp. 1–20, 2020, doi: 10.3390/su12145573.

Publication VI

C. Silva, P. Faria and Z. Vale, "Using Supervised Learning to Assign New Consumers to Demand Response Programs According to the Context," IEEE International Conference on Environment and Electrical Engineering (EEEIC), Prague, Czech Republic, pp. 1-6, 2022

Resumen

Los consumidores activos ahora tienen un mayor poder gracias al concepto de la "smart grid". Para evitar el uso de combustibles fósiles, el lado de la demanda debe proporcionar flexibilidad a través de eventos de respuesta a la demanda. Sin embargo, seleccionar a los participantes adecuados para un evento puede ser complejo debido a la incertidumbre de la respuesta. Los autores diseñan una Tasa del Consumidor Contextual para identificar a los participantes confiables según su desempeño anterior. En el presente estudio de caso, los autores abordan el problema de los nuevos jugadores sin información previa. De esta manera, se compararon dos métodos diferentes para predecir su tasa. Además, los autores también hacen referencia a la prueba de privacidad del consumidor en el conjunto de datos con y sin información que pueda llevar a la identificación de los participantes. Los resultados encontrados demuestran que, para la metodología propuesta, la información privada no tiene un impacto significativo en la atribución de una tasa.

Using Supervised Learning to Assign New Consumers to Demand Response Programs According to the Context

Cátia Silva, Pedro Faria, Zita Vale
GECAD – Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development, 4249-015 Porto, Portugal
cvcds@isep.ipp.pt; pnf@isep.ipp.pt; zav@isep.ipp.pt

***Abstract*—Active consumers have now been empowered thanks to the smart grid concept. To avoid fossil fuels, the demand side must provide flexibility through Demand Response events. However, selecting the proper participants for an event can be complex due to response uncertainty. The authors design a Contextual Consumer Rate to identify the trustworthy participants according to previous performances. In the present case study, the authors address the problem of new players with no information. In this way, two different methods were compared to predict their rate. Besides, the authors also refer to the consumer privacy testing of the dataset with and without information that could lead to the participant identification. The results found to prove that, for the proposed methodology, private information does not have a high impact to attribute a rate.**

Keywords—Active Consumers, Decision Tree, Demand Response, Random Forest, Spatial Flexibility

I. INTRODUCTION

The progression to a future without fossil fuels in the power and energy systems includes the smart grid concept, which presents the Distributed Generation (DG) option such as renewable technologies [1]. However, the volatile behaviours from the sources, such as sun and wind, will jeopardise the reliability and security of the network. In this way, the demand side must provide more flexibility in changing the existing paradigm – where the supply follows the demand needs [2]. With the introduction of the Demand Response (DR) programs, the active consumers are empowered, and their influence in the market increases. By pursuing the signals given by the community managing entity, active consumers should change their load profile by participating in the market transactions to provide a smooth transaction of the renewable technologies into the energy market [3].

Yet, most active consumers have no or low information regarding the market transactions since their contribution was always indirect. Furthermore, predicting behaviour from the demand side can be rather difficult. For instance, industrial and commercial consumers can be more predictable since their routines are more stable, and there are successful DR cases that prove this statement. But, for the domestic type, which represents a more complex problem since human behaviour depends on distinct contexts and factors, finding a way to motivate their participation can be extremely complex. The literature refers that, from a smaller consumer's perspective, from a smaller consumer perspective, the literature refers that comfort is crucial, and being willing to forfeit would require a good motive and a good incentive [4][5].

In this way, giving an important role to such uncertain players is highly risky. Active communities should be managed with the proper tools by an experienced entity. It will take time, education, and resources until active consumers make rational decisions on their own that benefit both parties [6]. Until then, the literature must gather knowledge to design a proper solution capable of dealing with the uncertainty from both active consumers' behaviour and the volatile behaviour of the DG resources.

To contribute, the authors of the present paper introduce an approach that is qualified to complete the previously mentioned task. Although the focus of the present paper is the active consumers, the proposed methodology is being built to be also capable of dealing with all the resources from an active community. For instance, DG, prosumers, energy storage systems and electric vehicles [7]–[9].

With this, the authors believe that the context in which the DR event is triggered is crucial for the active consumers' continuous participation. In other words, understanding their availability and flexibility for different contexts can be crucial in selecting the proper participants in a community for a requested reduction event. For instance, external factors such as the time of day, the day of the week, or even the temperature can impact the active consumer response to an event. In this way, gathering this knowledge is important to reduce uncertainty. The authors design a Contextual Consumer Rate (CCR) to classify each consumer according to their performance in previous events in the same context to deal with this. The aggregator has more confidence in selecting the most trustworthy participants according to a certain context. The baseline scenario for the proposed methodology presented in this paper starts with a power flow analysis from the Distribution System Operator (DSO). When a voltage limit violation is identified, this entity requires a load reduction to all the aggregators in the nearby communities. Here, a DR event is triggered, and the event must be prepared with the information from the participants. The innovation from previous works by the authors is a new phase where the new players – with no DR performance and therefore no CCR, are classified, and a rate is attributed: Rate Prediction. In the present case study, the authors compare two supervised machine learning methods, both used in classification: Decision Trees (DT) and Random Forest (RF).

The objective of the present paper is to build a model capable of attributing a CCR to a new player. In this study, as

This work has received funding from FEDER Funds through COMPETE program and from National Funds through (FCT) under the projects UIDB/00760/2020, PRECISE (PTDC/EEI-EEE/6277/2020), CEECIND/02887/2017, and SFRH/BD/144200/2019.

978-1-6654-8537-1/22/$31.00 ©2022 IEEE

innovation and contribution from the previous works done by the authors [7], this new phase was added to the methodology, and two different supervised learning models were compared: Decision Tree and Random Forest. Although private information may be needed – such as the location of the active consumer, the authors want to understand the impact of this knowledge.

Five sections divide the present paper. After the introduction, a more detailed explanation of the methodology is presented, followed by the case study definition and a discussion of the results. Finally, the conclusions withdrawn are summarised.

II. Methodology

The complexity of managing a local community becomes higher with the empowerment of the consumers. As the focus of the new paradigm introduced by the smart grid concept, the active consumers' flexibility is crucial to maintaining the system's reliability and security. In this way, the authors proposed a methodology capable of dealing with the response uncertainty of these new players, as can be seen in Figure 1.

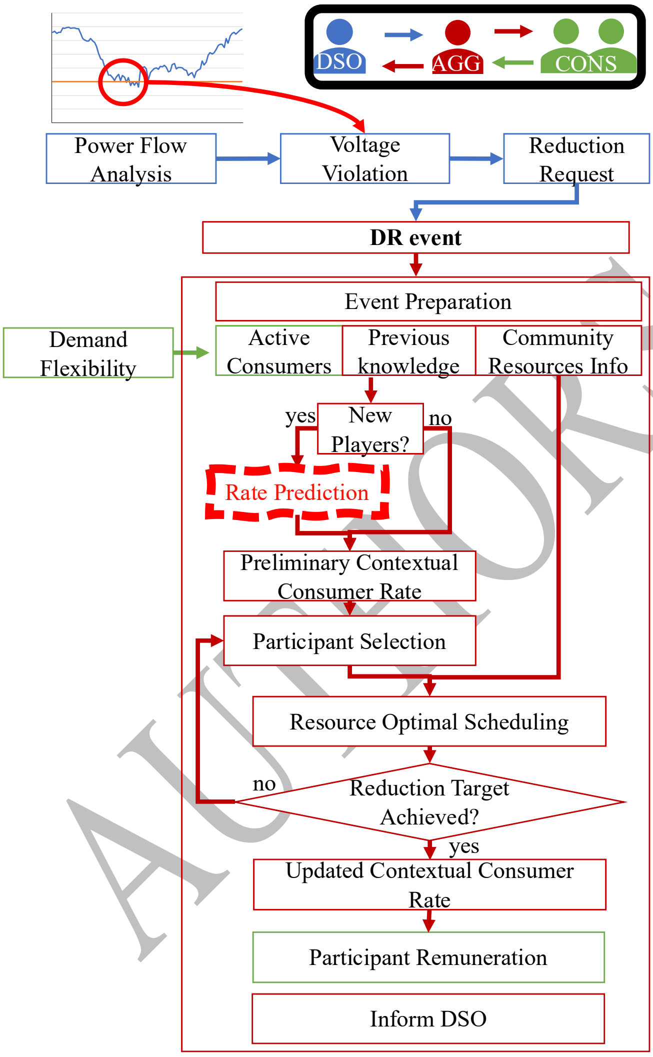


Fig. 1. Proposed Methodology – focus on rate prediction from new players.

The baseline scenario for the proposed methodology simulates a voltage limit violation identified by the DSO (its actions are represented with a blue line in Figure 1). A reduction request is sent to the community managers to trigger a DR event. The aggregator (represented with the red line and mentioned as AGG) gathers all the data to prepare for the event. In the same stage, the expected demand flexibility for the event context by the active consumers (represented with a green line) is also collected. The aggregator searches for new players from the demand side – new participants with no information regarding DR events performance and, therefore, no CCR. In this step, the authors intend to predict their response to the event context to attribute the proper CCR. This rate is useful for classifying the active consumers and selecting the proper participants according to the DR event context. Detailing the formulation of the CCR, Figure 2 represents all the components for both stages: preliminary and updated. The first one is used to aid in participation selection. The update includes each participant's performance, comparing the requested and the actual response.

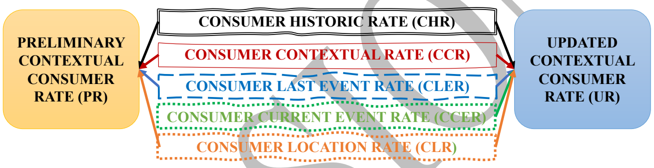


Fig. 2. Contextual Consumer Rate formulation – Preliminary and Updated.

As mentioned before, the context, in the authors' opinion, is crucial for the performance of an active consumer. Is a domestic consumer disposed to give up on an air conditioning when the temperature is above 30ºC? The comfort for this type of player is important, so their performance might be poor. However, if the period in which the event was triggered is between 1 PM and 3 PM? What if this player is at work during this period? Although the air conditioning example might not be applied for this case, a dishwasher or a washing machine schedule can be moved. Participation might be more acceptable since active consumer comfort is not jeopardised in this scenario. However, both parties must agree when the DR contract is made. Considering all these factors, the authors included in the CCR several independent rates: Consumer Historical Rate (CHR), Consumer Context Rate (CCtR), Consumer Last Event Rate (CLER), and Consumer Location Rate (CLR) and Consumer Current Event Rate (CCER).

CHR characterizes the player's historical performance average in previous events in similar contexts. CCtR gathers the expected behaviour from the players from two perspectives: weather (temperature) and time (weekday and period). CLER illustrates the active consumer performance in the last event of the same context. CLR disseminates the spatial flexibility concept, considering that the aggregator has grid bus information regarding where the violation was detected. Equation (1) adds CLR along with CHR, CLER and CCtR for the preliminary CCR.

$$PR = \omega_{P\_CHR} CHR + \omega_{P\_CLER} CLER + \omega_{P\_CLR} CLR + \omega_{P\_CCtR} CCtR \quad (1)$$

Focusing on the Rate Prediction stage, for the present paper, two different methods will be compared: DT and RF. The first one can be defined as a hierarchical exemplification of relationships that contain nodes and connections [10]. This method is mainly used for grouping purposes, and like a tree, DT has a root, branches, nodes, and leaves. Starting from the root, the data is separated in sequence until the leaf node is achieved [11]. On the other hand, RT is based on a DT and can be used for classification and regression [12]. The RT predicts by averaging the prediction of each component tree.

Overall, the literature says that RT has much better predictive accuracy than a single decision tree, and it can work well with default parameters [13].

For both methods, the training database will be composed of the remaining members of the community information. For validation, the contextual information from the current event and the availability of the new players are considered. To measure the performance from the selected methods, the authors opt to use Mean absolute error (MAE). This indicator measures the accuracy of continuous variables, as CCR was considered a continuous variable, and it is defined in (2) [14].

$$MAE = \frac{1}{n}\sum_{n=1}^{N} |y_i - y_i| \tag{2}$$

Attributed a CCR to all the active consumers in the community, the Resource Optimal Scheduling phase starts. In this stage, the main goal is to minimize the operational costs from the aggregator perspective, achieving the reduction target. The detailed formulation from this optimization can be consulted in [15].

After, the aggregator must understand if the selected participants were enough to suppress the request or if more should be called – a comparison between actual and requested reduction. This stage is where the uncertainty of the active consumers is tested. If the players respond according to the expected, their result in the Updated Consumer Contextual Rate (UR) is positive. Otherwise, they are penalized in both rate performance and the remuneration phase. The formulation of UR can be seen in (4).

$$\mathrm{UR} = \omega_{U\_CHR}\,\mathrm{CHR} + \omega_{U\_CLER}\,\mathrm{CLER} + \omega_{U\_CSR}\,\mathrm{CSR} + \omega_{U\_CCtR}\,\mathrm{CCtR} + \omega_{U\_CCER}\,\mathrm{CCER} \tag{4}$$

The major difference between the preliminary and the updated CCR is the CCER. This independent rate considers the actual response of the consumer to the event: if responded as requested, the resulting rate is high. The opposite applies, and the active consumer is penalized with a lowered value of RR. So, this independent rate is the only one obtained during the event and shows the raw performance.

For the proposed methodology, UR is highly important. The authors believe that proper remuneration can be a key factor for continuous participation. The Participant Remuneration Phase was included, and the compensation value is defined according to the player's performance.

Finally, the DSO is informed of the load reduction value from this community and the load shifted to other periods – the selected DR program in this situation. This must be highlighted that both real-time and planning perspectives can be applied to the proposed methodology. In other words, from a real-time perspective, by applying the load shifting program, the Aggregator may shift to a period with other voltage limit violations without having acknowledged, causing even more problems in the future. However, from the planning perspective, for instance, a weekly-based, DSO must provide all the expected voltage limit violations, and the aggregator avoids these periods.

III. Case Study

In the current section, the authors define the case study and the scenarios used to prove the viability of the proposed methodology. Since the focus of the present paper is the comparison between DT and RF, Table I defines the features used in the training dataset – period, temperature, day of the week and day of the month are crucial to identify the context in which the event is triggered. Personal information that could lead to the identification of the active player was also included to better differentiate from other players. For instance, the active consumers are divided according to their distance from the bus where the voltage limit violation was identified to identify the new participants.

TABLE I. Scenario Definition

Features	Type	Scenario 1	Scenario 2
Period	Integer	x	x
Temperature	Decimal	x	x
Day of Week	Integer	x	x
Day of Month	Integer	x	x
Location	Integer	x	
Availability	Binary	x	x
Method		DT	RF

In Figure 3, different zones are represented – zone 1 is the farthest and zone 5 is the closest.

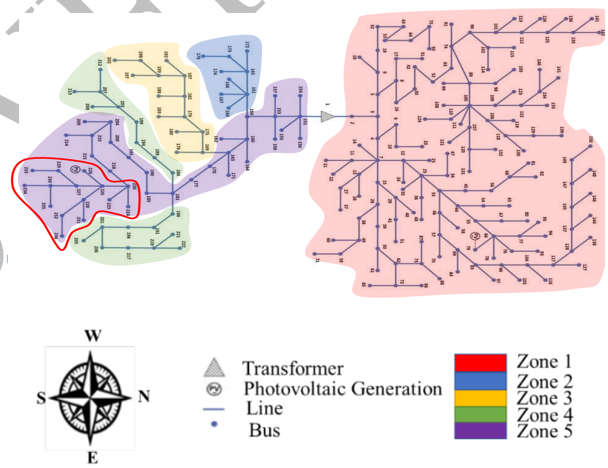


Fig. 3. Zone Definition according to the voltage limit violation detected.

Although other voltage limit violations can be included, the authors believe that each one should have its model since zone 1 to zone 5 can define distinct locations leading to misunderstanding.

Regarding Figure 4, the aggregator is working with a weekly-based perspective – having the information of all the expected voltage limit violations thought the week. So, it is important to gather all the information regarding the contextual features. The days are divided into a 15 minute-period resulting, for instance, in 672 periods in one week.

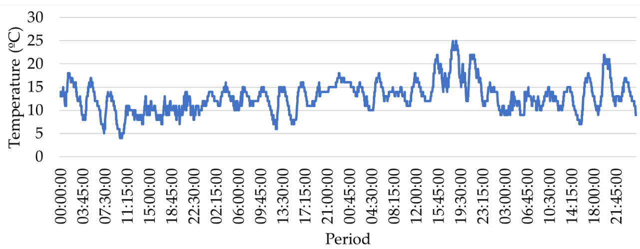


Fig. 4. The temperature registered throughout the week – features.

Going back to Table I, besides comparing two different methods (DT vs RF), the authors also are aware of the privacy problems that could arise from this solution. In this way, two scenarios were designed where only one of them has the location feature. More than the availability to participate, the location zone from where the consumer is participating could lead to a more accurate player association. Although the idea to use this information is far from real identification, cybersecurity is increasingly an important topic in energy system solutions.

With both scenarios, the authors can understand the real necessity of having this information and how this knowledge impacts the results from the proposed methodology perspective.

IV. Results and Discussion

In the current section, the authors analyse and discuss the results obtained from comparing methods for both scenarios: including or not the location feature to obtain the CCR for new players.

Firstly, the authors compare the rules obtain from both methods limiting the number of leaves to 5. After to further searching the selected methods' capability, the authors increased the number of leaves from 5 to 10.000, testing their performance with both MAE and the accuracy percentage from the validation dataset.

The models were implemented using python language resorting to the *sklearn* library. When comparing the running times, DT was faster. The validation dataset always had 20% when splitting the database, and the training dataset had the remaining. Starting with scenario 1 – where the location feature is included, Figure 5 shows the resulting rules for both DT and RF. By analysing the DT results in Figure 5 a), if the active consumer does not have availability in this context, the CCR attributed is 2.1. Otherwise, if the period exceeds 662, the CCR attributed is 3.5. But if the period is less than 662 and the temperature is higher than 15.5ºC, the CCR attributed is 3.6. However, if the temperature is lower than 15.5ºC and the period is higher than 29, the CCR assigned is 2.9, otherwise is 3.6. So, with these results, the aggregator can only assign the new players' rates between 2 and 4 if rounded. It must be noticed that features like the day of the week, day of the month and the location were not included in this DT with five leaves.

Focusing on Figure 5 b), where the results from RT are presented, the authors can see the similarities between this and the prior method. So, if the active consumer is not available in the event context, the CCR attributed is 2.1. If the active consumer is available and the period is higher than 662, the CCR attributed is 3.5. However, if the period is less than 662 and the temperature is higher than 15.5ºC, the CCR attributed is 3.6. But, if the temperature is lower than 15.5ºC and the period is higher than 29, the CCR assigned is 2.9, otherwise is 3.6. Again, for this perspective, the aggregator can assign to the new participants' rates between 2 and 4. And still, features such as the day of the week, day of the month and the location were not included.

Moving to the results from scenario 2, the authors found out that both method rules were equal to the first scenario – the location did not influence the 5five leaves approach.

The authors went into more detail and selected five different consumers from each method's results and studied them.

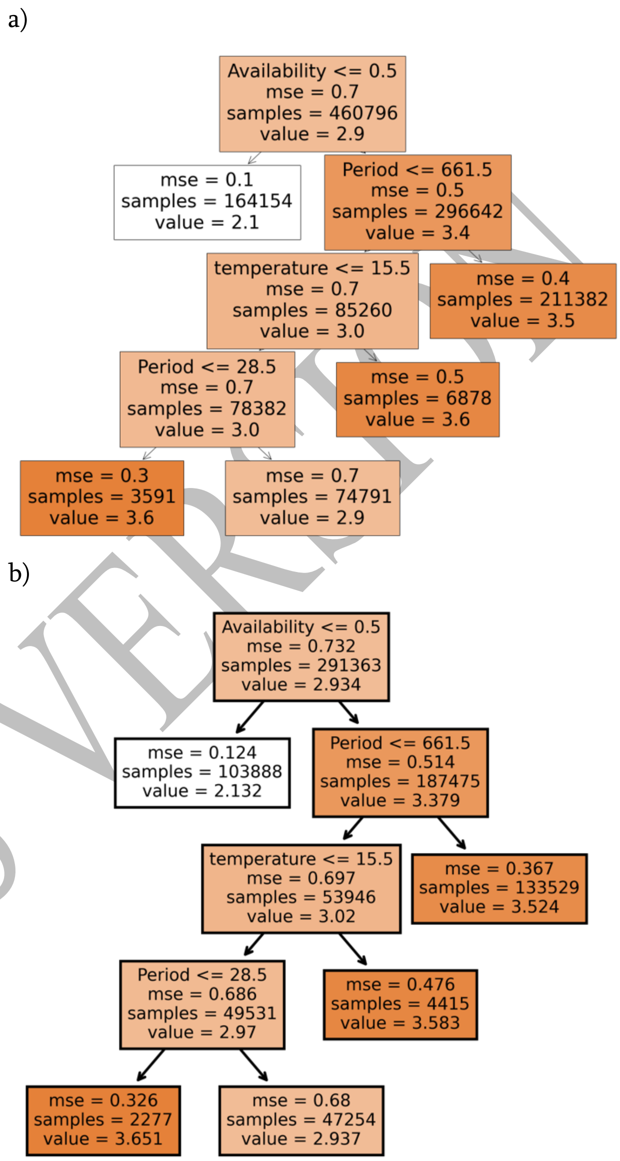


Fig. 5. Results from Scenario 1 comparison where a) Decision Tree and b) Random Forest.

Table II shows the attributed CCR for each scenario, according to each method. Again, the results are similar, seeing the differences only with more than three decimals' places. Although different consumers, there were only five options to attribute being all the same.

TABLE II. Random Consumers Results

RF	Scenario 1	3,53	2,13	3,52	2,93	3,52
	Scenario 2	3,53	2,13	3,52	2,93	3,52
	Real	4	2	2	2	4
DT	Scenario 1	3,52	2,13	3,52	2,93	3,52
	Scenario 2	3,52	2,13	3,52	2,93	3,52
	Real	4	2	4	3	4

According to Figure 5, the consumers within positions 1, 3 and 5 from Table II probably followed the rules and were available to participate. The period when the DR event was triggered was superior to 662. Regarding the individuals in position two from Table II, they were not available for the event. Finally, the participants from position 3 in Table II had the availability to participate, the period was inferior to 662 but higher than 29, and the temperature was below 15.5ºC.

With the results found, the authors realised it would be better to search deeper and make a sensitivity test to understand the impact of more leaves on the CCR prediction. Table III and Table IV show the results for both scenarios within 5 to 10.000 leaves. The first one refers to the DT results and the second to RF results. The MAE and the accuracy of the validation dataset are presented. The better performance values are highlighted in these tables in a grey colour. The blue colour represents the samples where scenario 1 differs from scenario 2 – meaning that the location feature could impact the rules since it is the only modification between them. Most of cases, the MAE decreases whenever the number of leaves increases.

TABLE III. DECISION TREE SENSITIVITY TEST

Leafs	Scenario 1		Scenario 2	
	MAE (#)	Accuracy (%)	MAE (#)	Accuracy (%)
5	0,4645	64,00	0.4645	64,00
20	0,4432	62,04	0.4431	62,09
35	0,4336	66,00	0.4336	66,00
50	0,4263	67,08	0.4263	67,08
100	0,4111	68,24	0.4111	68,24
500	0,3708	70,42	0.3706	70,24
5,000	0,3629	70,24	0.3618	70,65
10,000	0,3633	69,86	0.3618	70,65

Starting by analysing scenario 1, the MAE did follow the previous logic until reaching the 10.000 leaves. The previous sample had a lower value of MAE and a higher value of accuracy. However, it was not the highest in this scenario – reached with 500 leaves, a total of 70.42% of accuracy. Regarding scenario 2, the results were similar excepting the three final samples. With 500 leaves, the MAE difference was 0.002 and prejudice on the accuracy decreased to 70.24%. The value of MAE for the last two tests was the same, and the accuracy value – was the highest within the DT method.

The RF sensitivity test results show similar results to DT - if rounded to the decimals, a difference cannot be noticed. In Table IV, these disparities can be found for both scenarios, and the previous conclusions can also be applied in this case. Again, the highest accuracy found in scenario one was reached with 500 leaves, superior to this method – 70.54%.

TABLE IV. RANDOM FOREST SENSITIVITY TES

Max leaf nodes	Decision Tree			
	Scenario 1		Scenario 2	
	MAE (#)	Accuracy (%)	MAE (#)	Accuracy (%)
5	0.4642	64,00	0.4642	64,00
20	0.4434	62,09	0.4434	62,09
35	0.4327	66,00	0.4327	66,00
50	0.4253	67,16	0.4253	67,16
100	0.4089	68,25	0.4089	68,25
500	0.3708	70,54	0.3705	70,35
5000	0.3628	70,39	0.3618	70,68
10000	0.3631	69,99	0.3618	70,68

Concerning scenario 2, the three final samples should again be highlighted. With 500 leaves, the MAE difference was 0.003 in this case, and with prejudice on the accuracy – decreasing to 70.35%. The value of MAE for the last two tests was the same, and the accuracy value – was the highest within the RF method.

Considering that five leaves result in a 64% accuracy, to achieve a less than 10% improvement, it is necessary to increase the number of leaves a total of 2000 times more. The authors believe this could be a reasonable value – avoiding high processing times and getting satisfactory results, mainly since the range between 2 and 4 seems fair to both the remaining consumers and new ones. None of them is getting the worst-case scenario – it is more difficult to increase their CCR and get higher remuneration values. On the other hand, giving the best rate to a new player with no historical information can be a wrongful approach and jeopardise the fairness of the solution.

V. CONCLUSION

To successfully implement the smart grid concept in the whole energy system, the literature must find the proper solution to integrate Distributed Generation and active consumers into the market. Both are unpredictable and volatile, but to maintain the reliability and security of the network, the end-users must provide flexibility.

The authors of the present paper believe that dealing with the uncertainty and finding the proper motivation can be useful to guarantee the continuous contribution of the small players. Industrial and commercial consumers have more stable schedules. On the other hand, domestics are the more representative type of human behaviour – contexts have a higher impact. To deal with the response uncertainty in Demand Response events, a Contextual Consumer Rate was defined to classify the performance of each active consumer. Selecting the proper participants can be crucial to having a successful approach.

The authors believe that knowledge regarding previous experiences can be useful for future events. The present paper studied two methods to attribute this trustworthy rate to new players with no historical information: Decision Trees and Random Forests. One of the concerns also addressed by the authors was the active consumer privacy: understanding the impact of their current location on the models. The results found that this feature was not critical to fulfilling the goal. Through a sensitivity test, the authors also found out that five leaves could be a reasonable number to achieve an accuracy value above 50%.

The authors intend to study more features that could impact the active consumer behaviour to reduce the response uncertainty from a DR event in future works.

REFERENCES

[1] Z. Baum, R. R. Palatnik, O. Ayalon, D. Elmakis, and S. Frant, “Harnessing households to mitigate renewables intermittency in the smart grid,” Renewable Energy, vol. 132, pp. 1216–1229, Mar. 2019, doi: 10.1016/j.renene.2018.08.073.

[2] A. Conchado, P. Linares, O. Lago, and A. Santamaría, “An estimation of the economic and environmental benefits of a demand-response electricity program for Spain,” Sustainable Production and Consumption, vol. 8, pp. 108–119, Oct. 2016, doi: 10.1016/j.spc.2016.09.004.

[3] Y. Chen et al., “Quantification of electricity flexibility in demand response: Office building case study,” Energy, vol. 188, p. 116054, Dec. 2019, doi: 10.1016/j.energy.2019.116054.

[4] D. Liu, Y. Sun, Y. Qu, B. Li, and Y. Xu, “Analysis and Accurate Prediction of User’s Response Behaviour in Incentive-Based Demand Response,” IEEE Access, vol. 7, pp. 3170–3180, 2019, doi: 10.1109/ACCESS.2018.2889500.

[5] S. Wang, F. Luo, Z. Y. Dong, and Z. Xu, “Coordinated residential energy resource scheduling with human thermal comfort modelling and renewable uncertainties,” in IET Generation, Transmission and Distribution, 2019, vol. 13, no. 10, pp. 1768–1776. doi: 10.1049/iet-gtd.2018.5355.

[6] S. Sekizaki, I. Nishizaki, and T. Hayashida, “Decision making of electricity retailer with multiple channels of purchase based on fractile criterion with rational responses of consumers,” International Journal of Electrical Power & Energy Systems, vol. 105, no. September 2018, pp. 877–893, Feb. 2019, doi: 10.1016/j.ijepes.2018.09.011.

[7] C. Silva, P. Faria, and Z. Vale, “Finding the Trustworthy Consumers for Demand Response Events by Dealing With Uncertainty,” in 2021 IEEE International Conference on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), Sep. 2021, pp. 1–6. doi: 10.1109/EEEIC/ICPSEurope51590.2021.9584667.

[8] C. Silva, P. Faria, and Z. Vale, “Managing Smart City Power Network by Shifting Electricity Consumers Demand,” in Sustainable Smart Cities and Territories International Conference, Apr. 2022, vol. 253, pp. 81–91. doi: 10.1007/978-3-030-78901-5_8.

[9] C. Silva, P. Faria, and Z. Vale, “Aggregation of Prosumers in the Context of Demand Response and Distributed Generation Remuneration and Scheduling,” in 2020 IEEE/PES Transmission and Distribution Conference and Exposition (T D), 2020, pp. 1–5. doi: 10.1109/TD39804.2020.9300003.

[10] B. Charbuty and A. Abdulazeez, “Classification based on decision tree algorithm for machine learning,” Journal of Applied Science and Technology Trends, vol. 2, no. 01, pp. 20–28, 2021.

[11] H. Zhou, J. Zhang, Y. Zhou, X. Guo, and Y. Ma, “A feature selection algorithm of decision tree based on feature weight,” Expert Systems with Applications, vol. 164, p. 113842, 2021.

[12] Z. Zhang, J. Peng, Z. Xu, X. Wang, and J. Meersmans, “Ecosystem services supply and demand response to urbanization: A case study of the Pearl River Delta, China,” Ecosystem Services, vol. 49, p. 101274, Jun. 2021, doi: 10.1016/J.ECOSER.2021.101274.

[13] N. Hasan and M. Alam, “Envisaging Industrial Perspective Demand Response Using Machine Learning,” Lecture Notes on Data Engineering and Communications Technologies, vol. 90, pp. 331–342, 2022, doi: 10.1007/978-981-16-6289-8_28.

[14] E. Jumin, F. B. Basaruddin, Y. Bte. M. Yusoff, S. D. Latif, and A. N. Ahmed, “Solar radiation prediction using boosted decision tree regression model: A case study in Malaysia,” Environmental Science and Pollution Research, vol. 28, no. 21, pp. 26571–26583, 2021, doi: 10.1007/s11356-021-12435-6.

[15] C. Silva, P. Faria, and Z. Vale, “Managing Smart City Power Network by Shifting Electricity Consumers Demand,” Lecture Notes in Networks and Systems, vol. 253, pp. 81–91, Apr. 2021, doi: 10.1007/978-3-030-78901-5_8.

Publication VII

C. Silva, P. Faria, B. Canizes and Z. Vale, "Real-Time Approach for Managing Power Network by Shifting Electricity Consumers Demand," 2022 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Novi Sad, Serbia, p. 1-5, 2022

Resumen

El concepto de Ciudades Inteligentes está evolucionando desde la etapa de proyecto hacia el mundo real. Los electrodomésticos se vuelven más inteligentes y permiten la comunicación bidireccional, lo cual es un gran avance hacia la implementación de la respuesta a la demanda y el empoderamiento de los consumidores activos en el mercado energético. Sin embargo, gestionar comunidades locales con estos nuevos participantes es complejo y la entidad detrás de ellos necesita el conocimiento y las herramientas adecuadas. Por lo tanto, los autores proponen una metodología para gestionar óptimamente a los consumidores activos en eventos de respuesta a la demanda. El estudio en el presente artículo se realiza desde una perspectiva en tiempo real. El operador del sistema de distribución detecta una violación de voltaje y solicita una reducción de carga al Agregador, que son los 96 consumidores activos, a través del desplazamiento de carga. La metodología propuesta se aplicó a ocho escenarios y se encontró el número correcto de participantes en respuesta a la demanda para el caso de estudio.

.

Real-Time Approach for Managing Power Network by Shifting Electricity Consumers Demand

*Note: Sub-titles are not captured in Xplore and should not be used

Cátia Silva, Zita Vale, Pedro Faria and Bruno Canizes
Polytechnic of Porto
Porto, Portugal
cvcds@isep.ipp.pt; zav@isep.ipp.pt; pnf@isep.ipp.pt; bmc@isep.ipp.pt

***Abstract*—The Smart Cities concept is evolving from the project stage to the real world. Appliances become smarter and enable bidirectional communication – a huge step toward implementing demand response and empowering active consumers in the energy market. However, managing local communities with these new players is complex, and the entity behind them needs the right knowledge and tools. The authors thereby propose a methodology to manage the active consumers on DR events optimally. The study in the present paper is done from a real-time perspective. The distribution system operator detects a voltage violation and requests a load reduction to the Aggregator, the 96 active consumers, through load shifting. The proposed methodology was applied to eight scenarios, and the correct number of demand response participants for the case study was found.**

Keywords*— *Active Consumers, Demand Response, Flexibility, Load Shifting, Power Flow

I. Introduction

The current systems infrastructure is not ready for the introduction of the Smart Grid concept[1]. Great challenges, namely on the distribution level regarding congestion avoidance and voltage control, can be avoided with the flexibility provided by the participants in Demand Response (DR) program [2]. By managing the system with several active communities, the Distribution System Operator (DSO) must guarantee the constraint satisfaction of the distribution network since the Distributed Generation (DG) resources' behavior is highly uncertain [3]. So, requests for a reduction on critical periods are sent to the Aggregator – responsible for an active community, and by managing all the resources associated, demand peaks can be alleviated [4].

With advanced metering infrastructures, bidirectional communication enables DR events by offering information and signals to the new active players to participate in the energy market transactions [5]. The managing entity – mostly aggregators- gives signals – and the active consumers with DR contracts must be compensated for the events[6]. Some programs allow the Aggregator to control the appliances and properly manage them, ensuring the security and reliability of the system [7]. So, developing smart buildings and smart homes, giving the right tools for the active consumers is a great step to successfully implementing DR in the real energy market [8]. However, the use of such technologies results in large amounts of data, concerns regarding data security, safety, and privacy [9].

This work has received funding from the European Union's Horizon 2020 research and innovation program under project DOMINOES (grant agreement No 771066), from FEDER Funds through COMPETE program, and from National Funds through (FCT) under the projects UIDB/00760/2020, MAS-SOCIETY (PTDC/EEI-EEE/28954/2017), CEECIND/02887/2017, and SFRH/BD/144200/2019.

The designed method to successfully implement DR in the real market should be able to manage these matters[10]. Thereby, taking a step forward from previous works [11], [12], the authors propose a methodology to aid the Aggregator in dealing with the complex task of managing the local community when problems on the network request reductions trigger DR events [13].

In this paper, the study developed initiates with a magnitude voltage violation detected by the DSO, verifying that this value is below the limit imposed. Then, the load reduction request is sent to the Aggregator. A DR event is triggered with a signal, and it is expected to demand flexibility from the consumer's side. If the actual reduction equals the requested reduction, the participants are compensated, and their load is shifted to an adequate period according to their preferences. The DSO is informed of the load reduction by the Aggregator, and a new power flow is performed to verify that the voltage violation was solved with the requested load reduction. However, this is a real-time approach so, the Aggregator has no information regarding the following periods where the load is shifted. This fact could result in further limit violations.

The approach presented by the authors intent to reduce this risk – the load can be scheduled in a wider interval, and not all the reduction should be attributed to one period only. Besides, another study discussed in the present paper refers to the number of participants needed to mitigate the voltage limit violation. The method starts with a minimum number of participants until calling all the community to participate, if necessary. The active consumers will be called randomly without any previous selection regarding their characteristics. The innovation from previous works refers to the availability from the participants at the time of the DR event. This information will impact the results from the managing strategy perspective because the requested reduction may not be the actual reduction from participants.

The present paper is structured with five different sections—first, an introduction to the topic with the motivations of the study and innovations from previous works. After, a detailed explanation of the proposed methodology. Then, a case study section is presented, giving a base to work. Next, the results will be analysed and discussed. Finally, the conclusions withdrawn will be reviewed.

.

II. Materials and Methods

Managing the flexibility provided by the active consumers in a local community can be a complex task – the right methods and tools must be applied by the Aggregator – entity behind the community's supervision. In this way, the authors proposed a method to successfully operate the network in a real-time perspective – as shown in Figure 1, the focus of the present paper study.

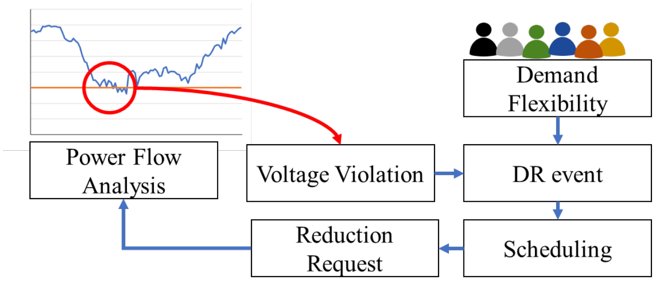


Fig. 1. Proposed Methodology

When the DSO detects a voltage violation in the power flow analysis, it requests a load reduction to the Aggregator, when the violation was detected, and a DR event must be triggered. From the active consumers, it is expected to demand flexibility for the time of the event. The available consumers are then included in the scheduling phase. A linear programming approach is then employed to optimally manage the community, dealing with several types of small active resources. In this way, the goal is to maximize the Aggregators' profit, minimize operational costs from the community and fairly remunerate active consumers. The objective function is presented in (1) [14].

$$Min.OF = \sum_{p=1}^{P}[P_{DG(p,t)}C_{DG(p,t)}] + \sum_{c=1}^{C}[P_{DR(c,t)}C_{DR(c,t)}] + \sum_{s=1}^{S}[P_{Sup(s,t)}C_{Sup(s,t)}] + P_{NSP(t)}C_{NSP(t)} \quad (1)$$

$$c,t,p,s \in \mathbb{Z} : c,t,p,s > 0$$

PDG is the power for each p resource; PDR is the flexibility from each c consumer; PSup is the power from an external supplier; PNSP is the non-supplied power (NSP). The respective costs are attached to these variables, such as CDG is the cost for each g resource; CDR is the cost of flexibility from each c consumer; CSupplier is the cost of the external supplier; CNSP is the cost of NSP. The objective function (1) is subject to the constraints (2) to (7). First, the network power balance - Equation 2, is defined to achieve the equilibrium between consumption and generation. So, the sum of the requested reduction to the consumer initial load (Pinitial) should be equal to the total generation from DG units and external suppliers.

Second, the NSP variable is included to avoid network problems in extreme situations, for instance, when the generations mean, and DR programs cannot suppress the demand side needs. So, in normal situations, it should be equal to zero. Finally, the forecasting error of DG units is not considered.

$$\sum_{c=1}^{C}[P^{initial}_{(c,t)} - P_{DR(c,t)}] = \sum_{p=1}^{G}[P_{DG(g,t)}] + \sum_{s=1}^{S}[P_{Sup(s,t)}] \quad (2)$$

$$+P_{NSP(t)} \qquad c,t,g,s \in \mathbb{Z} : c,t,g,s > 0$$

Regarding the constraint related to consumer participation in DR events, (3) represents the maximum contribution requested from an active consumer. Therefore, it is expected that each participant contributes with the amount requested from the Aggregator.

$$P_{DR(c,t)} \leq P^{Max}_{DR(c,t)} \qquad c,t, \in \mathbb{Z} : c,t > 0 \quad (3)$$

To bound the DG units, three equations are employed – (4) and (5). With these equations, the Aggregator can restrict the upper and lower thresholds and the total value of generation provided from this source.

$$P^{Min}_{DG(g,t)} \leq P_{DG(g,t)} \leq P^{Max}_{DG(g,t)} \qquad g,t, \in \mathbb{Z} : p,t > 0 \quad (4)$$

$$\sum_{p=1}^{P}[P_{DG(g,t)}] \leq P^{Total}_{DG(g,t)} \qquad g,t, \in \mathbb{Z} : p,t > 0 \quad (5)$$

Finally, the External Supplier constraints are represented by (6) and (7), constraining the maximum capacity and the total amount of generation provided from this source to suppress the demand side needs.

$$P_{Supplier(s,t)} \leq P^{Max}_{Sup(s,t)} \qquad s,t, \in \mathbb{Z} : s,t > 0 \quad (6)$$

$$\sum_{s=1}^{S}[P_{Supplier(s,t)}] \leq P^{Total}_{Sup(s,t)} \qquad s,t, \in \mathbb{Z} : s,t > 0 \quad (7)$$

Performed the scheduling phase, the reduction is requested to the active consumers, and the load is shifted to another period according to the consumers' preferences. The reduction information is given to DSO to perform other power flow considering the results, and the active consumers who participated in the event are compensated to incentivize further participation. The innovation of the present work, in respect to the previous, is achieved with a real-time perspective, understanding the interval of participants needed to suppress the limit violation detected.

III. Case Study

The present section has the details regarding the case study based on real data. Several scenarios were formed to prove the viability of the proposed methodology. The low voltage distribution network is based on a real distributed grid and has 236 buses. It is operated under a radial topology with a total installed power of 679.65 kVA. There are 96 residential consumers connected to this network, from which two have rooftop PV panels.

The power flow was performed using the MATPOWER tool, in which the simulation and analysis are done through the Newton Rapson method. Using this traditional method for power flow analyses was possible since the used network has a low R/X ratio. Otherwise, methods like forward and backward sweep should be used. The convergence criteria used was ε=1x10-8. The method converges in an average of =~3 iterations for each period. For the linear optimization, the lp solve package from the R software environment.

The days are divided into periods of 15 minutes and a whole week is considered, starting on Monday. The lower limit voltage assumed in this case study is 0.95 p.u. The upper limit is 1.05 p.u. A lower voltage bound limit violation was detected on period 460, representing Friday at 6:45 PM, as shown in Figure 2. These voltage values are the minimum values verified when comparing all buses. The DR event is trigged upon lower voltage bound limit violation detection, and participants should reduce the amount contracted at the time requested to be further scheduled according to the mentioned range.

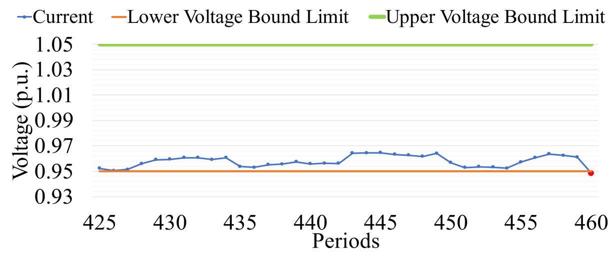


Fig. 2. Real-time Limit Violation detection

As mentioned earlier, the DR program known as load shifting is applied to mitigate limit violation throughout the day – the programmed consumption is moved forward in time to another period. Normally, the notice period to participate in more or less 0.3 seconds for each period. Therefore, it was assumed that shifted consumption should be scheduled randomly within a range agreed between the two parties. In this study, a between 5 hours after the DR event but never 24 hours after the same – a range of 19 hours. Figure 3 presents expected load consumption for the range where the load can be shifted. This data is before the DR event is triggered, where the initial load consumption (PInitial) was 383.7 kW, and the maximum value of flexibility provided by the 96 active consumers (P DR max) was 105.9 kW, represented with red and yellow colors, respectively.

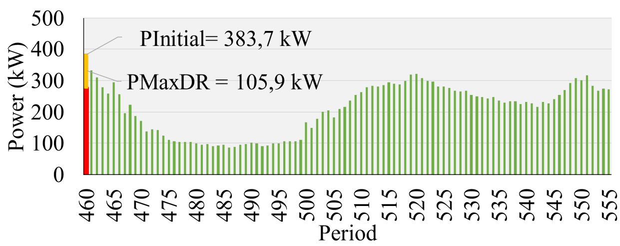


Fig. 3. Prediction of the Load Consumption before DR event

Being a real-time simulation, no information regarding the later periods is known, so the load is shifted without considering the limit violations that could be triggered in the future. In the present paper, a sensibility analysis is performed to understand the number of participants needed in the DR event to suppress this violation problem. The method starts with a minimum of 12 active consumers until achieving the totality of the community – 96 consumers reducing the total amount of 105.9 kW. With a step of 12 consumers, a total of 8 scenarios is performed, and the participants are chosen randomly without any previous selection regarding their characteristics. Although no information on the latter consumption is provided, to avoid additional violations upon the event, the shifted load is assigned to different periods according to the consumer needs – also to prevent any discomfort from the consumer perspective. The remuneration for the participation is a monetary value of 0.22 m.u./kW. With this, a comparison between the scenarios is also performed to understand the impact of the expenses from the Aggregator perspective.

IV. Results and Discussion

Throughout the present section, the authors analyze and discuss the results focusing on the Demand side and their performance on DR events. As already mentioned, eight scenarios are explored, simulating the results after applying the shifting on the reduced load from period 460. In this period, a lower voltage bound limit violation was detected, as shown in Figure 2, and the authors aim to find the number of participants required to solve this problem. Although multiple voltage events were triggered, the authors focus on only one in this study. Also, the goal is to not trigger any other lower voltage bound limit violation on the periods after – from where the load reduced on period 460 was shifted.

The assumption made earlier should be highlighted – the load can only be randomly scheduled between 5 hours after the DR event but never 24 hours after the same, resulting in a range of 19 hours. In this way, the results show the time frame where the load could be shifted. The results obtained from the eight scenarios can be found in Figure 4 and Figure 5. The scenarios were separated according to the results after the new power flow test – lower voltage bound limit violation was detected or not. So, the scheduling phase was performed for each scenario, considering that participants always reduce the amount requested from the Aggregator. With this, the power flow phase was again executed to understand if the problem persists.

Each scenario is identified by "SX," where the X indicates the number of participants in the referred scenario. By analysing Figure 4, the results from six of the eight scenarios are presented according to the number of elements, i.e., S12, when 12 active consumers are participating in DR events. The column chart represents the load consumption after the event comparing with the line curve from the expected load without triggering the event. Also, the voltage results from the second power flow phase are presented. The red dot identifies the periods where a limit violation was identified. In these six scenarios, the Aggregator could not achieve the goal – the lower voltage bound limit violation of period 460 can still be detected.

A zoomed perspective is given on the time of the event showing the amount reduced on each scenario. Scenario S12, where 12 active consumers were expected to provide flexibility at the time of the event. The value reduced on period 460 was 14.73 kW. As shown in Figure 4 a), this amount was insufficient to solve the lower voltage bound limit violation detected. The load shifted did not cause problems in the periods after. Moving to scenario S24, a total of 29.35 kW was reduced, and this amount was shifted without triggering further complications.

Following scenario S36, the consumption value decreased from 383.71 kW to 340.21kW, but the violation was still identified later.The differences between initial and actual predictions from this scenario are noticed on the interval between period 510 and period 520, but no other limit violation was detected. Regarding scenario S48, the Aggregator requested a total of 57.18 kW to the 48 active consumers. There was no success in eliminating lower voltage bound limit violation, but again, the load shifted did not trigger others. Reaching the 60 participants at the DR event, the reduced load was 70.87 kW, which was still insufficient to achieve the goal.

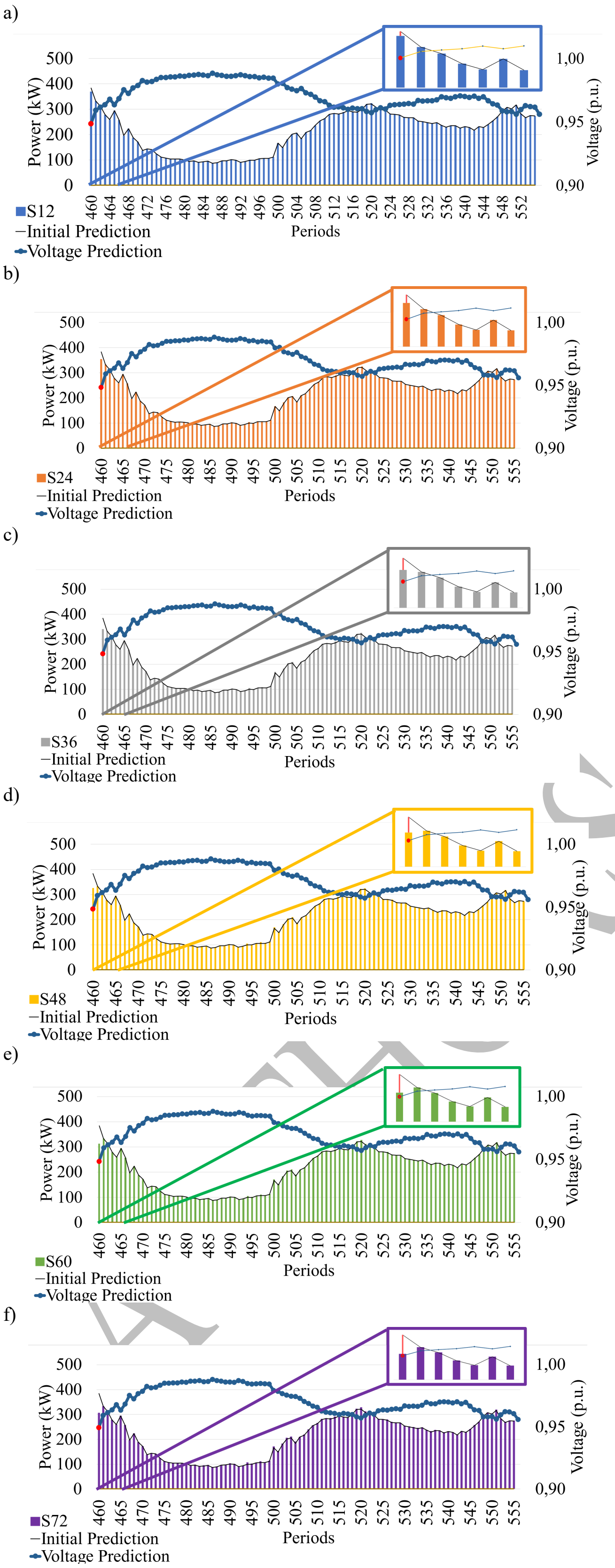


Fig. 4. Limit violation detected after DR a) S12, b)S24, c) S36, d) S48, e) S60 and f) S27 participants

Figure 4 f) presents the results from the sixth scenario, where the limit violation was not yet solved with the reduction of 77.89 kW. Although the actual and predicted consumption differences are higher, it was not enough to trigger other lower voltage-bound limit violations. Figure 5 shows the results of the scenarios where the – lower voltage bound limit violation of period 460 was solved. So, it can be concluded that, for this study and with the assumptions considered, the appropriate number of participants is between 72 and 84 active consumers, which results in a reduction between 77.89 kW and 92.86 kW.

Figure 5 a) represents scenario S84 where the voltage result was above the limit – 0.952 p.u. Regarding the final scenario, where all the community consumers participate, the total reduction was 105.91 kW to stay higher than the limit violation – 0.963 p.u. The approach on distributing the load shifting along 19 hours instead of attributing the whole reduction to one period only came out as successful.

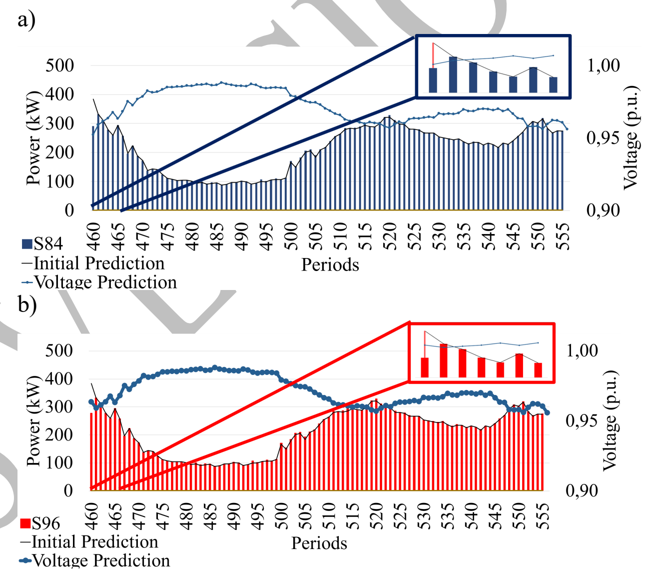


Fig. 5. Limit violation detected after DR a) S84, b) S96 participants

With the lower voltage bound limit violation resolved, the Aggregator must compensate the active consumers, which helped on this task to encourage continued participation in the following events and offset the discomfort caused. As mentioned in the case study section, the remuneration value was equal to all the consumers – 0.22 m.u./kW and equaled the maximum electricity tariff price contracted to motivate continuous participation. The results for each scenario are presented in Table I, with the amount of reduction and the subsequent total remuneration value.

TABLE I. REMUNERATION PER SCENARIO

# Participants	Reduced Amount (kW)	Total Remuneration (m.u./kW)
12	14.73	3.24
24	29.35	6.46
36	43.50	9.84
48	57.18	13.04
60	70.87	16.05
72	77.89	18.30
84	92.86	21.59
96	105.91	24.47

As the previous results show, the first six scenarios could not solve the limit violation, represented with red color on Table I. In the first scenario, the Aggregator attributes to the 12 participants a total of 3.24 m.u. Almost the double was reduced on scenario S24, resulting in the compensation of 6.46 m.u./kW. With more than 12 participants comparing with the previous scenario, S36 compensation was 9.84 m.u. for the 43.50 kW reduced. The participants called on the fourth scenario cut a total of 57.18kW, receiving 13.04 m.u. In scenario S60, the Aggregator paid a total remuneration of 16.05 m.u. for 70.87 kW of the requested reduction. Now, on the interval between 72 and 84 participants, the difference between the amount of reduction is around 15 kW which is equivalent to the remuneration of 18.30 m.u. and 21.59 m.u., respectively.

In the final scenario, with all the community, the Aggregator spent 24.47 m.u. To conclude the discussion on this section, it should be emphasized that under these conditions, the 72 to 84 can be the proper interval, but to understand further, more parameters should be considered. For instance, they were obtaining the bus location where the fault was found and requesting the reduction from the active consumers in the nearby areas. When considering the availability and the willingness of the active consumers at the time of the event, the response can be uncertain. Although there are some DR programs where the managing entity has power over the appliance, the final decision is always dependent on consumer behavior. Furthermore, 72 to 84 active consumers are more than 75% of the community to reduce the same amount that the aggregator requests. That is if all community is willing to participate in DR events and give away their comfort to help on the network matters. As Nicholas Good [15] reminds us, most of the studies are shaped, given end-users as always rational and economic agents, and the uncertainty behind their random behavior must be considered. Although the proposed methodology has implemented a remuneration stage, it might not encourage all the consumers. Although the economic incentive might persuade the majority, each one of the consumers has different motivations and behaviors. Therefore, the community manager must consider the uncertainty of active consumer's responses, understanding their availability and willingness to participate in a certain context

V. Conclusions

The authors present a tool to optimally manage the small resources in real-time, resorting to DR programs and the active consumers' flexibility. From a wider perspective, when the DSO detects a limit violation on the network power flow, it sends reduction requests to the Aggregator – triggering the DR events. According to the results, it was possible to find the proper interval of participants to mitigate the problem found. However, utilizing almost 75% of the community might not be feasible in the real world. So, considering and understanding the availability and willingness of the participants in such a context is essential. Also, understand the impacts of the DR programs, such as load shifting, in the network could also be a key topic – the communication and information exchange between DSO and Aggregator is important for the successful implementation of DR programs in the real market. From this perspective, the goal was achieved, and no other voltage limit violation was triggered with the scheduled load from the DR event. As future works, when finding the bus location where the fault was found, the method should request the reduction from the active consumers in the nearby areas and the applicability of the proposed system within a day with multiple voltage events.

References

[1] S. Zafar, V. Maurya, A. Blavette, G. Camilleri, H. ben Ahmed, and M. P. Gleizes, "Adaptive Multi-Agent System and Mixed Integer Linear Programming Optimization Comparison for Grid Stability and Commitment Mismatch in Smart Grids," Proceedings of 2021 IEEE PES Innovative Smart Grid Technologies Europe: Smart Grids: Toward a Carbon-Free Future, ISGT Europe 2021, 2021, doi: 10.1109/ISGTEUROPE52324.2021.9640019.

[2] B. Zeng, X. Wei, B. Sun, F. Qiu, J. Zhang, and X. Quan, "Assessing capacity credit of demand response in smart distribution grids with behavior-driven modeling framework," International Journal of Electrical Power and Energy Systems, vol. 118, p. 105745, 2020, doi: 10.1016/j.ijepes.2019.105745.

[3] L. Calearo, C. Ziras, K. Sevdari, and M. Marinelli, "Comparison of Smart Charging and Battery Energy Storage System for a PV Prosumer with an EV," Proceedings of 2021 IEEE PES Innovative Smart Grid Technologies Europe: Smart Grids: Toward a Carbon-Free Future, ISGT Europe 2021, 2021, doi: 10.1109/ISGTEUROPE52324.2021.9640120.

[4] O. Abrishambaf, P. Faria, L. Gomes, J. Spínola, Z. Vale, and J. Corchado, "Implementation of a Real-Time Microgrid Simulation Platform Based on Centralized and Distributed Management," Energies (Basel), vol. 10, no. 6, p. 806, Jun. 2017, doi: 10.3390/en10060806.

[5] R. Faia, B. Canizes, P. Faria, Z. Vale, J. M. Terras, and L. v. Cunha, "Optimal Distribution Grid Operation Using Demand Response," in 2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), Oct. 2020, pp. 1221–1225. doi: 10.1109/ISGT-Europe47291.2020.9248858.

[6] J. Tran, L. Gajewski, N. Varghese, P. Pfeifer, S. Krahl, and A. Moser, "Deep Reinforcement Learning for Modeling Market-Oriented Grid User Behavior in Active Distribution Grids," Proceedings of 2021 IEEE PES Innovative Smart Grid Technologies Europe: Smart Grids: Toward a Carbon-Free Future, ISGT Europe 2021, 2021, doi: 10.1109/ISGTEUROPE52324.2021.9640167.

[7] N. Mahmoudi, E. Heydarian-Forushani, M. Shafie-khah, T. K. Saha, M. E. H. Golshan, and P. Siano, "A bottom-up approach for demand response aggregators' participation in electricity markets," Electric Power Systems Research, vol. 143, pp. 121–129, 2017, doi: 10.1016/j.epsr.2016.08.038.

[8] S. Kashyap, C. Schaffer, C. Muck, and C. Plank, "Intelligent Web-platform for Enabling Microgrids and Energy Sharing," Proceedings of 2021 IEEE PES Innovative Smart Grid Technologies Europe: Smart Grids: Toward a Carbon-Free Future, ISGT Europe 2021, 2021, doi: 10.1109/ISGTEUROPE52324.2021.9640134.

[9] S. Singh and A. Kumar, "Demand response program solution to manage congestion in transmission network considering uncertainty of load," in 2017 8th International Conference on Computing, Communication and Networking Technologies (ICCCNT), 2017, pp. 1–6. doi: 10.1109/ICCCNT.2017.8203983.

[10] H. Morais, P. Faria, and Z. Vale, "Demand response design and use based on network locational marginal prices," International Journal of Electrical Power & Energy Systems, vol. 61, pp. 180–191, Oct. 2014, doi: 10.1016/j.ijepes.2014.03.024.

[11] C. Silva, P. Faria, and Z. Vale, "Rating the Participation of Electricity Consumers in Demand Response Events," in International Conference on the European Energy Market, EEM, Sep. 2020, vol. 2020-Septe, pp. 1–5. doi: 10.1109/EEM49802.2020.9221907.

[12] C. Silva, P. Faria, and Z. Vale, "Study of Multi-Tariff Influence on the Distributed Generation Remuneration," in International Symposium on Distributed Computing and Artificial Intelligence, 2019, pp. 14–19.

[13] P. Faria and Z. Vale, "A Demand Response Approach to Scheduling Constrained Load Shifting," Energies (Basel), vol. 12, no. 9, p. 1752, May 2019, doi: 10.3390/en12091752.

[14] C. Silva, P. Faria, and Z. Vale, "Rating the Participation in Demand Response Programs for a More Accurate Aggregated Schedule of Consumers after Enrolment Period," Electronics (Basel), vol. 9, no. 2, p. 349, Feb. 2020, doi: 10.3390/electronics9020349.

[15] N. Good, "Using behavioural economic theory in modelling of demand response," Applied Energy, vol. 239, pp. 107–116, Apr. 2019, doi: 10.1016/j.apenergy.2019.01.158.

Publication VIII

C. Silva, P. Campos, P. Faria and Z. Vale, "Exploring Dataset Patterns for New Demand Response Participants Classification," 21st International Conference on Practical Applications of Agents and Multi-Agent Systems (PAAMS), 2023

Resumen

Existe una tendencia creciente hacia enfoques centrados en el consumidor que integran recursos de generación distribuida en el sector de energía y electricidad. Sin embargo, esto añade complejidad a la gestión de las comunidades a medida que se introducen nuevos participantes. Los autores han diseñado un sistema de tasa confiable (TR por sus siglas en inglés) para abordar este problema de selección de participantes para eventos de respuesta a la demanda basándose en su desempeño previo. El objetivo es evitar molestias para los consumidores y reducir los costos de los agregadores mediante una selección justa de los participantes. Sin embargo, esto plantea un desafío para los nuevos jugadores sin historial de rendimiento. Este estudio tiene como objetivo desarrollar un método para asignar el TR a los nuevos jugadores. Con este propósito, los autores utilizaron el agrupamiento supervisado y el descubrimiento de subgrupos para identificar las características relevantes del conjunto de datos sin comprometer la privacidad, y luego emplearon técnicas como árboles de decisión, bosques aleatorios y aumento de gradiente extremo para asignar el TR adecuado a cada jugador. El rendimiento de los métodos se ha evaluado utilizando métricas como precisión, exhaustividad, recuperación y puntuación F1.

Exploring Dataset Patterns for New Demand Response Participants Classification

Cátia Silva[1], Pedro Campos[2,3,4], Pedro Faria[1], and Zita Vale[1]

[1] Intelligent Systems Associated Laboratory (LASI),
Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD), Polytechnic of Porto (P.PORTO), Porto, Portugal
[2] Laboratory of Artificial Intelligence and Decision Support, LIAAD INESC TEC
[3] Faculty of Economics, University of Porto R. Dr. Roberto Frias, 4200-464 Porto - Portugal
[4] Statistics Portugal
cvcds@isep.ipp.pt;pcampos@fep.up.pt;
pnf@isep.ipp.pt;zav@isep.ipp.pt

Abstract. There is a growing trend towards consumer-focused approaches integrating distributed generation resources in the power and energy sector. This, however, adds complexity to community management as new players are introduced. The authors have designed a trustworthy rate (TR) system to address this issue of selecting participants for demand response events based on their previous performance. The aim is to avoid discomfort for consumers and reduce aggregator costs by selecting participants fairly. However, this poses a challenge for new players with a performance history. This study aims to develop a method to assign the TR to new players. For this purpose, the authors used supervised clustering and subgroup discovery to identify the relevant features of the dataset without compromising privacy after employing techniques such as Decision Trees, Random Forest, and Extreme Gradient boosting to assign the appropriate TR to each player. The performance of the methods has been evaluated using metrics such as accuracy, precision, recall, and f1 score.

Keywords: Classification, Demand Response, Subgroup Discovery, Supervised Clustering, Uncertainty.

1 Introduction

In the power and energy sector, all the players are working toward decarbonizing the system by replacing fossil fuels with renewable-based Distributed Generation (DG) technologies, such as wind and solar. However, these renewable sources have uncertain and non-programmable behavior, leading to a new paradigm where generation no longer follows demand needs [1]. Consumers must provide flexibility to avoid negative impacts on grid management, and Demand Response (DR) programs are an effective solution for this. The definition of consumers is changing as they become new market players in the energy system [2]. But they need proper knowledge to participate effectively. While many consider consumers as rational and economic agents, the reality may differ, and they require time, education, and resources to make better judgments [3].

So, despite the need for consumer flexibility through DR programs, business models do not include or cannot deal with the uncertainty associated with these new resources. Consumer participation in the market is indirect due to the small load flexibility provided and the high response uncertainty [4]. Aggregators manage active communities by gathering all the load flexibility from community members and entering the market on their behalf, but their response is only guaranteed if participation is voluntary [5]. The volatile behavior from consumers and DG units increases the network's complexity. To deal with this problem, the authors have developed a trustworthy rate (TR) to classify consumers based on the context in which DR events are triggered. The trustworthy rate is based on the participant's performance in previous events, and if their performance is good, they receive a high rate and better rewards. Otherwise, if their performance is poor, penalties are applied. The aggregator then uses the trustworthy rate to select the appropriate participants for the DR events triggered. However, this approach relies on historical information on the consumer. As innovation from previous works, such as [6] and [7], for new participants, the authors want to discover the patterns for specific combinations of characteristics that will help classify each consumer using the TR. Based on prior knowledge, supervised clustering and subgroup discovery are used to similar group objects into these predefined categories, assuming a target variable *a priori*. Decision trees, random forests, and Extreme Gradient Boosting (XGBoost) will be used and compared for classification tasks. In general, XGBoost performs better than random forests on large datasets, while random forests may perform better on smaller datasets with fewer features. Decision trees remain a useful tool for understanding the underlying relationships in data by learning simple decision rules inferred from the data features and can be a good starting point for more complex machine learning models.

The paper is structured into five main sections. The first section contains the introduction, which sets the context and outlines the paper's main objectives and research questions. In the second section, the proposed methodology is described in detail. The third section presents the case study, defining the different scenarios. The fourth section discusses the results of the study. Finally, the conclusions are drawn in the last section of the paper.

2 Proposed Methodology

In the present section, the authors define the proposed methodology to manage and select DR resources considering the triggered event context optimally and fairly. Following Figure 1, DR participants identification, Optimal Scheduling, and Remuneration are the three main steps, where the first is the focus of this study.

As soon as the DR event is triggered, the entity responsible for active community management – the aggregator, should decide which resources are needed to achieve the reduction target. Reducing the uncertainty response and enhancing DR participants' performance are the two key goals behind the proposed rate for selecting the proper DR participants – the Trustworthy Rate (TR). For the authors, this is an important step to avoid discomfort for the participants and increase the profit from the aggregator – preventing calling unnecessary participants. For instance, avoiding turning off the air conditioning or shifting the washing machine program to a different schedule at times of need might increase the motivation to participate in DR events. To do this, it is important to understand the contexts in which the players have more availability.

The idea is to characterize the DR participants with a contextual rate that evaluates the performance for the given context, easing the task of deciding which ones should participate in future events. So, in an early stage, the TR is defined as a preliminary TR (PTR) that depends on three independent rates: Context Rate (CR), Historic Rate (HR), and Last Event Rate (LER).

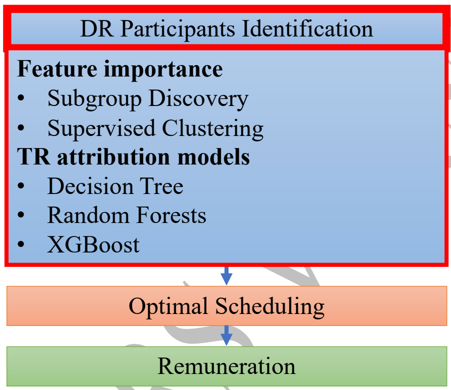


Fig. 1. Proposed methodology.

HR is the average TR from previous events that occurred in similar contexts. The LER alludes just to the last event to avoid misleading. Furthermore, considering the recorded weather and the time the event is triggered, CR depends on the active consumer's availability and willingness to participate.

The study for this paper focuses on this step and the fact that aggregator needs to have historical information on new players. In previous works, for this case, the TRassigned was the lowest, and the participant must earn the trust of the aggregator. However, understanding the behavior of similar participants might lead to a pattern, which can be used to attribute a more accurate TR to this new player.

Following this assumption, the authors intend to find patterns in the dataset to discover which features have more impact on the rate and then classify the participants. Finally, the authors will apply useful techniques such as supervised clustering and subgroup discovery for exploratory data analysis and identifying complex relationships.

According to [8], using an unsupervised clustering algorithm does not necessarily guarantee that objects of the same class or type will be grouped. Some form of supervision or labeling is required to ensure that objects with the same label are grouped into the same cluster. This procedure helps the algorithm identify which attributes or features are important for determining the similarity between objects and which objects should be grouped based on their shared labels or classes [9]. In this way, supervised clustering can be useful in applications with prior knowledge about the classes or labels of the data and where the goal is to group similar objects into these predefined categories, as in the present study. Subgroup discovery, explored by [10], aims to find interesting subsets of data that exhibit a certain property or behavior. It involves identifying subgroups or subsets of data significantly different from the rest in terms of their characteristics or attributes [11].

For the TR attribution, three classification methods are compared: Decision Trees, Random Forests, and XGBoost. Decision trees work by recursively splitting the input data into smaller subsets based on the value of a certain feature. Each split creates a new decision node, and the process continues until a stopping criterion is met, such as reaching a certain depth or minimum number of samples in a node. The final nodes of the tree are called leaves and represent the predicted value for a given input. Decision trees are easy to interpret and visualize but can be prone to overfitting. Random forests are an extension of decision trees that create a collection of decision trees and aggregate their results to make a final prediction [12], [13]. Each tree is trained on a random subset of the data and a random subset of the features, which helps reduce overfitting and improve performance. Random forests are often used for classification tasks and can handle categorical and continuous features. XGBoost is a powerful ensemble method that builds upon the concept of decision trees [14]. It trains a sequence of decision trees that each try to correct the errors made by the previous tree. XGBoost is known for its speed and scalability. While all three algorithms are based on decision trees, random forests, and XGBoost are designed to reduce overfitting and improve performance. Random forests use multiple trees and random sampling to create a more robust model, while XGBoost uses a gradient descent optimization approach to iteratively improve the performance of individual trees.

3 Case Study

The historical information used as input for the case study was taken from previous work by the authors [6] and [7]. An active community where the aggregator triggered several DR events throughout the month. Information such as availability, period, day of the week, day of the month, and temperature were withdrawn. Table 1 shows an initial dataset summary. For the current case study and considering the number of samples from each rate – where rate 1 and rate 5 have fewer observations, the authors created a new range group. So, from now on, the participants with TR lower than three will be in group -1; TR equal to 3 will be in group 0; and TR higher than three will be in group 1. In addition, the authors added new information for this paper based on Portuguese Statistics National Institute (INE - Instituto Nacional de Estatística)data for the North of Portugal, such as the building year, age group, and education level [15]. Table 2 presents the labeling used for the mentioned data. The authors widely discussed the chosen information, considering privacy issues from the participant's perspective. So, the aggregator has some knowledge regarding the participant, which could lead to distinguishing them from others without jeopardizing their privacy. With the information from INE, the authors gathered the percentage of participants from each label and adapted it for the initial dataset. This makes it possible to find patterns and withdraw knowledge using supervised clustering and subgroup discovery. Ultimately, the classification can be performed after finding the important features.

Table 1. Characterization of the number of occurrences for each rate [7].

Day of Month	Day of Week	Temperature	Period	Rate 1	Rate 2	Rate 3	Rate 4	Rate 5
1	1	16	61	17	77	102	179	25
3	3	13	253	19	119	130	132	0
5	5	11	445	7	132	130	131	0
8	1	12	733	14	120	131	135	0
10	3	14	925	2	123	151	124	0
12	5	14	1117	15	77	98	172	38
15	1	17	1405	12	66	147	156	19
17	3	17	1597	5	120	141	134	0
19	5	16	1789	13	133	114	140	0
22	1	19	2077	24	101	56	187	32
24	3	11	2269	8	126	143	123	0
26	5	14	2461	9	135	132	124	0
			Total	145	1329	1475	1737	114

Table 2. Labeling for the new input information – categorical variables.

Building year	Label	Age group		Label	Education level		Label
> 1945	A	>25	Men	HJ	None		NN
1946 - 1960	B		Women	MJ	Basic education	1º	BU
1961 - 1970	C					2º	BD
1971 - 1980	D	25-64	Men	HM		3º	BT
1981 - 1990	E		Women	MM	Secondary education		BS
1991 - 1995	F						
1996 - 2000	G	>65	Men	HI			
2001 - 2005	H		Women	MI			
2006 - 2021	I				Higher education		ES

4 Results and Discussion

The results from the case study were achieved using libraries written using R language. The dataset was previously handled regarding missing values and categorical variables. Missing values can occur due to various reasons. For instance, the malfunctioning of a smart plug can lead to measurement errors. Categorical variables represent qualitative data that fall into distinct categories, such as those selected in Table 2. Although tree-based algorithms can directly handle these variables, for XGBoost, the authors used one-hot encoding, creating a binary column for each category. After performing both pattern definition methods and rules for TR attribution, the results are analyzed and discussed.

4.1 Dataset patterns

Firstly, the dataset was tested using subgroup discovery. This technique process involves selecting a target variable of interest and searching for subsets of the data that exhibit significant differences concerning that variable. The library used was *rsubgroup* developed by Martin Atzmueller [16]. As input, the authors provided the dataset, the target, and the set of configuration settings, including the mining method, the quality function, the maximum number of patterns to be discovered, and the parameter to control whether irrelevant patterns are filtered during pattern mining. The quality function chosen was adjusted residuals, where the difference between the observed and expected samples is divided by an estimate of the standard error, according to Equation (1).

$$\text{Adjusted residual} = (\text{Observed value} - \text{Expected value}) / \text{Standard error of the residuals} \quad (1)$$

Table 3 shows the results of subgroup discovery, showing the rules for each TR group and the quality value. According to the rules created, none of the new features was considered important for this technique. The most used were availability, temperature, day of the week, period, and by order.

All the quality values are positive and below 20, presenting the lower ones for TR group 0. A positive value for this quality function indicates that the observed value is higher than predicted by the model, adjusted for sample size. This suggests the presence of an outlier or unusual observation that is not captured by the model and may indicate the need to include additional factors in the model or investigate further. Furthermore, for the goal of the case study, the authors need features that do not rely on historical information.

Table 3. Subgroup Discovery Results.

Trustworthy Rate Group	Rules	Quality
<3	"Availability=0.000" "DayofWeek=1.000"	18.17
	"temperature[16.5;∞[" "Availability=0.000" "DayofWeek=1.000"	14.65
	"Availability=0.000"	14.17
3	"temperature]-∞;13.5[" "Availability=1.000"	5.92
	"temperature]-∞;13.5[" "Period]-∞;829[" "Availability=1.000"	5.44
	"temperature]-∞;13.5["	5.26
>3	"temperature[16.5;∞[" "Availability=1.000"	18.53
	"Availability=1.000"	15.23
	"DayofWeek=1.000"	12.01

The dataset was tested using a supervised clustering technique, which resorted to a *supclust* library developed by Marcel Dettling and Martin Maechler [17]. This library can perform both "PELORA" and "WILMA" algorithms. The authors have chosen the first one since it performs the selection and supervised grouping of predictor variables in large datasets, where most parameters were considered the default. Only *noc*, the number of clusters that should be searched for on the data, was revised. Equation (2) shows the default quality function used to evaluate this technique – the within-cluster sum of squares (WSS), where *i* ranges over the observations in the cluster, *j* ranges over the clusters, x_i is the i-th observation, c_j is the centroid of the j-th cluster, and d(x_i, c_j) is the distance between the i-th observation and the j-th cluster centroid.

$$\text{WSS} = \sum_i \sum_j d(x_i, c_j)^2 \qquad (2)$$

Results from the supervised clustering algorithm can be seen in Table 4. Regarding the criterion used to evaluate the clusters, the results from Table 4 are relatively high. A high WSS indicates that the observations within the cluster are relatively spread out. However, the results from *pelora* method show the features that have a stronger association with the labels assigned to the data points, which is the purpose of this section. For the first group, where TR 1 and TR 2 are considered, the availability, day of the week, and building year were impactful features. In the next group, with only TR 3 samples, most of the features were included, excluding the day of the month. Regarding the final group, availability was selected as the representative entry. From this, the authors can move to the next phase, considering all the features except the day of the month that was not mentioned in any of the performed techniques. The following subsection compares the three selected classification methods used for TR rule definition.

Table 4. Supervised Clustering Results.

Trustworthy Rate Group	Features	Quality
<3	Availability	2884.79
	DayofWeek and Availability	2864.62
	Availability and Building Year and DayofWeek	2859.15
3	temperature	2937.35
	Temperature and Availability and Building Year and DayofWeek and Age Group and Period	2921.81
	Temperature and Availability and Building Year and DayofWeek and Age Group and Education level	2916.97
>3	Availability and temperature	3076.53
	Availability and DayofWeek	3038.97
	Availability and temperature and Building Year and Age Group and Education Level	3027.37

4.2 TR attribution models

The first method to be tested is decision trees resorting to the *rpart* package [18]. The dependent variable in the model is "TR", and the independent variables are all other

variables in the "train" dataset. The "method" parameter is set to "class" indicating a classification problem, and the "maxdepth", "minsplit", and "minbucket" parameters are used to control the size and complexity of the tree. The "cp" parameter is set to a small value, which controls the tree's complexity and helps avoid overfitting.
According to the results in Table 5, for TR less than 3, the following conditions must be met: Availability is 1, Temperature is between 13 and 15 degrees Celsius, and Building Year is either A, B, C, or F. Additionally, when Availability is 0, the TR will be less than 3. For TR equal to 3, the participant must have Availability equals 1 and Temperature is less than 12 degrees Celsius, or Availability is 1 and Temperature is between 13 and 15 degrees Celsius, and Building Year is either D, E, G, H, or I. For TR greater than 3, Availability is 1 and Temperature is between 12 and 13 degrees Celsius, or Availability is 1 and Temperature is greater than or equal to 15 degrees Celsius.

Table 5. Decision tree results.

Trustworthy Rate	Rules
<3	when Availability is 1 & Temperature is 13 to 15 & Building Year is A or B or C or F
	when Availability is 0
3	when Availability is 1 & Temperature < 12
	when Availability is 1 & Temperature is 13 to 15 & Building Year is D or E or G or H or I
>3	when Availability is 1 & Temperature is 12 to 13
	when Availability is 1 & Temperature >= 15

Table 6 presents the confusion matrix for the decision tree model – where from the dataset, 80% were used for training and 20% used for testing. The matrix shows the predicted versus actual values for the three groups: "TR< 3", "TR=3", and "TR> 3". The model correctly predicted 70 instances and misclassified 121 instances as equal to 3 and 103 as superior to 3.

Table 6. Confusion matrix for Decision tree.

		Predicted results		
		< 3	3	> 3
Actual	< 3	70	33	3
	3	121	110	109
	> 3	103	147	264

For the group TR equal to 3, the model correctly predicted 110 instances and misclassified 33 instances as inferior and 147 as superior. For the last group, the model correctly predicted 264 instances, misclassified 3 instances as "TR< 3" and 109 instances as "TR=3". Moving on to the random forest technique, where the R library has the same name, and the default parameters were considered, only using the data training predictors and the dependent variable TR as input [19]. Table 7 presents the resulting confusion matrix for the Random Forest. The first row of the matrix shows that out of 303 instances with the actual class value of TR inferior to 3, 143 instances were correctly classified, 95 instances were misclassified as TR equal to 3, and 65 instances were misclassified as TR superior to 3. Similarly, the second row of the matrix shows that out of 286 instances with the actual class value of TR equal to 3, 110 instances were misclassified as inferior, 93 instances were correctly classified, and 83 instances were misclassified as TR superior 3. The third row shows that out of 371 instances with the actual class value of TR superior to 3, 78 instances were misclassified as inferior, 85 instances were misclassified as TR equal to 3, and 208 instances were correctly classified.

Table 7. Confusion matrix for Random Forest.

		Predicted results		
		< 3	3	> 3
Actual	< 3	143	95	65
	3	110	93	83
	> 3	78	85	208

The final classification model is XGBoost, similarly to the random forest, the library used in R has the same name [20]. The authors adjusted the algorithm's parameters and, besides the input data, limited the maximum number of boosting iterations to 1000; the evaluation metric used to measure the performance of the model during training was multiclass classification error rate; the objective function used to optimize the model was multiclass classification problems and the number of classes in the target variable. The minimum train error obtained was 0.19 at iteration 803 – after this value was not modified. Table 8 presents the confusion matrix for the XGBoost model. By analyzing the results, from the 283 instances with the actual class value of TR inferior to 3, the model correctly classified 114 instances, misclassified 91 instances as TR equal to 3 and misclassified 78 instances as superior.

Table 8. Confusion matrix for XGBoost.

		Predicted results		
		< 3	3	> 3
Actual	< 3	114	91	78
	3	98	100	99
	> 3	74	98	208

Similarly, the second row shows that out of 297 instances with the actual class value of TR equal to 3, the model misclassified 98 instances as inferior, correctly classified 100 instances, and misclassified 99 instances as superior. The third row of the matrix indicates that out of 380 instances with the actual class value of TR superior to 3, the model misclassified 74 instances as TR inferior to 3, 98 instances as 3, and correctly classified 208 instances. Resorting to the confusion matrix created in the previous tables, the authors have chosen four commonly used metrics for evaluating the selected classification models: accuracy, precision, recall, and F1 score. Accuracy measures the percentage of correct predictions made by the model, while precision measures the percentage of true positive predictions out of all predicted positives. In other words, a high accuracy score indicates that the model correctly predicts most instances, while high precision can help reduce false positives. Conversely, Recall measures the percentage of true positive predictions out of all actual positives. When false positives are costly, precision is a useful metric, while recall is useful when false negatives are costly. Finally, the F1 score is a metric that balances precision and recall and is particularly useful for imbalanced datasets. By combining these metrics, the authors can gain a more comprehensive understanding of the performance of the selected classification models. Table 9 shows the results. According to the results, there is a small variability in the performance of each method across the different metrics. For example, random forests showed the highest Precision among the three methods, while decision trees had the highest Recall. From the aggregator perspective, using the decision tree model for this dataset might lead to better results since the overall performance evaluation had higher results.

Table 9. Classification models evaluation metrics results.

Metric functions	Method	TR group		
		< 3	3	> 3
Accuracy	Decision Trees	0.59	0.52	0.65
	Random Forest	0.58	0.51	0.65
	XGBoost	0.57	0.53	0.62
Precision	Decision Trees	0.51	0.37	0.49
	Random Forest	0.40	0.31	0.60
	XGBoost	0.40	0.34	0.55
Recall	Decision Trees	0.31	0.28	0.76
	Random Forest	0.47	0.28	0.55
	XGBoost	0.40	0.35	0.54
F1	Decision Trees	0.38	0.32	0.60
	Random Forest	0.43	0.29	0.57
	XGBoost	0.40	0.34	0.54

5 Conclusion

In conclusion, the energy sector is transforming decarbonization with a shift toward renewable-based technologies. DR programs provide a solution by enabling consumers to provide flexibility and avoid negative impacts on grid management. Still, their response can be uncertain. Therefore, the authors developed a trustworthy rate, considering previous performances, to select the optimal participants for the event considering the context. For the study in the present paper, the authors went a step further and wanted to create models for participants without any DR experience. Considering the features selected by the subgroup discovery and supervised clustering techniques, the authors were able to develop three different models and compare their performances. The results prove that availability is an important, crucial feature in defining the TR for a participant. Furthermore, the temperature felt at the event context and the building year are also considered for the rule definition. Regarding overall performance, Decision Trees and Random Forest had similar Accuracy, Recall, and F1 Score values, while XGBoost generally had lower scores across all metrics. However, decision Trees and Random Forest significantly improved Recall and F1 Score for TR superior to 3, while XGBoost performed more consistently across all groups.

Acknowledgements

This work has received funding from FEDER Funds through COMPETE program and from National Funds through (FCT) under the project COLORS (PTDC/EEI-EEE/28967/2017). The work has also been done in the scope of projects UIDB/00760/2020, CEECIND/02887/2017, and SFRH/BD/144200/2019, financed by FEDER Funds through COMPETE program and from National Funds through (FCT).

References

[1] B. Prabadevi *et al.*, “Deep Learning for Intelligent Demand Response and Smart Grids: A Comprehensive Survey,” Jan. 2021, doi: https://doi.org/10.48550/arXiv.2101.08013.

[2] C. Silva, P. Faria, Z. Vale, and J. M. Corchado, “Demand response performance and uncertainty: A systematic literature review,” *Energy Strategy Reviews*, vol. 41, p. 100857, May 2022, doi: 10.1016/j.esr.2022.100857.

[3] I. Ilieva, B. Bremdal, and S. Puranik, “Bringing Business and Societal Impact Together in an Evolving Energy Sector,” *Journal of Clean Energy Technologies*, vol. 7, no. 3, pp. 42–48, 2019, doi: 10.18178/JOCET.2019.7.3.508.

[4] N. Ahmed, M. Levorato, and G. P. Li, “Residential Consumer-Centric Demand Side Management,” *IEEE Trans Smart Grid*, vol. 9, no. 5, pp. 4513–4524, 2018, doi: 10.1109/TSG.2017.2661991.

[5] M. Khorram, M. Zheiry, P. Faria, and Z. Vale, “Energy consumption management in buildings in the context of voluntary and mandatory demand response programs in smart grids,” *IEEE PES Innovative Smart Grid Technologies Conference Europe*, vol. 2020-October, pp. 275–279, Oct. 2020, doi: 10.1109/ISGT-EUROPE47291.2020.9248750.

[6] C. Silva, P. Faria, and Z. Vale, “Rating consumers participation in demand response programs according to previous events,” *Energy Reports*, vol. 6, pp. 195–200, Dec. 2020, doi: 10.1016/j.egyr.2020.11.101.

[7] C. Silva, P. Faria, and Z. Vale, “Classification of New Active Consumers Performance According to Previous Events Using Decision Trees,” *IFAC-PapersOnLine*, vol. 55, no. 9, pp. 297–302, 2022, doi: 10.1016/j.ifacol.2022.07.052.

[8] S. H. Al-Harbi and V. J. Rayward-Smith, “Adapting k-means for supervised clustering,” *Applied Intelligence*, vol. 24, no. 3, pp. 219–226, 2006, doi: 10.1007/s10489-006-8513-8.

[9] C. F. Eick, N. Zeidat, and Z. Zhao, “Supervised clustering - Algorithms and benefits,” *Proceedings - International Conference on Tools with Artificial Intelligence, ICTAI*, pp. 774–776, 2004, doi: 10.1109/ICTAI.2004.111.

[10] M. Atzmueller, “Subgroup discovery,” *Wiley Interdiscip Rev Data Min Knowl Discov*, vol. 5, no. 1, pp. 35–49, 2015, doi: 10.1002/widm.1144.

[11] S. Helal, “Subgroup Discovery Algorithms: A Survey and Empirical Evaluation,” *J Comput Sci Technol*, vol. 31, no. 3, pp. 561–576, 2016, doi: 10.1007/s11390-016-1647-1.

[12] L. Breiman, J. H. Friedman, R. A. Olshen, and C. J. Stone, *Classification And Regression Trees*. Routledge, 2017. doi: 10.1201/9781315139470.

[13] L. Breiman, “Random Forests,” *Mach Learn*, vol. 45, no. 1, pp. 5–32, 2001, doi: 10.1023/A:1010933404324.

[14] T. Chen and C. Guestrin, “XGBoost: A Scalable Tree Boosting System,” in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, in KDD ’16. New York, NY, USA: Association for Computing Machinery, 2016, pp. 785–794. doi: 10.1145/2939672.2939785.

[15] I. N. de Estatística, “Censos 2021,” *Censos*, 2021. https://censos.ine.pt/xportal/xmain?xpgid=censos21_main&xpid=CENSOS21&xlang=pt

[16] Martin Atzmueller, “rsubgroup: Subgroup Discovery and Analytics.” 2021. [Online]. Available: https://cran.r-project.org/web/packages/rsubgroup/index.html

[17] M. Dettling and M. Maechler, “supclust: Supervised Clustering of Predictor Variables Such as Genes.” 2021. [Online]. Available: https://cran.r-project.org/web/packages/supclust/index.html

[18] T. Therneau, B. Atkinson, and B. Ripley, “rpart - Recursive Partitioning and Regression Trees.” 2022. [Online]. Available: https://cran.r-project.org/web/packages/rpart/rpart.pdf

[19] A. Liaw and M. Wiener, “Breiman and Cutler’s Random Forests for Classification and Regression.” 2022. [Online]. Available: https://cran.r-project.org/web/packages/randomForest/randomForest.pdf

[20] T. Chen *et al.*, “xgboost: Extreme Gradient Boosting.” 2023. [Online]. Available: https://cran.r-project.org/web/packages/xgboost/vignettes/xgboost.pdf