UNIVERSIDAD DE SALAMANCA

DOCTORAL THESIS

Decision Support for Participation in Electricity Markets considering the Transaction of Services and Electricity at the Local Level

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Doctor Degree in Informatics Engineering

DEPARTAMENTO DE INFORMÁTICA Y AUTOMÁTICA
FACULTAD DE CIENCIAS

October, 2022

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/133086/2017 and COVID/BD/152167/2021 from November 2017 to May 2022.

Thesis Type

This Ph.D. thesis is based on articles published by the author during his Ph.D. work in international journals, book chapters, and conference proceedings. The core work of this Ph.D. is composed by seven publications. Six that have been published in five international journals indexed at JCR, and one in conference proceedings:

I. Ricardo Faia, Pedro Faria, Zita Vale, and João Spinola, "Demand response optimization using particle swarm algorithm considering optimum battery energy storage schedule in a residential house," Energies, vol. 12, no. 9, pp. 1218–1223, Apr. 2019, doi: 10.3390/en12091645. **(2019 Impact Factor: 2.709)**;

II. Fernando Lezama, Ricardo Faia, Pedro Faria, and Zita Vale, "Demand Response of Residential Houses Equipped with PV-Battery Systems: An Application Study Using Evolutionary Algorithms," Energies, vol. 13, no. 10, p. 2466, May 2020, doi: 10.3390/en13102466. **(2020 Impact Factor: 3.004)**;

III. Ricardo Faia, João Soares, Tiago Pinto, Fernando Lezama, Zita Vale, and Juan M. Corchado, "Optimal Model for Local Energy Community Scheduling Considering Peer to Peer Electricity Transactions," IEEE Access, vol. 9, pp. 12420–12430, 2021, doi: 10.1109/ACCESS.2021.3051004. **(2021 Impact Factor: 3.367)**;

IV. Ricardo Faia, João Soares, Muhammad A. Fotouhi Ghazvini, John F. Franco, and Zita Vale, "Local Electricity Markets for Electric Vehicles: An Application Study Using a Decentralized Iterative Approach," Frontiers Energy Research, vol. 9, Nov. 2021, doi: 10.3389/fenrg.2021.705066. **(2020 Impact Factor: 3.30)**;

V. Ricardo Faia, Tiago Pinto, Zita Vale, and Juan M. Corchado, "Portfolio optimization of electricity markets participation using forecasting error in risk formulation," International Journal Electric Power Energy Systems, vol. 129, 2021, doi: 10.1016/j.ijepes.2020.106739. **(2020 Impact Factor: 4.63)**;

VI. Ricardo Faia, Tiago Pinto, Zita Vale, and Juan M. Corchado, “Prosumer Community Portfolio Optimization via Aggregator: The Case of the Iberian Electricity Market and Portuguese Retail Market,” Energies, vol. 14, no. 13, p. 3747, 2021, doi: 10.3390/en14133747. **(2021 Impact Factor: 3.004)**;

VII. Ricardo Faia, Tiago Pinto, Zita Vale, and Juan M. Corchado, “A Local Electricity Market Model for DSO Flexibility Trading,” in International Conference on the European Energy Market, EEM, 2019, vol. 2019-September, doi: 10.1109/EEM.2019.8916563.

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"Education is the most powerful weapon which you can use to change the world."

Nelson Mandela.

Acknowledgments

My first words are to express my gratitude to my supervisors. Special thanks to my supervisor Professor Zita Vale for the trust placed in me, believing in the value of my work, guidance, and support that she has provided me over the last few years. A notable word of thanks to my tutor and co-supervisor, Professor Juan Manuel Corchado, for his prompt availability and support, especially regarding administrative issues. A very special word of thanks to my friend and co-supervisor Professor Tiago Pinto, for the support, motivation, friendship, and for sharing his knowledge and experience when discussing the scientific and technical aspects related to the developed work and others research activities. To the three of you, I would like to dedicate the results of this Ph.D. work.

I would also like to thank to my girlfriend, Alexandra, who always supported me even in her bad moments, and for the motivation she always gives me. For my mother, father, and sister, a big thank you for all the support given throughout this phase. You are all part of the success of this Ph.D. thesis.

I also express my word of thanks to the GECAD team, especially to Brígida, Bruno, Cátia, Fernando, Filipe, Francisco, Gabriel, João, Luís, Omid, Pedro, and Professor Sérgio Ramos, who have all contributed largely to the success of this work in any particular way. Finally, I also thank to Fundação para a Ciência e a Tecnologia (FCT) for the support through the Ph.D. grant and to the Department of Electrical and Computer Engineering of Instituto Superior Técnico (IST) from Lisbon, in special Professor Hugo Morais, for hosting me during my secondment.

Abstract

The growing concerns regarding the lack of fossil fuels, their costs, and their impact on the environment have led governmental institutions to launch energy policies that promote the increasing installation of technologies that use renewable energy sources to generate energy. The increasing penetration of renewable energy sources brings a great fluctuation on the generation side, which strongly affects the power and energy system management. The control of this system is moving from hierarchical and central to a smart and distributed approach. The system operators are nowadays starting to consider the final end-users (consumers and prosumers) as a part of the solution in power system operation activities. In this sense, the end-users are changing their behavior from passive to active players. The role of aggregators is essential in order to empower the end-users, also contributing to those behavior changes. Although in several countries aggregators are legally recognized as an entity of the power and energy system, its role being mainly centered on representing end-users in wholesale market participation.

This work contributes to the advancement of the state-of-the-art with models that enable the active involvement of the end-users in electricity markets in order to become key participants in the management of power and energy systems. Aggregators are expected to play an essential role in these models, making the connection between the residential end-users, electricity markets, and network operators. Thus, this work focuses on providing solutions to a wide variety of challenges faced by aggregators.

The main results of this work include the developed models to enable consumers and prosumers participation in electricity markets and power and energy systems management. The proposed decision support models consider demand-side management applications, local electricity market models, electricity portfolio management, and local ancillary services.

The proposed models are validated through case studies based on real data. The used scenarios allow a comprehensive validation of the models from different perspectives, namely end-users, aggregators, and network operators. The considered case studies were carefully selected to demonstrate the

characteristics of each model, and to demonstrate how each of them contributes to answering the research questions defined to this work.

Keywords: Aggregator; Decision-support Models; Electricity Markets; Electricity End-users; Local Ancillary Services; Local Electricity Markets.

Resumen

La creciente preocupación por la escasez de combustibles fósiles, sus costos y su impacto en el medio ambiente ha llevado a las instituciones gubernamentales a lanzar políticas energéticas que promuevan la creciente instalación de tecnologías que utilizan fuentes de energía renovables para generar energía. La creciente penetración de las fuentes de energía renovable trae consigo una gran fluctuación en el lado de la generación, lo que afecta fuertemente la gestión del sistema de potencia y energía. El control de este sistema está pasando de un enfoque jerárquico y central a un enfoque inteligente y distribuido. Actualmente, los operadores del sistema están comenzando a considerar a los usuarios finales (consumidores y prosumidores) como parte de la solución en las actividades de operación del sistema eléctrico. En este sentido, los usuarios finales están cambiando su comportamiento de jugadores pasivos a jugadores activos. El papel de los agregadores es esencial para empoderar a los usuarios finales, contribuyendo también a esos cambios de comportamiento. Aunque en varios países los agregadores están legalmente reconocidos como una entidad del sistema eléctrico y energético, su papel se centra principalmente en representar a los usuarios finales en la participación del mercado mayorista.

Este trabajo contribuye al avance del estado del arte con modelos que permiten la participación activa de los usuarios finales en los mercados eléctricos para convertirse en participantes clave en la gestión de los sistemas de potencia y energía. Se espera que los agregadores desempeñen un papel esencial en estos modelos, haciendo la conexión entre los usuarios finales residenciales, los mercados de electricidad y los operadores de red. Por lo tanto, este trabajo se enfoca en brindar soluciones a una amplia variedad de desafíos que enfrentan los agregadores.

Los principales resultados de este trabajo incluyen los modelos desarrollados para permitir la participación de los consumidores y prosumidores en los mercados eléctricos y la gestión de los sistemas de potencia y energía. Los modelos de soporte de decisiones propuestos consideran aplicaciones de gestión del lado de la demanda, modelos de mercado eléctrico local, gestión de cartera de electricidad y servicios auxiliares locales.

Los modelos propuestos son validan mediante estudios de casos basados en datos reales. Los escenarios utilizados permiten una validación integral de los modelos desde diferentes perspectivas, a saber, usuarios finales, agregadores y operadores de red. Los casos de estudio considerados fueron cuidadosamente seleccionados para demostrar las características de cada modelo y demostrar cómo cada uno de ellos contribuye a responder las preguntas de investigación definidas para este trabajo

Palabras clave: Agregador; Modelos de Apoyo a la Decisión; Mercados Eléctricos; Usuarios Finales de Electricidad; Servicios Auxiliares Locales; Mercados Eléctricos Locales

Resumo

As crescentes preocupações com a falta de combustíveis fósseis, com seus cuscos e seus impactos no meio ambiente têm levado instituições governamentais a criarem políticas energéticas que promovam a instalação cada vez maior de tecnologias que utilizam fontes renováveis de energia para gerar eletricidade. A crescente penetração de fontes de energia renovável traz uma grande flutuação na geração, o que afeta fortemente a gestão do sistema de energia. O controlo desse sistema está a mudar de uma abordagem hierárquica e central para uma abordagem inteligente e distribuída. Atualmente, os operadores do sistema começam a considerar os utilizadores finais (consumidores e *prosumers*) como parte da solução nas atividades de operação do sistema de energia elétrico. Nesse sentido, os utilizadores finais estão a mudar o seu comportamento de utilizadores passivos para ativos. O papel dos agregadores é realmente essencial para potencializar os utilizadores finais, contribuindo também para essas mudanças de comportamento. Embora em vários países os agregadores sejam legalmente reconhecidos como entidade do sistema de energia elétrico, o seu papel centra-se principalmente na representação dos utilizadores finais na participação no mercado grossista de eletricidade.

Este trabalho contribui para o avanço do estado da arte com modelos que permitem o envolvimento ativo dos utilizadores finais nos mercados de eletricidade para se tornarem participantes-chave na gestão do sistema elétrico de energia. Espera-se que os agregadores desempenhem um papel essencial nestes modelos, fazendo a ligação entre os utilizadores finais residenciais, os mercados de eletricidade e os operadores de rede. Assim, este trabalho foca-se em fornecer soluções para uma ampla variedade de desafios enfrentados pelos agregadores.

Os principais deste trabalho incluem a participação dos consumidores e *prosumers* nos mercados de eletricidade e na gestão dos sistemas de energia e energia. Os modelos de suporte desenvolvidos consideram aplicações de gestão do lado do consumidor, modelos de mercado local de eletricidade, gestão de portfólio de eletricidade e serviços auxiliares locais.

Os modelos propostos são validados através de casos de estudo baseados em dados reais. Os cenários utilizados permitem uma validação abrangente dos modelos a partir de diferentes perspetivas, nomeadamente utilizadores finais, agregadores e operadores de rede. Os casos de estudo considerados foram criteriosamente selecionados para demonstrar as características de cada modelo e demonstrar como cada um deles contribui para responder às questões de pesquisa definidas neste trabalho.

Palavras-chave: Agregador; Modelos de Apoio à Decisão; Mercados de Eletricidade; Usuários Finais de Eletricidade; Serviços Auxiliares de Sistema Locais; Mercados Locais de Eletricidade.

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Acronyms

ACO	Ant Colony Optimization
AS	Ancillary Services
BEMS	Building Energy Management Systems
CI	Computational Intelligence
CHP	Combined Heat and Power
DE	Differential Evolution
DER	Distributed Energy Resources
DR	Demand Response
DSM	Demand Side Management
DSO	Distributed System Operator
EC	European Commission
EM	Electricity Market
EMS	Energy Management Systems
ENTSO-E	European Transmission System Operator Network
ESS	Energy Storage Systems
EU	European Union
EV	Electric Vehicles
FiT	Feed-in Tariffs
GECAD	Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development
GHG	Greenhouse Gas
HEMS	Home Energy Management System
HVAC	Heating, Ventilation and Air Conditioning
HyDE-DF	Hybrid Differential Evolution with Decay Function
LEC	Local Energy Community
LEM	Local Electricity Markets
MILP	Mixed Integer Linear Programing
MOPSO	Multi-objective Particle Swarm Optimization
NLP	Non-Linear Programming
OPF	Optimal Power Flow
P2P	Peer-to-Peer
P2V	Peer-to-Vehicle
PES	Power and Energy Systems

Ph.D.	Doctor of Philosophy
PSO	Particle Swarm Optimization
RAM	Random Access Memory
RES	Renewable Energy Sources
SG	Smart Grid
TSO	Transmission System Operator
VPP	Virtual Power Plant

Chapter 1

Introduction

1 Introduction

The motivation for the development of this Doctor of Philosophy (Ph.D.) thesis is presented in section 1.1, which leads to the definition of the related research questions and objectives, presented in section 1.2. The key contributions of the developed work and the related publications are described in section 1.3. Finally, section 1.4 presents the outline and organization of the Ph.D. thesis document.

1.1 Motivation

Today's societies are highly dependent on electrical energy consumption. Considering that societies are composed of rational beings, which always search for the best possible comfort, the electricity consumption needs to increase in order to satisfy them. Considering this behavior, the institutional government has been fighting the consequences that a drastic increase of electricity consumption brings, imposing and suggesting different actions. The European Union (EU) has shown great concern, from an early stage, regarding climate change, environmental and energy issues [1]. The reduction of greenhouse gas (GHG), the share of energy renewable-based generation, and the energy efficiency are considered by the EU as key aspects in the future of electric power systems. Still, they can also condition the consumption and production of electrical energy. In September of 2020, the EU published in [2] a revision of the defined targets of [3] maintaining the following trends: reduction of GHG emissions by at least 40% from the levels of 1990; the target of 32% of renewable energy consumption share; and the energy efficiency should be improved at least 32,5% by 2030. The *"European Green Deal"* created on 1st December of 2019 [4] constitutes a collection of policy initiatives purposed by the European Commission (EC) with the propose of getting the EU climate neutral in 2050. To obtain neutrality, EU extends its goals for other different sectors, including construction, biodiversity, energy, transport, and food. More ambitious targets, aligned with the "*European Green Deal*" and defined in [5], identify goals for an economy with net-zero GHG emissions by 2050 [6]. By analyzing the EC report published on 26th October of 2021 [7], it is possible to conclude that the previously published directives are starting to show results. According to the report results, the power sources using fossil fuels were for the first time (2020) exceeded by power sources using renewables; in specific 38% for renewables, 37% for fossil fuels and 25% for others (nuclear fission). Regarding GHG emissions values, the report also presents encouraging results: in 2020 a value of 31% (compared with 1990 values) is registered as the verified reduction. This value is largely due to the Covid-19 pandemic situation, but the pre-set target of 40% by 2030 is expected to be easily achieved.

The consequent large integration of renewable energy sources (RES) (e.g., wind, solar, among others) has variable production, and the installed power is often not an effective production. Since the behavior of RES differs from conventional energy sources, the integration of RES with particularities presented in reference [8] is reflected in the power and energy systems (PES) and brings different challenges to its normal operation [9]. The problems provoked by large scale-RES penetration in the PES can be mitigated by installing of energy storage systems (ESS) [10], [11]. The integration of RES and ESS needs a sophistical energy management system (EMS) for successful integration [12], [13]. EMS can be oriented to obtain single or multiple objectives, still that the most common are economic objectives [14]. These objectives can be fulfilled at the transmission, distribution, or end-user level. In this way, the application of EMS at the end-user level can contribute to the empowerment of electricity end-users (consumers and prosumers) meeting EU guidelines.

With higher distributed energy resources (DER) penetration and utilization, customers are becoming more active players in the electric grid, either as prosumers or by participating in demand-response (DR) programs offering a variety of system benefits [15], [16]. DR can be considered a tool to maintain the stability of PES from the demand side [17]. DR programs were initially designed and implemented for industrial and commercial customers, hence residential customers were out of this initial scope due to the small DR contribution that each one could offer [18]. Resources aggregation is one of the promising solutions identified to include the residential consumers as participants in DR events and markets and make use of their flexibility potential. In this sense, the aggregator entity gains a solid role in PES [19]. The application scope of aggregators is not just limited to aggregating DR. In fact, the literature offers several other different types, e.g., a load aggregator mainly gathers the load flexibility of residential customers; a production aggregator (e.g., virtual power plant (VPP)) groups small generation units [20]; an EV aggregator groups individual EVs [21]. In this way, an aggregator is a legal agent and can participate in electricity power market (intraday, day ahead, etc.), and in regulating or balancing markets.

With the increase of RES installation in small end-user facilities, households' consumers have become prosumers with the ability not only to meet their needs but also to sell surplus energy, generating some profits. Given the impossibility of prosumers' surplus energy being sold on the wholesale market due to minimum quantity restrictions, aggregators play a fundamental role in this process [22]. Portfolio optimization appears as a management tool that can give support to electricity sellers and buyers. In a traditional portfolio optimization problem, the solution is composed of the allocation of capital within different investments opportunities. The portfolio application on EM allocates electricity within different markets (day-ahead markets, real-time markets, bilateral contracts, forward) [23]. Aggregators can make the use of portfolio techniques to find the best schedule of their aggregated electricity to obtain the best transactions in the electricity market, considering all available options [24].

The RES installation also has an impact in the feed-in tariffs (FiT) value. Initially the creation of FiT aimed to increase the number of DER installations to meet the imposed environmental targets. This effect was also reflected at the household level with high adherence to the installation of small generation PV units. A gradual decrease in FiT has been observed over the years (e.g., in Portugal, in 2019, the FiT was 95 €/MWh, and in the current year (2022), the FiT is 45 €/MWh). As a result, these decreases may have an impact on RES companies' profits or encourage higher levels of self-consumption, e.g. when consumers with PV systems have ESS installed [25], [26]. The main challenges arise during high generation periods, during which RES production surpasses a prosumer demand, and therefore, overall generation may not be fully utilized. If a ESS is not available, the surplus energy could be curtailed or fed back into the grid [27]. Curtailment can lead prosumers to invest in lower generation capacity and reduce the profitability of the installed capacity. Feeding into the grid brings other issues, such as the requirement for a fair price, since the existing heavily subsidized feed-in tariffs may not be viable as the number of prosumers increases.

Consequently, a significant need for drastic changes in the EM emerges, comprising both the retail and wholesale markets. Accordingly, the EC promptly the restructuring and liberalization of EM in the EU. This process emerged in 1996 with the directive 96/92/EC of the European Parliament and Council, introducing competition in the electricity markets (EM) that could increase efficiency and reduce electricity prices. However, the market competition was threatened by discriminatory access to transmission and distribution networks and market dominance. To combat the previous situation, the EU introduced in 2003 the

2003/54/EC directive (replacing 96/92/EC). This directive guarantees transparency in electricity prices, non-discriminatory access to market and network and promotes the separation of entities related to the exploration of transmission and distribution systems. The third energy package introduced in 2009 (2009/72/EC) replaced the last 2003/54/EC published directive. It reinforced the separation of legal ownership of network operation from suppliers and generation, emphasizes the consumers' right to free choice of suppliers, and strengthens cross-border trading in the EU. In 2019, Directive 2019/944 with the name "Common rules for the internal market for electricity" was published. It focuses on creating a truly integrated and competitive, consumer-centered, flexible, fair, and transparent electricity market in the EU. Directive 2019/944 imposes rules on consumer empowerment and protection. Also, this directive promotes the final end-user of electricity with the possibility to evolve from a passive player to an active player. Furthermore, it promotes their enrolment in the power system through the creation of new business opportunities [28].

Endowing end-users with a more active role in the EM are leading to the emergence of Local Electricity Markets (LEM). LEM are arising as a prosumer-centered model with the possibility for sellers and buyers to find the best market opportunities [29]. Furthermore, LEM can contribute to the empowering of users [30], as these are implemented locally and designed for the participation of consumers and prosumers, complying with the guidelines of the EU for the energy communities [31], [32]. LEM can have two main proposes, one of them being electricity trading [33], where prosumers and consumers can transact electricity without necessarily a central authority. The other propose is flexibility trading [34], where a central entity (e.g., aggregator, distributed system operator (DSO)) request flexibility in a specified local area to solve grid issues [35]. LEM could also support ancillary services (AS) provisions at the local level [36]. These types of models have come into great focus in the literature [37], and there is a need to create methodologies to support and guide the users in real-world applications.

1.2 Objectives

The need for electricity end-users (prosumers and consumers) to become active players in PES, and EM in particular; and the lack of suitable decision support methodologies that can enable them coping with the new challenges, especially via entities such as aggregators, are some of the relevant acknowledged constraints in the current state of the art. The research problems that arise from this gap highlight the need for improved solutions to assist the decisions and operation of aggregators. This enables consumers and prosumers to adapt their behaviors in order to gain better benefits for themselves and for the system. As a result, it is essential to consider the participation of consumers and prosumers at different levels, namely: in the management of PES, participation in wholesale markets and AS markets, and in LEM participation. Normally, individual consumers or prosumers cannot meet the requirements to participate in the activities listed above or do not have the knowledge, capability, will or capacity to do so. In this context, the role of the aggregator becomes fundamental for the empowerment of the consumers and prosumers in EM and PES. In sum, the gaps are focused on aggregator, prosumer and consumer activities involving the participation in PES and EM. The main research question established in this Ph.D. was identified by the significant breakthroughs that are necessary to cover the identified gaps:

Q0 - Can innovative aggregator-oriented business, market and flexibility models boost prosumers/consumers active participation in future PES?

In order to respond to research question *Q0*, there is a need to divide the main question into different sub-research questions. Therefore, the following group of research questions arises:

Q1 - How can consumption flexibility and demand response models enable the participation of prosumers/consumers in a fair and efficient way, with benefit for all the involved players and the system?

Q2 – How can electricity market models be improved to enable an efficient and intensive use of local resources (distributed generation, EV, demand flexibility, and storage)?

Q3 - How can players improve their participation in future EM considering the new and evolving opportunities including, aggregators, energy communities, and LEM?

Q4 - How can we take full advantage of local resources for implementing new models for AS provision with benefit(s) to distribution system operators and local players including prosumers and consumers?

Q5 - How can prosumers/consumers use their flexibility in an efficient and advantageous way in their own installations and to respond to implicit and explicit flexibility requests?

The hypothesis of this Ph.D. work aims at demonstrating that electricity end-users (prosumers and consumers), namely households, can have an active participation in PES and EM. This can bring benefits not only to themselves but also to other stakeholders (e.g., DSO, aggregator, etc.) participating in the smart grid. In order to prove this hypothesis, four central topics are identified and will be the subject of study of this work: demand-side management, LEM, electricity portfolio management, and local ancillary services.

The development of this Ph.D. must result in a decision support methodology capable of guiding consumers and prosumers in their daily energy management activities, considering the participation in EM and contributing to the management of PES. It is also needed to develop models that include the possibility of residential end-users (prosumers and consumers) executing demand-side management actions; the option of prosumers and consumers participating in LEM transacting electricity between them; the opportunity to use the portfolio management methods to find the best markets to allocate their transactions and the possibility of providing ancillary services to upper levels. The expected implementation models should consist mostly of optimization solutions, simulation models, and analyses. Exact methods (e.g., Mixed Integer Linear Programming (MILP)) or intelligent search algorithms (e.g., Particle Swarm Optimization (PSO)) should be applied to solve the optimization problems.

The conclusions of this Ph.D. work will be supported by experiments based on real data provided from both laboratory and real environments. The hosting institution Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD) will provide all software and hardware necessary to develop and test the created models.

Taking into account the previously explained hypothesis and ensuring the answers to the identified research questions, the following objectives are considered:

1. <u>Development of a methodology for optimization of demand response (flexibility) of residential households,</u>
    a. Analyze different resources to support demand response such as, ESS, PV-systems, and controllable loads
    b. Evaluation of model scalability considering many households managed by an aggregator
    c. Explore the value of flexibility for the grid and distribution operator

2. Development of new electricity market models at the local level for households' participation
    a. Analyze existing published models and solutions for LEM models
    b. Evaluate the benefits of local transactions for all involved players
    c. Comparing the centralized and distributed resolution methodologies
3. Development of methodology of portfolio optimization for an aggregator to enable the households' participation in EM
    a. Examine the influence of the risk in the portfolio allocation assets (electricity in different markets)
    b. Analysis of the participation of an energy community in the wholesale market through an aggregator
4. Investigate the possibility of households providing AS contributing with an active role in the distribution grid operation
    a. Simulation of an action-based market at the local level to negotiate the flexibility needed for solving problems in a distribution grid
5. Optimization and Simulation of scenarios based on real and simulated data to test and validate the models
    a. Testing and validating different optimization methods
    b. Simulation of scenarios based on real EM' data
    c. Analysis of the realistic scenarios simulation results using the developed system to support market players' actions

1.3 Contributions and Publications

The realization of the defined objectives and the consequent success of responses to the specified research questions fully cover the goals defined in the Ph.D. scholarship (reference SFRH/BD/133086/2017 and COVID/BD/152167/2021) in the scope of the "Ph.D. Studentships and Post-Doctoral Fellowships" and "Exceptional Grants to Mitigate the Impact of COVID-19" respectively, both from the programme of FCT (*Fundação para a Ciência e a Tecnologia* - Science and Technology Foundation). In addition, the results obtained in the scope of this thesis also partially cover the objectives and results of several national and international R&D projects with the participation or coordination of GECAD, the hosting institution for the development of the research activities of this Ph.D. The considered projects are:

- TradeRES – New Markets Design & Models for 100% Renewable Power Systems. Funded by the European Union's Horizon 2020 research and innovation program under grant agreement 864276;

To TradeRes project (ongoing), the work of this Ph.D. contributed to developing electricity transaction models within energy communities. Although the results obtained will not be reported here, they are presented in the deliverables of the project.

- CENERGETIC – Coordinated ENErgy Resource manaGEment under uncerTainty considering electrIc vehiCles and demand flexibility in distribution networks. PTDC/EEI-EEE/28983/2017;

The models developed within the scope of this work related to EV and their integration into the local context also contributed to the CENERGETIC project (finalized). The results reported from the publications that constitute the work of this Ph.D. were also reported in the projects deliverables.

- MAS-Society – Multi-Agent Systems SemantiC Interoperability for simulation and dEcision supporT in complex energY systems, reference no. PTDC/EEI-EEE/28954/2017;

In the MAS-Society project (finalized), the work developed in this Ph.D. essentially contributed to the application of the portfolio theory to support participating players in the electricity markets. Therefore, the results reposted in this work, considering the portfolio theory application, are part of the projects results.

- DOMINOES – Smart Distribution Grid: A Market Driven Approach for the Next Generation of Advanced Operation Models and Services, under the H2020 grant agreement no. 771066;

For the DOMINOES project (finalized), this Ph.D. work contributed to models developed for acquiring AS at the local level using the available flexibility provided by small electricity end-users. Accordingly, the results obtained from the application of these models were reported in the deliverables of the project had a different case study from those presented in this document.

- CONTEST – Innovative CONsumer aggregation to improve demand response and Tariff design for Energy and Services Transactions, reference no. SAICT-POL/23575/2016;

Considering the CONTEST project (finalized), the model that includes the aggregator as a DR service provider developed in this Ph.D. work contributed to the project's outcomes. The presented results in this work are not reported in the projects deliverables.

- DREAM-GO – Enabling Demand Response for short and real-time Efficient And Market Based smart Grid Operation – An intelligent and real-time simulation approach. Funded by the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement no. 641794;

In the scope of DREAM-GO (finalized), the models developed in this Ph.D. work contributed to the DR actions implementation using metaheuristic algorithms. The results obtained with the DR models reported in this document were part of the projects results.

The results and the work achieved during the development of this Ph.D. thesis ensured the publication of nineteen scientific papers. Ten papers were presented and published in the proceedings of top-level conferences in the fields of power systems and computer science; one book chapter has been published in a book dedicated to LEM; and ten journal papers have been published in JCR[1] indexed journals with impact factors. Seven of the published papers compose the core of this Ph.D. thesis (six published in scientific international journals and one in scientific international conference proceedings) by fulfilling the proposed objectives and answering the research questions. The seven papers are presented in Appendix A. Core Publications, and their fundamental contributions to cover this Ph.D. thesis' objectives are presented in chapter 2. The seven core publications of this Ph.D. work are as follows:

I. Faia, R., Faria, P., Vale, Z., & Spinola, J. (2019). Demand response optimization using particle swarm algorithm considering optimum

[1] Journal Citation Reports (JCR): https://jcr.clarivate.com/.

battery energy storage schedule in a residential house. *Energies*, *12*(9), 1645.

II. Lezama, F., Faia, R., Faria, P., & Vale, Z. (2020). Demand response of residential houses equipped with PV-battery systems: An application study using evolutionary algorithms. Energies, 13(10), 2466.

III. Faia, R., Soares, J., Pinto, T., Lezama, F., Vale, Z., & Corchado, J. M. (2021). Optimal model for local energy community scheduling considering peer to peer electricity transactions. IEEE Access, 9, 12420-12430.J

IV. Faia, R., Soares, J., Ghazvini, M. A. F., Franco, J. F., & Vale, Z. (2021). Local Electricity Markets for Electric Vehicles: An Application Study Using a Decentralized Iterative Approach. Frontiers in Energy Research, 563.

V. Faia, R., Pinto, T., Vale, Z., & Corchado, J. M. (2021). Portfolio optimization of electricity markets participation using forecasting error in risk formulation. International Journal of Electrical Power & Energy Systems, 129, 106739.

VI. Faia, R., Pinto, T., Vale, Z., & Corchado, J. M. (2021). Prosumer community portfolio optimization via aggregator: The case of the iberian electricity market and portuguese retail market. Energies, 14(13), 3747.

VII. Faia, R., Pinto, T., Vale, Z., & Corchado, J. M. (2019, September). A local electricity market model for DSO flexibility trading. In 2019 16th International Conference on the European Energy Market (EEM) (pp. 1-5). IEEE.

In addition, there are three manuscripts submitted for publication in international journals with preprints available in public mode to complement and reinforce the realization of the proposed objectives. These papers are available in Appendix B. Preprints.

I. Faia, R., Lezama, F., Pinto, T., Faria, P., Vale, Z., Terras, J., & Albuquerque, S. (2022). A Simulation of Market-based Non-Frequency Local Ancillary Services Procurement Based on Demand Flexibility.

II. Faia, R., Morais, H., Pinto, T., Lezama, F., Vale, Z. (2022). Indoor Temperature Evolution Modelling Through Computational Intelligence

III. Faia, R., Lezama, F., Vale, Z., Soares, J., Pinto, T., Corchado, J. M. (2022). Local Electricity Markets – Review

The combinations of the contributions provided by the work developed in the scope of the Ph.D. work results in different models able to support the decisions of aggregators, prosumers and consumers in the participation of EM and management of PES. Figure 1-1 presents the conceptual overview of the study in this Ph.D.

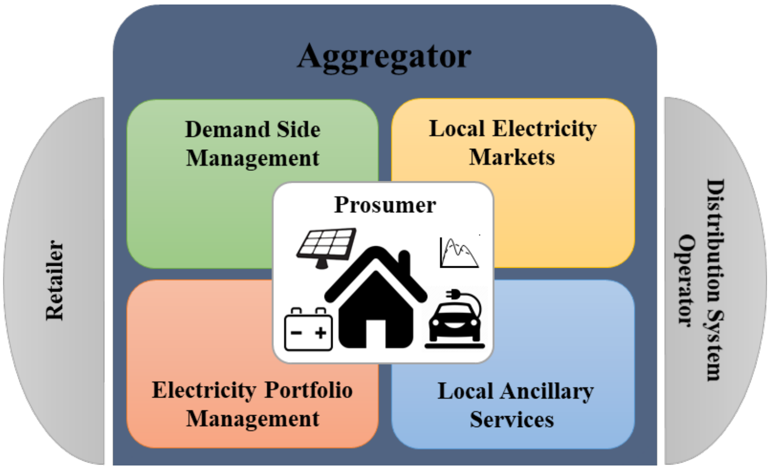

Figure 1-1 – Conceptual overview of the work developed

Figure 1-1 presents the conceptual overview of the work developed in this Ph.D., with the representation of the prosumer in the center. This figure highlights the aggregator as an important entity to enable the prosumer participation in some activities and the key components that underlie the main activities that prosumers can participate or get involved in. The four main components presented in Figure 1-1 integrate the decision support features that enable: *(i)* demand-side management that includes the possibility of consumers and prosumers to modify their consumption demand (presented in *Core Paper I* [38] and *Core Paper II* [39]); *(ii)* the participation in LEM, considering the possibilities for electricity transactions with neighbors (presented in *Core Paper III* [40] and *Core Paper IV* [41]); *(iii)* the possibility of using electricity portfolio management techniques, choosing the best opportunities to perform the transactions (presented in *Core Paper V* [42] and *Core Paper VI* [43]); and the possibility of providing ancillary services from the local level through a novel market structure (present in *Core Paper VII* [44]).

All developed modules are created with focus on consumer and prosumer activities, considering them as a central entity in the proposed system.

Generation resources (PV generators) and storage resources (home batteries and EV batteries) are considered on the prosumer or consumer side. Therefore, through optimization and simulation approaches, the implemented methodologies and models provide the best solution considering the available resources and the purpose for which they are intended.

To support prosumers in demand side management (DSM) actions the models presented in *Core Paper I* [38] and *Core Paper II* [39] and *Other Paper I-V* in [45]–[49] have been proposed. *Core Paper I* and *Core Paper II* [39] consider the possibility of prosumers realizing DR in order to minimize the costs of energy usage. *Core Paper I* [38], provides a single application for the prosumers to realize DR without contracting other entities (e.g., aggregator). The solution is obtained considering two different approaches (exact and non-exact). *Core Paper II* [39] considers a service provision by an aggregator to perform DR, in which prosumers' houses pay a fee to the aggregator as compensation for the provided service. This paper provides a model to schedule the best options to execute the DR. To obtain the solution, the aggregator solves the optimization problem by considering metaheuristic algorithms (non-exact resolutions).

The support for the prosumers' participation in LEM is presented in *Core Paper III* [40], *Core Paper IV* [41], and also in *Other Paper VI-IX* [50]–[53]. In *Core Paper III* [40] a centralized solution is obtained considering that prosumers realize peer-to-peer (P2P) transactions and use the main grid as a backup. In this study, an exact solution was found to minimize the overall costs of the community members. *Core Paper IV* [41] presents a study of a LEM model that includes prosumers and EVs. An iterative and distributed solution was proposed to solve the problem.

Electricity portfolio management support was analyzed in *Core Paper V* [42] and *Core Paper VI* [43] and also *Other Paper X* [54] and *Other Paper XI* [55]. *Core Paper V* [42] considers the participation of an aggregator in different market possibilities supported by portfolio optimization analyses. The model proposed in *Core Paper VI* [43], comprises the aggregator participation in the wholesale electricity market (a spot market and six intraday market sessions) or the purchase of electricity from a retailer.

Regarding the local AS participation, the support is given by the models proposed in *Core Paper VII* [44], *Other Paper XII* [56] and *Preprint I* [57]. These works comprise simulation studies. In *Core Paper VII* [44], a local market for AS services provisions has been proposed, prosumers and consumers can respond to the flexibility request with offers of demand reductions. The offers are selected according to an asymmetric auction mechanism. *Preprint I* [57] also presents a local AS provision market for voltage bus and current lines control. This work analyses different types of consumers behaviors in submitting offers on the local AS provision market.

1.4 Document Structure

This thesis document contains three chapters. This chapter presents the introduction and exposes the motivation for developing this Ph.D. thesis, a background overview of the most significant subjects related to this work, the identified research questions and objectives, and a summary of the key contributions.

Chapter 2 describes the contributions of this thesis, explaining the research questions and discussing how each core paper addresses these questions, accomplishing the determined objectives. The chapter contains the key contributions of this Ph.D. work, in which each subsection addresses a specific topic associated with a research question.

Finally, chapter 3 presents the most relevant conclusions and findings completed from the developed work. Perspectives of future research are also presented in this final chapter.

Chapter 2

Contributions

2 Contributions

This chapter presents the key contributions of the developed work and discusses how each of the core papers of this Ph.D. thesis addresses the presented research questions. The fulfilment of the Ph.D. objectives is also described as a result of several key contributions.

2.1 Introduction

Adequate models and methodologies are fundamental to provide support for the small electricity end-users (consumers and prosumers) in EM participation and PES management involvement. Using these models and methods, electricity end-users (consumers and prosumers) are able to obtain advantages from participating in the multiple activities discussed in the motivation of this work. The research questions stated in the introduction section and the subsequent characterization of the Ph.D. work's objectives were motivated by the current gap in the literature regarding this form of support for small electricity end-users in EM participation and PES management involvement.

As a result of this Ph.D. research, several models and methods have been developed, which is crucial to overcome the field's limitations. Furthermore, the obtained results contribute to the progress of the current state of the art by offering solutions to the research questions that have been defined as relevant to such development.

Table 2-1 presents the relation between each publication and the key contributions of this thesis. The identified key contributions are also associated with each related objective defined previously. Publication "Core *Paper" I* to *VII* [38]–[44] represents the core publications (six journal papers and one conference paper) of this Ph.D. work, previously introduced in section 1.3. The "*Other*" column identifies supplementary scientific publications, in total twelve (seven conference papers, four journal papers and one book chapter), that have also been published in the scope of this Ph.D. research, complementing with additional results the achievements of the core publications. Additionally, the *"Preprint"* column considers important unpublished papers that give complementary support for this Ph.D. work, three in total; these papers have been submitted to JCR journals and were briefly presented in section 1.3.

Table 2-1 - Ph.D. thesis key contributions, related objectives, publications, and preprints.

Key Contributions	Related Objectives	Publications								Preprint		
		Core							Other			
		I	II	III	IV	V	VI	VII	I-XII	I	II	III
		[38]	[39]	[40]	[41]	[42]	[43]	[44]	[45]-[56]	[57]	[58]	[59]
Demand Side Management	1 (see section 2.2)	X	X						[45] [46] [47] [48] [49]			
Local Electricity Markets	2 (see section 2.3)			X	X				[50] [51] [52] [53]			X
Electricity Portfolio Management	3 (see section 2.4)					X	X		[54] [55]			
Local Ancillary Services	4 (see section 2.5)							X	[56]	X		
Experiments	5 (see section 2.6)	X	X	X	X	X	X	X		X	X	

As can be seen from Table 2-1, the key contributions are covered by at least one core publication. In addition, other publications and preprints resulted from this Ph.D. study and address particular issues on the related topics, complement and extend the core papers' achievements. The objectives of this Ph.D. work are completed or partially fulfilled by one of the contributions presented in Table 2-1. The research questions can be related to one or more key contributions. The following sections present each of the key contributions, the link with the respective research question(s), and specifics how the created core papers attend to the contributions that give response to the research questions of this Ph.D. work.

2.2 Demand Side Management

Section 2.2 responds to Q1 - *How can consumption flexibility and demand response models enable the participation of prosumers/consumers in a fair and efficient way, with benefit for all the involved players and the system?*

DSM concept was introduced to enable energy demand adaptation from the consumers' side, avoiding high consumption peaks and enabling full use of generation in times of surplus [60]. According to [61], DSM is defined as an arrangement of actions to encourage electricity end-users to modify their energy consumption pattern to match the demand with the available supply. Reference [62] states that DSM first promoted, in the past, the engagement of the consumers in a market that has historically been 'invisible' to them. Industrial large consumers were initially, the targeted players of DSM programs due to their ability to cause considerable adjustments on the system level. The adoption of smart metering infrastructures facilitates the transaction of DSM from the industrial to the residential sector [63]. However, applying these programs to residential customers is not as straightforward since the direct control of loads could compromise the user's privacy and affect the user's comfort [64]. Then an approach that considers a stand-alone DSM application where DR is performed is presented.

Core Paper I [38] proposes a DSM methodology applied to a generic house to minimize the costs of energy usage. The methodology considers a DR optimization approach considering the availability of other resources. The users can perform DR actions in their facilities without any contracts with demand response service providers. Figure 2-1 presents the implementation scheme of work proposed in *Core Paper I* [38].

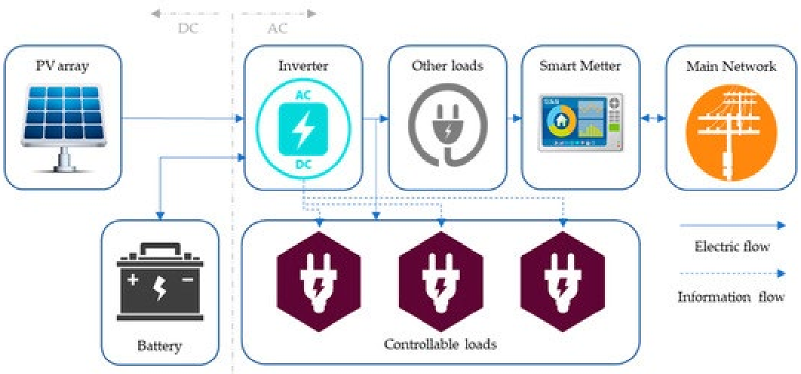

Figure 2-1 – Implementation scheme of the proposed work in *Core Paper I [38]*

PV generation use is considered free of costs and thus a priority for the residential user. The connection with the grid is considered bidirectional (the electricity can flow both ways). In general, the consumer can benefit from the PV generation, ESS, and DR actions to minimize the cost of consumption from the main grid. The consumer can explore periods when electricity is cheapest to meet consumption and charge the ESS, and look for periods when electricity is most expensive to sell it to the main grid. An optimization based on the PSO metaheuristic is executed to optimize the operation costs, considering that the user has storage units and is also enabled to apply DR in specific loads.

Core Paper II [39] extends the concept from *Core Paper I* [38], by proposing a parallel-based approach to solve the problem by considering several houses. An energy service provision is considered, which performs the optimizations, and makes the results available for each house.

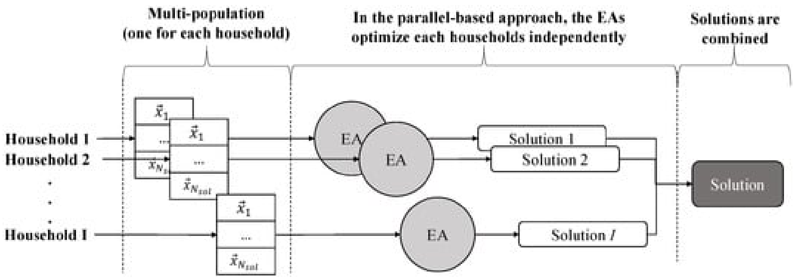

Figure 2-2 – Parallel-based approach proposed in *Core Paper II [39]*

To explore the scalability of the model presented in *Core Paper I* [38], the case study in *Core Paper II* [39] was expanded to twenty different houses with the possibility of each one controlling three different loads. In this work, the PV generation and ESS resources are also considered. Five different computation intelligence algorithms were used to solve the optimization problem. Considering the results, the computational intelligence (CI) algorithms using the parallel-based approach provide better solutions for a large number of households.

In *Other Paper III* [47], a framework for aggregator and households interaction was proposed to aggregate flexibility from the demand side. As the central entity, the aggregator performs the optimization of the households' resources. This optimization reduces its energy costs and gets revenues by selling the flexibility provided by the DR capabilities of households. In the case study, a set of 1000 households with PV generation and storage systems were considered. The distribution system operator (DSO) can also take advantage of the end-users' flexibility. *Other Paper IV* [48] presents a model to minimize the investments cost in a distribution network expansion. Results regarding the use of flexibility from the end-users' side show that a reduction in investment costs was achieved. *Other Paper I* [45] presents another model where DSO can take advantage of the flexibility available on the end-users side. The cost of the distribution network operation activity is minimized considering the costs of power losses and flexibility acquisition. Attending to the discomfort caused by the DR implementations, a multi-objective model that minimizes both the energy bill and the demand response quantity (measured in kW) was proposed in *Other Paper II* [46]. A multi-objective PSO is used to solve the problem and find the optimal pareto frontier. With the solutions of the pareto front, the user can choose one of the solutions that meets its requirements. Whereas a greater comfort will lead to a higher energy bill value, and on the other hand, a lower energy bill value will lead to greater discomfort.

The contribution of this part of the Ph.D. work is a model that provides to the prosumers or consumers the possibility of executing DSM actions in their facilities considering a single application (*Core Paper I* [38]) and provided by an energy service provider (*Core Paper II* [39] and *Other Paper III* [47]) (objective 1.a). The role of the aggregator is also a focus of the proposed model and acts as an intermediate to sell the flexibility provided by the consumers and prosumers through the DR actions (objective 1.b). DSO is another main entity considered in the developed model, showing the benefits that it can take from the flexibility of prosumers and consumers in the management of PES (objective 1.c). This contribution provides the answer to the research question considered in this section (Q1), partially covers the research question Q5, and fully accomplishes the first objective of this Ph.D. work.

2.3 Local Electricity Markets

Section 2.3 responds to *Q2 – How can electricity market models be improved to enable an efficient and intensive use of local resources (distributed generation, EV, demand flexibility, and storage)?*

LEM is a new concept, and a coherent definition is not presented yet. Therefore, a consensual definition is necessary for the LEM implementation and related contributions. The models developed in the scope of this contribution are aligned with the definition of LEM provided by [65]:

A local electricity market is a market platform for trading locally generated (renewable) electricity among residential agents within a geographically and socially close community. Security of supply is ensured through connections to a superimposed electricity system (e. g., national grid or adjacent local electricity markets).

LEMs admit the direct participation of electricity end-users and small producers in the EM, thus promoting their empowerment [66] and the formation of local energy communities. In comparison with the other markets, LEM requires sellers (producers and prosumers) and buyers (prosumers and consumers) and a backup system (main grid or retailer) in order to ensure the supply of electricity. With the possibility of prosumers increasing their sales with the transactions on LEMs, these structures can have an important impact on the local RES installation [67]. Furthermore, reducing energy costs is defined as the main objective for the local markets participants, increasing the independence from retailers' companies [68].

Preprint III [59] conducts a literature review paper on the topic of research articles related to LEMs. The work presents a review that identifies and discusses the different proposed approaches regarding LEM structures. A survey on projects and publication addressing the LEM structures is realized for this purpose. Regarding regulation and legislation that encourage the LEM creation, an analysis is also executed in the review. The key contribution of the conducted review is the proposed classification of LEM structures, which is based on the content explored in the literature review.

Core Paper III [40] proposes a mathematical optimization model to optimize the total community energy costs, considering the possibility of agents realizing P2P transactions in LEM. Figure 2-3 presents the conceptual structure presented by the *Core Paper III* [40].

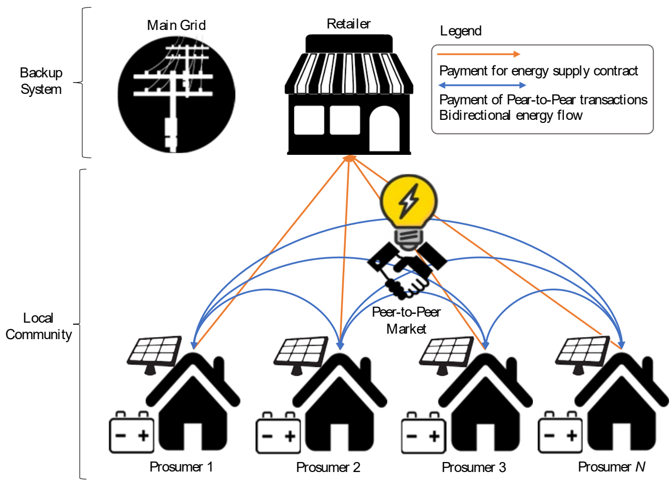

Figure 2-3 – Conceptual LEM proposed in *Core Paper III [40]*

The proposed model considers a local energy community (LEC) with PV generators and ESS installed in each community member facility. The members characterized by prosumers have two different possibilities to buy electricity (retailer or in P2P mode) and two other possibilities for selling electricity (main grid or P2P mode). The problem was modeled considering a MILP with the minimization of energy costs summation of each prosumer. A social welfare solution is set based on the best set of P2P transactions among the community members. Savings of up to 15% were obtained when scenarios with P2P transactions and without P2P transactions were compared.

The inclusion of electric vehicles (EV) in LEM was explored in *Other Paper VIII* [52], and *Core Paper IV* [41]. The model proposed in *Other Paper VIII* [52] considers the inclusion of EVs as buyers in LEM with a peer-to-vehicle (P2V) market. Thus, the work considers an optimization model that simulates a LEM between prosumers and EVs with P2V electricity transactions. The case study considers an energy community composed of households, commercial and industrial prosumers, and EVs, totaling fifteen prosumers and twenty EV. Three prosumers' households had an EV each, and it is considered that if the EV is parked at the house, it should charge the battery from the electricity provided by the prosumer. The rest of the EVs are parked at different points of the community grid and charge the battery with electricity from the retailer or the P2V market.

Due to scalability problems that the *Other Paper VIII* [52] model presented, a distributed methodology was developed to solve the P2V market problem with a large number of members in the energy community. *Core Paper IV* [41] has presented this methodology. Figure 2-4 presents the methodology proposed in *Core Paper IV* [41].

The process presented in Figure 2-4 considers the prosumers, EVs, and one coordinator. The prosumers are the sellers, EVs the buyers, and the coordinator is responsible for ensuring the P2V market operation. Each prosumer and EV realize their own optimization considering the possibility of buying and selling electricity in the P2V market. The transactions of P2V market for each prosumer and EV are communicated to the coordinator, and the error (balance between sales and buys) is calculated. The convergence is tested according to the error value. If the balance condition is not verified, the coordinator must send the information to the prosumers and EV, which will limit the transactions in the P2V market. The process is repeated until convergence is verified. The presented methodology makes it possible to find results for a large energy community (50 prosumers and 40 EVs) within an acceptable time. Comparing the results of centralized implementation presented in *Other Paper VIII* [52] with the distributed application, the difference in total costs is minimal, but the optimization time difference is significantly higher.

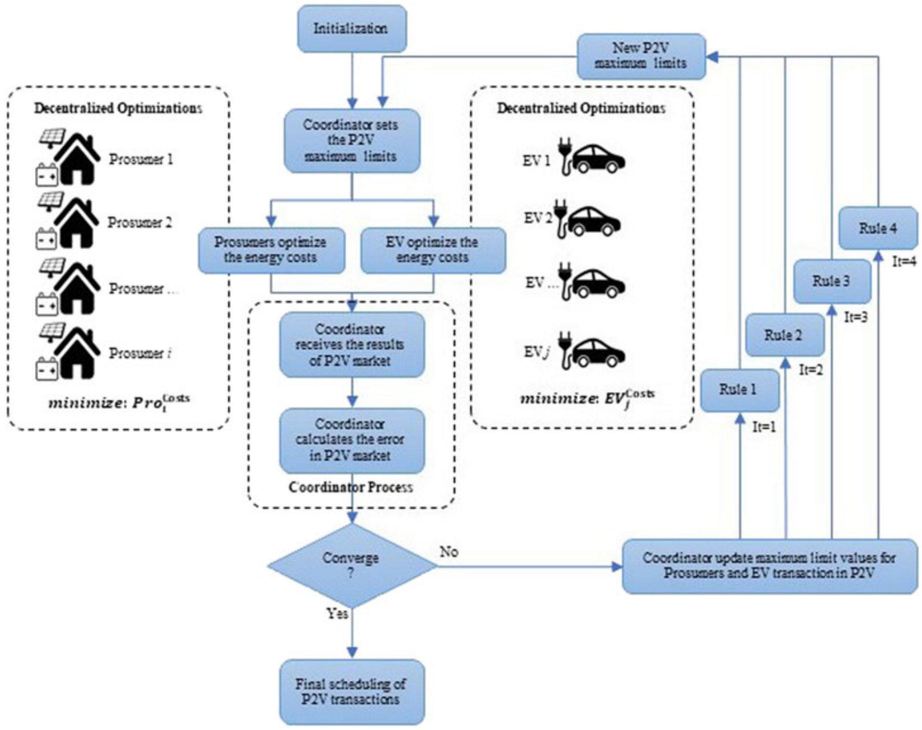

Figure 2-4 – Methodology proposed in *Core Paper IV [41]*

Other Paper VI [50] consists of a book chapter and presents a review dedicated to the practical implementation of LEM. This review aims to identify the practical implementations of LEM that are currently deployed or ongoing and what these practical implementations consider as research directions for the future. Bidding strategies were identified as one of the research directions most enunciated in the list of works analyses. In this way, the works *Other Paper VII* [51] and *Other Paper IX* [53] were developed.

In the scope of LEM, *Other Paper VII* [51] presents a day-ahead LEM bidding optimization. The LEM bidding is formulated as a bi-level optimization problem, where the upper-level problem is the agent’s profit maximization, and the lower-level problem is the maximization of the energy transacted in LEM. A learning method is proposed, where each agent can learn with their submitted bids and offers in the LEM. In order to determine the bids and offers accepted and the clearing price, an auction-based symmetric model is implemented and run in each period. Ant Colony Optimization (ACO) was a computation intelligence method implemented in this work as provider of learning strategy capabilities. An extension of the previous work is presented in *Other Paper IX* [53], but with the inclusion of an aggregator to enable the participation of the energy community members in the wholesale market. The problem was modeled as a multi-leader single-follower bi-level optimization problem. The same computation intelligence method (ACO) was used to solve the problem. With the day-ahead LEM bidding model it is possible to reduce the user costs and increase the profits of small producers according to the results of the two previous works. It is possible due to the small price obtained in the LEM compared to the one provided by the retailer or aggregator.

The contribution of developed methodologies presented throughout this section of this Ph.D. work is the provision of different LEM models and related support to consumers, prosumers, and small producers in their participation. Objective 2.a. is covered by the two developed reviews, one of them already published and the other presented as a preprint. The accomplishment of Objective 2.b. is demonstrated in most of the publications enunciated in this section (excluding the review paper). Objective 2.c. is achieved by the two publications comparing of the centralized and distributed resolution. The LEM presented models show efficient and intensive use of the local resources, thus providing the answer to the research question addressed in this section (*Q2*).

2.4 Electricity Portfolio Management

Section 2.4 responds to *Q3 – How can players improve their participation in future electricity markets considering the new and evolving opportunities including, aggregators, energy communities, and LEM?*

Traditional portfolio optimization consists in finding the optimal selection of various proportions of various assets. The portfolio selection problem was laid by Markowitz in 1952 [69], applying the problem to the finance field. The portfolio application in EM can be divided into two different variants, investor applications and management applications [23]. In the scope of this Ph.D. work, portfolio optimization is used for the management application. Reference [70] presents the first model of portfolio application to the EM as a management application. The authors investigate the energy allocation problem for a power producer allowing for three trading options. To measure the risk in portfolio application, reference [71] presents four different measures, based on a mean-variance metric. These measures are based on the historical prices, however, in recent markets such as LEM these metrics may not show good results as the price history is still very scarce.

In order to overcome this issue, *Core Paper V* [42] presents a portfolio optimization for EM participation considering the forecasting errors as the measure of risk transactions. Figure 2-5 presents an overview of the proposed framework developed considering portfolio optimization.

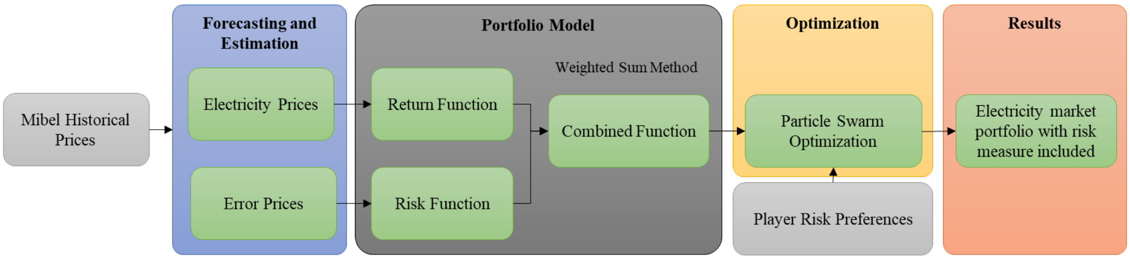

Figure 2-5 – Conceptual framework proposed in *Core Paper V [42]*

As presented in Figure 2-5, the proposed framework considers a portfolio model with risk measurement based on the variability of EM prices. The risk measure is obtained considering the error of the forecast and estimation methods. Compared with the other considered risk measures where a risk value is assumed for each market, the proposal is formulated considering the accuracy of the forecast and estimation method for each market and each moment. In this sense there are moments of negotiation in the same market where the value of risk negotiation is different, reflecting the different volatility of prices in different time periods in each market.

The proposed framework transforms the portfolio optimization problem from a multi-objective (two objectives) problem to a single objective (one objective) problem using an aggregated function. However, with the transformation to one objective, the user should define a trade-off coefficient, a requirement to specify the exposure to the risk/return. The case study considers an aggregator with the possibility to transact electricity within five different markets with different requirements. This aggregator only operates as an intermediary and does not control any of its members' assets. A PSO metaheuristic is proposed to solve the optimization problem, thus finding solutions in an acceptable execution time. The optimization process can be used as decision support to EM players.

Core Paper VI [43] considers a portfolio optimization for an energy community represented by an aggregator. Compared to *Core Paper V* [42], in this study, the aggregator has control over the individual assets of the community, namely PV and ESS. On the other hand, no metric is considered in the study to measure the risk of participating in the different markets. Figure 2-6 presents the proposed approach of *Paper VI*.

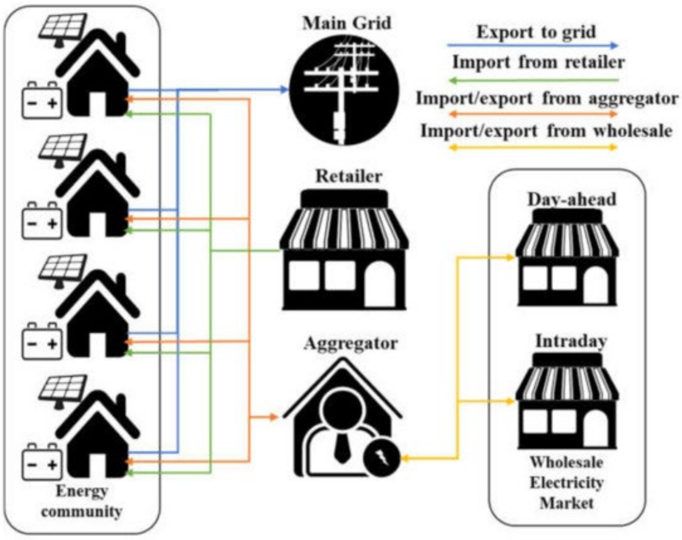

Figure 2-6 – Approach proposed in *Core Paper VI [43]*

As Figure 2-6 shows, the approach proposed in *Core Paper VI* [43] considers an energy community composed of prosumers, an aggregator, a retailer and wholesale market, and the main grid acting as a backup system. Prosumers can buy electricity from the retail or wholesale market (via aggregator) and sell to the main grid or the wholesale market (via aggregator). As participation in the wholesale market requires a minimum participation volume, the use of an aggregator acting as an intermediary is essential. In this way, the aggregator receives a fee from each prosumer of the community for the transactions carried out between the energy community and the wholesale market. The participation in the wholesale market is simulated considering the MIBEL possibilities with a wholesale market and an intraday market with six different sessions.

The developed study intends to minimize the overall energy community costs and was formulated as a MILP model. The obtained solution considers the best scheduling of ESS installed in each household and the purchases and sales of electricity in the considered markets. A community with 50 prosumers is considered in the case study, and two different scenarios were compared (with and without wholesale participation). The scenario with the participation in the wholesale market presents the best results, demonstrating that the prosumers' participation in the wholesale market via aggregators brings significant advantages for the whole energy community.

Two additional works were developed considering the portfolio theory application to EM participation and are presented in *Other Paper X* [54] and *Other Paper XI* [55]. In addition to representing a contribution to the application of portfolios in EM, these publications show how other types of metaheuristics can be successfully applied to the same problem. In *Other Paper XI* [55], the differential evolution (DE) method was applied and compared with PSO showing better results for solving the addressed problem.

The presented models in Electricity Portfolio Management section address the research question Q3 and fully accomplish the third objective of this Ph.D. work. Objective 3.a. is covered by the study published in *Core Paper V* [42] demonstrating the influence of risk in the EM negotiations considering the portfolios theory. Objective 3.b. is fulfilled with the publication *Core Paper VI* [43], in which the aggregator represents an energy community in wholesale market negotiations. The *Other Paper X* [54] and *Other Paper XI* [55] presented in this section provide additional contributions by applying metaheuristics in solving the portfolio theory problems. In this contribution, the models presented highlight the role of the aggregator as an essential entity for facilitating small players' participation in markets in which they cannot participate directly.

2.5 Local Ancillary Services

Section 2.5 responds to *Q4 – How can we take full advantage of local resources for implementing new models for AS provision with benefit(s) to distribution system operators and local players including prosumers and consumers?*

The variability behavior of RES, which often results in a mismatch between the available generation and consumption needs, increases the reserve requirements of power systems. These reserves are usually guaranteed by AS acquisition. Considering the "*Directive on common rules for the internal market for electricity*" [72], ASs are necessary for the operation of transmission and distribution systems, including frequency and non-frequency (e.g., voltage control, black start capabilities, and reactive power compensations) services [73]. European Transmission System Operator Network (ENTSO-E) focuses on DER as important assets that must be offered for the DSOs and transmission system operators (TSO) using active system management techniques to access the flexibility in the distribution grid [74]. This procurement of DER (such as ESS) as AS could expand these technologies and provide opportunities for them in the future grid planning and stability. Therefore, the term Local Ancillary Services was mentioned in [75] as the services obtained by DSO aggregating resources in the operation of the local market and transferring them to the TSO. The role of the aggregator is once again critical to enable connected DERs, prosumers, and consumers located at the low level of networks to provide AS to DSO, as discussed by [76].

Core Paper VII [44] presents a local market model to trade AS in order to help DSO to avoid problems with network operation. Figure 2-7 presents the case study proposed in *Core Paper VII* [44].

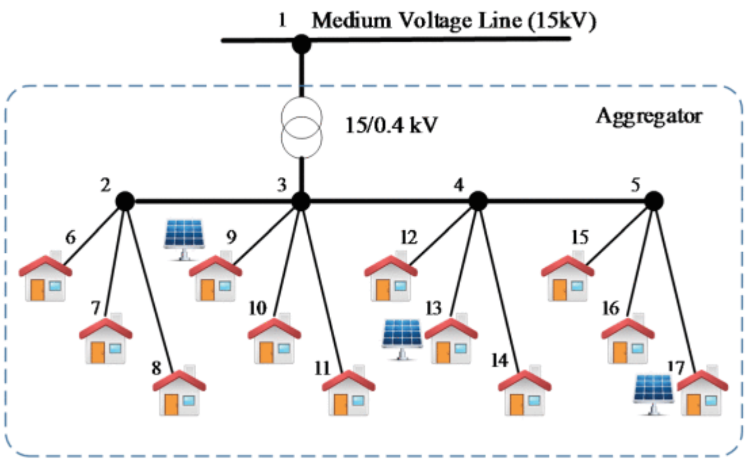

Figure 2-7 – Case study proposed in *Core Paper VII [44]*

Figure 2-7 is used to explain the proposed methodology. According to the figure, a set of prosumers constituting a LEC is presented, and an aggregator is available to represent the LEC. DSO is responsible for ensuring the network's normal operation and activating the AS when needed. The proposed approach of *Core Paper VII* [44] considers the possibility of DSO acquiring the necessary AS in the LEC to keep the network in normal operation. The necessary ASs for each period is determined by DSO based on the forecasts of demand and generation. After this step, DSO communicates to the aggregator the required amount. The aggregator is responsible for organizing the LEM for AS acquisitions with its members. An asymmetric pool-based market model is used, in which the aggregator defines the quantity needed, and the community members submit their offers with a respective price and energy amount. The offers are ordered from the lowest to the highest price, and the quantity is accumulated. When the accumulated amount exceeds the quantity desired by the aggregator, all offers up to that point are accepted, and this intersection determines the market price (clearing price). After carrying out this procedure for the periods indicated by the DSO, the aggregator communicates the results, where it identifies the elements that will provide the services. During operation, the DSO may request these services if necessary.

In the case study of *Core Paper VII* [44], the DSO used AS to realize congestion management activities. In this way, DSO identifies two periods when the total demand of LEC exceeds the rated power of connection with the main grid (transformer 15/0.4 kV), and aggregator realizes two auction sessions in LEM for selecting the AS providers. In the operation mode, to avoid the congestion in transform, the DSO actives the AS avoiding the problems.

Other Paper XII [56] expands on the core idea of *Core Paper VII* [44], but the transacted AS is used to control the bus voltage magnitudes. A coordination mechanism between prosumers, aggregator, and DSO is proposed for AS acquisition at low voltage levels. The case study is based on low voltage network with 26 buses, five prosumers and seven consumers. Once the DSO finalizes the day-ahead analysis, six periods are identified to perform the AS procurement. The procurement is done considering an asymmetric pool model where the bids with lower prices are accepted until the amount of electricity is sufficient to solve the problem. This process is repeated for each period identified by the DSO. The activation of the contracted AS is realized in real-time. From the presented results, the problems were solved considering the active participation of the consumers and prosumers.

Preprint I [57] presents an extended version of *Core Paper VII* [44] and *Other Paper XII* [56]. In this study, the DSO intends to solve the problem with bus voltage levels and maximum current lines. In this sense, DSO executes analyses for a day-ahead operation based on forecasts of demand and generation, identifying the periods with foreseen problems. The aggregator is also considered and executes the procurement of AS also based on the asymmetric pool market model. Finally, the DSO communicates the results, and the selected offers are activated during the operation mode. Compared with *Core Paper VII* [44], the case study was increased from 17 to 237 buses, 12 to 98 connected electricity users, and the price definition of offers was created considering three different strategies. In one of these strategies, it is considered a random behavior of the user. In the other two, some intelligence is introduced in players' offers, which allows defining the offer price by taking into account the offer amount. Analyzing the results, the problems detected by DSO were avoided by using the AS contacted at the local level, since the strategy used by the users in the price offer definition impacts the operational network costs.

Preprint II [58] presents a study that is fundamental for further extending and developing the models related to the key contribution presented in this section. The *Preprint II* [58] presents a temperature emulation model in an office room considering the heat transaction between adjacent rooms and the exterior. The model also includes Heating, Ventilation, and Air Conditioning (HVAC) control in order to introduce energy into the room so that the temperature level desired by the user is reached. This model can be used for future development of models to optimize the energy spent by HVAC on temperature control and use the flexibility that the model allows to obtain to participate in the supply of AS. The temperature model was tested and validated in eleven different parts of an office building. In this way, the flexibility of the eleven aggregated rooms could participate in the AS market through an aggregator.

The implementation of the auction-based market model (asymmetric pool) for the negotiation of AS inside of LEC constitutes the key contribution of this section, being achieved in the works presented by *Core Paper VII* [44] and *Preprint I* [57]. In the presented methodologies, the role of the aggregator is essential not only to establish the connection between the LEC and the network operator, in this case, the DSO, but also for organizing the market sessions where AS are acquired. In this sense, it is possible to show that the end-users can play an active role in the management of the PES. Therefore, the contributions fulfill objective 4, answering the research question presented at the beginning of this section (Q4), and also partly covering the research question Q5.

2.6 Experiments

This section aggregates relevant contributions related to the analysis of the results achieved from the models and methods proposed in each of the key contributions mentioned in this Ph.D. work. Additionally, this section fully covers objective 5 of this thesis. Table 2-2 presents an overview of the characteristics of the main models developed in this Ph.D. work.

Table 2-2 – Models characteristics.

Publication	Ref.	Field	Problem	Decision technique	Solution type	Method
Paper I	[38]	PES	DSM	Optimization	Non-exact	PSO
Paper II	[39]	PES	DSM	Optimization	Non-exact	CI
Paper III	[40]	EM	P2P	Optimization	Exact	MILP
Paper IV	[41]	EM	LEM	Optimization	Non-exact	Iterative
Paper V	[42]	EM	Portfolios	Optimization	Non-exact	PSO
Paper VI	[43]	EM	Portfolios	Optimization	Exact	MILP
Paper VII	[44]	EM/PES	LEM-AS	Simulation	Non-exact	
Other I	[45]	PES	Operation (AC OPF model)	Optimization	Exact	NLP
Other II	[46]	PES	DSM	Optimization	Non-exact	MOPSO
Other III	[47]	PES	DSM	Optimization	Exact	MILP
Other IV	[48]	PES	Expansion planning (DC OPF model)	Optimization	Exact	MILP
Other V	[49]	EM	Optimal coalition formation	Optimization	Non-exact	HyDE-DF
Other VII	[51]	EM	Strategic bidding	Optimization	Non-exact	ACO
Other VIII	[52]	EM	P2P	Optimization	Exact	MILP
Other IX	[53]	EM	Strategic bidding	Optimization	Non-exact	ACO
Other X	[54]	EM	Portfolios	Optimization	Non-exact	Hybrid
Other XI	[55]	EM	Portfolios	Optimization	Non-exact	DE
Other XII	[56]	EM/PES	LEM-AS	Simulation	Non-exact	
Preprint I	[57]	EM/PES	LEM-AS	Simulation	Non-exact	
Preprint II	[58]	PES	Temperature emulation model	Optimization	Non-exact	HyDE-DF

*Publications Other Paper VI [50] and Preprint III [59] are excluded because are review works

Table 2-2 lists all developed models and respective publications. When compared to Table 2-1, this table is missing two publications, related to literature reviews works, as they do not propose new specific models. As previously identified in the introductory section, the fields (PES and EM) of application of this Ph.D. work are also the fields where the models presented in Table 2-2 were developed. Seven of the models are applied on general PES problems, ten in the EM domain, and two include both fields. These (*Core Paper VII* [44] and *Preprint I* [57]) are identified with both fields since they consider activity in PES using the flexibility of end-users to support the operation of the network, and in EM because this flexibility is obtained through a market-based pool model.

The problems addressed by the models are categorized into ten groups, being that DSM and Portfolios are the topics addressed by a larger number of publications, with four appearances each one. In this categorization publications

Other Paper I [45] and *Other Paper IV* [48] are highlighted, which are considered applications of optimal power flow (OPF), being that in one of them the alternated current (AC) model is applied and in the other the direct current (DC) model. The *Other Paper V* [49] presents a non-common problem type inside of the developed models. Optimal coalition formation considers the creation of groups for flexibility provision considering a metric of fairness (Shapley value) for the price of coalition definition. Considering the used decision technique, the majority of models consider optimizations, and only two consider simulations. The two models of simulation decision technique also addressed the same LEM-AS problem. Both are used in the negotiation of AS at the local level. Strategic bidding as optimization methodologies could be applied to these works, e.g. as applied in models *Other Paper VII* [51] and *Other Paper IX* [53].

Solution type is categorized into two different categories, exact (six entries) providing the best solution (optimal) respecting all problem constraints, and non-exact (thirteen entries) when typically, a near-optimal but always feasible solution is obtained. In the method column, different possibilities are considered, although they can be grouped into mathematical and metaheuristic resolution methods. The MILP and NLP are mathematical resolution methods, ACO, DE, HyDE-DF, and PSO are metaheuristic resolution methods. *Core Paper II* [39] method label is considered CI since, in this work, five different metaheuristics are implemented and compared, highlighting the vortex search algorithm for the best results. *Core Paper VI* [41] considers an iterative method, in this specific case, the proposed model is solved iteratively, and in each iteration, a MILP is realized. The difference between iteration to iteration is the bounds of some variables. *Other Paper X* [54] presents a hybrid method that uses a metaheuristic (PSO) and a mathematical method (MILP).

The use of metaheuristics to find solutions to the problems modeled in this work constitutes an additional contribution. In several cases, metaheuristics were applied due to the characteristics of the tackled problems and the flexibility those techniques provide regarding modelling and application (objective function and constraints), they are adaptable to any type of problem (linear and non-linear), they allow a reliable solution to be obtained in a short execution time, are free to use and can be implemented in any programming language. They can also be programmed in any hardware device (e.g., Arduino).

Different case studies are created based on real conditions and scenarios to test and validate the implemented models. The experiments and validations under real or near-real environments are essential to validate models' acceptability and precision in PES real-world application. Therefore, the characteristics of the analyzed case studies are summarized in Table 2-3, highlighting the main involved players and markets.

Table 2-3 – Summary of case studies' characteristics.

Publication	Players			EMs types			DR	Network Analyses
	End-users	Aggregator	DSO	LEM	Retailer	Wholesale		
Core I	X	-	-	-	X	-	X	-
Core II	X	X	-	-	X	-	X	-
Core III	X	X	-	X	X	-	-	-
Core IV	X	X	-	X	X	-	-	-
Core V	-	X	-	-	-	X	-	-
Core VI	X	X	-	-	X	X	-	-
Core VII	X	X	X	X	-	-	-	X
Other I	X	-	X	-	X	-	X	X
Other II	X	-	-	-	X	-	X	-
Other III	X	X	-	-	X	-	X	-
Other IV	X	-	X	-	X	-	X	X
Other V	X	-	X	-	-	-	-	-
Other VII	X	X	-	X	-	X	-	-
Other VIII	X	X	-	X	X	-	-	-
Other IX	X	-	-	X	X	-	-	-
Other X	-	X	-	-	-	X	-	-
Other XI	-	X	-	-	-	X	-	-
Other XII	X	X	X	X	-	-	-	X
Preprint I	X	-	X	X	-	-	-	X
Preprint II	X	-	-	-	-	-	-	-

*Publications *Other Paper VI* [50] *and Preprint III* [59] *are excluded* because are review works

Analyzing Table 2-3 is possible to see a clear picture of the involved players, considered EMs, DR usage, and also the inclusion of the power network in the experiments. These case studies are categorized based on the characteristics presented in Table 2-3; which have been selected with respect to the key contributions presented in Table 2-1.

The first group of characteristics regards the number of players involved in the case studies. The group includes different types of end-users, the inclusion of aggregator and DSO. The inclusion of end-users is presented in sixteen of nineteen entries. For this classification, end-users include the consumers, prosumers, and producers. In *Core Paper V* [42], *Other Paper X* [54], and *Other*

Paper XI [55] the end-users are considered as aggregated elements, which is why they are not marked in this category. Regarding the inclusion of aggregator in the carried-out simulations, it is present in 58% of them. The main function of the aggregator is to provide services to end-users, such as DR controlling loads and ESS management (*Core Paper II* [39] and *Other Paper III* [47]), providing the best schedule of LEM transactions (*Core Paper III* [40], *Core Paper IV* [41] and *Other Paper VIII* [52]), representing end-users in the wholesale market (*Core Paper V* [42], *Core Paper VI* [43], *Other Paper VII* [51] and *Other Paper XI* [55]), and acting as a LEM operator (*Core Paper VII* [44] and *Preprint I* [57]). The involvement of DSO in the simulations is related to the control of the network operations, as in *Core Paper VII* [44], in which the DSO manages the congestion of the grid or in *Preprint I* [57], in which it controls the magnitude voltage of the buses and the maximum admissible current in the lines.

Regarding EMs, three types have been considered in the case studies of the thesis papers. Seven papers include LEM options, from which two simulate P2P transactions, and the others simulate community-based markets with pool-based models. Eleven papers consider the inclusion of retail markets. The retail market is important because it ensures electricity supply when other options (LEM or wholesale) are unsuccessful. Thus, consumers and prosumers establish long-term contracts with retailers. Wholesale market options are included in five papers. In this set of works, *Core Paper VI* [43] is highlighted because it simulates the MIBEL wholesale market, since this Ph.D. work has been developed in Portugal and Spain, which are the two members of MIBEL.

The use of DR in six considered papers has two purposes, namely, minimizing the costs of electricity acquisition (*Core Paper I* [38], *Core Paper II* [39], *Other Paper II* [46] and *Other Paper III* [47]), and minimizing the costs of DSO operation and planning investments (*Other Paper I* [45] and *Other Paper IV* [48]). The network analyses were done in four papers; these analyses consist of the application of power flow to obtain the values of network variables (*Core Paper VII* [44] and *Preprint I* [57]) and the optimal power flow application to minimize the operational costs (*Other Paper I* [45] and *Other Paper VI* [50]).

Table 2-4 presents the number of end-users and assets considered in the case studies of the *Paper*s elaborated in this Ph.D. work. The number of end-users is divided into three elements, the consumers, prosumers, and producers. The number of assets considers the PV, ESS, EV, controllable loads, and small combined heat and power (CHP) units.

Table 2-4 – Assets considered in case studies'.

Publication	Number of end-users			Number of assets				
	Consumers	Prosumers	Producer	PV	ESS	EV	Con. Loads	Small CHP
Core I	-	1	-	1	1	-	3	-
Core II	-	20	-	20	20	-	60	-
Core III	-	20	-	20	20	-	-	-
Core IV	-	50	-	50	50	40	-	-
Core V	-	-	aggregated	-	-	-	-	-
Core VI	-	50	-	50	50	-	-	-
Core VII	8	4	-	4	-	-	-	-
Other I	94	2	-	2	-	-	-	-
Other II	-	1	-	1	1	-	3	-
Other III	-	1000	-	1000	1000	-	3000	-
Other IV	9	-	-	2	-	-	-	-
Other V	-	12	-	-	-	-	-	-
Other VII	5	20	5	20	-	-	--	5
Other VIII	-	15	-	15	16	20	-	-
Other IX	3	3	3	3	-	-	-	3
Other X	-	-	aggregated	-	-	-	-	-
Other XI	-	-	aggregated	-	-	-	-	-
Other XII	7	5	-	5	-	-	-	-
Preprint I	63	33	-	33	-	-	-	-
Preprint II	11 rooms	-	-	-	-	-	-	-

*Publications *Other Paper* VI [50] and Preprint III [59] are excluded because are review works

When analyzing the number of end-users from Table 2-4 it is possible to see that prosumers are the most explored entity. *Other Paper III* [47] is worth highlighting due to the inclusion of 1000 prosumers in the case study. However, the consumers are also considered in the case studies in smaller numbers when compared to the number of prosumers. The producers considered in the case studies are few in number and are only present in 2 papers (*Other Paper VII* [51] and *Other Paper IX* [53]). This is because it is not common to use small generators connected to the system without being associated with a consumer (e.g., the actual prosumers). *Core Paper V* [42], *Other Paper X* [54] and *Other Paper XI* [55] consider aggregated producers, and the aggregator is only aware of the amount of energy, not knowing or having control over how many elements compose it. Considering the number of assets, the most used is the PV generators, but ESS is also widely used. In most cases, the end-users that consider PV-ESS systems have great saving costs compared to using one asset (PV or ESS) alone. The use of EV is only explored in two papers. Still, their integration proved efficient in LEM's operation, allowing them to participate as a player and thus increase market liquidity. The column of controllable loads means that it is possible to reschedule the consumption of some specific loads depending on some reason related to DR. The *Other Paper III* [47] work is highlighted as it uses 3000 controllable loads managed by an aggregator in order to respond to a DSO flexibility request. Considering the small CHP units presented in the two case studies (*Other Paper VII* [51] and *Other Paper IX* [53]), both are considered in small numbers. This type of asset is modeled by a non-linear mathematical function, which makes it difficult to find an optimal solution in an acceptable time for the process. In both papers that contain the CHP units, the optimization process is performed by metaheuristics to overcome the difficulties that the CHP modeling adds.

2.7 Summary

The core publications of this Ph.D. work represent the response to the main research question presented in this thesis, *Q0 - Can innovative aggregator-oriented business, market and flexibility models boost prosumers/consumers active participation in future PES?*

The work developed in this Ph.D. work answers the specific research questions placed in this thesis, ultimately resulting in the developed decision support models. The decision support models contribute to the improvement of end-users' participation in EM and PES management. The capabilities of the decision support models developed in the scope of this Ph.D. have been evaluated through the tests and validations using case studies based on scenarios created with realistic data. The positive achievements resulting from realistic simulation conditions support the thesis that aggregator-oriented models can empower end-users in active participation in the future of PES. Table 2-5 presents a summary of the key contributions of this thesis, including the specific contributions within each main addressed topic.

Table 2-5 – Ph.D. contributions overview.

Key Contributions	**Specific Contribution**	**Publications**								**Preprint**		
		Core							Other			
		I	II	III	IV	V	VI	VII	I-XI	I	II	III
Demand Side Management	Minimize energy costs	X	X						[46] [47]			
	Curtailment								[45] [48]			
Local Electricity Markets	P2P			X					[50] [52]			X
	Auction-based								[50] [51] [53]			X
	Community-based				X				[50]			X
Electricity Portfolio Management	Risk-free						X		[54] [55]			
	Risk-constrained					X						
Local Ancillary Services	Voltage control								[56] [57]	X		
	Congestion management							X	[57]	X		
	Auction-based							X	[56] [57]	X		
Experiments	Optimizations	X	X	X	X	X	X		[45] [46] [47] [48] [49] [51] [52] [53] [54] [55]			
	Simulations							X	[56] [57]	X		
	Metaheuristics	X	X			X			[46] [49] [51] [53] [54] [55]		X	
	MILP			X	X		X		[45] [47] [48] [52]			

The key contributions also identified in Table 2-5 are covered at least by one of the core papers, being complemented by the other papers and the preprints. Then, as Table 2-5 shows, the specific contributions are identified inside each key contribution. Thirteen different groups were identified, where Optimization, Metaheuristics, and MILP are the most evidenced. All defined objectives inside the scope of this Ph.D. are fulfilled by the results achieved in the realized experiments. Furthermore, the defined specific research questions are answered with the presented contributions in the scope of this Ph.D. work, which together achieve the answer to the main research question.

Chapter 3

Conclusions and Future Work

3 Conclusions and Future Work

This chapter concludes the thesis document by presenting the most relevant conclusions of this work in section 3.1, and identifying the perspectives for future development in section 3.2.

3.1 Main Conclusions and Contributions

The large-scale integration of RES, such as solar and wind energy, boosted as means to minimize the carbon footprint, has leading to a change in the operation and control of worldwide PES. This change has led to the adoption of approaches to control the demand, minimizing the unbalance between generation and demand brought by RES production fluctuation. Recent EC guidelines suggest a significant involvement of electricity end-users (consumers and prosumers) in PES. For this, they must be involved in the electricity system's management and planning and play an active role in the EM. The emergence of the aggregator allowed electricity end-users to benefit from advantages they did not have before, such as participation in wholesale markets. In this way, the aggregator allows the electricity end-users to have greater importance, as, through an intermediary, they became able to participate in the system actively. In the field of EMs, changes are also occurring to introduce a competitive behavior in the electricity wholesale market and, more recently, the liberalization of the retail market. Bringing small players to the market is paving the way to the emergence of LEM. Current LEM approaches found in the literature have been very successful and are beginning to appear in practice, bringing electricity end-users to greater involvement in the system. They allow electricity end-users to transact their own electricity locally and also to negotiate services that network operators can use to operate the system.

In this context, with the new possibilities for electricity end-users active participation in the system, novel decision support and simulation models are necessary to deal with new challenges. This thesis work contributed with the proposal of new models and methods focusing on the referred difficulties, oriented to support the end-users decisions in the future activities that the new EM models provide and in the possible active participation in the PES management. As core contribution, this work focused on the study of aggregator-oriented models to boost the electricity end-users' (prosumers and consumers) active participation in future PES. Therefore, it addressed the consumers or prosumers as the central entity of the activities.

Four key contributions, including demand-side management, LEM, electricity portfolio management, and local ancillary services, have been addressed. In addition, other specific contributions can be highlighted, such as using mathematical techniques to solve linear models, and metaheuristics for non-linear and complex optimization, and creating different case studies to evaluate the proposed models.

Although the LEM concept is considerably new, the literature related to it is increasing significantly. A relevant additional contribution of this Ph.D. work is related to the LEM concept with the development of two literature reviews papers. One of these works, which is already published, has provided a review of the practical LEM implementations. The other, provided as a pre-print in this thesis, presents an analysis about currently proposed LEM structures, projects including LEM and legislation to encourage LEM appearance. It was evidenced that a common definition and description of LEM should be adopted, e.g., some authors consider P2P as the name for local electricity commerce and other LEM. Another identified issue is the structures that may exist within this market segment and the diverse proposals for their organization.

The contributions of this work are based on different models addressing mainly the consumers and prosumers through the aggregator. From the consumer and prosumer side, different aspects have been addressed, such as the inclusion of PV generation, ESS units, and EVs. Some of the developed models also consider the inclusion of small CHP units as an individual entity to produce electricity to be transacted in LEMs. However, some aspects arising with CHP operation are necessary to create or improve the developed methodologies. On the other hand, the role of the aggregator in PES has been widely discussed both in the literature and in real-world applications. However, new business models must be developed or adjusted in order to enable the widespread of LEM applications in practice.

This thesis work contributed with approaches to help the electricity end-user in their empowerment inside of the PES and EM scope. The proposed models are focused on the aggregator's role and are oriented to support the electricity end-user in its PES and EM activities. The research results addressed the research question (Q0) and the five research questions (Q1 to Q5), presented in section 1.2. At least one model was developed for each of the four main activities identified. These models are constructed to address specific problems and, at the same time, possibly overcome the initially identified gap. As such, *Core Paper II*, *III*, *IV*, *V* and *VI* present different models that simulate activities where the aggregator is the provider, and the electricity end-user's are the customers. In this sense, the gap was identified, namely where there was a lack of models and solutions that assist the aggregator in the provision of services. For the literature, the implemented and published models are also an asset, as they allow interested parties to follow and implement them.

The findings resulting from the development of models and methods, from the achievement of responses to the research questions, and from the consequent accomplishment of all the defined objectives, enabled the test and the validation of the identified hypothesis. Therefore, it is possible to conclude that several of the models developed in this thesis can be applied in real environments. However, others still cannot since the activity they intend to address lacks legislation and regulation aligned with the current and future needs for continuous PES and EM evolution. The work developed in the scope of this thesis has resulted in the publication of nineteen main papers, ten of them published in JCI journals, and contributed to six projects in total, which three are nationals and three are international.

3.2 Perspectives of Future Work

The results achieved in the scope of the work developed in this thesis provide several advances for the development of methodologies where the electricity end-user is considered a central entity. In this sense, the developments that have been carried out can enhance different lines of future research, namely the following:

- Demand-side management
    - Elaborate an optimization model for demand-side management considering different shiftable assets in order to minimize the total electricity costs;
    - Apply demand-side management techniques considering the emulation of different thermal loads, e.g, heat pumps
- Local electricity markets

- Explore the applications of distributed optimization methods to simulate the LEM behaviors. Considering mathematical approaches, alternating direction method of multipliers (ADMM) or metaheuristics in distributed format;
- Investigate the application of the blockchain approach in the LEM payments layer to ensure the security and privacy;
- Employ new sources of generation in the electricity end-users to increase the liquidity of LEM structures, e.g., the use of hydrogen fuel cells for power generation;
- Further detail the considered network constraints in LEM simulations to investigate the influence of local transactions in the network power flow analyses.

- Electricity portfolio management
  - Improve the proposed method to include LEM as a different market option for electricity end-users to allocate electricity;
  - Apply robust optimization in portfolio management problems to deal with the variability of price forecasting.
- Local ancillary services
  - Development of an optimization model for flexibility provision of AS participation considering time-shiftable assets (clothes washing and dryer machine, dishwasher, microwave, blender, and others) and power-shiftable assets (EVs and HVAC load);
  - Application of bidding optimization strategies to simulate electricity end-users' participation in new developed local AS structures.

Some of the presented future work has been considered not only as further research directions of this work, but it is also compliant with the core of ongoing national and international research projects hosted by GECAD, namely the following:

- TradeRES – New Markets Design & Models for 100% Renewable Power Systems. Funded by the European Union's Horizon 2020 research and innovation program under grant agreement 864276;

The development of electricity trading models within an energy community and how the energy community can provide services to the grid operator, will be the topics to be studied within the scope of the TradeRES project.

- RETINA - REal-Time support Infrastructure and Energy management for Intelligent carbon-Neutral smArt cities. Funded by Fundação para a Ciência e a Tecnologia, NORTE-01-0145-FEDER-000062;

For the RETINA project, the study of EVs in the provision of AS will be the focus of this study. For future developments, decentralized approaches based on bender decomposition will be taken into account.

- PRECISE - Power and Energy Cyber-Physical Solutions with Explainable Semantic Learning, Funded by Fundação para a Ciência e a Tecnologia, NORTE-01-0145-FEDER-000062.

The DSM models, suggested as future works, can be included in the PRECISE project to contribute to the development of oriented solutions for the management of building energy systems.

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Appendix

Appendix A. Core Publications

Core Publication I

Ricardo Faia, Pedro Faria, Zita Vale, and João Spinola, "Demand response optimization using particle swarm algorithm considering optimum battery energy storage schedule in a residential house," Energies, vol. 12, no. 9, pp. 1218–1223, Apr. 2019, doi: 10.3390/en12091645. **(2019 Impact Factor: 2.702)**;

Resumen

La respuesta a la demanda (demand response en inglés) como recurso distribuido ha demostrado su importante potencial para los sistemas de energía. Es capaz de proporcionar una flexibilidad que, en algunos casos, puede ser una ventaja para suprimir la imprevisibilidad de la generación distribuida. La capacidad para participar en programas de respuesta a la demanda para pequeñas o medianas instalaciones ha sido limitada; con las nuevas regulaciones de la política, esta limitación podría ser sobrepasada. Los prosumidores son una nueva entidad que se considera al mismo tiempo productor y consumidor de energía eléctrica, y que pueden aportar excedentes de producción a la red. Además, la toma de decisiones en instalaciones con diferentes recursos de generación, sistemas de almacenamiento de energía y flexibilidad de la demanda se vuelve más compleja según el número de variables consideradas. Este artículo propone una metodología de optimización de la respuesta a la demanda para su aplicación en una casa residencial genérica. En este modelo, los usuarios pueden realizar acciones de respuesta a la demanda en sus instalaciones sin ningún contrato con proveedores de servicios de respuesta a la demanda. El modelo considera casas residenciales que cuentan con los dispositivos necesarios para llevar a cabo las acciones de respuesta a la demanda. La generación fotovoltaica, la capacidad de almacenamiento disponible y la flexibilidad de las cargas se utilizan como recursos para encontrar la programación óptima de mínimos costos de operación. Los resultados presentados se obtienen utilizando una optimización de enjambre de partículas (particle swarm optimization en inglés) y se comparan con una solución determinista para probar el rendimiento del modelo. Los resultados muestran que el uso de la respuesta a la demanda puede reducir el costo operativo diario.

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Demand Response Optimization Using Particle Swarm Algorithm Considering Optimum Battery Energy Storage Schedule in a Residential House

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Received: 4 March 2019; Accepted: 25 April 2019; Published: 30 April 2019

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Abstract: Demand response as a distributed resource has proved its significant potential for power systems. It is capable of providing flexibility that, in some cases, can be an advantage to suppress the unpredictability of distributed generation. The ability for participating in demand response programs for small or medium facilities has been limited; with the new policy regulations this limitation might be overstated. The prosumers are a new entity that is considered both as producers and consumers of electricity, which can provide excess production to the grid. Moreover, the decision-making in facilities with different generation resources, energy storage systems, and demand flexibility becomes more complex according to the number of considered variables. This paper proposes a demand response optimization methodology for application in a generic residential house. In this model, the users are able to perform actions of demand response in their facilities without any contracts with demand response service providers. The model considers the facilities that have the required devices to carry out the demand response actions. The photovoltaic generation, the available storage capacity, and the flexibility of the loads are used as the resources to find the optimal scheduling of minimal operating costs. The presented results are obtained using a particle swarm optimization and compared with a deterministic resolution in order to prove the performance of the model. The results show that the use of demand response can reduce the operational daily cost.

Keywords: demand response; distributed generation; particle swarm optimization; prosumer

1. Introduction

The future of power systems has been guided of a new structure where consumers (end-users) are considered as a central entity. This vision is presented in the Strategic Energy Technology (SET) plan of the European Union [1]. The transformation of end-users' roles allows these entities to have an active contribution in electric power systems. The prosumer is a new concept that has its origin in the proliferation of Distributed Generation (DG) in end-user facilities. The Prosumer definition is presented in Reference [2], where prosumers are considered agents that can either consume or produce energy. The integration of renewable energy sources (RESs) and energy storage systems results in the increase the complexity of energy management. In Reference [3], some methods to optimize renewable energy systems management are revised.

Regarding demand response (DR) programs, the potential for participation in facilities is significantly increased by the distributed energy resources and especially the energy storage systems. With the participation in DR programs, the roles of the consumers change from a passive entity to an active entity that manages both local consumption and generation resources [4]. DR constitutes a modification of load profile in response to monetary or price signals, and thus provides flexibility and aims to help power systems during peak hours of demand or contingencies cases [5]. As the DR programs are able to reschedule part of the load, the use of these programs is a way to increase the flexibility of the grid management, avoiding the need to invest in more capacity [6].

Categorizing DR programs, it can be divided into two main categories: incentive-based DR programs and price-based DR programs. The incentive-based DR programs are referred to as the first category for DR programs, where the consumers can offer an incentive to change their consumption patterns. Direct load control programs, load curtailment programs, demand bidding programs, and emergency demand reduction programs are examples of incentive-based DR programs. The "price-based DR programs" are the second category of DR programs, where the consumers are charged with different rates at different consumptions times. Therefore, the retail electricity tariff is affected by the cost of electricity supply. The price-based DR programs types are a time of use pricing, critical peak pricing, real-time pricing, and inclining block rate [7]. Advanced infrastructure metering is needed to implement DR programs at the residential, commercial, or industrial level. Such infrastructure (i.e., smart meters) is able to measure and store energy utilization at different times and also obtain the current usage information remotely.

The European Union has shown significant interest in the concept of smart metering. According to [8], it is expected by 2020 to invest ~45 million euros for 200 million smart electricity meters and 45 million smart meters of natural gas. This facilitates the application of DR programs in most electrical facilities.

Regarding the formulation of DR optimization problems, linear programming (LP) or nonlinear programming (NLP) can be used. Frequently the DR problems are able to use binary decision variables for determining the status (ON or OFF) of various consumers or appliances; in these situations, mixed-integer linear programming (MILP) or mixed-integer nonlinear programming (MINLP) may be used. In Reference [9], the authors use MILP to optimize DR and generate scheduling in a residential community grid using renewable energies, batteries, and electric vehicles. In this optimization, a minimization problem of purchased energy costs of the residential community has been solved. In Reference [10] a cost minimization in smart building microgrid considering DR optimization and day-ahead operation is implemented using MILP. This case study is composed of two different smart buildings with 30 and 90 houses. During the optimization process, the optimal schedule of house appliances is found. Another MILP approach is applied in Reference [11], showing how strategies like DR can achieve suitability in any region considering the presence of high penetration of renewable-based generation.

An example of NLP applied for DR optimization is presented in Reference [12], where the unit commitment problem for a microgrid is solved. The optimization problem finds the amount of load reduction and paid incentives for each time interval. Another example of MINLP has been presented in Reference [13], which considers the minimization of purchase gas and electricity from the grid by including the consumption of different loads at different periods. The optimal day-ahead scheduling of resources in energy hubs is determined.

The DR application in end consumers has been over time applied through an aggregator. It works as a service provider, and the DR services must be paid to this provider. In Reference [14], an aggregation of thermostatically controlled loads for performing DR is presented. In this case, the air conditioning consumption is considered as the load. The aggregation services are not restricted to the application of DR programs, in Reference [15] an aggregation of generalized energy storage can be found. The aggregator storage is used to participate in the energy and regulation market. DR programs targeting independent users, without the need of contracts or service providers, are also possible [16,17]. These applications are considered independent because the user is not connected to any aggregator. Usually, when the application is independent the user has a device installed in its house to control the loads. In Reference [16], the controller is a PV inverter, while in Reference [17], a home energy management system is used. The controllable loads can be divided into passive (i.e., air conditioning, fridges, washing machine) and active (i.e., DG, ESS, vehicle-to-grid, PV) loads [18]. In References [16,19] the DR is applied on discrete loads, which only have two states: on or off.

With focus on artificial intelligence (AI), its application in power systems has increased in the past years. The metaheuristics are a very popular part of AI for solving optimization problems. These techniques have acceptable performance in order to solve engineering problems by finding a near-optimal solution with a limited computation burden. Metaheuristics can be applied in problems with a large number of decision variables and easily adapted to a problem that has several constraints [20]. A PSO variant is used in Reference [17] for finding the optimal operation of price-driven demand response with a load shifting dispatch strategy for photovoltaic, storage battery, and power grid systems. The optimization algorithm is implemented on Home Energy Manage System. In Reference [21], the PSO algorithm is also used. The DR is optimized considering the variation of electricity price imposed by DSO to provoke a consumption reduction. In the microgrid environment [22], a PSO is used for solve the DR optimization problem. In this case a dynamic pricing model is considered for increase the profit of costumers. In Reference [23] a PSO algorithm is proposed to optimize the performance of a smart microgrid in a short term to minimize operating costs and emissions. Other algorithms like genetic algorithm [24], simulated annealing [25], and differential evolution [26] are frequently used algorithms to solve DR optimization problems.

The present paper proposes DR optimization considering the optimal battery schedule in a residential house with Photovoltaic (PV) generation. A PSO approach is implemented to solve the optimization problem (MILP), and the results are compared with a deterministic resolution (CPLEX solver). The consumer (residential house) is provided with independent management that approaches the several resources capabilities and contributions for the minimization of energy bought from the grid. The main contributions of this paper are as follows.

(1) To perform DR without any contract with the DR service provider—this presented methodology allows the user to perform DR actions without any connection with DR services provider. The consumer is provided with independent management that approaches the several resources capabilities and contributions for the minimization of bought energy from the grid.
(2) The implementation of PSO which is a very simple metaheuristic to implement, open access, multiplatform (Windows, MacOS, Linux, etc.), executable from an Arduino/Raspberry and also is the cheapest implementation option. Referring to the presented solution in [16], which uses a CPLEX solver for MATLAB/TOMLAB platform, the implementation of the PSO is a much affordable solution, once that MATLAB and TOMLAB are non-open access. PSO can be implemented in an open access environment and can be executed in free simple platforms, such as Python.
(3) The proposed methodology represents an optimization problem that can considerably improve the consumer's energy savings—the combined use of resources (PV production, storage capacity, and loads flexibility) allows for a significant reduction in daily operation costs. The optimal solution obtained by PSO has a daily cost of 3.28 €, while an operation without PV production, storage capacity and loads flexibility has a cost of 16.83 € per day, which is five times higher than PSO result for best scenario. If one considers a base scenario that was obtained by using a simple management mechanism considering the PV production and storage capacity, the daily cost is 9.33 €, which is three times higher than PSO result for the best scenario. The assessment of PSO can be verified in the comparison of the base scenario and the optimized base scenario with the PSO. The daily costs with PSO decreases 1.38 €.

The paper is structured into seven sections: In Section 1 an introduction about DR and how to solve DR problems is presented. Section 2 presents the proposed methodology; in Section 3 the problem formulation is presented. Section 4 presents the algorithm (PSO) and its adaptation to the problem formulation. In Section 5, the case study is presented as well as all input variables and PSO parameters. Section 6 presents the results, and the conclusions are presented in Section 7.

2. Proposed Methodology

With the goal to reduce the electricity bill of the end consumers is introduced the presented methodology. This methodology aims to minimize the operation costs considering the batteries and flexibility provided by the DR actions. The costs minimization considered the grid, the PV systems, energy storage batteries, and consumption flexibility through load scheduling. The end consumer is connected to the grid, and has a tariff contract that allows selling energy in the grid in exchange for monetary payment. This methodology is able to be expanded to other consumers with different conditions and with different numbers of resources. Figure 1 presents the context scheme of the idea proposed. This scheme is typical for a household prosumer. The scheme of Figure 1 has a unit generation (PV), energy storage system (ESS) (battery), one inverter module, the controllable and noncontrollable loads, and a smart meter.

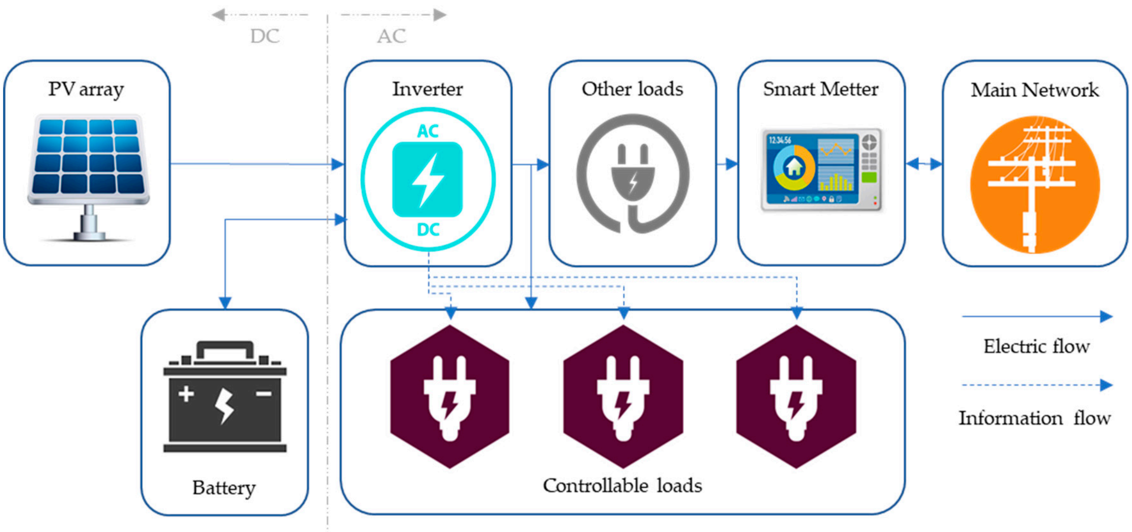

Figure 1. Implementation scheme of the proposed work.

For household, the use of PV generation is considered free (the generation unit is household property). In this paper, the PV generation is considered priority above all others, meaning that when it is available it will always be used either by load's necessities, battery charge, or injection in the grid. The connection with the grid is considered bidirectional. The PV rated power is usually limited by a contract between retailer and household. This limitation occurs because it can be a source of problems for the physical grid. In this way, it is difficult to reach a situation in which, as limit case if no injection to the grid is allowed, the PV is higher than the load plus the energy that can be used to charge the battery. However, if it happens, the inverter will disconnect the PV in order to avoid overvoltage. In Figure 1 one can see power flows and information flows. The information flows are connected to the inverter and controllable loads. In this case, the inverter is enabled with a control and management system that allows controlling loads, adding DR actions in household installation.

In general, the consumer can take advantage of the use of PV generation, ESS, and DR actions to minimize the cost of consumption from the grid. The consumer can look for the periods where electricity is cheaper to satisfy the consumption and charge the ESS, and the periods where the electricity price is most expensive to sell the excess electricity from the facility. Thus, it can be considered as a management system for the consumer to improve his energy bill.

Figure 2 is a representative illustration of the load's control using relays. The controller, in this case, is a component of the inverter. Each controllable load must have one relay associated with it, which allows for its control. So, when the controller sends the signal to the relay, the load is connected or disconnected from the electrical circuit. In this case, this control is considered a DR cut (direct load control). The scheme in Figure 2 considers only one relay for simplification; however, the proposed methodology is able to consider several relays, one for each load in the facility.

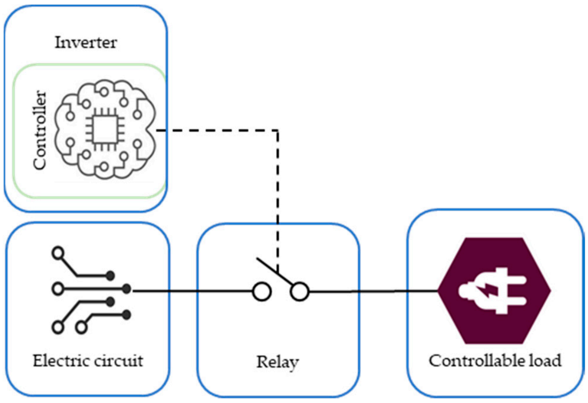

Figure 2. The control scheme for the demand response (DR) cut with one load.

3. Problem Formulation

The mathematical formulation is presented throughout this section. With the formulation presented it is intended to simulate the interaction of a consumer with the grid. The main goal is to minimize the operation costs, considering that the user has storage units and is also enabled to do DR in specific loads. The presented optimization model is considered a mixed-integer linear problem. Equation (1) presents the objective function.

$$Minimize\ f = Energy\ Bill + DR\ Curtailment \tag{1}$$

Equation (1) is comprised of the sum of two different parcels: the energy bill present in Equation (2) and the DR curtailment present in Equation (3). The Energy Bill represents the cost of buying and selling energy, and the DR curtailment refers to cost weighting associated with kWh curtailment.

In Equation (2) the variable P_t^{grid} represents the flow of energy between household and grid, $I_t^{grid\ in}$ is an indicator variable for power flow into the grid and control the energy buy $\left(I_t^{grid\ in} = 1\right)$ and energy sell $\left(I_t^{grid\ in} = 0\right)$, $C_t^{grid\ in}$ represents the cost of buying electricity and $C_t^{grid\ out}$ represents the cost of selling electricity. The Energy bill in Equation (2), consider the costs of buying electricity $\left(I_t^{grid\ in} \times P_t^{grid}\right) \times C_t^{grid\ in}$ and the revenues of selling electricity $\left(\left(1 - I_t^{grid\ in}\right) \times P_t^{grid}\right) \times C_t^{grid\ out}$. In each period (t) the user can make a single operation (buy or sell).

$$Energy\ Bill = \sum_{t=1}^{T}\left[\left(\left(I_t^{grid\ in} \times P_t^{grid}\right) \times C_t^{grid\ in} - \left(\left(1 - I_t^{grid\ in}\right) \times P_t^{grid}\right) \times C_t^{grid\ out}\right) \times \frac{1}{\Delta t}\right] + DCP \tag{2}$$

$$I_t^{grid\ in} = \begin{cases} 1,\ if\ P_t^{grid} > 0 \\ 0,\ otherwise \end{cases} \qquad \forall t \in \{1, \ldots, T\}$$

Also, in Equation (2) the term $\left(\left(1 - I_t^{grid\ in}\right) \times P_t^{grid}\right)$ represents the power sent to the network. The term Δt is used for to adjust the consumption to the tariff price because normally the tariff is available in €/kWh and the optimization can be scheduled at different time intervals (e.g., 15 min). *DCP* represents the daily contracted power cost. If the term P_t^{grid} has a positive value during optimization it means that there is electricity consumption from the network. However, if it has a negative value it means that there is a sale of electricity to the network. Equation (3) presents the DR curtailment.

$$DR\ Curtailment = \sum_{t=1}^{T}\left(\sum_{l=1}^{L} P_{l,t}^{cut} \times X_{l,t}^{cut} \times W_{l,t}^{cut}\right) \quad (3)$$

If the DR curtailment equation is implemented the cost of load is cut with the use of weights, and in fact does not have cost for the user. The variable $P_{l,t}^{cut}$ represents the cut energy of load (l) in period (t), the $X_{l,t}^{cut}$ represents the decision binary variable to active the cut of load (l) in period (t), and $W_{l,t}^{cut}$ represents the cut weight of load (l) in period (t). The term $\left(P_{l,t}^{cut} \times X_{l,t}^{cut} \times W_{l,t}^{cut}\right)$ shows the interest of the user to perform cut in load (l) in period (t).

Equation (4) represents the balance between load and generation, $P_{b,t}^{bat}$ represents the energy charged or discharged by baterry (b) in period (t). If the value of $P_{b,t}^{bat}$ is less than 0 the battery is discharging, otherwise, if the value of $P_{b,t}^{bat}$ is greater than 0, the battery is charging. The variable $P_{p,t}^{PV}$ represents the photovoltaic production of unit p at period t, and P_{t}^{load} corresponds to the value of load at period t.

$$P_t^{grid} = P_t^{load} + \sum_{b=1}^{B} P_{b,t}^{bat} - \sum_{l=1}^{L} P_{l,t}^{cut} \times X_{l,t}^{cut} - \sum_{p=1}^{P} P_{p,t}^{PV},\ \forall t \in \{1,\ldots,T\} \quad (4)$$

The Equation (5) shows the balance of battery systems.

$$E_{b,t}^{stor} = E_{b,t-1}^{stor} + P_{b,t}^{bat} \times \frac{1}{\Delta t},\ \forall t \in \{2,\ldots T\},\ \forall b \in \{1,\ldots,B\} \quad (5)$$

Variable $E_{b,t}^{stor}$ represents the state of the battery b in period t, in other words, it represents the amount of energy it has available. So, by Equation (5) the current battery state is obtained by adding the previous state $E_{b,t-1}^{stor}$ to the value of the variable $P_{b,t}^{bat}$.The power term $P_{b,t}^{bat}$ in Equation (5) is multiplied by $\frac{1}{\Delta t}$ to convert power into energy units. The system is governed by the following constraints (Equations (6)–(10)).

$$-P_t^{grid\ min} \le P_t^{grid} \le P_t^{grid\ max}\ \forall t \in \{1,\ldots,T\} \quad (6)$$

$$P_{l,t}^{cut} = P_{l,t}^{cut\ max}\ \forall l \in \{1,\ldots,L\},\ \forall t \in \{1,\ldots,T\} \quad (7)$$

$$0 \le E_{b,t}^{stor} \le E_{b,t}^{stor\ max}\ \forall b \in \{1,\ldots,B\},\ \forall t \in \{1,\ldots,T\} \quad (8)$$

$$-P_{b,t}^{dch\ max} \le P_{b,t}^{bat} \le P_{b,t}^{ch\ max}\ \forall b \in \{1,\ldots,B\},\ \forall t \in \{1,\ldots,T\} \quad (9)$$

$$X_{l,t}^{cut} = \begin{cases} 1 \\ 0 \end{cases} \forall l \in \{1,\ldots,L\},\ \forall t \in \{1,\ldots,T\}. \quad (10)$$

In Equation (6), the variable $P_t^{grid\ min}$ and $P_t^{grid\ max}$ represent the limit values for variable P_t^{grid}. Equation (7) identifies that $P_{l,t}^{cut}$ can only take the maximum value $P_{l,t}^{cut\ max}$. The $P_{b,t}^{bat}$ variables can take a value between $-P_{b,t}^{dch\ max}$ and $P_{b,t}^{ch\ max}$; if the value of $P_{b,t}^{bat}$ is less than zero it represents a discharge and if the value is greater than zero it represents a charge. The variable $X_{l,t}^{cut}$ is a binary variable and represents a decision variable. When $X_{l,t}^{cut}$ is equal to 1 the cut of load (l) at period (t) is active.

4. Particle Swarm Optimization

PSO was proposed by Kennedy and Eberhart in 1995, and it is a random search algorithm that simulates the foraging and flocking of birds in nature [27]. When birds look randomly for food in a given area, each bird can be associated with a single solution and can be considered as a particle in the swarm.

For PSO implementations assume that it has j particles in the n-dimensional search space and each particle represent a solution in the search space. Equation (11) presents the position vector of particle j and in Equation (12) the velocity vector for particle j.

$$\vec{x}_i^j = \left(x_{i,1}^j, x_{i,2}^j, \ldots, x_{i,n}^j\right) \tag{11}$$

$$\vec{v}_i^j = \left(v_{i,1}^j, v_{i,2}^j, \ldots, v_{i,n}^j\right) \tag{12}$$

where, $\vec{x}_i^j$. represents the position vector of particle j for n. variables at iteration i. The $\vec{v}_i^j$ represents the velocity vector of particle j for n variables. When the search process starts, both vectors are generated randomly between the respective limits of the n variables.

Equation (13) represents the velocity update equation. This equation is composed of three different components: the $w_i^j \vec{v}_i^j$ component represents the previous positions in memory search, $c1_i^j r1_i^j\left(P_{best}^j - \vec{x}_i^j\right)$ corresponds to the cognitive learning component, and $c2_i^j r2_i^j\left(G_{best} - \vec{x}_i^j\right)$ is a global learning component. Equation (14) represents the position update.

$$\vec{v}_{i+1}^j = w_i^j \times \vec{v}_i^j + c1_i^j \times r1_i^j \times \left(P_{best}^j - \vec{x}_i^j\right) + c2_i^j \times r2_i^j \times \left(G_{best} - \vec{x}_i^j\right) \tag{13}$$

$$\vec{x}_{i+1}^j = \vec{v}_{i+1}^j + \vec{x}_i^j \tag{14}$$

where, $\vec{v}_{i+1}^j$ is the velocity vector at iteration $i+1$; w_i^j represents the inertia weight obtained through Equation (15); $c1_i^j$ and $c2_i^j$ are acceleration coefficients, which are obtained by Equations (16) and (17), respectively; and $r1_i^j$ and $r2_i^j$ are two uniformly distributed random numbers independently generated within [0,1] for the n-dimensional search space. $P_{best}^j = \left(x_{pbest,1}^j, x_{pbest,2}^j, \ldots, x_{pbest,n}^j\right)$ denotes the historical best position and $G_{best} = \left(x_{gbest,1},\ x_{gbest,2}, \ldots,\ x_{gbest,n}\right)$ denotes the population historical best position. Equation (15) presents an inertia weight.

$$w_i^j = w^{max} - \left(\frac{w^{max} - w^{min}}{i^{max}}\right) \times i \tag{15}$$

where, w^{max} is the maximum value for inertia weight, w^{min} is the minimum value for inertia weight, and i^{max} represents the maximum value of iterations. The inertia weight present in Equation (15) is a linear decreasing method during the search process. The inertia weight reduction ensures strong global exploration properties in the initial phase and strong local exploitation properties in the advanced phase. The inertia weight is calculated at each iteration and is the same for the set of particles at each iteration [28]. Equations (16) and (17) present the acceleration coefficients calculation:

$$c1_i^j = c_1^{max} - \left(\frac{c_1^{max} - c_1^{min}}{i^{max}}\right) \times i \tag{16}$$

$$c2_i^j = c_2^{min} + \left(\frac{c_2^{max} - c_2^{min}}{i^{max}}\right) \times i \tag{17}$$

where, c_1^{max} and c_1^{min} are the maximum and minimum values for the personal acceleration coefficient, respectively. $c1_i^j$ decreases over the iterations, which means that the acceleration component for the personal position at the beginning of the search is high allowing exploration. The parameters c_2^{min} and c_2^{max} represent the minimum and maximum values for the global acceleration coefficient. $c2_i^j$ increases over the iterations, which means that the acceleration component for the global position at the end of the search is high allowing exploitation. The encoding of the solutions is crucial for the success of the algorithm. Equation (18) shows the encoded vector used for solving the problem present in Section 2.

$$\vec{x}_i^j = \left[\left\{P_{1.1}^{bat}, \ldots,\ P_{B,T}^{bat}\right\}, \left\{X_{1.1}^{cut}, \ldots,\ X_{L,T}^{cut}\right\}\right] \tag{18}$$

where, $\left\{P^{bat}_{1.1}, \ldots, P^{bat}_{B,T}\right\}$ is a group of continuous variables representing the electricity amount of charge or discharge in each battery (b) at period (t) and $\left\{X^{cut}_{1.1}, \ldots, X^{cut}_{L,T}\right\}$ are binary variables to enable the possibility of performed cut action in load (l) at period (t). Therefore, particle $\vec{x}$ has dimensions of $n = B \times T + L \times T$. This encoding allows a direct evaluation in Equation (1).

The PSO implementation starts by defining the search space limits by setting the lower and upper bounds of each variable. In Equation (19), xlb^j represents the lower limits for the solution of j particle and xub^j in Equation (20) represent the upper limit for j particle.

$$xlb^j = \left[\left\{-P^{dch\ max}_{1.1}, \ldots, -P^{dch\ max}_{B,T}\right\}, \left\{X^{cut\ min}_{1.1}, \ldots, X^{cut\ min}_{L,T}\right\}\right] \tag{19}$$

$$xub^j = \left[\left\{P^{ch\ max}_{1.1}, \ldots, P^{ch\ max}_{B,T}\right\}, \left\{X^{cut\ max}_{1.1}, \ldots, X^{cut\ min}_{L,T}\right\}\right] \tag{20}$$

$$\vec{x}^{\,j}_1 = rand\left[xlb^j, xub^j\right] \tag{21}$$

Equation (21) presents the process of initialization where the initial solution was created. In this case, a random process into allowed bounds is executed. $rand\left[xlb^j, xub^j\right]$ is a random number within the lower xlb^j and the upper xub^j bounds of j particle for n variables.

Equation (22) presents the boundary constrains method. The search process over the iterations will generate new solutions that may not be within the initially stipulated limits. To address this issue the boundary control strategies are used to repair infeasible individuals. In this paper is used a boundary control technique known as bounce-back [20].

$$\vec{x}^{\,j}_i = \begin{cases} \mathrm{rand}\left(xlb^j, \vec{x}^{\,j}_i\right) & if\ \vec{x}^{\,j}_i < xlb^j \\ \mathrm{rand}\left(\vec{x}^{\,j}_i, xub^j\right) & if\ \vec{x}^{\,j}_i > xub^j \\ \vec{x}^{\,j}_i & otherwise \end{cases} \tag{22}$$

In contrast to random reinitialization (the most used control technique), bounce-back uses the information on the progress towards the optimum region by reinitialized the variable value between the base variable value and the bound being violated. Making use of domain knowledge about the problem, the Equations (23) and (24) is proposed as a direct repair equation. The Equation (23) concerns the direct repair of $E^{stor}_{b,t}$.

$$E^{stor}_{b,t} = \begin{cases} 0 & if \quad E^{stor}_{b,t} < 0 \\ P^{ch\ max}_{b,t} & if\ E^{stor}_{b,t} > E^{stor\ max}_{b,t} \\ E^{stor}_{b,t} & otherwise \end{cases} \quad \forall b \in \{1, \ldots, B\},\ \forall t \in \{1, \ldots, T\} \tag{23}$$

Although boundary control is used it can only control the variables P^{bat} and X^{cut}, the variable E^{stor} is a variable of control and balance, and when it is repaired other variables are necessarily changed. For the repair process E^{stor} is needed to test two different conditions, $E^{stor}_{b,t} < 0$ represents a greater discharge than the allowed one, being that it fixes the variable to the minimum value. $E^{stor}_{b,t} > E^{stor\ max}_{b,t}$ means that the battery has a charge greater than the allowed, the value of maximum energy in the battery is fixed in maximum that can accumulate. Equation (24) presents the direct repair for P^{bat} variable.

$$P^{bat}_{b,t} = \begin{cases} E^{stor}_{b,t} - E^{stor}_{b,t-1} & if \quad E^{stor}_{b,t} < 0 \\ E^{stor}_{b,t} - E^{stor}_{b,t-1} & if\ E^{stor}_{b,t} > E^{stor\ max}_{b,t} \\ P^{bat}_{b,t} & otherwise \end{cases} \quad \forall b \in \{1, \ldots, B\},\ \forall t \in \{2, \ldots, T\} \tag{24}$$

P^{bat} is repaired in Equation (22), but with the direct repair used in Equation (23) the variable P^{bat} may not be correct, and it is necessary to perform direct repair on it. So, a battery power level test is performed, if $E^{stor}_{b,t} < 0$ the value for $P^{bat}_{b,t}$ is equal to the difference between the battery power level in the previous period $E^{stor}_{b,t-1}$ and the current period $E^{stor}_{b,t}$. The same rule is applied when the battery power level is greater than the allowed maximum $E^{stor}_{b,t} > E^{stor\ max}_{b,t}$.

The particles should be evaluated according to a fitness function $f'\left(\vec{x}\right)$, Equation (25), including objective function $f\left(\vec{x}\right)$ Equation (1) and constrains violation $pf\left(\vec{x}\right)$.

$$f'\left(\vec{x}\right) = f\left(\vec{x}\right) + pf\left(\vec{x}\right) \tag{25}$$

$$pf\left(\vec{x}\right) = \begin{cases} \sum\limits_{t=1}^{T} t \times \rho & if\ P^{grid}_t \leq P^{grid\ min}_t \cap\ P^{grid}_t \geq P^{grid\ max}_t \\ 0 & otherwise \end{cases} \quad \forall t \in \{1, \ldots, T\} \tag{26}$$

where, $pf\left(\vec{x}\right)$ in Equation (26) represents the penalty value for a solution $\vec{x}$. Despite the application of bounce-back method Equation (22) and direct repair methods (23) and (24), the solution may still be infeasible. The penalty value is obtained checking the limits of variable P^{grid}_t for every period. In each period that the variable is out of limit is counted and multiplied by a penalty amount ρ, the sum of all individual (per period) penalties represents the total penalties per each solution.

Pseudocode of the PSO algorithm is presented in Algorithm 1.

Algorithm 1. PSO pseudocode.

INITIALIZE
Set control parameters w^{max},w^{min},c_1^{max},c_1^{min},c_2^{max},c_2^{min}, j^{max}, and i^{max}.
Create an initial Pop (Equation (21)) and initial velocities.
IF Direct repair is used THEN
    Apply direct repair to unfeasible individuals
END IF
Evaluate the fitness of Pop (Equation (25)).
Create a P_{best} vector for every particle.
Create a G_{best} vector of the swarm.
FOR i = 1 to i^{max}
    FOR j = 1 to j^{max}
        Velocity update (Equation (13))
        Position update (Equation (14))
        Update w_i, $c1_i$ and $c2_i$ (Equations (15)–(17))
        Verify boundary constraints for P^{bat} (Equation (9))and X^{cut} (Equation (10))
        IF Boundary constraints are violated THEN
            Apply boundary control (Equation (22))
        END IF
        Verify boundary constraints for E^{stor} (Equation (8)) and P^{bat} (Equation (9))
        IF Boundary constraints are violated THEN
            Apply direct repair (Equations (23) and (24))
        END IF
        Evaluate fitness of $\vec{x}$ (Equation (25)).
        Verify boundary constraints for P^{grid} (Equation (6))
        IF P^{grid} is out of limits THEN
            Apply penalty function (Equation (26))
            Update fitness value (Equation (25))
        END IF
        Update P_{best} vector for i particle.
    END FOR
    Update G_{best} vector of the swarm.
END FOR

Basically, if in the evaluation process constraints violations are identified, the individual is randomly repaired using the initialization process from Equation (22). The pseudocode of Algorithm 1 is displayed step-by-step, starts with the definition of the parameters related to the PSO. The search begins with the creation of the initial population. After being evaluated, the best position of each particle and the best position of the population are defined. The main cycle starts, and at each iteration of the main cycle, another cycle is performed for each particle. For each particle a new velocity is generated, updated, verified, and evaluated. When all particles repeat the process, the value of the best personal position of each particle and the best overall position of the population is updated.

5. Case Study

This section presents the case study. The optimization problem was solved using PSO metaheuristic and compared to a solution obtained by a CPLEX solver in MATLAB™/TOMSYM™ environment to compare the results.

The proposed methodology addresses a Portuguese consumer and complies with actual Portuguese legislation, which allows small producers (consumers with local generation) to use the energy produced to satisfy the own load necessities and sell it to the grid. The consumer has a supply power contract of 10.35 KVA with the retailer, and it is characterized by three different periods: peak, intermediate, and off-peak [29]. The prices applied to a consumer operation are present in Table 1. The input prices in Table 1 are real values of a Portuguese retailer (https://www.edp.pt/particulares/energia/tarifarios), which provides a realistic case study. The prosumer can inject his excess production into grid, but a limit is imposed by the retailer. The maximum value injected into grid is half of its contracted power, approximately 5.1 kW. The real prices and real condition inclusion in this problem contribute to more accurate in this study and prove the real value of the methodology application.

Table 1. Prices of the different periods and contracted power.

Parameter	Energy (€/kWh)			Contracted Power (€/Day)
	Peak	Intermediate	Off-Peak	
Buy from grid	0.2738	0.1572	0.1038	0.5258
Periods	10.30 h–13 h 19.30 h–21 h	08 h–10.30 h 13 h–19.30 h, 21 h–22 h	22 h–02 h 02 h–08 h	
Sell to grid		0.1659 *		–
DR weight	0	0.2	0.4	

* is used for all periods.

The DR weights present in Table 1 are defined by the consumer taking into account the energy price variation within the day, adapted from [16]. The use of DR is more appreciated when the energy is cheaper, so the weight of 0 is given in peak periods (highest price). With this weight distribution, the DR actions are expected to be executed during peak periods. Equation (3) gives the amount of DR actions contributing to the objective function. It does not represent costs for the consumer, but is rather a consumer's preference that influences the scheduling. In Table 2 are presented the problem input variables adapted from [16].

The system has two PV panels with different production, one has a maximum production of 7.5 kW and other has a maximum production of 2.5 kW. This PV panels and the battery storage unit are connected to the inverter. The battery can receive power from the PV production or the grid. In this case study, the inverter has two functionalities: the first is to convert the power from DC to AC and vice versa; the other functionality is to give the signal to manage certain loads. In this study, three different loads are considered: a dishwasher, an air conditioner, and a water heater. Figure 3 shows the disaggregated consumption and PV generation forecasts. In this case study, the forecast is performed for the next 24 h. In real-time operation, the forecast can be updated at every instant. Each time that user update the forecast can perform a new optimization. Regarding the influence of the forecasting results on optimization, in the case that the presented day-ahead forecasting strategies in References [30,31] are considered, the forecasting error, using Supporter Vector Machine algorithms to predict the values for the next 24 h, will be 9.11%.

Table 2. Problem input variables.

Parameters	Symbol	Value	Units
Maximum power injected to grid	$-P_t^{grid\ min}$	−5.1	kW
Maximum power required from grid	$P_t^{grid\ max}$	1000	kW
Maximum power accumulated in battery	$E_{b,t}^{stor\ max}$	12	kW
Maximum energy of battery discharge	$-P_{b,t}^{dch\ max}$	−6/4	kWh
Maximum energy of battery charge	$P_{b,t}^{ch\ max}$	6/4	kWh
Total Periods	T	96	–
Total of controllable loads	L	3	–
Total of batteries	B	1	–
Total of PV units	P	2	–
Adjust parameter	Δt	4 *	–

* The factor of 4 comes from the fact that there are four 15-min periods in an hour.

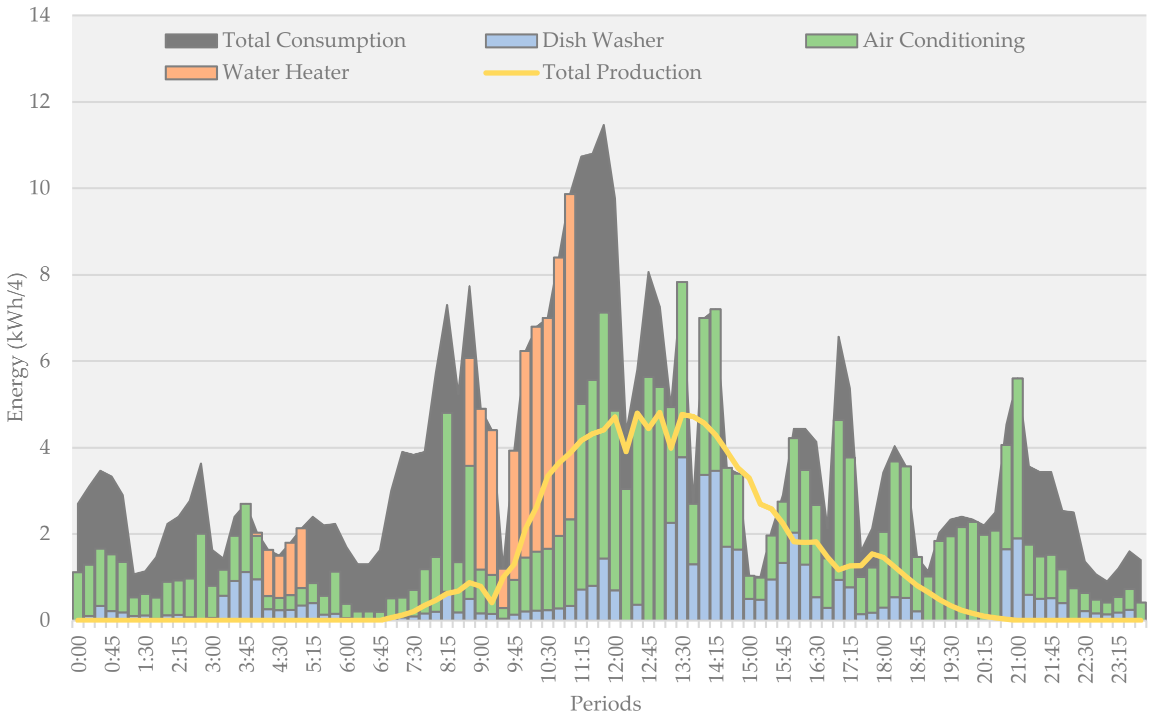

Figure 3. Disaggregated consumption by appliance and photovoltaic (PV) generation.

Figure 3 presents a typical load profile with a peak of 11.5 kW at ~11.45 h. The consumption per controllable load is present in Figure 3 with different colors. The total consumption includes the sum of all loads and the same situation for PV but is the sum of two PV units. The peak of production is forecasted between the 12.00 h and 13.30 h with 6 kW. In some periods, such as 10:30, the sum of the controllable loads corresponds to the total consumption. Table 3 presents the parameters for PSO; they were obtained from a previous study.

Table 3. Particle swarm optimization (PSO) parameters used.

Parameters	Symbol	Value
Population size	j^{max}	500
Maximum numbers of iterations	i^{max}	500
Maximum inertia weight	w^{max}	0.4
Minimum inertia weight	w^{min}	0.9
Maximum cognitive weight	c_1^{max}	1.5
Minimum cognitive weight	c_1^{min}	0.5
Maximum global weight	c_2^{max}	1.5
Minimum global weight	c_2^{min}	0.5
Number of evaluations	–	250,000
Number of trials	–	30

The member of evaluation is equal to $j^{max} \times i^{max}$ and presents the number of fitness function is evaluated during the search process. Considering that the PSO is an algorithm of a random nature, a group of 30 trials is performed. With a sample of 30 results, it is possible to extract a more robust conclusion from the application of the PSO to the problem in question.

6. Results

This section presents the results and analysis obtained from the implementation of the proposed methodology and respective case study. Table 4 presents the results for Equation (1) in both the CPLEX (deterministic) obtaining the optimal value, and PSO obtained an approximate resolution. Four different scenarios were created considering the resources combination: the scenario "PV + Bat + DR" combine the all available resources (PV production, the storage capacity and loads flexibility), scenario "PV + Bat" combines the PV production and storage capacity resources and "PV" scenario only considers the PV production resource. The nonoptimized value is used as a base case scenario and was obtained by using a simple management mechanism; the scenario "PV + Bat" considers PV production and storage capacity, and the "Without resources" scenario does not consider any resource. Analyzing the results of CPLEX for the set of scenarios can conclude that "PV + Bat + DR" presents the smallest fitness function. It can be said with resources combinations brings benefits for household management.

Table 4. Results for Equation (2) (€/day).

Resources Combination Scenarios		CPLEX	PSO		
			Min	Mean	STD
Values optimized	PV + Bat + DR	3.1874	3.2771	3.3381	0.0469
	PV + Bat	7.8652	7.9454	8.0595	0.1169
	PV	8.8478	8.8478	8.8478	0
Nonoptimized values	PV + Bat	9.3298			
	Without resources	16.8570			

The analysis of results is performed for the "PV + Bat + DR" scenario. The results present in Table 4 of PSO correspond to 30 trials. The minimum value that the PSO reached is 2.8% higher when compared with CPLEX value. Analyzing the standard deviation (std) value for the sample of PSO results is possible to conclude that it is relatively small and the values of the 30 trials should be relatively close to the mean value. The STD analysis is important because it is a measure that expresses the degree of dispersion of 30 trials solutions. Figure 4 presented the results related to the DR actions applied to the profile shown in Figure 3.

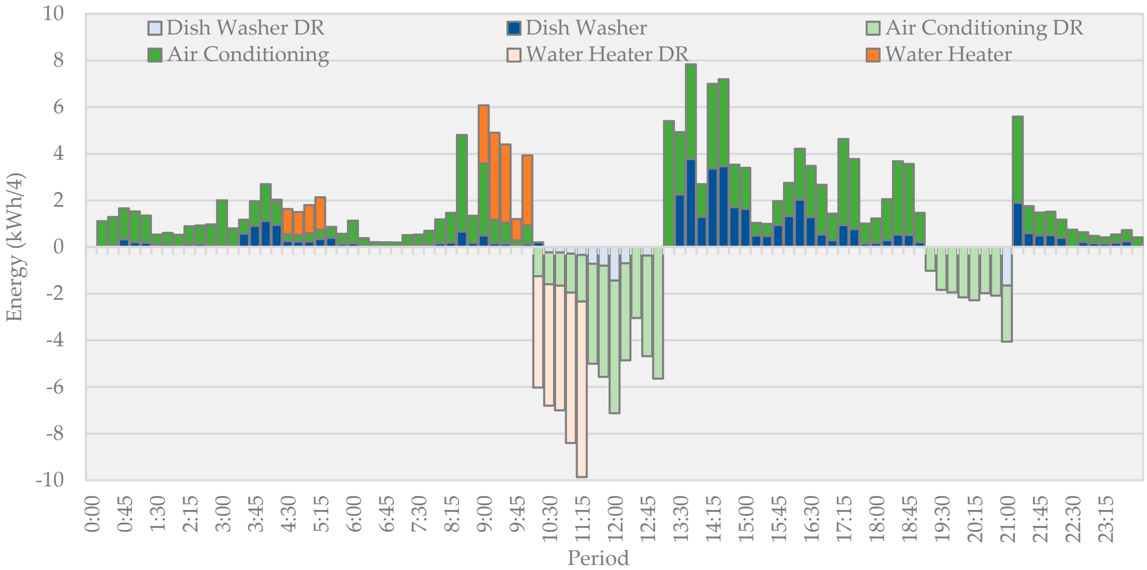

Figure 4. DR result regarding initial profile.

In Figure 4, the positive values correspond to the consumption of appliances that had no changes with the application of the methodology. Negative values are energy that has been reduced due to cut of loads. With the loads cut, reduction of 63% in the total consumption of three loads (dish washer, air conditioner, and water heater) was obtained. The DR actions are performed during 10.00 h to 13.00 h and 19.00 to 21.00. Crossing this information with Table 1, one can see that these periods correspond to a peak hour, precisely when energy is more expensive. During peak hours the consumption with the present optimization methodology is 44.8 kW, without its application and not considering PV generation and energy storage systems, the consumption will be 115.4 kW. This reduction represents 20% reduction of total daily consumption. In this way, it is concluded that the present methodology has an impact on the consumption of peak hours. In Figure 5 are presented the total load consumption (controllable and noncontrollable loads), the battery actions (charge and discharge), and the final load (load consumption plus battery charge).

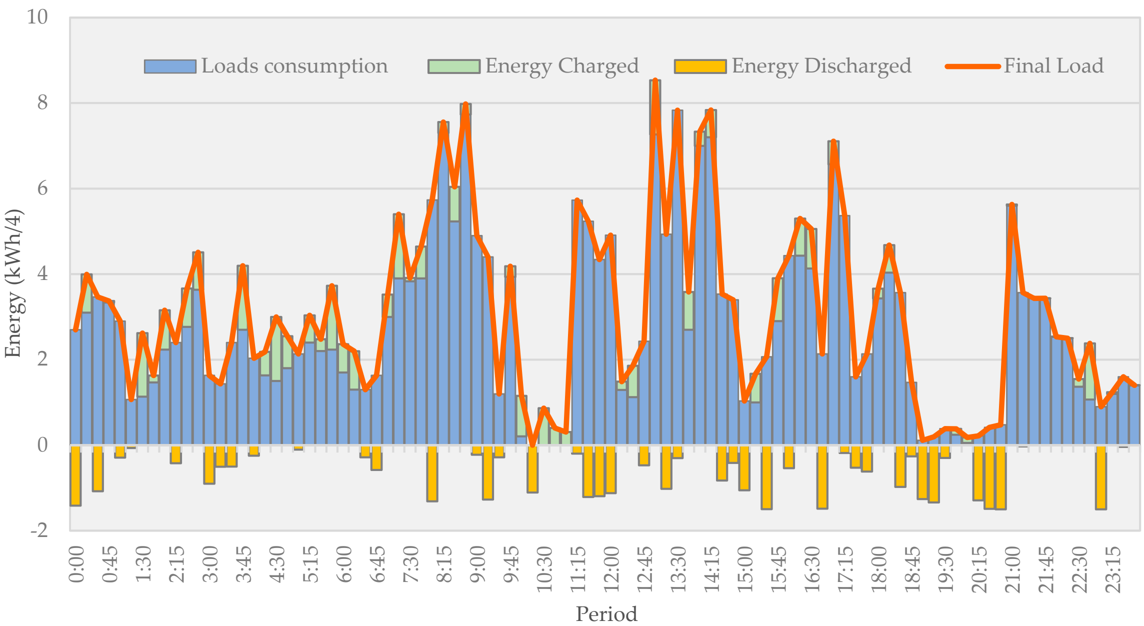

Figure 5. Load consumptions, battery actions, and final load scheduling.

Figure 5 shows that due to this condition, the generation (see Figure 3) exceeds the consumption needs, and in this case, the energy surplus will either be used to charge the battery or sell to the grid. In this way, the user avoids buying energy from the grid to charge the battery and to meet consumption necessities. The battery discharge cycles are mostly represented between 11.00 and 21.00 periods that correspond to a peak and intermediate hour. Table 5 presents a summary of the results obtained by both methods applied.

Table 5. Summary of results.

Scenario	Method	Equation (1)	Equation (2)	Equation (3)	Daily Costs (€)	Daily Revenues (€)	Monthly Costs (€)
PV + Bat + DR	CPLEX	3.1874	3.1874	0	6.9380	3.7505	95.6233
PV + Bat + DR	PSO *	3.2771	3.2771	0	6.0565	2.7794	98.3140
PV + Bat	PSO *	7.9922	7.9922	0	8.5136	0.5683	239.7661
PV + Bat	Nonoptimized	9.3298	9.3298	0	9.3298	0	279.8928

* represent the values of trial with the minimum fitness value.

With the proposed methodology, the daily cost of operation for CPLEX is 3.18 (€) and 3.28 (€) for PSO, but if the PV system, battery and DR do not exist and the daily costs are 16.83 (€). When compared the results of Table 5 is possible to observe that daily cost for CPLEX is larger compared to PSO daily cost, but the value of revenues in CPLEX are also large than PSO values. With the case study present in Section 5, the value of Equation (1) is equal to Equation (2) in both of methods, which means that the value of Equation (3) is zero because Equation (1) is the sum of Equation (2) and (3). When Equation (3) has the value zero represents that the DR is performed on periods with weight equal to zero and do not have a contribution to Equation (1). Table 5 also presents the monthly costs, which are calculated considering that the profile present in Figure 3 is repeated for the 30 days of the month. The value obtained for PSO is 2.96 (€) higher.

7. Conclusions

The present work addresses a methodology for resource scheduling (PV battery, storage capacity, and load flexibility) in a residential house that has not any contract with a DR service provider. Usually, the DR services for residential consumers are available using a DR service provider. In contrast, in the presented methodology the user is independent of applying his preferences in decision-making. In this case, the PV inverter, installed to convert the PV production into DC to AC, can control the charge or discharge of the battery system and the interruption of the loads. The optimization results for $P^{bat}_{b,t}$ and $P^{cut}_{l,t}$ are the inputs for the PV inverter control to act on the battery system and controllable loads.

The optimization problem was solved using a stochastic method (PSO) and a deterministic method (CPLEX). The results obtained by PSO have a close approximation to the deterministic results. The simple implementation and open access possibility of programming PSO over different platforms are factors that potentiate its use in this type of problems. In fact, in the present work, it was possible to demonstrate the results of running a PSO-based algorithm on a connection with the inverter of the PV system for control of the connected loads and the charge or discharge of the battery storage system.

The numerical results presented demonstrate that it is possible to obtain advantages by using the optimal combination of available resources. Table 4 presents the fitness function value for different resources combination, showing that the scenario that combines the all available resources is the best. Although PSO can obtain near-optimal solutions, its solution using the best combination resource scenario is better than the normal operating solution. With the comparison between the base scenario and the same scenario with PSO optimization, it is possible to make the assessment of the PSO approach. The daily cost optimized by PSO for the base scenario is 14% lower compared with the obtained in the nonoptimized base scenario.

As the presented methodology was built for been applied in an independent agent, the agent facility (residential house) needs to be prepared with equipment to perform the actions that the presented method imposes. This condition may be a weakness of the methodology, as it will increase the initial investment in equipment. Assuming that the DR program is implemented efficiently, such investment can be recovered over time, as the user does not need to pay fees to any service provider to use the service. The use of PSO instead of CPLEX can make the initial investment more appealing, for reasons already discussed in the introduction.

For future work, an analysis incorporating more DR actions (e.g., reduction and shifting capabilities) in the presented methodology can be done. Also, robust optimization considering the forecast error in PV production and domestic consumption can also be made to analyze the impact of forecasts errors in the electricity bill.

Author Contributions: Investigation, R.F.; Methodology, P.F. and Z.V.; Resources, Z.V.; Software, R.F. and J.S.; Writing—original draft, R.F.; Writing—review & editing, P.F. and Z.V.

Funding: The present work was done and funded in the scope of the following projects: SIMOCE Project (P2020-23575) and UID/EEA/00760/2019 funded by FEDER Funds through COMPETE program and by National Funds through FCT. Ricardo Faia is supported by national funds through Fundação para a Ciência e a Tecnologia (FCT) with PhD grant reference SFRH/BD/133086/2017.

Conflicts of Interest: The authors declare no conflicts of interest.

Glossary/Nomenclature

Abbreviations	
AI	Artificial Intelligence
DR	Demand Response
DG	Distributed Generation
ESS	Energy Storage System
LP	Linear Programming
MATLAB	Matrix Laboratory
MILP	Mixed-integer Linear Programming
MINLP	Mixed-integer Nonlinear Programming
NLP	Nonlinear Programing
PSO	Particle Swarm Optimization
PV	Photovoltaic
RESs	Renewable Energy Sources
SET	Strategic Energy Technology
Indices	
b	Battery unit
n	Dimension
i	Iteration
l	Load unit
j	Particle
t	Period
p	Photovoltaic unit
Parameters	
$C_t^{grid\ in}$	Cost of buying electricity to the grid
$C_t^{grid\ out}$	Cost of selling electricity to the grid
$W_{l,t}^{cut}$	Cut weight of load
DCP	Daily contracted power cost
xlb^j	Lower bond for $\vec{x}^j$
$P_t^{grid\ max}$	Maximum limit for P_t^{grid}
i^{max}	Maximum number of iterations

j^{max}	Maximum numbers of particles
$P_{l,t}^{cut\ max}$	Maximum value for cut load
$P_{b,t}^{ch\ max}$	Maximum value for energy charge
$P_{b,t}^{dch\ max}$	Maximum value for energy discharge
c_2^{max}	Maximum value for global acceleration coefficient
w^{max}	Maximum value for inertia weight
c_1^{max}	Maximum value for personal acceleration coefficient
$E_{b,t}^{stor\ max}$	Maximum value of accumulated energy in battery
$P_t^{grid\ min}$	Minimum limit for P_t^{grid}
c_2^{min}	Minimum value for global acceleration coefficient
w^{min}	Minimum value for inertia weight
c_1^{min}	Minimum value for personal acceleration coefficient
Δt	Multiplicative factor related with the time to calculate energy
B	Number of batteries
L	Number of controllable loads
T	Number of Periods
ρ	Penalty value
$P_{p,t}^{PV}$	Photovoltaic production
xub^j	Upper bond for $\vec{x}^j$
P_t^{load}	Value of load
Variables	
$I_t^{grid\ in}$	Binary variable for control the flow direction
$P_{l,t}^{cut}$	Cut power of load
$X_{l,t}^{cut}$	Decision binary variable to active the cut of loads
$P_{b,t}^{bat}$	Energy charged or discharged by battery
$f(\vec{x})$	Fitness function
$f'(\vec{x})$	Fitness function with penalty
P_t^{grid}	Flow of energy between household and grid
P_{best}^j	Historical best position
w_i^j	Inertia weight
$pf(\vec{x})$	Penalty function
$c1_i^j$ and $c2_i^j$	Personal and global acceleration coefficients
G_{best}	Population historical best position
$\vec{x}_i^j$	Position vector
$E_{b,t}^{stor}$	State of the battery
$r1_i^j$ and $r2_i^j$	Uniform distribution random numbers
$\vec{v}_i^j$	Velocity vector

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Core Publication II

Fernando Lezama, Ricardo Faia, Pedro Faria, and Zita Vale, "Demand Response of Residential Houses Equipped with PV-Battery Systems: An Application Study Using Evolutionary Algorithms," Energies, vol. 13, no. 10, p. 2466, May 2020, doi: 10.3390/en13102466. **(2020 Impact Factor: 3.004)**;

Resumen

Los hogares equipados con recursos energéticos distribuidos, como unidades de almacenamiento y renovables, abren la posibilidad de autoconsumo de generación in situ, vender energía a la red, o hacer ambas cosas según el contexto de operación. En este artículo se desarrolla un modelo para optimizar los recursos energéticos de los hogares por parte de un proveedor de servicios de energía. Consideramos viviendas dotadas de tecnologías que apoyen la reducción real de la factura energética y por tanto realicen acciones de respuesta a la demanda. Se desarrolla una formulación matemática para obtener la programación óptima de los dispositivos domésticos que minimice la factura de energía y las acciones de reducción de respuesta a la demanda. Además del modelo de programación, el enfoque innovador de este documento incluye algoritmos evolutivos utilizados para resolver el problema bajo dos enfoques de optimización: (a) el enfoque no paralelo combina las variables de todos los hogares a la vez; (b) el enfoque paralelo aprovecha la independencia de las variables entre los hogares utilizando un mecanismo multipoblacional y optimizaciones independientes. Los resultados muestran que el enfoque basado en paralelo puede mejorar el rendimiento de los algoritmos evolutivos probados para instancias más grandes del problema. Por lo tanto, mientras aumenta el tamaño del problema, es decir, aumenta el número de hogares, la metodología propuesta será más ventajosa. En general, el algoritmo búsqueda de vórtice (vortex search en inglés) supera a todos los demás algoritmos probados (incluida la conocida evolución diferencial y la optimización de enjambre de partículas) logrando alrededor de un 30 % mejor desempeño en todos los casos, lo que demuestra su eficacia para resolver el problema propuesto.

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Demand Response of Residential Houses Equipped with PV-Battery Systems: An Application Study Using Evolutionary Algorithms

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Received: 12 April 2020; Accepted: 9 May 2020; Published: 14 May 2020

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Abstract: Households equipped with distributed energy resources, such as storage units and renewables, open the possibility of self-consumption of on-site generation, sell energy to the grid, or do both according to the context of operation. In this paper, a model for optimizing the energy resources of households by an energy service provider is developed. We consider houses equipped with technologies that support the actual reduction of energy bills and therefore perform demand response actions. A mathematical formulation is developed to obtain the optimal scheduling of household devices that minimizes energy bill and demand response curtailment actions. In addition to the scheduling model, the innovative approach in this paper includes evolutionary algorithms used to solve the problem under two optimization approaches: (a) the non-parallel approach combine the variables of all households at once; (b) the parallel-based approach takes advantage of the independence of variables between households using a multi-population mechanism and independent optimizations. Results show that the parallel-based approach can improve the performance of the tested evolutionary algorithms for larger instances of the problem. Thus, while increasing the size of the problem, namely increasing the number of households, the proposed methodology will be more advantageous. Overall, vortex search overcomes all other tested algorithms (including the well-known differential evolution and particle swarm optimization) achieving around 30% better fitness value in all the cases, demonstrating its effectiveness in solving the proposed problem.

Keywords: demand response; energy service provider; energy storage system; evolutionary algorithms; optimization; photovoltaic generation

1. Introduction

In the current environmental world scenario, countries are adopting a series of counter measures in what regards to the use of energy, renewable sources and DG (Distributed generator) [1]. In fact, the European Union, according to the EU (European Union) renewable energy directive (2009/28/EC), is pushing to their country members to achieve strict targets such as the of penetration of 20% of renewables into the energy mix by 2020, and increase the quantity up to by 100% by 2050. Thus, in order to achieve such ambitious targets, it is expected a systematic and elaborated transformation of the electrical grid, in line with the ambitions of the EU [2].

In this scenario, new technologies such as PV (Photovoltaic) panels and battery systems emerge as a viable solution to promote the penetration of renewables at the local level of the distribution networks. Households equipped with PV generation and storage units became small producers (the so-called prosumers due to their condition of consumer and producer at the local level) and provide a new source of flexibility to the systems [3]. Also, prosumers allow the implementation of innovative energy management mechanisms to take advantage of DR (Demand Response) and on-site generation. The correct coordination and use of such devices, through effective management and optimization approaches, promises several benefits such as the reduction of energy bills for households and the reduction of carbon-emission footprints in general.

Different approaches have been proposed to address the optimization of households equipped with PV-battery systems. For instance, a MILP (Mixed-integer Linear Programming) problem was formulated in [4] for the management of a residential community grid with renewables, batteries, electric vehicles, and DR capabilities. This formulation searched for the minimization of purchased energy cost. In [5], a similar approach was used to minimize operation cost of a smart building considering DR and day-ahead energy resource management. In [6], the capabilities of MILP were tested again under a similar problem formulation, showing that DR can be very effective in different scenarios when a high penetration of renewables is available. On the other hand, some MINLP (Mixed-integer Non-linear Programming) have extended the mathematical formulation to include non-linearities and make the models close to real-world situations. For instance, in [7] a unit commitment problem of a microgrid is formulated to optimize the amount of load reduction and incentives given due to DR at different time intervals. Also, in [8], gas and electricity are included into the energy mix model, and the day-ahead energy scheduling is optimized for energy hubs. Some other approaches have explored the idea of an aggregator that works as an energy service provider. In this case, households can apply DR actions following incentives or responding to a direct control signals dictated by the aggregator. For instance, in [9], an aggregation of air conditioning loads is considered to perform DR actions. The study in [10] is not only limited to DR actions but also considers storage units to participate in energy and regulation markets. Also, in [11], a demand response simulator to study actions and schemes of users in distribution networks was proposed. The study took into account the technical validation of solutions including load reduction using a consumer-based price elasticity approach supported by real time pricing.

Finally, due to the complexity of the problem, EA (Evolutionary Algorithms) has been proposed in the literature trying to face issues such as scalability, memory requirements, time constraints, and other related problems that arise in the context of demand response and hybrid PV-battery systems. For instance, in [12], a bi-level formulation for optimal day-ahead price-based DR is proposed and solved by a hybrid approach in which a multi-population genetic algorithm is used for the upper level and distributed individual optimization algorithm for the lower level. Another hybrid genetic algorithm is used in [13] to consider the interaction of electricity retailers and DR. More recently, in [14] a PSO (Particle Swarm Optimization) algorithm is used for load shifting of appliances and the scheduling of PV and storage equipment using a home energy management system. In [15], the performance of evolutionary algorithms is compared solving a flexibility management model in which home appliances can perform DR actions. In addition, evolutionary algorithms have been used not only to optimize hybrid renewable energy systems [16] but also to coordinate the scheduling of PV-storage systems [17–19].

In this paper, we extend the model proposed in [20], for optimization of households equipped with PV-battery systems and DR capabilities. Different EAs, including DE (Differential Evolution, PSO, VS (Vortex Search, and other variants, are implemented to solve the optimization problem (MILP), and their performance and results are compared under two novel frameworks (one following the typical framework of EAs and another taking advantage of parallel computing). Households are provided with an independent management of resources minimizing energy bills and optimizing DR curtailment. With the objective of improving the minimization of electricity costs for households, with the support of an energy service provider, the contributions of this paper are as follows:

- An optimization framework for the optimization of PV-battery system of households minimizing energy bills and DR actions.

- A MILP formulation to optimize the resources of several households.
- Implementation of different EAs under two optimization approaches, one based on standard evolutionary computation and a second one taking advantage of parallel computing.
- Assessment of the effectiveness of EAs and the optimization framework under a case study considering up to 20 households.

The paper is organized as follows: after the introduction in Section 1; the proposed methodology and the mathematical formulation is presented in in Section 2; Evolutionary algorithms applied in this work are introduced in Section 3; Section 4 presents the two proposed optimization approaches employed with the use of EAs to make use of parallel computing; the case study and results are provided in Sections 5 and 6 respectively; and finally, the conclusions of this work are presented in Section 7.

2. Households Demand Response Optimization

In this section, is provided the description of the proposed optimization model, which aims to minimize the energy bill and the user discomfort. The change in the consumption pattern is considered to be a way of user discomfort. Since it is a rather complex problem to be computed at house level, the proposed methodology considers an Energy Service Provider that performs the optimization for a large set of households, and makes the results available for each one.

In each house, distributed energy resources are available, like PV generation, storage, and DR. Accordingly, each household is a prosumer (a consumer able to produce electricity), equipped with a PV and an energy storage system. Three appliances can be controlled by the optimization algorithm to reduce the consumption in periods when the electricity price is higher. For this, it is assumed that the household owns the needed control devices (e.g., plc). The PLC (Programmable Logic Controller) controller unit manages the consumption and generation resources in the houses according to the schedule received from the Energy Service Provider.

The mathematical formulation of the problem is an extension of [20] to consider up to I households (unlike the original model designed to target only one household). Thus, the formulation corresponds to a MILP model having as OF (Objective Function) Equation (1):

$$\text{Minimize } OF = Energy\ Bill + DR\ Curtailment\ Weight\ , \tag{1}$$

where *Energy Bill* represents the costs of buying and selling electricity, while *DR Curtailment Weight* quantifies the weight of the curtailment of loads due to DR. Thus, Equation (2) represents the energy bill that households must pay due to the flow of energy exchanged with the main grid:

$$Energy\ Bill = \sum_{i=1}^{I}\left(\sum_{t=1}^{T}\left(P_{i,t}^{\text{Grid In}} \times C_{i,t}^{\text{Grid In}} - P_{i,t}^{\text{Grid Out}} \times C_{i,t}^{\text{Grid Out}}\right) \times \frac{1}{\Delta t}\right) + Fix\ Cost_i\ , \tag{2}$$

where $P_{i,t}^{\text{Grid In}}$ represents the energy flow from the grid to the household, $C_{i,t}^{\text{Grid In}}$ represents the cost of buying energy, $P_{i,t}^{\text{Grid Out}}$ is the energy flow from household to the grid, $C_{i,t}^{\text{Grid Out}}$ corresponds to the revenue of selling energy to the grid, $\frac{1}{\Delta t}$ is a term that considers the modification of hourly values to another time interval (e.g., 15 min in this article), $Fix\ Cost_i$ represents the fixed tariff costs pay by each household. $i = \{1, ...I\}$ is used to identify households, and $t = \{1, ..., T\}$ for the periods. Notice that Equation (2) includes the sum of energy bill over all households. Therefore, minimizing this overall value corresponds to reduce the bill for each particular household. Moreover, the energy consumption/generation from households is independent, and thus, finding the minimum value for Equation (2) guarantees that the minimum possible bill for each household is obtained.

On the other hand, Equation (3) is used to calculate the weight of DR actions:

$$DR\ Curtailment\ Weight = \sum_{i=1}^{I}\left(\sum_{t=1}^{T}\left(\sum_{l=1}^{L}\left(P_{i,t,l}^{\text{Cut}} \times X_{i,t,l}^{\text{Cut}} \times W_{i,t,l}^{\text{Cut}}\right)\right)\right)\ , \tag{3}$$

where $P_{i,t,l}^{\text{Cut}}$ represents the energy load cuts, $X_{i,t,l}^{\text{Cut}}$ are binary decision variables indicating a DR action, $W_{i,t,l}^{\text{Cut}}$ represents the weight of energy cuts, $l = \{1, ..., L\}$ is used to represent loads available for DR.

It is important to point out, as explained in [20] that the energy bill (first term) and DR curtailment (second term) can be seen as opposite objectives in Equation (1). This is because the curtailment of loads reduces energy bills, but at the same time affects user comfort in different ways depending on user preferences. In this work, however, we decided to select the DR weights of energy cuts following a trend contrary to the buy from grid tariff to promote the use of DR when the price of energy is higher. Other assumptions and targets can be explored in future work.

Equation (4) represents the energy balance at each period:

$$P_{i,t}^{\text{Grid}} = P_{i,t}^{\text{Load}} + P_{i,t}^{\text{Bat}} - \sum_{l=1}^{L} \left(P_{i,t,l}^{\text{Cut}} \times X_{i,t,l}^{\text{Cut}} \right) - P_{i,t}^{\text{PV}}, \forall i \in \{1, ..., I\}, \forall t \in \{1, ..., T\}\ , \tag{4}$$

where $P_{i,t}^{\text{Grid}}$ represents the energy flow between grid and household, $P_{i,t}^{\text{Load}}$ represents consumption from non-controllable loads, $P_{i,t}^{\text{Bat}}$ corresponds to energy charge/discharge of batteries (charge or discharge) and $P_{i,t}^{\text{PV}}$ represents the energy generated by PV panels.

Equation (5) is applied to obtain the flow of energy between the grid to household:

$$P_{i,t}^{\text{Grid In}} = P_{i,t}^{\text{Grid}} \geq 0, \forall i \in \{1, ..., I\}, \forall t \in \{1, ..., T\}\ . \tag{5}$$

Equation (6) is applied to obtain the energy flow from households to the grid (exported energy):

$$P_{i,t}^{\text{Grid Out}} = P_{i,t}^{\text{Grid}} < 0, \forall i \in \{1, ..., I\}, \forall t \in \{1, ..., T\}\ . \tag{6}$$

Equation (7) represents the balance of the batteries for all households at all periods:

$$E_{i,t}^{\text{Bat}} = E_{i,t-1}^{\text{Bat}} + P_{i,t}^{\text{Bat}} \times \frac{1}{\Delta t}, \forall i \in \{1, ..., I\}, \forall t \in \{2, ..., T\}\ , \tag{7}$$

where $E_{i,t}^{\text{Bat}}$ is the state of the battery of household i at period t, and $E_{i,t-1}^{\text{Bat}}$ represents the previous state of the battery of household i at period $t-1$. Equation (7) is applied from the second to the last period of optimization, while $E_{i,1}^{\text{Bat}}$ is an input parameter of the case study.

Equation (8) is used to represent the bounds of $P_{i,t}^{\text{Grid}}$ variable:

$$P_{i,t}^{\text{Gridmin}} \leq P_{i,t}^{\text{Grid}} \leq P_{i,t}^{\text{Gridmax}}, \forall i \in \{1, ..., I\}, \forall t \in \{1, ..., T\}\ , \tag{8}$$

where $P_{i,t}^{\text{Gridmin}}$ corresponds to the lower bond and $P_{i,t}^{\text{Gridmax}}$ to the upper bound values of $P_{i,t}^{\text{Grid}}$.

Equation (9) represents the upper bound (maximum cut capacity) for the variable $P_{i,t,l}^{\text{Cut}}$:

$$P_{i,t,l}^{\text{Cut}} = P_{i,t,l}^{\text{Cutmax}}, \forall i \in \{1, ..., I\}, \forall t \in \{1, ..., T\}, \forall l \in \{1, ..., L\}\ . \tag{9}$$

Equation (10) presents the bonds for the variable $E_{i,t}^{\text{Bat}}$.

$$0 \leq E_{i,t}^{\text{Bat}} \geq E_{i,t}^{\text{Batmax}}, \forall i \in \{1, ..., I\}, \forall t \in \{1, ..., T\}\ , \tag{10}$$

where $E_{i,t}^{\text{Batmax}}$ are the upper bound of variables $E_{i,t}^{\text{Batmax}}$.

Equation (11) presents the bound for the variable $P_{i,t}^{\text{Bat}}$:

$$-P_{i,t}^{\text{Batdch}} \leq P_{i,t}^{\text{Bat}} \geq P_{i,t}^{\text{Batch}}, \forall i \in \{1, ..., I\}, \forall t \in \{1, ..., T\}\ , \tag{11}$$

where $-P_{i,t}^{\text{Batdch}}$ and $P_{i,t}^{\text{Batch}}$ are the lower and upper bounds of the variable $P_{i,t}^{\text{Bat}}$.

Equation (12) represents the bounds for the variable $X_{i,t,l}^{Cut}$.

$$X_{i,t,l}^{Cut} = \begin{cases} 1 \\ 0 \end{cases} , \forall i \in \{1, ..., I\}, \forall t \in \{1, ..., T\}, \forall l \in \{1, ..., L\} \,, \tag{12}$$

where variable $X_{i,t,l}^{Cut}$ can takes the value of '1' when the cut is active and the '0' when the cut is not active.

3. Evolutionary Computation

EC (Evolutionary Computation) is one of the three pillars of computational intelligence (along with artificial neural networks and fuzzy systems). EC includes a set of algorithms for optimization inspired in biological and evolutionary processes [21]. In fact, there are in the literature now a huge set of algorithms available for optimization, but in general, they can be grouped in some popular categories such as EA, SI (Swarm Intelligence), nature-inspired algorithms, natural computation, etc.

In this paper, we focus our attention in a class of algorithms that share some common mechanisms. This choice eases the experimental analysis since a fair comparison can be performed between the algorithms. Figure 1 illustrates the evolutionary mechanism employed by the selected EAs. Thus, in a first stage, an encoding of solutions and a fitness function are defined for a particular problem. The EAs act over an initial set of candidate solutions encoded as vectors (i.e., a population) that is iteratively updated through generations. The way in which new solutions are created from the initial population is what distinguish each EAs (i.e., each of the selected EAs has its own variation operator). Solutions' performance is measured by the fitness function, and at each generation, solutions with inferior performance are replaced by the new solutions with better performance. It is empirically proved that by the principles of natural selection (or artificial selection in this case), the population will gradually evolve towards an optimal fitness value.

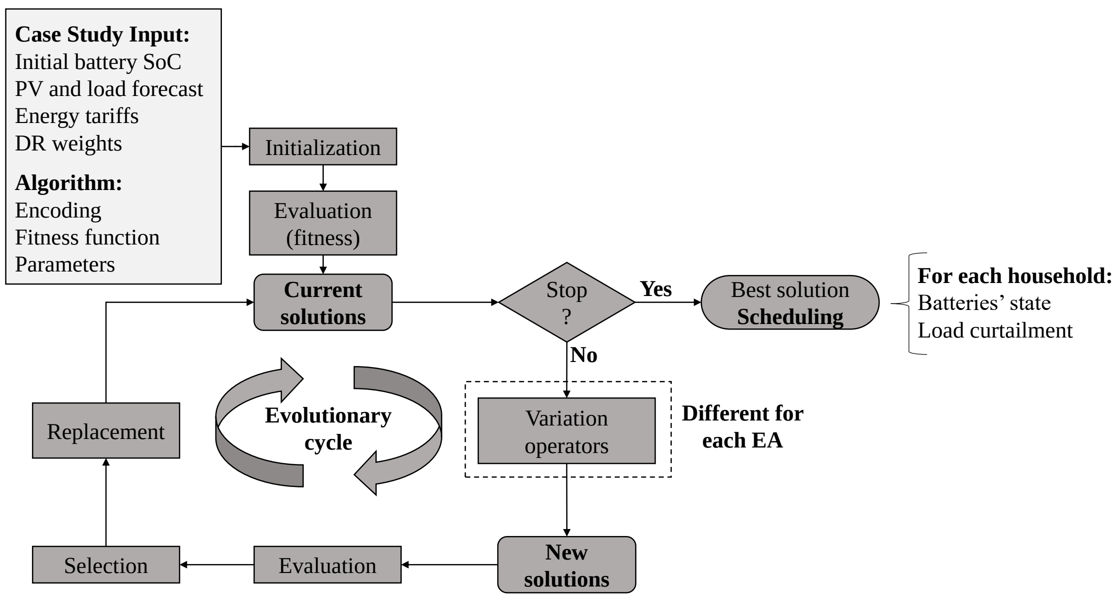


Figure 1. Typical optimization scheme of evolutionary algorithms. All the evolutionary algorithms used in this work follow this scheme.

We describe the solution encoding and fitness function shared by the selected EAs in Section 3.1. After that, a brief description of the chosen algorithms is provided in Section 3.2.

3.1. Solution Encoding and Fitness

The optimization problem searches for the optimal scheduling of charging and discharging cycles of batteries and the choice of which loads are used for DR curtailment, for each user (as stated in Section 2).

Therefore, the selected encoding should include all the information to validate a solution, and it is very similar to that used in [20], but generalized for I users. Figure 2 shows the structure of a given solution in our framework. The solution first include continues variables representing the charging/discharging state (positive for charging, and negative for discharging) of the users' battery, at all periods t, for each user i. Therefore, this set includes $T \times I$ variables Then, a second set of binary variables is used to indicate a cut action in all load l ('1' if load l is curtailed, and '0' if not), at all periods t, for each user i. Therefore, this second set includes $L \times T \times I$ binary variables. In general, a complete given solution to the problem is of dimension $D = T \times I \times (1 + L)$. The variables are bounded by:

$$\vec{xlb} = \{-P_{i,t}^{\text{dchmax}}, X_{i,l,t}^{\text{cutmin}}\}, \quad i = \{1, ..., I\}, t = \{1, ..., T\}, l = \{1, ..., L\}\ , \tag{13}$$

$$\vec{xub} = \{P_{i,t}^{\text{chmax}}, X_{i,l,t}^{\text{cutmax}}\}, \quad i = \{1, ..., I\}, t = \{1, ..., T\}, l = \{1, ..., L\}\ . \tag{14}$$

Thus, the EAs can generate initial populations with random candidate solutions between those bounds using a random function such as:

$$\vec{x}_j = \text{rand}(\vec{xlb}, \vec{xub}), \quad j = \{1, ..., N_{sol}\}\ , \tag{15}$$

where $\text{rand}(\vec{xlb}, \vec{xub})$ generates a random solution between the bounds defined in Equations (13) and (14), and N_{sol} is the size of the population defined by the user.

Since the formulation includes constraints that can be difficult to optimize by the algorithms, we apply some direct repair techniques to ease the generation of feasible solutions. Equation (16) presents the direct repair mechanism employed to keep variables $E_{i,t}^{\text{Bat}}$ into the allowed limits:

$$E_{i,t}^{\text{Bat}} = \begin{cases} 0, & if\ E_{i,t}^{\text{Bat}} < 0 \\ E_{i,t}^{\text{Batmax}}, & if\ E_{i,t}^{\text{Bat}} > E_{i,t}^{\text{Batmax}} \\ P_{i,t}^{\text{Bat}}, & otherwise \end{cases} \quad , \forall i \in \{1, ..., I\}, \forall t \in \{2, ..., T\}\ , \tag{16}$$

where variable $E_{i,t}^{\text{Bat}}$ represent the energy state of charge of the battery. $E_{i,t}^{\text{Bat}} < 0$ represents a discharge state greater than the allowed one, so that the variable is fixed to its minimum value. When $E_{i,t}^{\text{Bat}} > E_{i,t}^{\text{Batmax}}$, the battery has charged more energy than the allowed, thus, the value of maximum energy in the battery is fixed the maximum allowed value. After repairing the state of charge, variables $P_{i,t}^{\text{Bat}}$ should also being repaired as:

$$P_{i,t}^{\text{Bat}} = \begin{cases} E_{i,t}^{\text{Bat}} - E_{i,t-1}^{\text{Bat}}, & if\ E_{i,t}^{\text{Bat}} < 0 \\ E_{i,t}^{\text{Bat}} - E_{i,t-1}^{\text{Bat}}, & if\ E_{i,t}^{\text{Bat}} > E_{i,t}^{\text{Batmax}} \\ P_{i,t}^{\text{Bat}}, & otherwise \end{cases} \quad , \forall i \in \{1, ..., I\}, \forall t \in \{2, ..., T\}\ . \tag{17}$$

Notice that variable $P_{i,t}^{\text{Bat}}$ is repaired following the same conditions of Equation (16). This procedure guarantees feasible solutions, helping in the iterative process of the EAs.

Since the encoding has been designed to include all information needed to evaluate the mathematical model from Section 2, the fitness function is taken directly from Equation (1) including penalties due to the possibility of generate infeasible solutions. Therefore, the fitness value includes the energy bill (costs and revenues), fixed costs, and DR curtailment weight off all users plus penalties:

$$Fitness(\vec{x}_j) = f(\vec{x}_j) + p_{\text{function}}(\vec{x}_j)\ , \tag{18}$$

where $f(\vec{x}_j)$ is equivalent to Equation (1), and $p_{\text{function}}(\vec{x}_j)$ is a function that returns a penalty value associated with the violation of the limits of variable $P^{\text{Grid}}_{i,t}$ for each user i at each time t, defined as:

$$p_{\text{function}}(\vec{x}_j) = \sum_{i=1}^{I}\sum_{t=1}^{T}\rho_{i,t}\ , \tag{19}$$

$$\rho_{i,t} = \begin{cases} 0 - P^{\text{Grid}}_{i,t}, & \text{if } (P^{\text{Grid}}_{i,t} < 0) \\ P^{\text{Grid}}_{i,t} - P^{\text{Gridmax}}_{i,t}, & \text{if } (P^{\text{Grid}}_{i,t} > P^{\text{Grid min}}_{i,t}) \\ 0 \quad \textit{otherwise} \end{cases}\ , \tag{20}$$

where $\rho_{i,t}$ is a penalty factor related to the limits of variable $P^{\text{Grid}}_{i,t}$. Notice that direct repair methods are used to avoid as much as possible violations of constraints (see direct repair methods in [20]), yet, due to the stochastic nature of EAs, infeasible solutions may arise for large instances (as the result section shows).

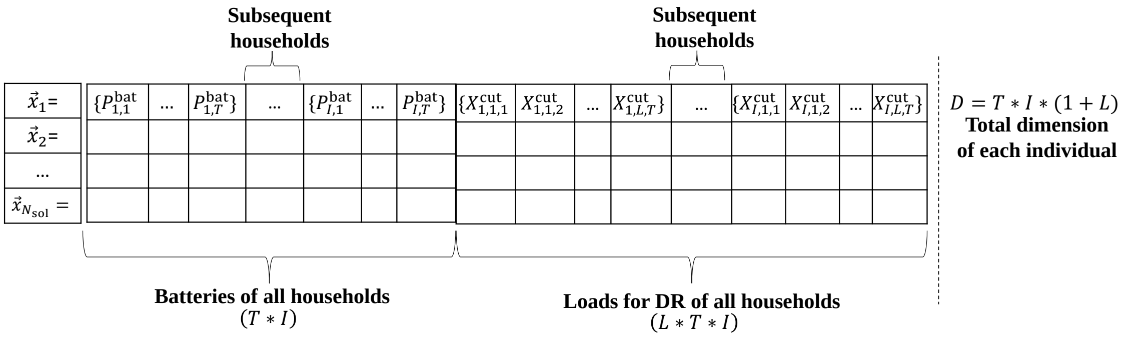


Figure 2. Solution encoding. The individual structure used by the EAs include all information needed to evaluate a solution.

3.2. *EAs Used for DR of Households*

Now that we defined the encoding of individuals and the fitness function, we apply EAs following the scheme from Figure 1 to solve the problem. In this paper, we apply DE and two of its variants hyde and HyDE (Hybrid Differential Evolution) (due to its success in many applications and easy implementation [22]), an improved version of the well-known PSO, and the vs [23]. In the following subsections, we provide a brief description of the algorithms, and their variation operators that distinguish each of them.

3.2.1. Differential Evolution

DE uses a Pop (Population) of individuals $\vec{x}_{j,i,G} = [x_{1,i,G}, ..., x_{D,i,G}]$, where G is the number of iterations, $i = [1, ..., NP]$ is the index of individuals in the population, and $j = [1, ..., D]$ is the index for the variables to optimize. In the initialization stage, NP solutions are generated randomly within lower and upper ranges $\vec{xlb}$ and $\vec{xub}$. In the standard form of DE, the so-called DE/rand/1 algorithm, new solutions are created applying a mutation and recombination operator defined by:

$$\vec{m}_{i,G} = \vec{x}_{r1,G} + F(\vec{x}_{r2,G} - \vec{x}_{r3,G})\ , \tag{21}$$

$$\vec{t}_{j,i,G} = \begin{cases} \vec{m}_{i,G} & \text{if } (\text{rand}_{i,j}[0,1] < \text{Cr}) \vee (j = \text{Rnd}) \\ \vec{x}_{j,i,G} & \text{otherwise} \end{cases}\ , \tag{22}$$

where $\vec{x}_{r1,G}, \vec{x}_{r2,G}, \vec{x}_{r3,G} \in$ Pop are three random individuals from the Pop, mutually different from each other. F and Cr are the mutation and recombination parameters of DE, usually set in the range $[0,1]$. The fitness function, (i.e., Equation (18)), is used to evaluate the performance of new individuals.

An elitist selection procedure is applied in DE by replacing solution with worse performance than the new generated ones. A detailed explanation of DE can be found in [24,25].

3.2.2. Hybrid Adaptive DE

HyDE is a new self-adaptive version of DE proposed in [25]. The distinguish HyDE variation operator, known as "DE/target-to-$perturbed_{best}$/1", modifies the well-known DE/target-to-best/1 strategy [22] perturbing the best individual (similar to the evolutionary PSO [26]). HyDE also integrate a self-adaptive parameter mechanism (taken from the jDE (Self-Adaptive Differential Evolution algorithmm [27]). The main operator of HyDE is defined as follows:

$$\vec{m}_{i,G} = \vec{x}_{i,G} + F_i^1(\epsilon \cdot \vec{x}_{\text{best}} - \vec{x}_{i,G}) + F_i^2(\vec{x}_{r1,G} - \vec{x}_{r2,G}) \, , \tag{23}$$

where F_i^1 and F_i^2, are scale factors in the range $[0,1]$ independent for each individual i, and $\epsilon = \mathcal{N}(F_i^3, 1)$ is a random perturbation factor following a normal distribution with mean F_i^3 (random number in the range $[0,1]$) and standard deviation 1. F_i^1, F_i^2 and F_i^3 are updated at each iteration with the same rule of jDE algorithm (see Section III.B of [25]).

3.2.3. Hybrid Adaptive DE with Decay Function

HyDE-DF is an improved version of HyDE used for function optimization [28]. The main different in its operation is the incorporation of a decay function that allows a transition in the iterative process from the main operator of HyDE (Equation (23)) to the basic operator of DE (Equation (21)):

$$\vec{m}_{i,G} = \vec{x}_{i,G} + \delta_G \cdot [F_i^1(\epsilon \cdot \vec{x}_{\text{best}} - \vec{x}_{i,G})] + F_i^2(\vec{x}_{r1,G} - \vec{x}_{r2,G}) \quad , \tag{24}$$

where δ_G is a decreasing function (from $1 \rightarrow 0$) that gradually mitigates the influence towards x_{best}, and takes advantage of the inherent DE exploitation capabilities in later stages of the evolutionary process. The decay factor at each generation G is calculated as:

$$\delta_G = e^{1-1/a^2}; \qquad \text{with} \qquad a = (GEN - G)/GEN \quad . \tag{25}$$

δ_G factor alleviate the premature convergence effect towards the best individual in the population (i.e., due to the term $F_i^1(\epsilon \cdot \vec{x}_{best} - \vec{x}_{i,G})$). Such transition also allows an enhance exploration phase in the early stages of evolution, and improves exploitation in later stages of the optimization. HyDE-DF achieved third place (out of 36 algorithms) in the 100-digit challenge at CEC/GECCO 2019 [29].

3.2.4. PSO-LVS

PSO [20] belongs to the class of SI, in which particles (solutions to the problem) coordinate their actions by modifying their position towards the optimum value. Particles are evaluated in the fitness function and improve their position in each iteration using the following variation operator:

$$x_{j,i,G}^{\rightarrow} = x_{j,i,G-1}^{\rightarrow} + v_{j,i,G}^{\rightarrow} \, , \tag{26}$$

$$v_{j,i,G}^{\rightarrow} = w_G \cdot v_{j,i,G-1}^{\rightarrow} + c1_G \cdot rand() \cdot (P_i^{\text{best}} - x_{j,i,G-1}^{\rightarrow}) + c2_G \cdot \text{rand}() \cdot (G^{\text{best}} - x_{j,i,G-1}^{\rightarrow}) \, , \tag{27}$$

where $v_{j,i,G}^{\rightarrow}$ represents the velocity vector, w_G is the inertia weight, $c1_G$ and $c2_G$ are the are acceleration coefficients for personal and global component, rand() is a uniformly distributed random number, P_i^{best} is the historical best position obtained by particle i while G^{best} is the population historical best position obtained by the swarm.

PSO-LVS (PSO with Local Vortex Search) (Equation (28)) is a variant of PSO developed by the authors that includes a local search based on the VS algorithm. The movement of PSO-LVS is therefore obtained by following equation:

$$x_{j,\vec{i},G} = \begin{cases} x_{j,\vec{i},G} = x_{j,i,\vec{G}-1} + v_{j,\vec{i},G} & if,\ \mathrm{rand}() \leq P^{\mathrm{PSO}_G} \\ p(\vec{m}/\mu,\Sigma) = \frac{1}{\sqrt{(2\pi)^d|\Sigma|}}\exp\left\{-\frac{1}{2}(\vec{x}-\mu)^G\Sigma^{-1}(\vec{x}-\mu)\right\} & otherwise, \end{cases} \tag{28}$$

where P^{PSO_G} is a probability factor that switch between PSO standard equation and VS. Another difference is that μ in Equation (29) is replaced by G^{best}. In addition, $P^{\mathrm{PSO}_G} = 0.9^{\frac{G}{8}}$ is a probability that decreases in function of the number of generations. With this method, it is expected the execution of LVS (Local Vortex Search) in later stages of the iterative process.

3.2.5. Vortex Search

VS is classified as a single-solution-based metaheuristic, although it has an analogous framework to the EAs selected for this study. In each iteration, N given number of neighbor solutions are generated using a multivariate Gaussian distribution around the initial solution using:

$$p(\vec{m}/\mu,\Sigma) = \frac{1}{\sqrt{(2\pi)^d|\Sigma|}}\exp\left\{-\frac{1}{2}(\vec{x}-\mu)^G\Sigma^{-1}(\vec{x}-\mu)\right\}, \tag{29}$$

where d represents the dimension, $\vec{x}$ is the $d \times 1$ vector of a random variable, μ is the $d \times 1$ vector of sample mean (center), and Σ is the covariance matrix. The N solutions generated with this function are evaluated in the fitness function, and the best solution replaces the initial single-solution. The radius of search is gradually reduced during the iterative process, favoring exploitation capabilities in the final iterations. This process is iterative repeated until a stop criterion is achieved [23].

4. Non-Parallel and Parallel-Based Approaches

In this paper, given the nature of the mathematical formulation, and the independence of variables between households, we propose two approaches to use the EAs. In the first approach illustrated in Figure 3, so-called non-parallel approach, all variables are combined in a single encoding (explained in Section 3.1). Thus, the EAs use their variation operators over the whole set of variables, until a stop criterion is achieved. This is the typical form in which an EA is applied to solve a given problem.

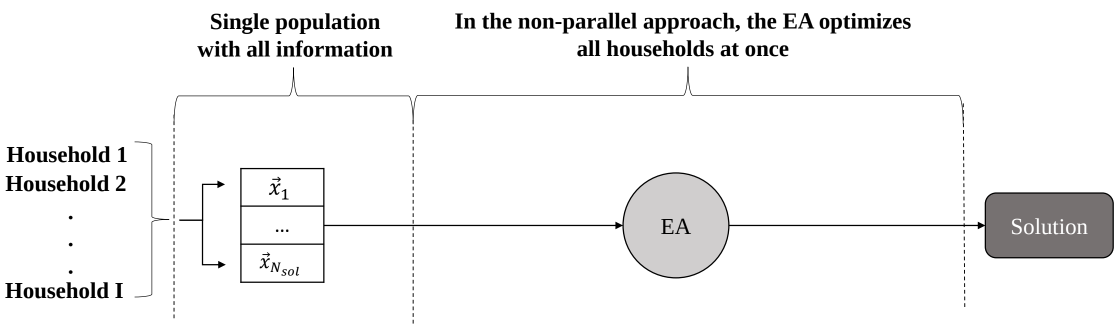


Figure 3. The non-parallel approach optimizes all variables in one population. This is in line with the typical mechanism of EAs.

However, the problem formulation assume that each household scheduling is independent from each other, since their resources are individual and not shared among them. Thus, in the second approach illustrated in Figure 4, variables are divided in groups corresponding to each household. After that, multi-populations are generated and optimized independently by a chosen EA.

The independent solutions are combined in a post-optimization stage, to calculate the total costs of all households. While the solution returned by both approaches is equivalent, results show that breaking the groups of variables into sets corresponding to each household in fact improves the performance of the EAs. In addition, the parallel-based approach can make use of distributed computing, running in parallel different EAs and improving convergence times.

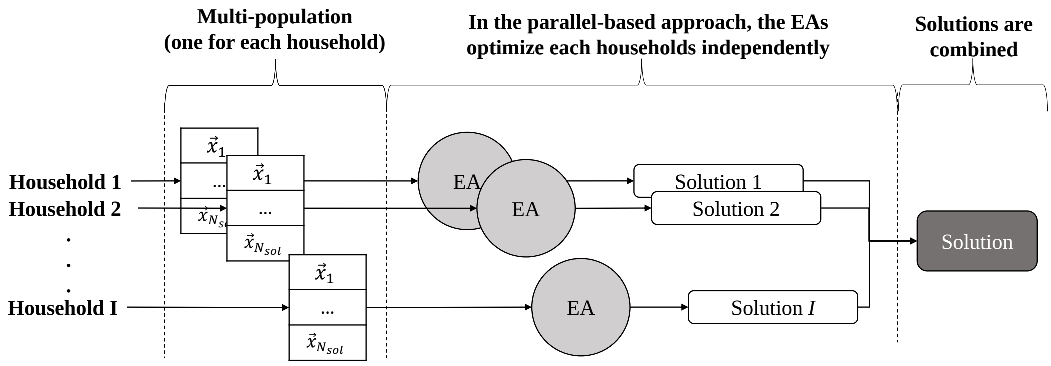


Figure 4. The proposed parallel-based approach breaks the solution into parts corresponding to the variables of each household. After that, each EA optimizes the variables and a post-optimization procedure combines the solutions into a single solution.

5. Case Study

We design a case study to evaluate our framework considering households representing prosumers complying with actual Portuguese legislation, which allows small producers (consumers with local generation) to use their energy to satisfy their own load needs, and inject excess of energy to the grid. We assume that households are equipped with PV panels with a maximum power capacity of 7.5 kW and a battery unit belonging to one of the four models showed in Table 1 (distributed randomly within the households). In addition, households equipped with controllable loads can reduce 10% on average of their total consumption.

Table 1. Battery models used for the case study, taken from [30].

	P^{chmax}	$-P^{\text{dchmax}}$	E^{Batmax}
Laboratory battery used in [20]	1.5 kW	−1.5 kW	12 kWh
Tesla Powerwall	5 kW	−5 kW	13.5 kWh
Alpha Smile	2.87 kW	−2.87 kW	14.5 kWh
Sonnen	3.3 kW	−3.3 kW	15 kWh

For consumption and PV generation, two sample power profiles were used to generate data of residential households. The profiles were built using real open datasets available at PES ISS website [31]. With these base profiles, up to 20 households' data was generated using a randomized function with a uniform distribution, ±25% around the base profiles.

Figure 5 shows the retail tariffs and PV generation of the base profiles. We assume that households have a power supply contract with a given retailer of 11 kW characterized by three different periods: peak (0.33 EUR/kWh), intermediate (0.16 EUR/kWh), and off-peak (0.093 EUR/kWh). We also consider a feed-in tariff of 0.095 EUR/kWh and a DR weight with a trend contrary to the buy from grid tariff, i.e., promoting the use of dr when the price of energy is higher (these weights are applied to the second term of Equation (1)). Tariffs are based on real values of a Portuguese retailer.

Figures 6 shows the aggregated consumption profiles of 20 households. Notice that the aggregated profile correspond to a typical profile since data from households is generated following base profiles, which in practice might not be the case. However, this paper is focused on the performance of EAs rather than the impact in the diversity of consumers. Further studies can be done considering households with diverse characteristics and their impact in costs and DR curtailment. Figure 7 the total aggregated consumption and generation of 20 households. Finally, input values of variables for each household are summarized in Table 2

Table 2. Input variables of the problem. Values are applied to each household.

Parameter	Variable	Value	Units
Maximum power injected to the grid	$P_{i,t}^{\text{Gridmax}}$	5.1	kW
Maximum power required from grid	$P_{i,t}^{\text{Gridmin}}$	1000	kW
Maximum battery capacity	$E_{i,t}^{\text{Batmax}}$	12, 13.5, 14.5, 15	kW
Battery charge/discharge rate	$B_{i,t}^{\text{Batch}} / B_{i,t}^{\text{Batdch}}$	1.5, 5, 2.87, 3.3	kWh
Initial state of charge of batteries	$E_{i,1}^{\text{Batmax}}$	0	kWh
PV maximum generation capacity	$P_{i,t}^{\text{PV}}$	7.5	kW
Total Periods	T	96	-
Total of controllable loads	L	3	-
Total of batteries	B	1	-
Total of PV units	-	1	-
Adjust parameter *	Δt	4	-

* 1The factor of 4 is used since there are four 15-min periods in an hour.

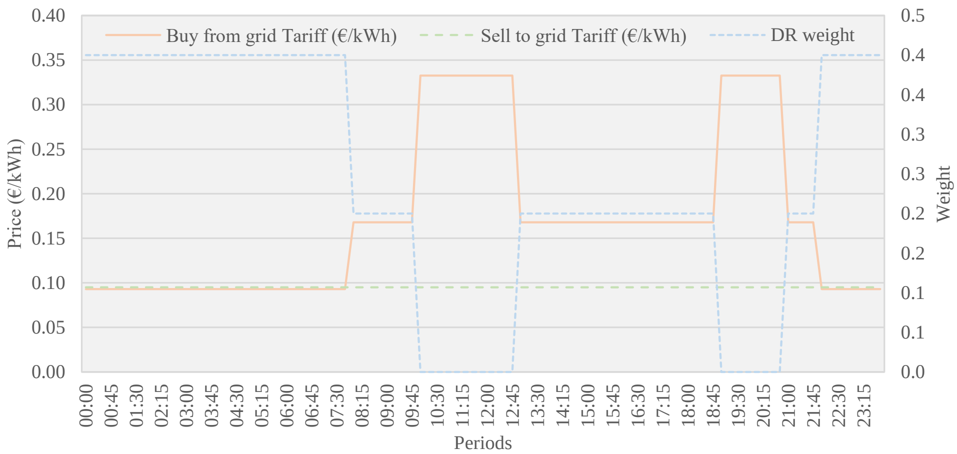


Figure 5. Considered tariffs and PV generation base profile.

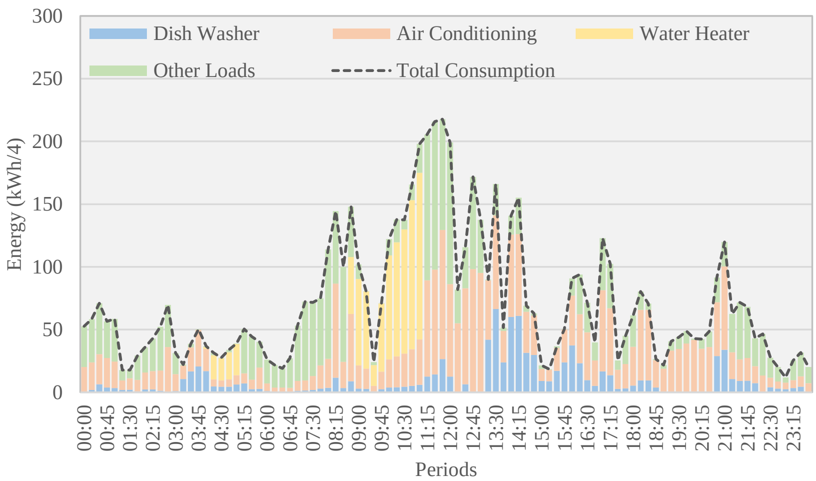


Figure 6. Aggregated loads and total consumption.

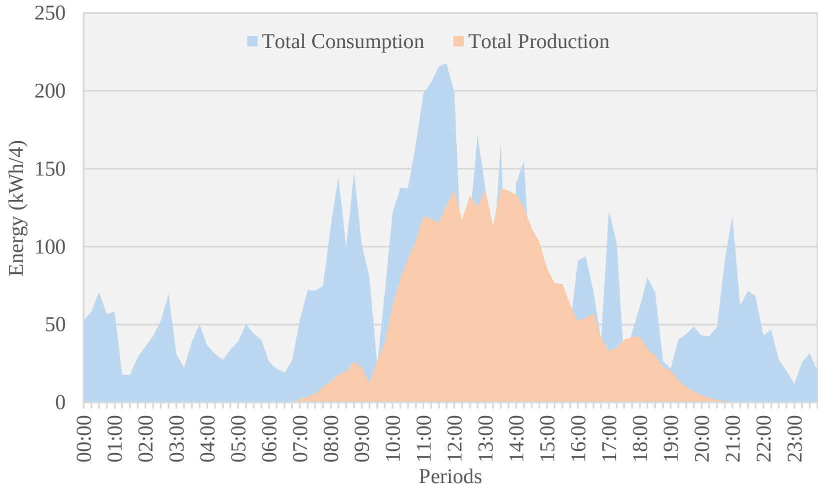


Figure 7. Aggregated consumption and production.

6. Results

We present the results of our methodology applied to the case study of Section 5. The experiments were implemented using MATLAB2018a, in a computer with Intel Xeon(R) E5-2620v2@2.1 GHz processor with 16GB of RAM running Windows 10. All the algorithms were run for 30 times (given the stochastic nature of eas), so the reported results correspond to the average of those runs.

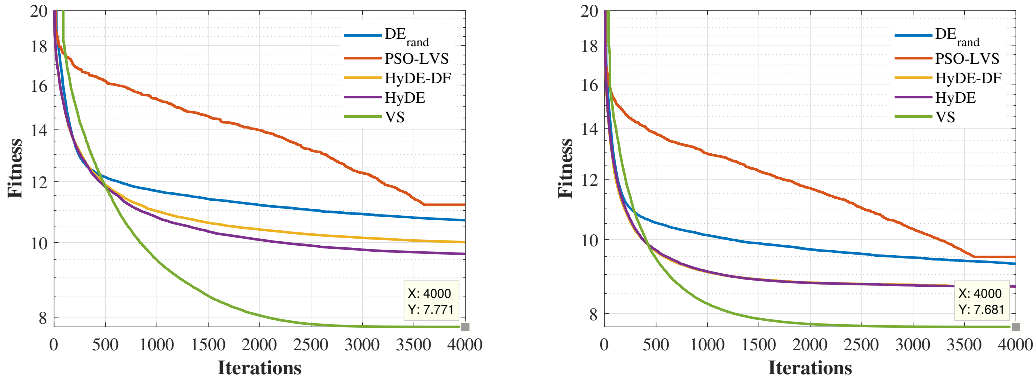
We perform four different experiments based on the number of households and the ea optimization approach. Table 3 show the four cases, identified by the letter C1-C4, related to the experiments. C1 is designed to assess the selected eas under the non-parallel approach considering two households. C2 also considers two households but under the parallel-based approach. C3 and C4 assess eas under non-parallel and parallel-based approaches respectively, but considering 20 households.

Table 3. Available equipment in houses for analyzing the impact of storage and dr.

Case	Two Households	20 Households	Non-Parallel	Parallel-Based
C1	✓		✓	
C2	✓			✓
C3		✓	✓	
C4		✓		✓

The parameters for each tested ea were selected following the recommendation of previous studies. Therefore, for de, the mutation factor and recombination constant (F and Cr) were set to 0.5 and 0.9 respectively [32]. hyde and HydE-DF [25] are a self-adaptive parameter versions but initial values for F^i and Cr where set to 0.5. For PSO-LVS the w_G inertia weight is linearly decreasing with the number of iterations between 0.9 and 0.4 [33]. The constants $c1_G$ is set 0.5 and $c2_G$ set 1.8. For variables boundary control Bounce Back method is used. VS algorithm does not have any parameter to configure [23]. To make a fair comparison, all the algorithms used a population of 20 initial solutions and run for 4e3 iterations.

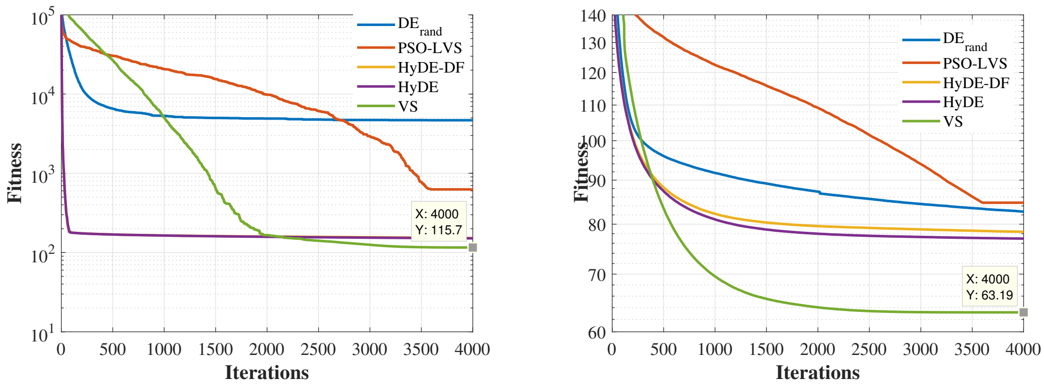
Figure 8 shows the convergence of the tested algorithms considering the two players and the non-parallel and parallel-based approaches (C1 and C2 cases). It can seem that VS presents the best convergence performance in both cases. HyDE-DF and HyDE show similar performance (in fact, convergence lines are overlapped in Figure 8b, which indicates that the improvements incorporated in HyDE-DF (that showed remarkable performance in the 100-digit challenge [29]) have almost no impact solving the proposed problem. Overall, the parallel-based approach seems to slightly improve the performance of all algorithms, without modifying the overall ranking of them. In fact, VS algorithm obtains a similar final valor.



(**a**) (**b**)

Figure 8. Average convergence of the tested EA considering two players under: (**a**) non-parallel approach (case C1); (**b**) parallel-based approach (case C2).

Figure 9 shows the results when increasing the number of players to 20 (C3 and C4 cases). In this case, while the non-parallel approach degrades the convergence performance of all EAs, the parallel-based approach keep the convergence performance and increasing only the final fitness value related with the cost of more households (see for instance Figures 8b and 9b). In summary, the parallel-based approach can help EAs in finding quality solutions for even large instances of the problem. Also, notice that DE_{rand} and PSO-LVS, apart from showing the worse performance, switch their convergence behavior when the non-parallel approach is used and the number of players increases (see for instance Figures 8a and 9a). That result shows evidence of their lack of robustness, since their performance should not be affected by the increase of the number of players



(**a**) (**b**)

Figure 9. Average convergence of the tested EA considering 20 players under: (**a**) non-parallel approach (case C3); (**b**) parallel-based approach (case C4).

We also analyze the average fitness and associated costs/revenues obtained by the EAs in all the cases. Tables 4–7 present the average values of fitness, time, daily bill and DR curtailment, as well as the calculation of fitness percentage improvement, taking as reference the worst fitness value in each case. Table 4 shows the average results obtained in the case C1. First thing to observe is that VS presents the lower fitness value, but also the higher optimization time. However, all EAs present similar optimization times (ranging from 1.15 to 1.5 min). Regarding costs/revenues, it is interesting to note that despite VS obtains the best fitness value, its daily costs (Daily Bill column in the table) is slightly higher than that obtained by DE. This is explained by column DR curtailment, which shows that DE activates DR curtailment in a higher degree than the other algorithms. While this is beneficial for the energy bill, it also represents a higher number of interruption of loads during the day, which can impact user comfort in some degree. Notice that DR curtailment in the formulation is not a monetary cost, but rather a weight associated with the interruption of loads. Future work can study the multi-objective nature of the formulation to optimize both terms in Equation (1) simultaneously. Finally, VS achieved the best performance with an improvement of around 30 % compared to PSO (worst algorithm for case C1).

Table 5 presents the results corresponding to case C2. It can seem that the general trends, as reported in case C1 results, are followed by the EAs when low number of households are considered. Mean Fitness and overall daily bills are slightly improved. Optimization times are equivalent, but it should be taken into account that column Time reflects the sum of the independent optimization of both households. Such optimizations can be done in parallel since are independent, reducing the optimization time by half, while obtaining better results regarding fitness and daily bills. In case C2, VS again achieved the best performance with an improvement of around 20 % compared to PSO (worst algorithm for case C2).

Table 4. Case C1: Fitness value and associated costs considering two households and non-parallel EAs.

	Fitness		Time	Costs	Revenues	Fixed	Daily	Monthly	DR	Imp
	mean	std	(min)	(€)	(€)	Costs (€)	Bill * (€)	Bill ** (€)		(%)
DE	10.69	0.46	1.16	9.29	−2.75	1.02	7.56	226.94	1.68	4.52
PSO	11.19	0.44	1.14	10.29	−2.11	1.02	9.21	276.25	0.75	0.00
HyDE	9.94	0.78	1.43	10.13	−1.21	1.02	9.95	298.43	0.00	11.23
HyDE-DF	9.59	0.83	1.42	9.78	−1.18	1.02	9.62	288.74	0.00	14.35
VS	7.77	0.08	1.48	9.09	−2.43	1.02	7.69	230.65	0.08	30.57

* Daily bills are calculated as buy Costs − sell Revenues + fixed Costs. ** Monthly bill on average considering 30 days.

Table 5. Case C2: Fitness value and associated costs considering two households and parallel-based EAs.

	Fitness		Time	Costs	Revenues	Fixed	Daily	Monthly	DR	Imp
	mean	std	(min)	(€)	(€)	Costs (€)	Bill * (€)	Bill ** (€)		(%)
DE	9.30	0.34	1.03	9.34	−2.80	1.02	7.56	226.84	0.54	2.03
PSO	9.49	0.22	1.05	9.79	−2.04	1.02	8.77	263.21	0.28	0.00
HyDE	8.64	0.41	1.31	9.66	−1.97	1.02	8.72	261.55	0.00	8.97
HyDE-DF	8.67	0.46	1.30	9.53	−1.67	1.02	8.88	266.46	0.00	8.68
VS	7.68	0.03	1.36	9.27	−2.62	1.02	7.67	230.18	0.00	19.06

* Daily bills are calculated as buy Costs − sell Revenues + fixed Costs. ** Monthly bill on average considering 30 days.

When the number of households increases, different conclusions are achieved. Tables 6 and 7 present the results corresponding to cases C3 and C4. The first thing to remark are the high fitness value reported by DE and PSO-LVS in case C3. Such high values are associated with the inability of both algorithms to find feasible solutions (i.e., the solutions include penalties explained in Equation (19)). Therefore, it is confirmed that these two algorithms are very sensitive to the increase in the number of households when the non-parallel approach is used. Such situation is corrected by the parallel-based approach, as Table 7 shows. In fact, the advantage of using this approach is stressed concerning fitness and daily bill values when the number of households is increased. Notice that since optimization times in the parallel-based approach correspond to the sum of independent optimizations, increasing the number of households affect notably the optimization times (see column Time of Table 7). However, such independent optimization can be performed in parallel reducing the time considerable depending the available parallel computing capacity. For instance, in MATLAB using four workers in the parallel pool (four parallel optimizations), the optimization time can be reduced by a factor of 5. Overall, VS achieved the best performance in both cases, with an improvement of around 22% compared to HyDE in case 3 (worst algorithm without considering DE and PSO due to reported infeasible solutions) and around 25% in case C4 compared to PSO.

Table 6. Case C3: Fitness value and associated costs considering 20 households and non-parallel EAs.

	Fitness		Time	Costs	Revenues	Fixed	Daily	Monthly	DR	Imp
	mean	std	(min)	(€)	(€)	Costs (€)	Bill * (€)	Bill ** (€)		(%)
DE	4672.93	2362.42	3.98	104.67	−35.33	10.24	79.57	2387.22	4.31	-
PSO	626.70	602.42	3.70	147.50	−19.79	10.24	137.94	4138.31	2.03	-
HyDE	149.45	3.86	4.93	150.40	−11.17	10.24	149.47	4484.04	0.02	0.00
HyDE-DF	148.58	4.26	4.93	150.59	−11.99	10.24	148.84	4465.34	0.03	0.58
VS	115.69	3.95	5.51	83.17	−33.48	10.24	59.93	1797.81	2.57	22.59

* Daily bills are calculated as Buy costs − Sell Revenues + Fixed Costs. ** Monthly bill on average considering 30 days.

Table 7. Case C4: Fitness value and associated costs considering 20 households and parallel-based EAs.

	Fitness		Time	Costs	Revenues	Fixed	Daily	Monthly	DR	Imp
	mean	std	(min)	(€)	(€)	Costs (€)	Bill * (€)	Bill ** (€)		(%)
DE	82.72	2.24	9.69	86.54	−31.95	10.24	64.83	1944.86	0.82	2.36
PSO	84.72	0.90	9.60	92.32	−25.01	10.24	77.55	2326.41	0.39	0.00
HyDE	77.83	2.40	11.87	89.79	−21.38	10.24	78.65	2359.42	0.02	8.13
HyDE-DF	76.77	2.24	11.77	89.21	−20.02	10.24	79.43	2382.86	0.00	9.38
VS	63.19	0.26	12.31	84.29	−31.53	10.24	63.00	1889.92	0.01	25.41

* Daily bills are calculated as Buy costs − Sell Revenues + Fixed Costs. ** Monthly bill on average considering 30 days.

7. Conclusions

In this paper, a different EAs are used to solve an optimization problem considering households with PV-battery systems and DR. Taking advantage of the independence of variables between households, two optimization approaches, non-parallel and parallel-based, are proposed. Results showed that EAs using the parallel-based approach provide solutions with better fitness value when the number of households increases. It was demonstrated that the direct application of an EA to larger instances of the problem (the non-parallel approach) has poor convergence capabilities (despite being very efficient when applied to one or two households). On the other hand, the proposed parallel-based approach showed excelled performance even when increasing the number of households. It is important to notice that the parallel-based approach is only valid for a framework as the one assumed in this work (which is actually a very likely real scenario due to the possible resistance of households to share data or equipment between peers), so changing such conditions might require a hybrid non-parallel and parallel approach. Overall, VS algorithm overcomes other tested EAs when using both optimization approaches. In fact, improvements of 30.57 % for case C1, 19.06 % for case C2, 22.59 % for case C3, and 25.41 % for case C4, were achieved with VS (best performance) compared to PSO (worst performance). Another advantage of the parallel-based approach is related to the possibility of using parallel computing to reduce optimization times while obtaining solutions with good quality. From the practical point of view, in this work we have envisaged the involvement of an Energy Service Provider that performs the optimization of households equipped with distributed energy resources (like PV generation, storage, and demand response) and the needed control devices. In this way, several business models can be explored by the Energy Service Provider within this framework. For instance, the service provider can charge a fee or commission from the total bill reduction achieved by the households, or receive incentives from upper level actors (such as the DSO) for the reduction of peak demand through DR. These two options, and other business model possibilities exploring the use of available infrastructure for practical implementations can be explored in future work. Another line of research for future work is related to the mathematical model. In this work, energy bill and DRdr curtailment are combined into a single objective formulation despite being terms that can be optimized in function of user preferences. Thus, multi-objective optimization versions of EAs can be employed to find Pareto optimal solutions. Moreover, a relation between DR curtailment and user comfort was not explicitly defined in this study, so another line of research can be followed concerning the modelling of user comfort. Finally, the practical implementation of EAs is also worth to be explored in future works. The parallel-based approach uses a multi-population similar to that used by coevolutionary algorithms, so testing those kinds of algorithms and their performance in this problem since a good research avenue. In addition, in this study the parallel-based approach was implemented sequentially, so optimization times reflect the sum of all independent optimizations. In a future study, the implementation of an actual parallel platform can be proposed to handle larger instances of the problem and assess the reaches and scalability of the approach.

Author Contributions: Conceptualization, F.L., P.F. and Z.V.; methodology, F.L. and R.F.; software, F.L. and R.F.; validation, F.L., R.F. and P.F.; writing—original draft preparation, F.L. and R.F.; writing—review and editing, P.F. and Z.V.; supervision, P.F. and Z.V. All authors have read and agreed to the published version of the manuscript.

Funding: This work has received funding from FEDER Funds through COMPETE program and from National Funds through (FCT) under the projects UID/EEA/00760/2019, and grants CEECIND/02887/2017 and SFRH/BD/133086/2017. This work has received funding from H2020 in scope of DOMINOES project.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

DE	Differential Evolution
DG	Distributed generator
DR	Demand Response
EA	Evolutionary Algorithms
EC	Evolutionary Computation
EU	European Union
HyDE	Hybrid Differential Evolution
HyDE-DF	HyDE with Decay function
jDE	Self-Adaptive Differential Evolution
LVS	Local Vortex Search
MILP	Mixed-integer Linear Programming
MINLP	Mixed-integer Non-linear Programming
OF	Objective Function
PLC	Programmable Logic Controller
Pop	Population
PSO	Particle Swarm Optimization
PSO-LVS	PSO with Local Vortex Search
PV	Photovoltaic
SI	Swarm Intelligence
VS	Vortex Search

Nomenclature

Indices

l	Controllable load
i	Household
t	Period

Parameters

$P_{i,t}^{\text{Load}}$	Consumption from non-controllable loads
$C_{i,t}^{\text{Grid In}}$	Cost of buying energy
$P_{i,t}^{\text{PV}}$	Energy generated by PV panels.
$P_{i,t,l}^{\text{Cut}}$	Energy load cuts
$Fix\ Cost_i$	Fixed tariff costs
$P_{i,t}^{\text{Gridmin}}$	Lower bond for buying energy
$P_{i,t}^{\text{Batdch}}$	Lower bound for discharge the battery
$C_{i,t}^{\text{Grid Out}}$	Revenue of selling energy
$P_{i,t}^{\text{Gridmin}}$	Lower bond for buying energy

$P_{i,t}^{\text{Batdch}}$	Lower bound for discharge the battery
$C_{i,t}^{\text{Grid Out}}$	Revenue of selling energy
Δt	Time adjust parameter
L	Total of controllable loads
I	Total of households
T	Total of periods
$E_{i,t}^{\text{Batmax}}$	Upper bound battery energy level
$P_{i,t}^{\text{Batch}}$	Upper bound for charge the battery
$P_{i,t}^{\text{Gridmax}}$	Upper bound for selling energy
$W_{i,t,l}^{\text{Cut}}$	Weight of energy cuts

Variables

$X_{i,t,l}^{\text{Cut}}$	Binary decision variables for DR action
$P_{i,t}^{\text{Bat}}$	Energy charge/discharge of batteries
$P_{i,t}^{\text{Grid}}$	Energy flow
$P_{i,t}^{\text{Grid Out}}$	Energy flow from household to the grid
$P_{i,t}^{\text{Grid In}}$	Energy flow from grid to the household
$E_{i,t}^{\text{Bat}}$	State of the battery

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Core Publication III

Ricardo Faia, João Soares, Tiago Pinto, Fernando Lezama, Zita Vale, and Juan M. Corchado, "Optimal Model for Local Energy Community Scheduling Considering Peer to Peer Electricity Transactions," IEEE Access, vol. 9, pp. 12420–12430, 2021, doi: 10.1109/ACCESS.2021.3051004. **(2021 Impact Factor: 3.367)**;

Resumen

La actual estrategia energética de la Unión Europea sitúa al usuario final como un participante clave en los mercados eléctricos. La Unión Europea ha fomentado la creación de comunidades energéticas para aumentar la penetración de las energías renovables y reducir el coste total de la cadena energética. Las comunidades de energía están compuestas principalmente por prosumidores, que pueden ser hogares con equipos de producción de energía de tamaño pequeño, como paneles fotovoltaicos en la azotea. El mercado eléctrico local es un concepto emergente que permite la participación activa del usuario final en los mercados eléctricos y es especialmente interesante cuando existen comunidades energéticas. Este artículo propone un modelo de optimización para programar transacciones peer-to-peer (punto a punto) a través del mercado eléctrico local, transacciones de red en el mercado minorista y gestión de baterías considerando la producción fotovoltaica de los hogares. Los prosumidores tienen la posibilidad de realizar transacciones de energía con el comercializador o con otros consumidores de su comunidad. El problema se modela usando programación lineal entera mixta, que contiene variables binarias y continuas. Se estudian cuatro escenarios y se analiza el impacto de los sistemas de almacenamiento de baterías y las transacciones entre pares. También se analizó el tiempo de ejecución del modelo propuesto según el número de prosumidores involucrados (3, 5, 10, 15 o 20) en la optimización. Los resultados sugieren que el uso de un sistema de almacenamiento de batería en la comunidad energética puede conducir a un ahorro de energía del 11 al 13 %. Además, combinar el uso de transacciones peer-to-peer y sistemas de almacenamiento de energía puede generar ahorros energéticos de hasta un 25 % en los costos generales de los miembros de la comunidad.

IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received December 3, 2020, accepted January 1, 2021, date of publication January 12, 2021, date of current version January 22, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3051004

Optimal Model for Local Energy Community Scheduling Considering Peer to Peer Electricity Transactions

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This work was supported in part by the European Union's Horizon 2020 Research and Innovation Programme under Project DOMINOES 771066; in part by the Fundo Europeu de Desenvolvimento Regional (FEDER) Funds through COMPETE Program; and in part by the National Funds through Fundação para a Ciência e a Tecnologia (FCT) under Project UIDB/00760/2020, Project CEECIND/01811/2017, and Project CEECIND /02814/2017. The work of Ricardo Faia was supported by the Ph.D. Grant from National Funds through FCT under Grant SFRH/BD/133086/2017.

ABSTRACT The current energy strategy of the European Union puts the end-user as a key participant in electricity markets. The creation of energy communities has been encouraged by the European Union to increase the penetration of renewable energy and reduce the overall cost of the energy chain. Energy communities are mostly composed of prosumers, which may be households with small-size energy production equipment such as rooftop photovoltaic panels. The local electricity market is an emerging concept that enables the active participation of end-user in the electricity markets and is especially interesting when energy communities are in place. This paper proposes an optimization model to schedule peer-to-peer transactions via local electricity market, grid transactions in retail market, and battery management considering the photovoltaic production of households. Prosumers have the possibility of transacting energy with the retailer or with other consumers in their community. The problem is modeled using mixed-integer linear programming, containing binary and continuous variables. Four scenarios are studied, and the impact of battery storage systems and peer-to-peer transactions is analyzed. The proposed model execution time according to the number of prosumers involved (3, 5, 10, 15, or 20) in the optimization is analyzed. The results suggest that using a battery storage system in the energy community can lead to energy savings of 11-13%. Besides, combining the use of peer-to-peer transactions and energy storage systems can potentially provide energy savings of up to 25% in the overall costs of the community members.

INDEX TERMS Local electricity market, local energy community, optimization, peer-to-peer transactions, prosumers.

I. INTRODUCTION

Distributed and renewable generation has emerged as a solution for the depletion of fossil fuel energy and for meeting energy sustainability targets, namely the greenhouse gas emissions limits imposed in some areas. For example, the European Union (EU) is targeting a reduction of at least 40% of greenhouse gas emissions by 2030, an increment of at least 32% share for renewable energy, and an improvement of at least 32.5% in energy efficiency, taking as basis 1990 levels [1]. In 2018, renewable generation accounted for 18.9% of the energy consumed in the EU [2], which already represents about 50% of the imposed levels. At the residential level, households can install smart devices and distributed energy resources (DER) such as photovoltaic (PV) modules, small scale wind turbines, and energy

The associate editor coordinating the review of this manuscript and approving it for publication was Hao Luo.

storage including plug-in electric vehicles (EV), to increase energy efficiency and reduce energy bills [3]. However, due to the increasing maturity of renewable energy production capabilities, the feed-in tariff which incentivized local generation sales to the grid is being reduced. In consequence, the reduction of feed-in tariffs may impact the motivation of consumers, slowing down the penetration of renewable sources and ultimately, failing in achieving the agreed targets.

Due to feed-in tariff reduction, in several locations, it is now more attractive for households to use generation surplus for self-consumption than selling to the grid [4]. Self-consumption is different among individuals depending on daily consumption profiles, which can vary with the habits and with the used electrical equipment.

The European Commission Strategic Energy Technology Plan [5] states that energy consumers are envisioned at the center of the future energy systems and shall be encouraged to install energy production sources. Peer-to-peer (P2P) energy trading emerges as a promising solution to empower the role of the end-users in energy systems [6]. Basically, P2P energy trading is a recent technology of energy management mechanism in smart grids [6]. In the scope of an energy community, P2P energy trading enables flexible energy trades between peers. In other words, in a P2P market, the excess of energy generation coming from many small-scale DERs is traded among local customers [7]. The prosumers can achieve a "win-win" situation by searching for a satisfactory trading price and by reaching an agreement in a seamless way. The marginal price of P2P electricity transactions should be cheaper than the retailer tariff and higher than the feed-in tariff (i.e., the price of electricity export to the grid) so that P2P can provide savings for buyers and profit for sellers [8]. The work in [9] highlights potential benefits of P2P energy trading: the maximization of renewable energy usage, the reduction of electricity cost, the shaving of peak load, the empowerment of the prosumers, and the minimization of network operation and investment costs. Although the potential benefits are fairly significant, research on P2P energy trading is still at an early stage and there is no consensus on what type of data sharing and processing infrastructure is more efficient and yields to the best results [3]. It is expected to reach an investment of USD 25 billion in microgrid markets by 2025 in USA [10], which will inevitably lead to the development of P2P market applications to empower prosumers and fulfill the niche market void.

In this article, a P2P market structure is proposed to allow energy transactions between users at a price that provides better benefits than current feed-in tariffs. In this way, consumers become active participants of the local market, having the possibility to take advantage of their surplus electricity without being limited by retailers.

Figure 1 presents the trading architecture proposed for a local community with N prosumers considering a conventional retail electricity market and a P2P market between the community members.

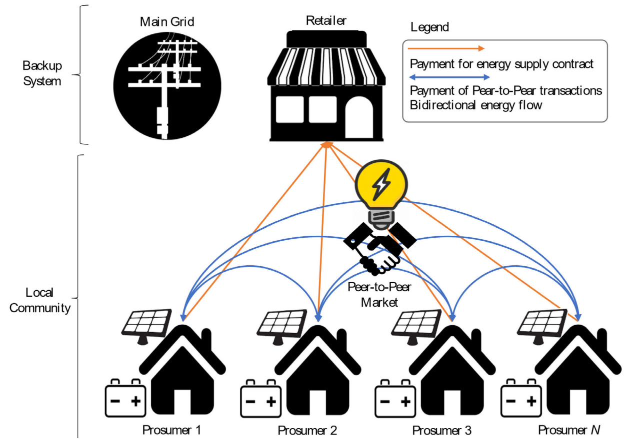

FIGURE 1. Proposed methodology.

As can be seen in Figure 1, we propose a local community scheduling considering the possibility of transacting energy with the retailer and in a market within the community with P2P transactions. The local community is composed by prosumers, each of them with a PV-battery system which is also scheduled in the optimization process. The community members have two different possibilities, namely, buy/sell electricity to the grid or transact energy with other community members. The optimization is used to determine the set of prosumers in each period that performed P2P transactions.

As the main contributions of this work, we highlight five aspects:

- An optimization model that determines the best P2P energy transactions in a local energy community with prosumers equipped with PV generation and energy storage systems;
- A deterministic mixed-integer linear programming (MILP) method, implemented in TOMLAB,[1] to determine the decision-making;
- The model includes realistic constraints, customer load profiles, PV systems, battery energy storage systems and market transactions constraints. Real Portuguese tariffs are used to generate realistic case studies;
- The presented model considers the active involvement of households in the electricity markets, in line with the goals of governmental institutions to reduce energy costs and carbon emissions;
- The proposed methodology considers an optimal solution combining demand side management (DSM) and P2P transactions integrated into the optimization process, characteristic that, to the best of the authors' knowledge and according to the analysis made by the authors in section II, is not proposed in the current literature.

The rest of this paper is divided into six sections: Section 2 presents the background on the DSM and P2P models. Section 3 shows the proposed methodology and the

[1]TOMLAB is a language for solving optimization problems considering MATLAB language (https://tomopt.com/tomlab/).

mathematical formulation developed in this research work. Section 4 describes the case study used to test the proposed methodology. Section 5 discusses and analyzes the results. Finally, Section 6 presents the conclusion of this work and provides future research directions.

II. BACKGROUND

This section presents a background on the energy costs optimization in smart grids. DSM applications in smart grids can be considered as one of the most innovative steps to minimize the operation costs [11]–[13]. These applications consider the optimization of house consumption by rescheduling the loads to periods when the electricity price is lower [14], [15]. With the installations of PV generators in residential houses and the development of load controlled systems for demand response, more comprehensive and complex approaches are emerging [16]. In previous referred works, authors consider the rescheduling of controllable loads and the use of PV generation and battery storage systems. A similar work is presented in [17], where authors reduce the computational effort by adopting evolutionary computation algorithms to solve the optimization problem. A different technique was implemented in [18] using case-based reasoning based on historical data to determine the reduction value for a demand response application. More recently, works that address the energy commerce between groups within smart grids have been proposed. In [19], a trading environment between neighbor microgrids was presented. In the case study, a smart grid with three microgrids was considered, and apart from the inter-micro-network market, six different markets were analyzed for trading electricity.

Energy transaction between households has emerged in recent years as a promising trend that should be adapted to minimize the costs of the electric bill. Reference [20] introduces a local market into the simulation. The problem was solved using a two-stage stochastic programming approach. The authors optimize the electricity costs of all microgrids members, allowing local transactions between microgrids and the possibility of buying energy into the wholesale market. Publication [21] determines the best portfolio option for the electricity transaction, considering the possibility of transacting electricity in local electricity markets. The authors in [22] consider an energy sharing approach between prosumers. The problem is solved considering a bi-level programming method using a function called demand and supply ratio. A Mixed Integer Non-linear Programming (MINLP) is used in work [23] to determine the P2P transaction considering 2 households and a horizon time of 8 periods (1h each). The influence of battery storage systems in P2P trading within a microgrid was explored in reference [24]. Works [22]–[24] consider the problem of local electricity transaction but do not consider the coordination of DSM with local transaction scheduling. In other words, these works cannot provide a coordinate solution of the local transaction to take the maximum benefits of households loads and storage systems. DSM approaches are used to optimize energy costs and are typically formulated as linear or non-linear problems [3]. Linear optimization is usually used to solve short periods of time and usually have a very short resolution time when compared with non-linear optimizations resolutions. Researchers to reduce the computation time burden of non-linear models are using approximate methods to reduce the resolution time [25]–[27].

TABLE 1 presents a comparison between works published considering P2P energy trading within an energy community. The proposed work is also included in TABLE 1 highlighting its contributions concerning the current literature.

A similar method to the one presented in this work was proposed in [26]; authors used a distributed approach to implement a DSM system combined with P2P trading. Due to the use of an approximate solution approach the work in [26] does not guarantee optimal solutions to the problem. In contrast, by using a deterministic solution approach (MILP), our method provides an optimal solution considering up to 20 players combining the DSM with P2P transactions. Typically, optimization methods that determine local market transaction using centralised approaches consider a small number of users involved due to the computational burden [22]–[24]. On contrast, methods that consider a large number of users use iterative process [3] or determine the local transaction after the DSM optimization is finished [8], [25].

The current literature reflects a lack of deterministic solution methods that include local electricity transactions considering more than four players. Thus, this work presents a deterministic method that can solve the problem under a case study considering up to 20 players. Our method also considers the coordination between DSM and local transactions, unlike most of the current approaches.

III. MATHEMATICAL FORMULATION

In this section, the mathematical formulation used to obtain the optimal social welfare costs of the community is fully presented. Equation (1) represents the objective function that minimizes the total cost of the energy community. Indeed, the objective function is equivalent to the social welfare of the community members, minimizing their energy costs.

$$\begin{aligned} minimize : obf = &\sum_{t=1}^{Nt}\sum_{i=1}^{Ni}\left(\pi_{t,i}^{buy\,Grid} \times P_{t,i}^{buy\,Grid}\right) \times \frac{1}{\Delta t} \\ &- \sum_{t=1}^{Nt}\sum_{i=1}^{Ni}\left(\pi_{t,i}^{sell\,Grid} \times P_{t,i}^{sell\,Grid}\right) \times \frac{1}{\Delta t} \end{aligned} \tag{1}$$

where t represents the period, i represents the prosumer, Nt the total number of periods, Ni the total number of prosumers, $\pi_{t,i}^{buy\,Grid}$ represents the price of buying electricity from the grid (time-of-use tariff), $P_{t,i}^{buy\,Grid}$ represents the amount of electricity purchased from the grid, $\pi_{t,i}^{sell\,Grid}$ represents the selling price of electricity to the grid (feed-in tariff) and $P_{t,i}^{sell\,Grid}$ represents the amount of electricity sold to the grid.

TABLE 1. **P2P energy trading works comparison.**

Reference	Year	Method	Solution type	Coordinate DSM with local transactions	Method to determine local marker transactions.	Number of users* involved in the optimization?
[22]	2017	Bi-Level Programming	Approximate	No	Included in the optimization	5
[23]	2017	Mixed Integer Non-linear Programming	Optimal	No	Included in the optimization	2
[24]	2018	Linear Programming	Optimal	No	Included in the optimisation	4
[25]	2018	Constrained Non-linear Programming	Approximate	Yes	After the optimization	3, 100
[3]	2019	Bi-Linear Programming	Near Optimal	Yes	Iterative process (ECO-Trade algorithm)	40
[26]	2019	Alternating Direction Method of Multipliers	Approximate	Yes	Included in the optimization	10
[8]	2020	Mixed-integer Linear Programming	Optimal	No	After optimization using coalition game theory	30
Proposed	2020	Mixed-integer linear Programming	Optimal	Yes	Included in the optimization	3,5,10,15,20

*users can be considered prosumers, consumers, and small producer.

The term Δt is used to adjust the tariff price to the optimization time intervals (e.g., 15 min). Equation (2) represents the power balance for each prosumer.

$$P_{t,i}^{gen} + P_{t,i}^{buy\,Grid} + P_{t,i}^{dch} + \sum_{j=1,j\neq i}^{Nj} P_{t,i,j}^{buy\,p2p} = P_{t,i}^{load} + P_{t,i}^{sell\,Grid} + P_{t,i}^{ch} + \sum_{j=1,j\neq i}^{Nj} P_{t,i,j}^{sell\,p2p} \quad \forall i \in Ni, \quad \forall j \in Nj,\ \forall t \in Nt \tag{2}$$

where $P_{t,i}^{gen}$ represents the generated power, $P_{t,i}^{dch}$ is the discharged power of the battery, $P_{t,i,j}^{buy\,p2p}$ corresponds to the electricity purchased in the P2P market, $P_{t,i}^{load}$ is the load, $P_{t,i}^{ch}$ is the power charged by the battery, $P_{t,i,j}^{sell\,p2p}$ corresponds to the electricity sold in the P2P market, j is the prosumer and Nj the total numbers of prosumers. The sum of variable $P_{t,i,j}^{p2p}$ over the index j gives the total value of each i buy in P2P transactions for each t index, whereas the sum in i index gives the total value of each j sale. Equation (3) and (4) represent the maximum limits of variables $P_{t,i}^{buy\,Grid}$ and $P_{t,i}^{sell\,Grid}$.

$$P_{t,i}^{buy\,Grid} \leq P_{t,i}^{\max\ buy\,Grig} \times Bin_{t,i}^{buy\,Grid} \quad \forall i \in Ni, \quad \forall t \in Nt \tag{3}$$

$$P_{t,i}^{sell\,Grid} \leq P_{t,i}^{max\ sell\,grig} \times Bin_{t,i}^{sell\,Grid} \quad \forall i \in Ni, \quad \forall t \in Nt \tag{4}$$

where $P_{t,i}^{\max\ buy\,Grig}$ represents the maximum amount of electricity to buy from the grid, $Bin_{t,i}^{buy\,Grid}$ is a binary variable that enables purchasing electricity from the grid if it is 1, $P_{t,i}^{max\ sell\,grig}$ represents the maximum amount of electricity sold to the grid, and $Bin_{t,i}^{sell\,Grid}$ is a binary variable that enables selling electricity to the grid if it is 1. Equation (5) is the constraint applied to the binary variables above.

$$Bin_{t,i}^{buy\,Grid} + Bin_{t,i}^{sell\,Grid} \leq 1, \quad \forall i \in Ni,\ \forall t \in Nt \tag{5}$$

Equation (5) restricts the transactions of electricity to either buy or sell energy in the same period for the same prosumer. Equations (6) and (7) represent the maximum limits of variable $P_{t,i,j}^{max\,buy\,p2p}$ and $P_{t,i,j}^{max\,sell\,p2p}$.

$$P_{t,i,j}^{buy\,p2p} \leq P_{t,i,j}^{max\,buy\,p2p} \times Bin_{t,i,j}^{buy\,p2p} \quad \forall i \neq j \in Ni, \quad \forall j \neq i \in Nj,\ \forall t \in Nt \tag{6}$$

$$P_{t,i,j}^{sell\,p2p} \leq P_{t,i,j}^{max\,sell\,p2p} \times Bin_{t,i,j}^{sell\,p2p} \quad \forall i \neq j \in Ni, \quad \forall j \neq i \in Nj,\ \forall t \in Nt \tag{7}$$

where $P_{t,i,j}^{max\,buy\,p2p}$ corresponds to the maximum limit for P2P purchase transactions, $Bin_{t,i,j}^{buy\,p2p}$ corresponds to a binary variable that enables purchasing electricity from j to i in P2P mode, $P_{t,i,j}^{max\,sell\,p2p}$ corresponds to the maximum limit for P2P electricity sale transactions, and $Bin_{t,i,j}^{sell\,p2p}$ corresponds to a binary variable that enables selling electricity from i to j in P2P mode. Both indices $i \neq j$ and $j \neq i$ represent prosumers, and must be different since $i = j$ or $j = i$ would represent a prosumer negotiating with himself. Equations (8) and (9) are implemented to restrict actions related to the transactions with the grid and P2P market.

$$Bin_{t,i}^{buy\,Grid} + \sum_{j=1,j\neq i}^{Nj} Bin_{t,i,j}^{sell\,p2p} \leq 1 \quad \forall i \in Ni,\ \forall t \in Nt \tag{8}$$

$$\sum_{j=1,j\neq i}^{Nj} Bin_{t,i,j}^{buy\,p2p} + Bin_{t,i}^{sell\,Grid} \leq 1 \quad \forall i \in Ni,\ \forall t \in Nt \tag{9}$$

Equation (8) imposes that it is not allowed to buy electricity from the grid to sell it in P2P mode, whereas equation (9) imposes that it is not possible to buy electricity in P2P mode to sell to the grid. The above restrictions were implemented assuming that it is always more expensive to buy/sell electricity from the grid than in P2P trading. Equation (10) corresponds to the balance of the P2P trading market.

$$\sum_{j=1,j\neq i}^{Nj}\sum_{i=1,i\neq j}^{Ni} P_{t,i,j}^{buy\,p2p} = \sum_{j=1,j\neq i}^{Nj}\sum_{i=1,i\neq j}^{Ni} P_{t,i,j}^{sell\,p2p} \quad \forall t \in Nt \tag{10}$$

Equation (10) imposes that the total amount of electricity purchased in P2P mode should be equal to the total amount of electricity sold in the same P2P mode. Equations (11) and (12) are applied to model the P2P market transactions.

$$\sum_{i=1,i\neq j}^{Ni} Bin_{t,i,j}^{buy\,p2p} + \sum_{j=1,j\neq i}^{Nj} Bin_{t,i,j}^{sell\,p2p} \leq 2 \quad \forall t \in Nt \tag{11}$$

$$\sum_{j=1,j\neq i}^{Nj} Bin_{t,i,j}^{buy\,p2p} + \sum_{i=1,i\neq j}^{Ni} Bin_{t,i,j}^{sell\,p2p} \leq 2 \quad \forall t \in Nt \tag{12}$$

Equations (11) and (12) ensure that each prosumer trade with another prosumer in each period. The model does not allow that one prosumer transacts electricity with two or more prosumers.

Equations (13) and (14) represent the limits for charge and discharge of the batteries.

$$P_{t,i}^{ch} \leq P_{t,i}^{max\,ch} \times Bin_{t,i}^{ch}, \quad \forall i \in Ni, \ \forall t \in Nt \tag{13}$$

$$P_{t,i}^{dch} \leq P_{t,i}^{max\,dch} \times Bin_{t,i}^{dch}, \quad \forall i \in Ni, \ \forall t \in Nt \tag{14}$$

where $P_{t,i}^{max\,ch}$ represents the maximum charge power, $Bin_{t,i}^{ch}$ is the binary variable associated with the charging state, $P_{t,i}^{max\,dch}$ represents the maximum discharge power, and $Bin_{t,i}^{dch}$ represents the binary variable associated with the discharge option. Equation (15) represents the limit imposed on the charging/discharging state. With equation (15), the charge and discharge actions are controlled so that they do not occur simultaneously.

$$Bin_{t,i}^{ch} + Bin_{t,i}^{dch} \leq 1, \quad \forall i \in Ni, \ \forall t \in Nt \tag{15}$$

Equation (16) presents the state of the batteries in each period.

$$E_{t,i}^{Bat} = E_{t-1,i}^{Bat} + P_{t,i}^{ch} \times \eta_i^{ch} - P_{t,i}^{dch} \times \frac{1}{\eta_i^{dch}} \quad \forall i \in Ni, \ \forall t \in Nt \tag{16}$$

where $E_{t,i}^{Bat}$ represents the state of the battery, $E_{t-1,i}^{Bat}$ represents the state of the battery in period $t-1$, η_i^{ch} corresponds to the efficiency of charge and η_i^{dch} to the efficiency of discharge. Equations (17) - (29) present the upper and lower bounds for the variables of the problem.

$$0 \leq P_{t,i}^{buy\,Grid} \leq P_{t,i}^{max\,buy\,Grid}, \quad \forall i \in Ni, \ \forall t \in Nt \tag{17}$$

$$0 \leq P_{t,i}^{sell\,Grid} \leq P_{t,i}^{max\,sell\,Grid}, \quad \forall i \in Ni, \ \forall t \in Nt \tag{18}$$

$$0 \leq P_{t,i}^{dch} \leq P_{t,i}^{max\,dch}, \quad \forall i \in Ni, \ \forall t \in Nt \tag{19}$$

$$0 \leq P_{t,i}^{ch} \leq P_{t,i}^{max\,ch}, \quad \forall i \in Ni, \ \forall t \in Nt \tag{20}$$

$$0 \leq P_{t,i,j}^{buy\,p2p} \leq P_{t,i,j}^{max\,buy\,p2p} \quad \forall i \neq j \in Ni, \quad \forall j \neq i \in Nj, \ \forall t \in Nt \tag{21}$$

$$0 \leq P_{t,i,j}^{sell\,p2p} \leq P_{t,i,j}^{max\,sell\,p2p} \quad \forall i \neq j \in Ni, \quad \forall j \neq i \in Nj, \ \forall t \in Nt \tag{22}$$

$$0 \leq E_{t,i}^{Bat} \leq E_{t,i}^{max\,Bat}, \quad \forall i \in Ni, \ \forall t \in Nt \tag{23}$$

$$0 \leq Bin_{t,i}^{buy\,Grid} \leq 1, \quad \forall i \in Ni, \ \forall t \in Nt \tag{24}$$

$$0 \leq Bin_{t,i}^{sell\,Grid} \leq 1, \quad \forall i \in Ni, \ \forall t \in Nt \tag{25}$$

$$0 \leq Bin_{t,i,j}^{buy\,p2p} \leq 1 \quad \forall i \neq j \in Ni, \quad \forall j \neq i \in Nj, \ \forall t \in Nt \tag{26}$$

$$0 \leq Bin_{t,i,j}^{sell\,p2p} \leq 1 \quad \forall i \neq j \in Ni, \quad \forall j \neq i \in Nj, \ \forall t \in Nt \tag{27}$$

$$0 \leq Bin_{t,i}^{dch} \leq 1, \quad \forall i \in Ni, \ \forall t \in Nt \tag{28}$$

$$0 \leq Bin_{t,i}^{ch} \leq 1, \quad \forall i \in Ni, \ \forall t \in Nt \tag{29}$$

where $E_{t,i}^{max\,Bat}$ represents the maximum battery capacity. Equations (17) - (23) bound the continuous variables, while equations (24) - (29) bound binary variables.

The total energy bill (EB) for each prosumer in the P2P market can be calculated according to equation IV.

$$\begin{aligned} EB_i = &\sum_{t=1}^{Nt} \left(\pi_{t,i}^{buy\,Grid} \times P_{t,i}^{buy\,Grid}\right) \times \frac{1}{\Delta t} \\ &- \sum_{t=1}^{Nt} \left(\pi_{t,i}^{sell\,Grid} \times P_{t,i}^{sell\,Grid}\right) \times \frac{1}{\Delta t} \\ &+ \sum_{t=1}^{Nt}\sum_{j=1,j\neq i}^{Nj} \left(\pi_{t,i,j}^{p2p} \times P_{t,i,j}^{buy\,p2p}\right) \times \frac{1}{\Delta t} \\ &- \sum_{t=1}^{Nt}\sum_{j=1,j\neq i}^{Nj} \left(\pi_{t,i,j}^{p2p} \times P_{t,i,j}^{sell\,p2p}\right) \times \frac{1}{\Delta t} + FixCost_i \\ &\forall i \in Ni, \end{aligned} \tag{30}$$

where $\pi_{t,i,j}^{p2p}$ represents the price in the P2P market for the transaction between prosumer i and prosumer j, and $Fix\ Cost_i$ is the fixed cost that each prosumer must pay to use the network.

EB contains five terms, as equation IV shows. The first term represents the costs of purchasing electricity from the grid; the second term is the revenue of selling electricity to the grid; the third term corresponds to the costs of buying electricity in P2P market; the fourth term represents the revenues of selling electricity in the P2P market and, finally; the fifth term corresponds to fixed costs paid by each prosumer. The fixed costs are paid directly to the retailer, and are defined in the energy supply contract established between retailer and prosumer. In fact, the sum of the EB of each prosumer without the fixed costs represents the objective function of equation (1). The costs and revenues in the P2P market are not implemented in the objective function since the sum of costs/profits over all player is 0.

To obtain the P2P price for the transactions, we chose the mid-market rate method presented in [4]. The method of price determination assumes that the exchange price is the average

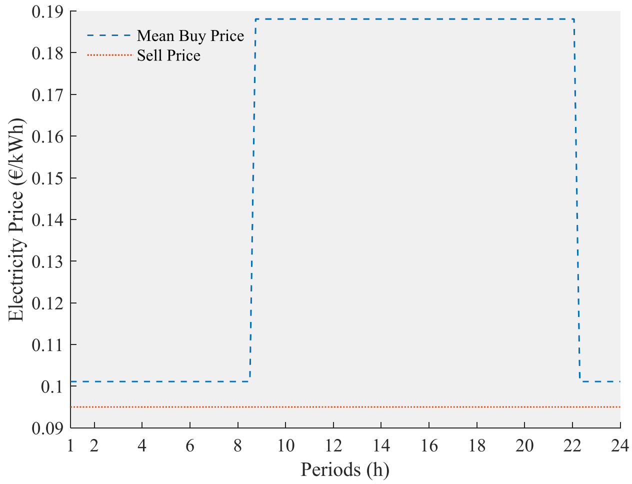

FIGURE 2. Average values of electricity grid prices in the local energy community.

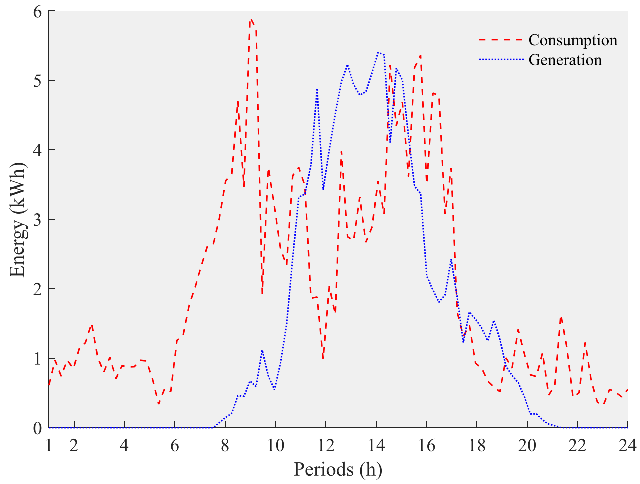

FIGURE 3. Average of consumption and generation in the local energy community.

of the electricity buying price and selling price:

$$\pi^{p2p}_{t,i,j} = \frac{\pi^{buy\,Grid}_{t,i} + \pi^{sell\,Grid}_{t,i}}{2}, \quad \forall i \in Ni, \ \forall t \in Nt \tag{31}$$

When a P2P transaction is executed, the price $\pi^{p2p}_{t,i,j}$ is determined by the seller (i).

IV. CASE STUDY

This section presents a case study to illustrate the use of the methodology proposed in section II. A local energy community with 10 prosumers is considered to presents the main results. To test the scalability of the approach, simulations were executed considering up to 20 prosumers. Each domestic prosumer is equipped with a PV-battery system installed in the household. Figure 2 presents the mean value of electricity prices used to buy and sell electricity within the energy community.

It is assumed that all consumers have contracted a bi-hourly tariff from a retailer. The maximum limit for electricity purchase from the grid is specified in the contract between retailer and prosumers. The prosumer is free to choose this limit but should be considered that higher limits have associated more expensive fixed costs. As can be seen in Figure 2, the buying price correspond to the average price of the ten prosumers. This price is always higher than the selling price. The selling price considered for this case study corresponds to the feed-in tariff defined by Portuguese legislation.[2] Selling electricity to the main grid is modelled as a constant price (see Figure 1). Each prosumer complying with the current Portuguese legislation, which allows small producers (consumers with local generation) to use their energy to satisfy their own load needs, can inject their surplus of energy to the grid.

Figure 3 presents the average consumption and generation profiles.

Figure 3 shows that the average consumption profile presents one peak in the morning (period 8) and another in the afternoon (period 15-17). The generation profile is a classic PV profile with a generation peak near to period 14h. A total of 54 kWh capacity for PV production and 128 kWh of capacity for the battery systems is installed. Each prosumer has a contract with a retailer for a maximum power supply. In the case study, one prosumer has a contract of 3.45 kVA, one 4.6 kVA, two 5.75 kVA, four 10.75 kVA and two 13.8 kVA. The prosumers in the case study pay an average of 0.49 €of fixed costs per day; it is assumed that the retailer has defined these costs. TABLE 2 presents the input variables used in the simulations.

For some parameters two different values appeared in TABLE 2, these correspond to the minimum and maximum values. The input parameters are different for each case study in order to consider prosumers with diverse characteristics.

V. RESULTS

This section presents and discusses the results of the case study presented in Section IV. The experiments were implemented using MATLAB2018a, in a computer with Intel Xeon(R) E5-2620v2@2.1 GHz processor with 16GB of RAM running Windows 10. TOMLAB optimization platform with the solver CPLEX has been used. Four different scenarios are simulated and compared. The scenarios are defined considering the battery usage and the possibility of transacting energy with P2P. The set of scenarios is:

- *Scenario A* – scenario without batteries and without P2P transactions. This scenario is considered the base case;
- *Scenario B* – scenario with batteries and without P2P transaction;

[2]Defined in Portaria n.° 115/2019 of Diário da República n.° 74/2019, Série I de 2019-04-15, https://data.dre.pt/eli/port/115/2019/04/15/p/dre/pt/html

[3]EDP comercial website: https://www.edp.pt/particulares/energia/tarifarios/.

TABLE 2. input parameters of the problem.

Parameters	Designation	Value	Units
Nt	Number of periods	96	-
Ni, Nj	Number of prosumers	10	-
$\pi_{t,i}^{buy\ Grid}$	Price for buying electricity from the grid*	0.1886 – 0.1008	€/kWh
$\pi_{t,i}^{sell\ Grid}$	Price for selling electricity to the grid	0.095	€/kWh
Δt	Multiplicative time factor	4	-
$\pi_{t,i,j}^{p2p}$	Prices for p2p transactions	0.1418 – 0.0979	€/kWh
$P_{t,i}^{max\ buyGrig}$	Limit for buying electricity from grid	3.45 – 13.8	kWh
$P_{t,i}^{max\ sell\ Grig}$	Limit for selling electricity to grid	1.725 – 6.9	kWh
$P_{t,i,j}^{max\ buy\ p2p}$	Limit for buying electricity in P2P market	3.45 – 13.8	kWh
$P_{t,i,j}^{max\ sell\ p2p}$	Limit for selling electricity in P2P market	3.45 – 13.8	kWh
$P_{t,i}^{max\ ch}$	Limit for battery charge	2 – 8	kWh
$P_{t,i}^{max\ dch}$	Limit for battery discharge	2 – 8	kWh
$E_{t,i}^{max\ Bat}$	Maximum capacity of the battery	5 – 20	kWh
$Fix\ Cost_i$	Fixed costs*	0.7267 – 0.240904	€/day
η_i^{ch}	Battery charge efficiency	0.9	%
η_i^{dch}	Battery discharge efficiency	0.9	%

*values obtained from a Portuguese retailer EDP commercial[3].

- *Scenario C* – scenario without batteries but considering P2P transactions;
- *Scenario D* – scenario with batteries and with P2P transactions.

The detailed results are presented for a simulation with 10 prosumers. In the end of this section, we have included simulations varying the number of prosumers to analyze the scalability of our approach.

TABLE 3 presents the results of the tested scenarios for 10 prosumers for one day of operation (96 periods of 15-minutes each).

The total costs presented in TABLE 3 correspond to the evaluation of objective function in equation (1). Also notice that consumption and production are considered the same in the four scenarios.

Comparing the scenarios without P2P transactions (*Scenario A* and *Scenario B*), *Scenario B* presents a cost reduction of 4.23 €, i.e. 11%, in comparison with *Scenario A*. When batteries are considered, there is less energy sold to the grid. This indicates that it is more benefic for prosumers to use the electricity they produce for their own consumption by making use of the batteries than to sell the electricity to the grid. Comparing the two scenarios without battery (*Scenario A* and *Scenario C*), *Scenario C* presents a reduction of 12% in total costs (4.48 €) compared with *Scenario A*. Without available storage, it is more profitable to sell electricity in P2P market than to sell it to the grid. Considering now the scenarios with battery systems (*Scenario B* and

TABLE 3. Results considering 10 prosumers.

	No battery	Battery
Without P2P transaction		
	Scenario A	*Scenario B*
Total costs (€)	37.07	32.84
Consumption (kWh)	482.03	482.03
Production (kWh)	321.38	321.38
Grid supply (kWh)	294.88	268.64
Grid sell (kWh)	129.37	93.46
Savings storage (€)	-	4.23 (11%)
With P2P transactions		
	Scenario C	*Scenario D*
Total costs (€)	32.59	27.79
Consumption (kWh)	482.03	482.03
Production (kWh)	321.38	321.38
Grid supply (kWh)	250.38	216.45
Grid sell (kWh)	88.40	39.51
P2P transaction (kWh)	44.50	72.53
Savings storage (€)	-	4.80 (13%)
Savings trade (€)	4.48 (12%)	5.05 (15%)
Savings total (€)	4.48 (12%)	9.28 (25%)

Scenario D), *Scenario D* has a reduction of 5.05 €(15%) compared with *Scenario B*. In the scenarios with P2P transactions (*Scenario C* and *Scenario D*), the battery enables a reduction of 4.80 €(13%) in the total operation cost. Comparing *Scenario A* with the most complete scenario (*Scenario D*), savings account for 9.28 €, i.e. 25%, in the later.

TABLE 4 presents the total electricity transaction for each prosumer considering all scenarios for the full considered day.

It is clear that the inclusion of batteries provides additional flexibility to the prosumers, having a direct influence on the electricity transactions and on the total costs.

Figure 4 presents the energy bill value for each prosumer for *Scenarios B,* and *D*. *EB* value is obtained after finalizing the optimization process using equation IV. The value of *EB* for all prosumers decreases when P2P transactions are enabled. For *Scenario B,* the average EB for one day of operation is 3.28 €, whereas for *Scenario D* it is 2.78 €, corresponding to a difference of 0.50 €representing a 15% of reduction.

Notice that in Figure 4, prosumer 9 presents an *EB* negative value indicating that this prosumer was able to make profits with P2P transactions. Therefore, his energy bill becomes negative. On average, comparing the results of *Scenario A* with the results of *Scenario D*, the prosumers have a decrease in cost of 0.93 €/day. If these scenarios are repeated every day of the year, a potential annual savings of 338 €per prosumer can be achieved. Figure 5 presents the contracted power, the battery capacity, and the P2P transactions of each prosumer for *Scenario D*.

Figure 5 presents two different vertical axes; the left-side vertical axis measures the P2P energy (purchased and sold) transacted in kWh, and the right-side vertical axis measures the contracted power and battery capacity in kW.

As explained before the contracted power limits the transactions between the prosumer and the grid in each period

TABLE 4. Electricity transactions for each individual household considering one day of operation [in kWh].

	Without P2P transaction				With P2P transaction							
	No Battery		Battery		No Battery				Battery			
	Scenario A		*Scenario B*		*Scenario C*				*Scenario D*			
	Grid		Grid		Grid		P2P		Grid		P2P	
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
Prosumer 1	25.78	2.34	24.73	0.53	16.41	2.34	9.36	0	12.19	0.57	13.21	0.45
Prosumer 2	31.33	8.57	27.90	3.37	26.40	6.47	4.93	2.10	20.60	1.54	8.62	2.90
Prosumer 3	38.01	24.03	35.23	19.87	37.36	15.80	0.65	8.24	36.00	7.78	1.90	14.03
Prosumer 4	12.78	6.63	11.85	5.24	12.49	4.91	0.29	1.72	12.80	2.16	0.41	4.31
Prosumer 5	27.49	13.66	23.61	7.90	25.04	10.82	2.46	2.84	21.65	4.56	3.85	5.19
Prosumer 6	37.37	30.83	34.58	28.15	36.81	16.19	0.56	15.62	35.49	8.81	2.31	22.03
Prosumer 7	18.32	3.14	17.02	1.11	14.06	3.13	4.25	0.01	10.79	1.32	7.32	0.81
Prosumer 8	43.92	10.91	39.67	4.61	33.15	8.91	10.76	2.00	26.47	3.35	17.49	5.08
Prosumer 9	17.92	19.05	16.42	19.13	17.46	11.49	0.47	10.09	16.35	7.07	1.41	14.14
Prosumer 10	41.96	10.21	37.62	3.55	31.18	8.33	10.77	1.88	24.13	2.34	16.00	3.58
Total	294.88	129.37	268.63	93.46	250.36	88.39	44.5	44.5	216.47	39.5	72.52	72.52

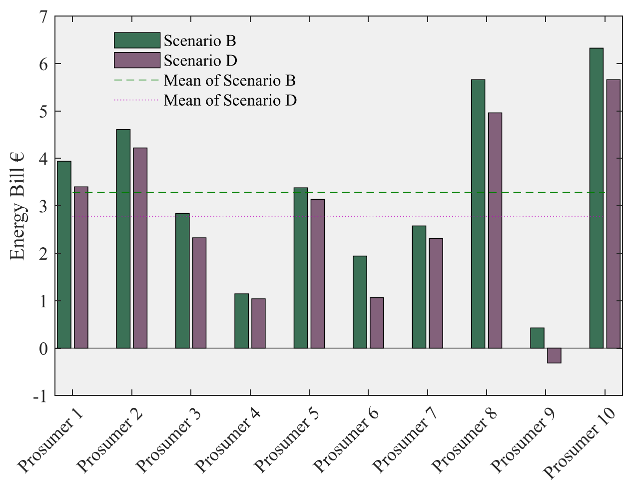

FIGURE 4. Energy Bill results for each prosumer in *Scenario B* and *Scenario D* for one day of operation.

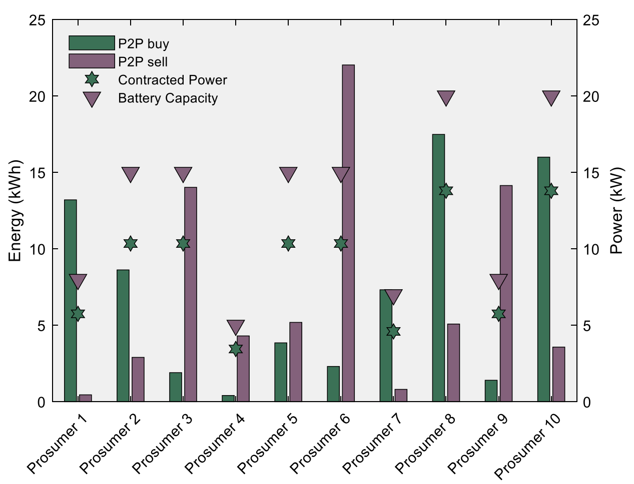

FIGURE 5. P2P trades in *Scenario D* with the contracted power and battery capacity.

and has a direct influence on the P2P transactions. As can be seen in Figure 5, prosumers 3 and 6 have the same contracted

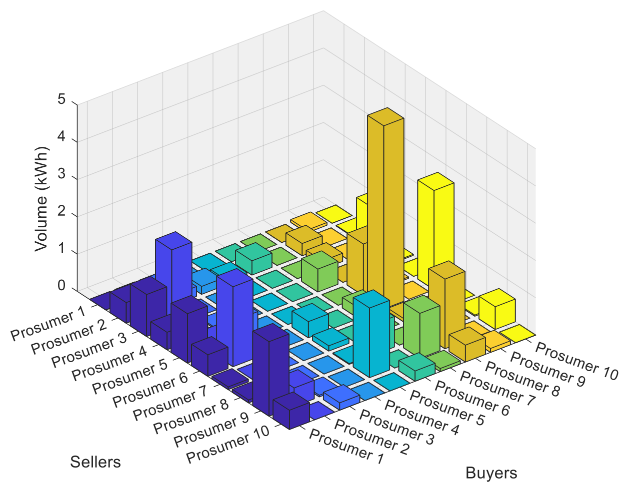

FIGURE 6. Volume of P2P electricity transactions for one day of operation in *Scenario D*.

power, but prosumer 6 presents a higher volume of electricity sold in the P2P market. Analyzing both figures 4 (showing the *EB*) and 5, prosumers 6 and 9 have the smaller energy bills and the higher values of energy transacted in P2P.

Figure 6 presents the electricity sellers in yy-axis, buyers in xx-axis and the transacted volume in zz-axis corresponding to the volume of electricity transacted between prosumers for the full day in *Scenario D*. The higher volume of energy transacted occurs between prosumer 8 (as a buyer) and prosumer 6 (as a seller) with a total of 4.91 kWh. Moreover, an average of 3.34 kWh was transacted in the P2P market by each prosumer in the referred day of operation.

Figure 7 presents the electricity purchased from the grid, the electricity sold to the grid, and the P2P transactions for *Scenario D*.

As can be seen in Figure 7, the tariff peak hours are between 9h to 22h as defined by the bi-horary tariff contracted with the grid/retailer. In these periods, the price of electricity is higher than the rest of periods (off-peak). In turn, the P2P transactions price is also higher in those peak periods.

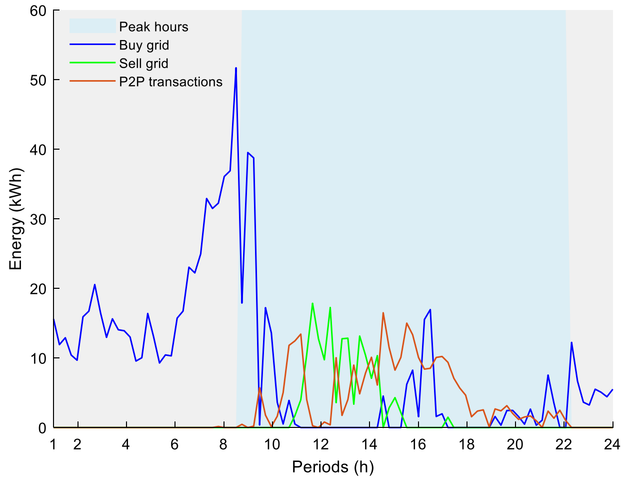

FIGURE 7. Accumulated electricity transactions with the grid and in P2P market for one day of operation in *Scenario D*.

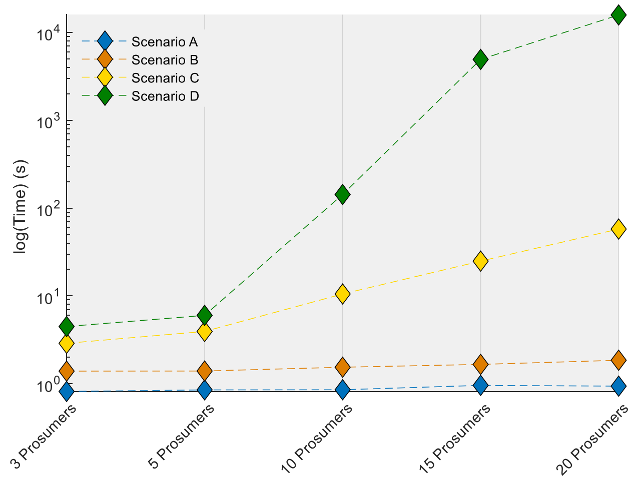

FIGURE 8. Optimization time results for one day of operation.

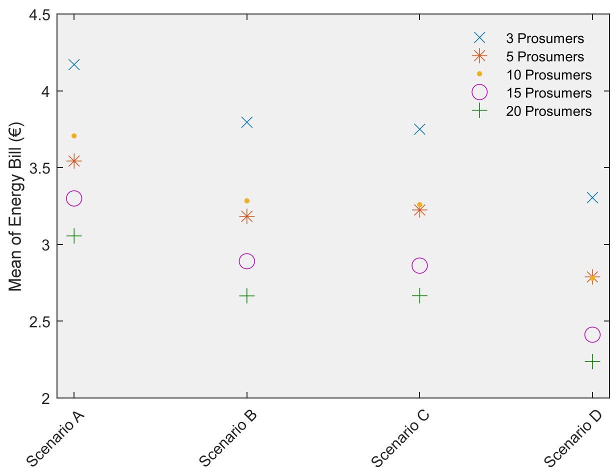

FIGURE 9. Mean results of energy bill considering the scenarios and number of prosumers.

However, P2P prices are always lower than the retailer's selling prices. Therefore, the P2P transactions have been realized during the peak periods, as Figure 7 illustrates. Another important fact is that the exceeding PV production from 8h to 20h (Figure 3) can be used to charge the batteries, to be injected to the grid, or to be traded with other prosumers (P2P). As can be seen in Figure 7, electricity is sold to the grid between hours 11h and 16h, which corresponds to the periods with higher PV production (see Figure 3). The P2P market is more attractive for the prosumer to sell the surplus of electricity for a higher profit. However, a part of the surplus electricity is still exported to the grid because prosumers with high PV production reach their maximum battery capacity, and eventually, there are not enough peers to carry out P2P transactions.

The implemented optimization procedure considering 10 prosumers (with total cost of 27.29 €, as showed in TABLE 3) took around 142.83 second. Therefore, to test the scalability of our model, we have run experiments considering 3, 5, 15 and 20 prosumers to obtain a sensitivity analysis of the optimization times. Figure 8 presents the execution time for the optimization process of all scenarios in TABLE 3, varying the number of prosumers from 3 to 20. The yy-axis uses a logarithmic scale. The faster optimization times are obtained with *Scenario A* considering 3 prosumers (0.81 s). The most time-consuming optimization corresponds to *Scenario D* with 20 prosumers, that took 15,869.68 s (4.41 h).

As can be seen in figure 8, *Scenario D* presents a higher optimization time. This is related to the number of variables involved in the optimization process. When the P2P transactions are included in the optimization, it is necessary to include all the possibilities that prosumers have to trade electricity. Also, notice that the number of prosumers does not have an impact in the optimization times for *Scenario A* and *Scenario B,* while having a clear impact for *Scenario C* and *Scenario D*. In *Scenario D,* an increment of 4.37 hours was registered in the optimization time when the number of prosumers was increased from 10 to 20.

Finally, Figure 9 presents a comparison of the mean energy bill considering the four scenarios and the total set of prosumers number. In each scenario presented in figure 9, five different values are shown corresponding to the different number of prosumers tested. The mean *EB* value registered a reduction when the numbers of prosumers increased. In the case of *Scenario D*, corresponding to the scenario with the best results, the mean value considering 20 prosumers registered a decrease of 1.07 €(32%) with regards to the case considering 3 prosumers only.

VI. CONCLUSION

This paper proposes a method for managing the energy resources of a local community considering P2P transactions, PV production, and storage systems. With the inclusion of P2P transactions, looking at the economic aspects, the overall costs of the energy community were lower and each prosumer was able to get a reduction in the energy bill. The best option, as demonstrated by simulation studies, is the combination of

P2P transactions with the usage of batteries (*Scenario D*). In fact, *Scenario D* led to the minimum overall costs for the community members, ensuring an average reduction of electricity costs of 0.93 €/day (9%) per prosumer compared *Scenario D* with *Scenario A*.

The proposed optimization method is consumer-centric having the ability to enable significant user participation in energy trading. Hence, enabling P2P transaction in the energy communities has the potential to encourage households to shift from consumers to prosumers.

The proposed methodology presents some limitations as it requires the existence of bidirectional information and physical energy flows between the involved prosumers. Also, in a real implementation, long execution times can be a drawback that needs to be solved. In the case of 20 prosumers, the optimization time was 4.41 h for the best scenario (*Scenario D*). Therefore, alternative and efficient methods that run near to real-time should be proposed.

In the future, we intend to explore metaheuristic methods (such as evolutionary computation) and decompositions methods (such as Benders decomposition) to solve the proposed problem and reduce the optimization time. In this way, the proposed model can be applied considering a higher number of prosumers.

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Core Publication IV

Ricardo Faia, João Soares, Muhammad A. Fotouhi Ghazvini, John F. Franco, and Zita Vale, "Local Electricity Markets for Electric Vehicles: An Application Study Using a Decentralized Iterative Approach," Frontiers Energy Research, vol. 9, Nov. 2021, doi: 10.3389/fenrg.2021.705066. **(2020 Impact Factor: 3.30)**;

Resumen

Los mercados locales de electricidad son soluciones emergentes para permitir el comercio local de energía para los usuarios finales y proporcionar servicios de soporte de red cuando sea necesario. En la literatura se han propuesto varios modelos de mercados eléctricos locales (LEM por sus siglas en inglés). El modelo de mercado peer-to-peer (punto a punto) aparece como una estructura prometedora entre los modelos propuestos. La estructura de mercado peer-to-peer permite transacciones de electricidad entre los participantes en un sistema de energía local a un costo menor. Fomenta la producción a partir de pequeñas tecnologías de generación de bajas emisiones de carbono. Las comunidades energéticas pueden ser el lugar ideal para implementar mercados eléctricos locales, ya que están diseñados para permitir un mayor crecimiento de las energías renovables y los vehículos eléctricos, al mismo tiempo que se benefician de las transacciones locales. En este contexto, se propone un modelo LEM considerando una comunidad energética con alta penetración de vehículos eléctricos en la que son posibles las transacciones prosumer-to-vehículo (P2V). Cada miembro de la comunidad energética puede comprar electricidad al minorista o a otros miembros, y vender electricidad. El problema se modela como una formulación de programación lineal de enteros mixtos (MILP por sus siglas en ingles) y se resuelve dentro de un proceso descentralizado e iterativo. La implementación descentralizada proporciona soluciones aceptables con un tiempo de ejecución razonable, mientras que la implementación centralizada suele dar una solución óptima a expensas de una escalabilidad reducida. Los resultados preliminares indican que existen ventajas para los vehículos eléctricos como participantes del LEM, y la implementación propuesta asegura una solución óptima en un tiempo de ejecución aceptable. Además, las transacciones P2V benefician a la red de distribución local y a la comunidad energética.

frontiers in Energy Research

ORIGINAL RESEARCH
published: 04 November 2021
doi: 10.3389/fenrg.2021.705066

Local Electricity Markets for Electric Vehicles: An Application Study Using a Decentralized Iterative Approach

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Specialty section:
This article was submitted to Smart Grids, a section of the journal Frontiers in Energy Research

Received: 04 May 2021
Accepted: 08 September 2021
Published: 04 November 2021

Citation:
Faia R, Soares J, Fotouhi Ghazvini MA, Franco JF and Vale Z (2021) Local Electricity Markets for Electric Vehicles: An Application Study Using a Decentralized Iterative Approach. Front. Energy Res. 9:705066. doi: 10.3389/fenrg.2021.705066

Local electricity markets are emerging solutions to enable local energy trade for the end users and provide grid support services when required. Various models of local electricity markets (LEMs) have been proposed in the literature. The peer-to-peer market model appears as a promising structure among the proposed models. The peer-to-peer market structure enables electricity transactions between the players in a local energy system at a lower cost. It promotes the production from the small low–carbon generation technologies. Energy communities can be the ideal place to implement local electricity markets as they are designed to allow for larger growth of renewable energy and electric vehicles, while benefiting from local transactions. In this context, a LEM model is proposed considering an energy community with high penetration of electric vehicles in which prosumer-to-vehicle (P2V) transactions are possible. Each member of the energy community can buy electricity from the retailer or other members and sell electricity. The problem is modeled as a mixed-integer linear programing (MILP) formulation and solved within a decentralized and iterative process. The decentralized implementation provides acceptable solutions with a reasonable execution time, while the centralized implementation usually gives an optimal solution at the expense of reduced scalability. Preliminary results indicate that there are advantages for EVs as participants of the LEM, and the proposed implementation ensures an optimal solution in an acceptable execution time. Moreover, P2V transactions benefit the local distribution grid and the energy community.

Keywords: decentralized control, energy community, local electricity markets, prosumer, electric vehicle

INTRODUCTION

Despite the pandemic that largely affected the automotive industry in 2020, the electric vehicle (EV) and renewable energy industry performed remarkably well (Lieven 2021; Wan et al., 2021). In fact, EV sale numbers in Europe increased to record numbers and all-time highs (up 137% from 2019), while the overall automotive industry was down by 20% year on year (Irle 2021). Most oil energy companies quickly shifted investments toward renewable energy projects and became more ESG[1]-

[1]Environmental, Social, and Governance (ESG) is a set of criteria and standards to enable socially and sustainable conscious decision investments within a company.

oriented, anticipating an earlier oil use peak (Strauch et al., 2020). The quicker energy transition motivated by the pandemic, the need to foster job creation, and new opportunities in the industry flag the importance to accelerate the conditions to accommodate a large penetration of EVs (Barbier 2020).

Most researchers agree that a large number of EVs in the grid will bring new operational challenges but also new opportunities (Fotouhi Ghazvini et al., 2019; Chung et al., 2019; Das et al., 2020). Challenges may include distribution lines and transformers' capacity limitations, overheating and overvoltage issues, bidirectional power flows (vehicle-to-grid), and market price increases (Gesevičius et al., 2021). Opportunities will include new business models, no-upfront cost grid services, improved renewable energy use, etc.

In this context, local electricity markets (LEMs) have been proposed as an effective tool to mitigate some bottlenecks of renewable and EV penetration in local distribution grids. Local markets are emerging in order to facilitate energy transactions among small producers and consumers in nearby energy communities (Mengelkamp et al., 2017). Their emergence is not targeting the replacement of wholesale markets and the retailing activity, but rather coexistence (Lezama et al., 2019a). Aggregators can participate in a LEM via load and EV aggregation as well (Lezama et al., 2019b; Masood et al., 2020). Among the different LEM models that have been proposed in the literature, the peer-to-peer (P2P) market model appears as a promising structure to reduce costs (Z. Zhang et al., 2020; Faia et al., 2021a).

A previous work proposed a centralized model to solve the optimal energy trading in a LEM between prosumers and EVs (Faia et al., 2021b). However, the scalability of the adopted centralized model is not enough, and the data privacy can be easily compromised. We believe that decentralized models can be a viable alternative to overcome issues previously raised, given the reduced number of resources involved in energy communities compared to region-wide scale problems. Therefore, a decentralized iterative approach is proposed in this study to solve energy management problems, considering the possibility of transactions in a prosumer-to-vehicle (P2V) market, thus enabling the prosumers to sell the surplus electricity production and to charge the EVs at a lower price than the retail market price. The price of electricity in the P2V market is assumed to be the most advantageous for both parties. The proposed model provides the integration of RESs and the empowerment of electricity end users in the power system, namely, by allowing prosumers and EVs to interact within the P2V market. The case study considers 90 players, composed of 50 domestic prosumers and 40 EVs; three different models of domestic battery systems; and seven different models of EVs. Real electricity tariffs from a Portuguese retailer and current feed-in tariff in the country are used in the case study. The main contributions of the study are as follows:

- A decentralized and iterative process is developed to determine electricity transactions among prosumers and EVs in a P2V market.
- Considering the reduction of the feed-in tariff, the proposed approach allows prosumers to have another option to sell electricity at higher price.
- Development of optimization models (prosumers and EVs) that include realistic constraints, prosumers load and generation profiles, photovoltaic (PV) systems, energy storage systems, and real and updated EV models.

The article is structured in six sections including this introductory section. A literature review is given in *Literature Review*. *Proposed Methodology* presents the proposed methodology, namely, formulation and the coordinator decision process. *Case Study* presents the details of the case study. Finally, *Results* presents the results and its discussion, while *Conclusion and Future Work*s provides the conclusions of the article.

LITERATURE REVIEW

Different designs of the LEMs and the market analysis of the proposed models have been presented in the literature. Absorbing the output of local generation from renewable sources by the flexible demand has been widely investigated. A P2P local electricity market model is developed in Z. Zhang et al.'s (2020) study which considers local energy trading and the uncertainty of the demand and PV generation. In this model, the load flexibility is characterized by time and power flexibility. The results reveal that this model could be used to enable the local balancing of the PV forecast power and the uncertain demand, while both consumers and PV owners could benefit from the local P2P market.

The P2P energy trading mechanism has also been used to coordinate the distributed energy generation and consumption (Matamoros et al., 2016) and the trading among the peers in a distribution network. C. Zhang et al., (2018) proposed an innovative platform for P2P energy trading using the game theory. The test results in a microgrid show that P2P trading can improve the local balance of consumption and generation. This trading mechanism can promote increased penetration of renewable energy sources in the grid.

A local electricity market model is developed in Sæther et al. (2021) to enable P2P electricity trading for a community of industrial buildings. The impact of local flexibility on the usage of DER technologies was investigated in that work; moreover, the contribution of the local market to peak demand management was assessed. The authors showed that the local market approach leads to more local usage of the distributed resources, eliminating the need to curtail DER power and reducing the grid feed-in.

A contract-based framework to enable local energy trading for electricity suppliers in different categories (i.e., small, medium, and large suppliers) is developed in Oprea and Bâra (2021). The model helps the suppliers obtain optimal contracts and trade the surplus power with an aggregator in a hierarchical electricity trading system. The distributed algorithm for electricity trading guarantees the optimal utility of both parties in various trading scenarios.

A day-ahead local energy market model is developed in Elbatawy and Morsi (2021) in which the residential consumers with home battery storage are the main participants. It uses the utility's distributed energy management system and the home energy management system based on the existing intercommunication system. Moreover, the provision of grid services, such as voltage support, transformer management, and phase balancing, as a result of this transactive market model, is investigated. The results show that the proposed market can contribute to grid services, while increasing the profits of the residential consumers.

Different auction mechanisms for the trade of electricity in a local market using blockchain mechanisms were investigated by Oprea and Bâra (2021). Suitable auction mechanisms for blockchain are proposed along with an adjustment of the price for both sellers and buyers after the initial clearing of the market at the classical auction levels. The simulation results show that this approach could improve the trading performance indicators.

The impact of local electricity trade on the operation of the distribution network is investigated in Lüth et al. (2020). It is concluded that exempting local trade and self-consumption from taxes could create distributional effects. That work proposes a novel market design that requires few legal amendments on the ownership and participation of renewable technologies to avoid the distributional effects of local markets, making them more attractive for the prosumers and consumers.

The work of Mustafa, Cleemput, and Abidin (Mustafa et al., 2016) provides security analysis for a proposed model of a local electricity market considering the privacy requirements of the users. Each user in this model buys or sells electricity in the local market via the supplier, and the supplier charges the user only for the electricity supplied to them by the grid and pays to them only for the exported electricity that was not traded in the local market. In this model, the DSO will also access the imported and exported electricity by all the users per supplier for each settlement period.

The aforementioned works indicate the potential of LEMs to benefit producers and consumers in energy communities. Nevertheless, further research on decentralized models is required to overcome scalability limitations when multiple agents are involved. Thus, *Proposed Methodology* presented the proposed methodology based on optimization models solved in a decentralized way.

PROPOSED METHODOLOGY

In this section, the details of the model used to characterize the transactions among the local prosumers and EVs are presented. The optimization models for prosumers and EVs are presented first and then the iterative process proposed for ensuring the balance in the P2V market is explained. The proposed methodology constitutes two different optimization models: prosumer model and EV model. Both of them are formulated as a MILP problem with the possibility of energy exchange among the retailers, the distribution grid, and the P2V market. It is assumed that EVs are able to buy electricity from a retailer or the P2V market. The models also consider the energy management system properties, using storage systems to obtain the best options for the user. **Figure 1** presents the model scheme of the implemented methodology.

As can be seen in **Figure 1**, in the implemented model, the prosumers can buy electricity from a retailer and sell to the main grid or in the P2V market; on the other hand, the EV can buy electricity from the retailer or directly from prosumers.

Formulation

The formulations are presented for each of the three agents: prosumers, EVs, and the coordinator in the respective subsections.

Prosumers

The prosumer operation is represented by the minimization of its energy costs across a set of time periods. Each agent i belonging to the set $\{1, \ldots, Ni\}$ optimizes its energy costs according to **Eq. 1** and subject to **Eqs 2–23**. Decision-making is done in a decentralized way, which means that each prosumer solves its own optimization process.

$$\textit{minimize } Pro_i^{\text{Costs}} = \sum_{t=1}^{Nt} \Big(P_{i,t}^{Retailer\ buy} \cdot ToU_{i,t} - P_{i,t}^{Grid\ sell} \cdot fit - P_{i,t}^{P2V\ sell} \cdot p^{P2V} \Big) \cdot \Delta t + FC_i, \tag{1}$$

where Pro_i^{Costs} represents the energy costs for the prosumer, $P_{i,t}^{\text{Retailer buy}}$ represents the electricity bought from a retailer, $ToU_{i,t}$ represents the time of use tariff contracted by the prosumer to the retailer, $P_{i,t}^{\text{Grid sell}}$ corresponds to the electricity sold in the distribution grid, fit is the feed-in tariff, $P_{i,t}^{\text{P2V sell}}$ represents the electricity sold in P2V market, p^{P2V} is the price of electricity in the P2V market, Δt represents the time adjustable parameter, FC_i corresponds to the daily fix cost paid by the prosumer, and Nt corresponds to the total number of periods. Indices t and i represent the respective period and prosumer. **Eq. 2** presents the power balance for prosumer agent i.

$$P_{i,t}^{Gen} + P_{i,t}^{\text{Retailer buy}} + P_{i,t}^{\text{Dch}} = P_{t,i}^{Load} + P_{t,i}^{\text{Grid sell}} + P_{i,t}^{\text{P2V sell}} + P_{i,t}^{\text{Ch}}, \forall t \in Nt, \tag{2}$$

where $P_{i,t}^{Gen}$ represents the electricity generated by the prosumer, $P_{i,t}^{\text{Dch}}$ represents the electricity discharged from the prosumer battery, $P_{t,i}^{Load}$ corresponds to the load demanded by the prosumer, and $P_{i,t}^{\text{Ch}}$ corresponds to the electricity charged by the prosumer battery. **Eqs 3–5** simulate the prosumer's transactions.

$$P_{i,t}^{\text{Retailer buy}} \le \overline{P}_{i,t}^{\text{Buy}} \cdot X_{i,t}^{\text{Retailer buy}}, \forall t \in Nt, \tag{3}$$

$$P_{i,t}^{\text{Grid sell}} \le \overline{P}_{i,t}^{\text{Sell}} \cdot X_{i,t}^{\text{Grid sell}}, \forall t \in Nt, \tag{4}$$

$$P_{i,t}^{\text{P2V sell}} \le \overline{P}_{i,t}^{\text{Sell P2V}} \cdot X_{i,t}^{\text{P2V sell}}, \forall t \in Nt, \tag{5}$$

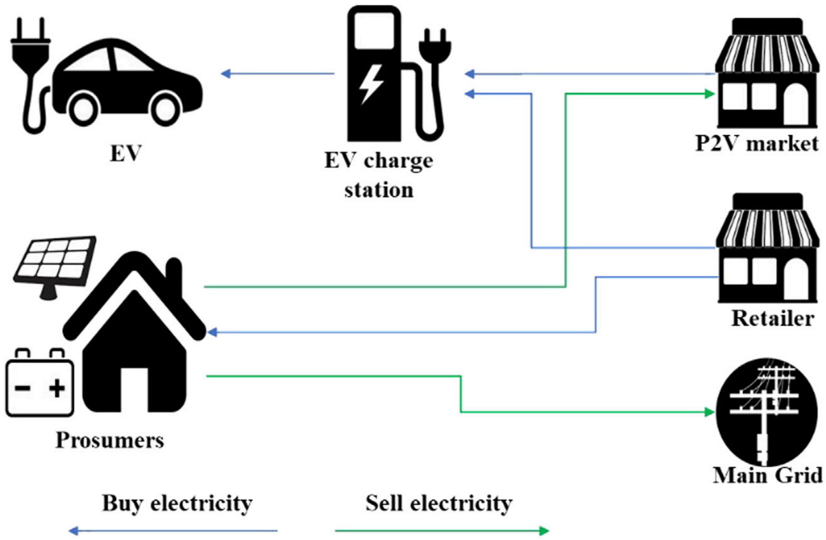

FIGURE 1 | Proposed model scheme.

where $\overline{P}_{i,t}^{\text{Buy}}$ represents the maximum buying limit for the prosumers, $X_{i,t}^{\text{Retailer buy}}$ corresponds to the binary variable for the buy action, $\overline{P}_{i,t}^{\text{Sell}}$ represents the maximum limit for the sales actions, $X_{i,t}^{\text{Grid sell}}$ is a binary variable for the sale on-grid actions, $\overline{P}_{i,t}^{\text{Sell P2V}}$ represents the maximum limit for the sales on P2V market, and $X_{i,t}^{\text{P2V sell}}$ represents the binary variable for the sales on P2V market. **Eqs 6**, **7** represent the prosumers' restrictions for buying and selling electricity.

$$X_{i,t}^{\text{Retailer buy}} + X_{i,t}^{\text{Grid sell}} \leq 1, \forall t \in Nt, \tag{6}$$

$$X_{i,t}^{\text{Retailer buy}} + X_{i,t}^{\text{P2V sell}} \leq 1, \forall t \in Nt, \tag{7}$$

where **Eq. 6** avoids simultaneous purchase from the retailer and selling to the grid. **Eq. 7** also controls simultaneous purchase from the retailers and selling to the P2V market. Sells to the grid and the P2V market can occur at the same time in this model. **Eqs 8–10** control charging and discharging decisions of the prosumers.

$$P_{i,t}^{\text{Ch}} \leq \overline{P}_{i,t}^{\text{Ch}} \cdot X_{i,t}^{\text{Ch}}, \forall t \in Nt, \tag{8}$$

$$P_{i,t}^{\text{Dch}} \leq \overline{P}_{i,t}^{\text{Dch}} \cdot X_{i,t}^{\text{Dch}}, \forall t \in Nt, \tag{9}$$

$$X_{i,t}^{\text{Ch}} + X_{i,t}^{\text{Dch}} \leq 1, \forall t \in Nt, \tag{10}$$

where $\overline{P}_{i,t}^{\text{Ch}}$ represents the maximum limit for the prosumers charge battery, $X_{i,t}^{\text{Ch}}$ represents the binary variable for the charge action, $\overline{P}_{i,t}^{\text{Dch}}$ corresponds to the maximum limit for the battery discharge of the prosumer, and $X_{i,t}^{\text{Dch}}$ corresponds to the binary variable for the discharge action. Simultaneously, only one action (charge and discharge) is possible and the binary variables control these actions. **Eq. 11**, **12** model the state of charge of the storage unit.

$$SoC_{i,1}^{\text{Bat}} = SoC_{i}^{\text{Bat Init}} + \left(P_{i,1}^{\text{Ch}} \cdot \eta_i^{\text{Ch}} - P_{i,1}^{\text{Dch}} \cdot \frac{1}{\eta_i^{\text{Dch}}}\right) \cdot \Delta t, \tag{11}$$

$$SoC_{i,t}^{\text{Bat}} = SoC_{i,t-1}^{\text{Bat}} + \left(P_{i,t}^{\text{Ch}} \cdot \eta_i^{\text{Ch}} - P_{i,t}^{\text{Dch}} \cdot \frac{1}{\eta_i^{\text{Dch}}}\right) \cdot \Delta t, \forall t \in [2, Nt], \tag{12}$$

where $SoC_{i,t}^{\text{Bat}}$ represents the state of charge of the storage unit, $SoC_{i}^{\text{Bat Init}}$ represents the battery unit's initial value; ef_i^{Ch} and η_i^{Dch} represent the efficiency of charge and discharge of the battery unit, respectively. **Equations 13–23** present the limits for the optimization variables of prosumer's operations.

$$0 \leq P_{i,t}^{\text{Retailer buy}} \leq \overline{P}_{i,t}^{\text{Buy}}, \forall t \in N_t, \tag{13}$$

$$0 \leq P_{i,t}^{\text{Grid sell}} \leq \overline{P}_{i,t}^{\text{Sell}}, \forall t \in N_t, \tag{14}$$

$$0 \leq P_{i,t}^{\text{P2V sell}} \leq \overline{P}_{i,t}^{\text{Sell P2V}}, \forall t \in N_t, \tag{15}$$

$$0 \leq P_{i,t}^{\text{Ch}} \leq \overline{P}_{i,t}^{\text{Ch}}, \forall t \in N_t, \tag{16}$$

$$0 \leq P_{i,t}^{\text{Dch}} \leq \overline{P}_{i,t}^{\text{Dch}}, \forall t \in N_t, \tag{17}$$

$$\underline{SoC}_{i,t}^{\text{Bat}} \leq SoC_{i,t}^{\text{Bat}} \leq \overline{SoC}_{i,t}^{\text{Bat}}, \forall t \in N_t, \tag{18}$$

$$X_{i,t}^{\text{Retailer buy}} \in \{0, 1\}, \forall t \in N_t, \tag{19}$$

$$X_{i,t}^{\text{Grid sell}} \in \{0, 1\}, \forall t \in N_t, \tag{20}$$

$$X_{i,t}^{\text{P2V sell}} \in \{0, 1\}, \forall t \in N_t, \tag{21}$$

$$X_{i,t}^{\text{Ch}} \in \{0, 1\}, \forall t \in N_t, \tag{22}$$

$$X_{i,t}^{\text{Dch}} \in \{0, 1\}, \forall t \in N_t, \tag{23}$$

where $\underline{SoC}_{i,t}^{\text{Bat}}$ and $\overline{SoC}_{i,t}^{\text{Bat}}$ represent the maximum and minimum capacity of the battery unit, respectively.

Electric Vehicles

This section presents the optimization model for the EV agents, which minimizes the daily operation cost through **Eq. 24**.

$$\boldsymbol{minimize: EV_j^{\mathrm{Costs}}} = \sum_{t=1}^{N_t}\left(\boldsymbol{P_{j,t}^{\mathrm{EV\ Retailer\ buy}}} \cdot \boldsymbol{ToU_{j,t}} + \boldsymbol{P_{j,t}^{\mathrm{P2V\ buy}}} \cdot \boldsymbol{p^{\mathrm{P2V}}}\right) \cdot \Delta_t + \boldsymbol{FC_j}, \tag{24}$$

where EV_j^{Costs} represents the costs for EV, $P_{j,t}^{\mathrm{EV\ Retailer\ buy}}$ corresponds to the electricity bought from a retailer, $ToU_{j,t}$ is the time of use tariff, $P_{j,t}^{\mathrm{P2V\ buy}}$ represents the electricity bought in the P2V market, p^{P2V} corresponds to the price of electricity in P2V market, FC_j represents the fixed costs for EV, and N_j represents the total number of EVs. **Eq. 25** represents the energy balance for the EVs.

$$\boldsymbol{P_{j,t}^{\mathrm{EV\ Retailer\ buy}}} + \boldsymbol{P_{j,t}^{\mathrm{P2V\ buy}}} = \boldsymbol{P_{j,t}^{\mathrm{EV\ Ch}}},\ \forall \boldsymbol{t} \in \boldsymbol{N_t}, \tag{25}$$

where $P_{j,t}^{\mathrm{EV\ Ch}}$ represents the electricity charged for EV battery. **Eqs 26**, **27** model the energy balance in EV batteries.

$$\boldsymbol{SoC_{j,1}^{\mathrm{EV\ Bat}}} = \boldsymbol{SoC_j^{\mathrm{EV\ Bat\ Init}}} + \left(\boldsymbol{P_{j,1}^{\mathrm{EV\ Ch}}} \cdot \boldsymbol{\eta_j^{\mathrm{EV\ Ch}}} - \boldsymbol{P_{j,1}^{\mathrm{EV\ Move}}}\right) \cdot \Delta_t, \tag{26}$$

$$\boldsymbol{SoC_{j,t}^{\mathrm{EV\ Bat}}} = \boldsymbol{SoC_{j,t-1}^{\mathrm{EV\ Bat}}} + \left(\boldsymbol{P_{j,t}^{\mathrm{EV\ Ch}}} \cdot \boldsymbol{\eta_j^{\mathrm{EV\ Ch}}} - \boldsymbol{P_{j,t}^{\mathrm{EV\ Move}}}\right) \times \Delta_t, \forall \boldsymbol{t} \in [2, \boldsymbol{Nt}], \tag{27}$$

where $SoC_{j,t}^{\mathrm{EV\ Bat}}$ represents the state of charge of the EV battery, $SoC_j^{\mathrm{EV\ Bat\ Init}}$ represents the initial state of EV battery, $\boldsymbol{\eta_j^{\mathrm{EV\ Ch}}}$ represents the efficiency of EV charge action, and $P_{j,t}^{\mathrm{EV\ Move}}$ represents the EV consumption during trips. **Eqs 28**, **29** limits the EV buying of electricity when they are on trip.

$$\boldsymbol{P_{j,t}^{\mathrm{EV\ Retailer\ buy}}} \le \boldsymbol{\overline{P}_{j,t}^{\mathrm{EV\ Buy}}} \cdot \boldsymbol{A_{j,t}^{\mathrm{EV\ Move}}}, \forall \boldsymbol{t} \in \boldsymbol{N_t}, \tag{28}$$

$$\boldsymbol{P_{j,t}^{\mathrm{P2V\ buy}}} \le \boldsymbol{\overline{P}_{j,t}^{\mathrm{EV\ P2V\ Buy}}} \cdot \boldsymbol{A_{j,t}^{\mathrm{EV\ Move}}}, \forall \boldsymbol{t} \in \boldsymbol{N_t}, \tag{29}$$

where $\overline{P}_{j,t}^{\mathrm{EV\ Buy}}$ represents the maximum limit for buying electricity, $A_{j,t}^{\mathrm{EV\ Move}}$ gives the indication if the EV is travelling (zero) or if is available to charge (one), and $\overline{P}_{j,t}^{\mathrm{EV\ P2V\ Buy}}$ represents the maximum limit for buying electricity in P2V market. **Eqs 30–33** present the maximum and minimum limits for the EV operation.

$$\boldsymbol{0} \le \boldsymbol{P_{j,t}^{\mathrm{EV\ Reatiler\ buy}}} \le \boldsymbol{\overline{P}_{j,t}^{\mathrm{EV\ Buy}}}, \forall \boldsymbol{t} \in \boldsymbol{N_t}, \tag{30}$$

$$\boldsymbol{0} \le \boldsymbol{P_{j,t}^{\mathrm{P2V\ buy}}} \le \boldsymbol{\overline{P}_{j,t}^{\mathrm{EV\ P2V\ Buy}}}, \forall \boldsymbol{t} \in \boldsymbol{N_t}, \tag{31}$$

$$\boldsymbol{0} \le \boldsymbol{P_{j,t}^{\mathrm{EV\ Ch}}} \le \boldsymbol{\overline{P}_{j,t}^{\mathrm{EV\ Ch}}}, \forall \boldsymbol{t} \in \boldsymbol{N_t}, \tag{32}$$

$$\boldsymbol{\underline{SoC}_{j,t}^{\mathrm{EV\ Bat}}} \le \boldsymbol{SoC_{j,t}^{\mathrm{EV\ Bat}}} \le \boldsymbol{\overline{SoC}_{j,t}^{\mathrm{EV\ Bat}}}, \forall \boldsymbol{t} \in \boldsymbol{N_t}, \tag{33}$$

where $\overline{P}_{j,t}^{\mathrm{EV\ Ch}}$ represent the maximum limit for EV maximum charge action and $\boldsymbol{\underline{SoC}_{j,t}^{\mathrm{EV\ Bat}}}$ and $\boldsymbol{\overline{SoC}_{j,t}^{\mathrm{EV\ Bat}}}$ represent the minimum and maximum level for the EV battery, respectively.

Coordinator

The coordinator is responsible for the process of ensuring the balance in the P2V market. The coordinator process is based on **Eqs 34**, **35** and applies four sequential rules. The first two rules limit the periods for prosumers' sells (**Eq. 36**) and EV buys (**Eq. 37**), respectively. On the other hand, the last two rules limit the amount of buy and sell electricity in periods in which transactions are possible. **Eq. 38** limits the maximum amount of electricity that each EV can buy in P2V market, and similarly, **Eq. 39** imposes a limit for prosumers' sales.

Eq. 34 presents the energy balance in P2V market.

$$\boldsymbol{Balance:} \sum_{i=1}^{N_i}\left(\boldsymbol{P_{i,t}^{\mathrm{P2V\ sell}}} \cdot \Delta_t\right) = \sum_{j=1}^{N_j}\left(\boldsymbol{P_{j,t}^{\mathrm{P2V\ buy}}} \cdot \Delta_t\right), \forall \boldsymbol{t} \in \boldsymbol{N_t}. \tag{34}$$

To ensure the balance in the P2V market, the aggregator executes four hierarchical rules. Thus, an error is calculated according to **Eq. 35** to indicate the difference between the sell and buy energy across all time periods.

$$\boldsymbol{Error} = \sum_{t=1}^{N_t}\left(\sum_{i=1}^{N_i}\boldsymbol{P_{i,t}^{\mathrm{P2V\ sell}}} \cdot \Delta_t - \sum_{j=1}^{N_j}\boldsymbol{P_{j,t}^{\mathrm{P2V\ buy}}} \cdot \Delta_t\right)^2. \tag{35}$$

The error can be obtained in each iteration of the process and considers the energy sold by the prosumers and bought by the EVs. When the process has been finalized, the value of error should be minimal.

Four different rules are created to achieve the minimal error and the convergence of the coordinator process. One algorithm per each rule is presented in order to facilitate the interpretation of the corresponding rule. The first rule is defined in **Eq. 36**.

$$\boldsymbol{Rule}1: \boldsymbol{\overline{P}_{j,t,(it=2)}^{\mathrm{EV\ P2V\ Buy}}} = \begin{cases} \boldsymbol{0} & \boldsymbol{if} \sum_{i=1}^{N_i}\boldsymbol{P_{i,t}^{\mathrm{P2V\ sell}}} = \boldsymbol{0} \\ \boldsymbol{\overline{P}_{j,t,(it=1)}^{\mathrm{EV\ P2V\ \mathit{buy}}}} & \boldsymbol{otherwise} \end{cases}, \forall \boldsymbol{t} \in \boldsymbol{N_t}, \forall \boldsymbol{j} \in \boldsymbol{N_j}. \tag{36}$$

Rule 1 is applied to update the values of EV electricity maximum buy limit in the P2V market for the second iteration. Considering this rule, the EV in the second iteration only can buy electricity in periods when the prosumers are available for sale. **Algorithm 1** presents the application process of rule 1.

Algorithm 1. Application of Rule 1 (**Eq. 36**)

1. Coordinator balance check (**Eq. 34**)
2. Error calculation (**Eq. 35**)
3. **If** $Error > 1 \times 10^{-2}$ kW and $it = 1$
4. **For** $t = 1: N_t$
5. **For** $j = 1: N_j$
6. **If** $\sum_{i=1}^{N_i} P_{i,t}^{\mathrm{P2V\ sell}} = 0$
7. $\overline{P}_{j,t,(it=2)}^{\mathrm{EV\ P2V\ buy}} = 0$
8. **Else If**
9. $\overline{P}_{j,t,(it=2)}^{\mathrm{EV\ P2V\ buy}} = \overline{P}_{j,t,(it=1)}^{\mathrm{EV\ P2V\ buy}}$
10. **End If**
11. **End For**
12. **End For**
13. $it = it + 1$
14. **Else If**
15. Converged solution
16. **End If**
17. Return the solution.

Eq. 37 presents the rule executed for the second iteration.

$$\boldsymbol{Rule}\ 2\text{: } \overline{\boldsymbol{P}}^{\mathbf{Sell}\,\boldsymbol{P2V}}_{\boldsymbol{i,t},(\boldsymbol{it}=3)} = \begin{cases} \mathbf{0} \quad \boldsymbol{if} \ \sum\limits_{j=1}^{N_j} \boldsymbol{P}^{\boldsymbol{P2V}\,\mathbf{buy}}_{\boldsymbol{j,t}} = \mathbf{0} \\ \overline{\boldsymbol{P}}^{\mathbf{Sell}\,\boldsymbol{P2V}}_{\boldsymbol{i,t},(\boldsymbol{it}=2)} \boldsymbol{otherwise}, \forall \boldsymbol{t} \in \boldsymbol{N_t}, \forall \boldsymbol{i} \in \boldsymbol{N_i}. \end{cases} \tag{37}$$

Rule 2 is applied to the maximum limit of electricity sell in the P2V market for the prosumers side. In this case, in periods where the EVs do not buy electricity in the P2V market, the maximum sales limit for prosumers in this same period is zero. **Algorithm 2** presents the application of rule 2.

Algorithm 2. Application of Rule 2 (**Eq. 37**)

Coordinator balance check (**Eq. 34**)
Error calculation (**Eq. 35**)
If $Error > 1 \times 10^{-2}$ kW and $it = 2$
  For $t = 1: N_t$
    For $i = 1: N_i$
      If $\sum_{j=1}^{N_j} P^{\text{P2V buy}}_{j,t} = 0$
        $\overline{P}^{\text{Sell P2V}}_{i,t,(it=3)} = 0$
      Else If
        $\overline{P}^{\text{Sell P2V}}_{i,t,(it=3)} = \overline{P}^{\text{Sell P2V}}_{i,t,(it=2)}$
      End If
    End For
  End For
  $it = it + 1$
Else If
Converged solution
End If
Return the solution.

Rule 3 in **Eq. 38** presents a new update for the maximum buy limit for EV buys in the P2V market.

$$\boldsymbol{Rule}\ 3\text{: } \overline{\boldsymbol{P}}^{\mathbf{EV}\,\boldsymbol{P2V}\,\mathbf{Buy}}_{\boldsymbol{j,t},(\boldsymbol{it}=4)} = \begin{cases} \dfrac{\sum_{i=1}^{N_i} \boldsymbol{P}^{\boldsymbol{P2V}\,\mathbf{sell}}_{\boldsymbol{i,t}}}{\boldsymbol{P}^{\boldsymbol{P2V}\,\mathbf{buy}}_{\boldsymbol{j,t}}} & \boldsymbol{if}\ \boldsymbol{P}^{\boldsymbol{P2V}\,\mathbf{buy}}_{\boldsymbol{j,t}} \geq \mathbf{0} \\ \overline{\boldsymbol{P}}^{\mathbf{EV}\,\boldsymbol{P2V}\,\mathbf{Buy}}_{\boldsymbol{j,t},(\boldsymbol{it}=3)} & \boldsymbol{otherwise} \end{cases}, \forall \boldsymbol{t} \in \boldsymbol{N_t}, \forall \boldsymbol{j} \in \boldsymbol{N_j}. \tag{38}$$

Using rule 3, the maximum limit for EVs to buy electricity in the P2V market is limited using the quantity available from prosumers. In this case, in each period that there is electricity sold by the prosumers, the maximum limit for the EVs available to buy will be limited. This limitation will be proportional, considering the maximum electricity available from prosumers. **Algorithm 3** presents the application of rule 3.

Algorithm 3. Application of Rule 3 (**Eq. 38**)

Coordinator balance check (**Eq. 34**)
Error calculation (**Eq. 35**)
If $Error > 1 \times 10^{-2}$ kW and $it = 3$
  For $t = 1: N_t$
    For $j = 1: N_j$
      If $P^{\text{P2V buy}}_{j,t} \geq 0$
        $\overline{P}^{\text{EV P2V Buy}}_{j,t,(it=4)} = \frac{\sum_{i=1}^{N_i} P^{\text{P2V sell}}_{i,t}}{P^{\text{P2V buy}}_{j,t} \geq 0}$
      Else If
        $\overline{P}^{\text{EV P2V Buy}}_{j,t,(it=4)} = \overline{P}^{\text{EV P2V Buy}}_{j,t,(it=3)}$
      End If
    End For
  End For
  $it = it + 1$
Else If
Converged solution
End If
Return the solution.

Rule 4 limits the maximum electricity sold by prosumers in the P2V market presented in **Eq. 39**.

$$\boldsymbol{Rule}\ 4\text{: } \overline{\boldsymbol{P}}^{\mathbf{Sell}\,\boldsymbol{P2V}}_{\boldsymbol{i,t},(\boldsymbol{it}=5)} = \begin{cases} \dfrac{\sum\limits_{j=1}^{N_j} \boldsymbol{P}^{\boldsymbol{P2V}\,\mathbf{buy}}_{\boldsymbol{j,t}}}{\boldsymbol{P}^{\boldsymbol{P2V}\,\mathbf{sell}}_{\boldsymbol{i,t}}} & \boldsymbol{if}\ \boldsymbol{P}^{\boldsymbol{P2V}\,\mathbf{sell}}_{\boldsymbol{i,t}} \geq \mathbf{0} \\ \overline{\boldsymbol{P}}^{\mathbf{SellP2V}}_{\boldsymbol{i,t},(\boldsymbol{it}=4)} & \boldsymbol{otherwise} \end{cases}, \forall \boldsymbol{t} \in \boldsymbol{N_t}, \forall \boldsymbol{i} \in \boldsymbol{N_i}. \tag{39}$$

In rule 4, the same process of rule 3 is applied, but for the maximum limit for prosumers sells in the P2V market. **Algorithm 4** presents the application of rule 4.

Algorithm 4. Application of Rule 4 (**Eq. 39**)

Coordinator balance check (**Eq. 34**)
Error calculation (**Eq. 35**)
If $Error > 1 \times 10^{-2}$ kW and $it = 4$
  For $t = 1: N_t$
    For $i = 1: N_i$
      If $P^{\text{P2V sell}}_{i,t} \geq 0$
        $\overline{P}^{\text{Sell P2V}}_{i,t,(it=5)} = \frac{\sum_{j=1}^{N_j} P^{\text{P2V buy}}_{j,t}}{P^{\text{P2V sell}}_{i,t}}$
      Else If
        $\overline{P}^{\text{Sell P2V}}_{i,t,(it=5)} = \overline{P}^{\text{Sell P2V}}_{i,t,(it=4)}$
      End If
    End For
  End For
  $it = it + 1$
Else If
Converged solution
End IF
Return the solution

Iterative Process

An iterative approach is adopted to solve the coordination process. This is illustrated by the block diagram in **Figure 2**. The coordinator is responsible for the perfect match between the sales of prosumers and purchases of the EVs in the P2V market. The optimizations of each prosumer and EV are independent, only needing the information of maximum

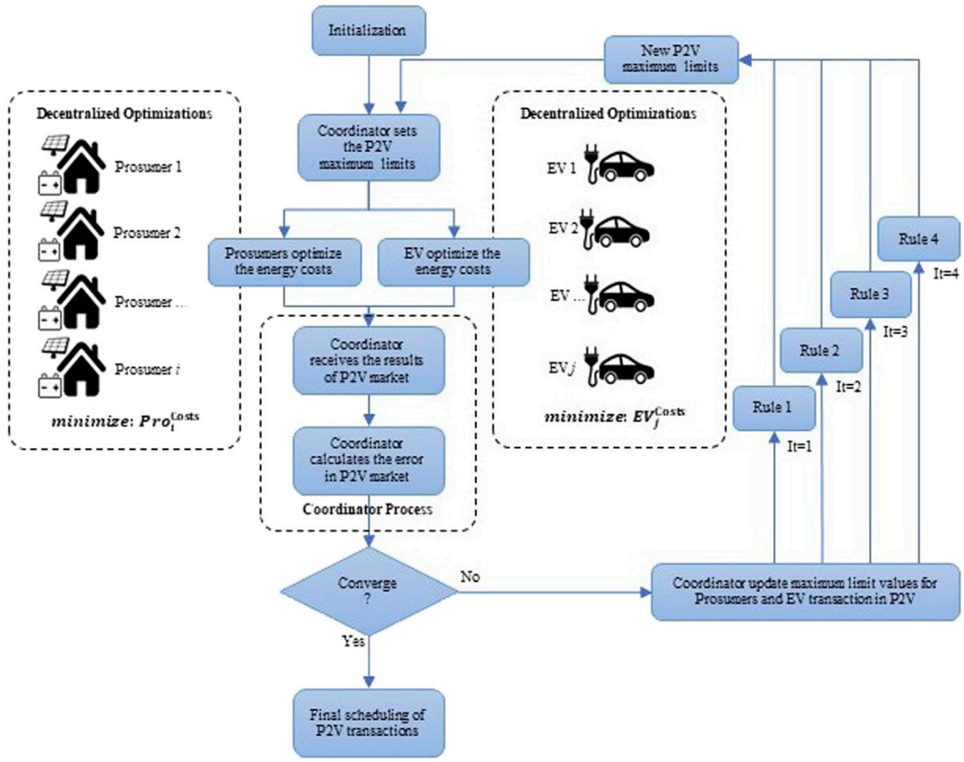

FIGURE 2 | Block diagram process.

limits for transaction in the P2V market provided by the coordinator.

The coordinator initializes the process, defines the maximum limits for prosumers and EV transactions in P2V market, and passes the information for each prosumer and EV. Both of those agents optimize their energy costs with the provided information of maximum limits for P2V transactions. Those optimizations run in a parallel and decentralized way in which prosumers and EVs receive and send the required data to the coordinator. The latter receives the P2V transaction information and determines the error considering the electricity sold by prosumers and bought from EV. The convergence is tested through two different criteria: the error value obtained by **Eq. 35** and the number of iterations. Considering the error, if the value is equal to or less than 0.001 kW, the process converges. On the other hand, when the process is completed, the limit of iterations (five) is reached. When none of the aforementioned conditions is verified, the process proceeds to the next iteration, and the maximum limits for P2V transactions are updated.

The created rules are applied in a sequential mode with respect to the number of respective iterations. During the iterative process, if the error condition is verified, the model converges, and all rules may not be applied. At the maximum, this process has five iterations.

CASE STUDY

To validate the proposed methodology, a case study with a set of 50 residential prosumers and 40 EVs is adopted.[2] In total, the community is constituted by 90 players. All community players have a contract with the retailer to supply the necessary electricity that defines the maximum limit for buying electricity, the maximum limit for injecting electricity into the grid, and the fixed costs. The prosumers and EVs can transact electricity in the P2V market, that is, prosumers' sell and EVs buy electricity, which presents the mean profiles of generation and conventional load.

The profiles presented in **Figure 3** are the mean profiles considering the 50 prosumers. The prosumers present a total consumption of 2001.89 kWh and 1,1417.82 kWh of total PV generation, which correspond to a mean of 40.04 kWh of consumption and 28.36 kWh of generation for each prosumer. The prosumer has installed 248.8 kW of produced capacity for PV generation, that is, a mean of 4.98 kW. **Table 1** presents the characteristic of batteries used in the prosumers' facilities.

Three different batteries for prosumers are selected in the case study. In total, there are 50 units of batteries, one per each prosumer. The three available battery types are randomly

[2]All data are available in the public datset: https://zenodo.org/record/4737293#.YJFWT7VKg2x.

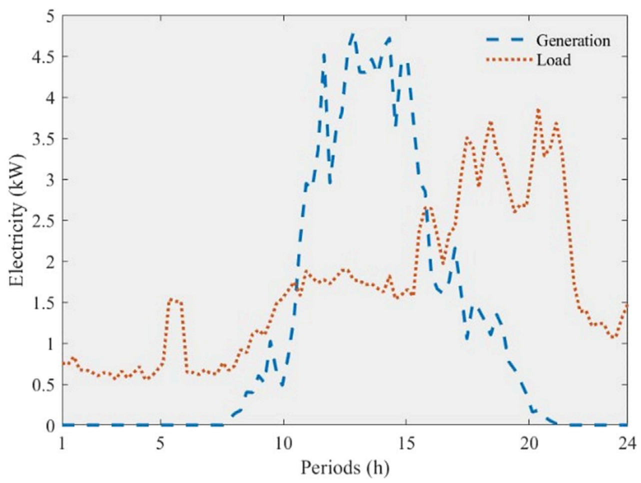

FIGURE 3 | Mean profiles of prosumers.

distributed among all prosumers. In total, the prosumers have 715 kWh of storage capacity installed. **Table 2** presents the characteristics of EVs used in the case study, while **Figure 4** presents the EV profiles.

Figure 4A presents the profiles of EV trips; most of the EV trips happen at 8:15 h and 19:45 h (36 trips). In mornings, the EV starts the movements at 6:15 h and stops at 23:30 h at night. Regarding the total number of periods, the EVs make 780 trips, which correspond to a mean of 8.3 trips per period. **Figure 4B** presents the mean profile of EV consumption. The peaks of consumption are verified in the same peak periods of EV movements.

The seven EV models presented in **Table 2** were also randomly distributed within the 40 available EV users. Tesla Model 3 Standard Range + is the most used model. Considering all EVs, they have 1916.60 kWh of capacity. **Table 3** presents the tariffs used in the case study. All buy tariffs are obtained in the EDP Comercial Portuguese electricity retailer.

Table 3 presents three different tariffs that the prosumers and EVs can contract with the retailer. The users should contract the tariff that best fits their needs. Contracted power corresponds to the maximum power that each user can demand from the distribution grid. Fixed costs are always associated with contracted power value; higher contracted power values are associated with higher values of fixed costs. The price of electricity varies in two different periods in the day. Off-peak period (during 22:15 to 8:00 h) are considered the cheapest periods, while peak time (between 8:15 to 22:00 h) is considered expensive. Regarding the sell tariff, the price is defined as linear and can be found in Ambiente. (2020). The limit for export of electricity to the grid is half of the contracted power. In the set of prosumers, 21 of them selected the tariff with 6.90 kVA contracted power, while in the set of EVs, 16 of them selected the tariff with 13.80 kVA contracted power. Price of the P2V market $(\boldsymbol{p^{P2V}})$ is obtained considering the mean between the minimum value of ToU tariffs $(\boldsymbol{min(ToU_{j,t})})$ and the feed-in tariff. The electricity price of the P2V market is 0.0686 €/kWh, while the minimum EV buy price is 0.0922 €/kWh and the price of export electricity to the grid (fit) is 0.045 €/kWh.

RESULTS

The results of the proposed methodology applied to the case study are shown in this section. The simulations were performed on a computer with an Intel Xeon(R) E5-2620v2@2.1 GHz processor with 16 GB of RAM running Windows 10. To emulate the optimization problem, a MATLAB 2018a with TOMLAB optimization add-on was used. The CPLEX solver was used to optimize the proposed model. The simulations are carried out for a time horizon of 24 h divided into 96 periods (15 min each). The

TABLE 1 | Prosumers batteries characteristics.

Brand	Model	Capacity (kWh)	Charge/discharge rate (kW)	Efficiency (%)	No
Sonnen	9.43	15.000	3.300	90	16
Tesla	Powerwall	13.500	5.000	90	18
Alpha	Smile	14.500	2.867	90	16

TABLE 2 | EV characteristics.

Brand	Model	Capacity (kWh)	Charge rate (kW)	Efficiency (%)	No
Honda	e	35.500	6.600	90	2
WV	ID.4	82.000	11.000	90	6
WV	e-Golf	35.800	7.200	90	8
Tesla	Model 3 Standard Range +	50.000	11.000	90	10
Peugeot	e-208	50.000	7.400	90	2
Nissan	Leaf	40.000	3.600	90	8
WV	e-UP!	36.800	7.200	90	4

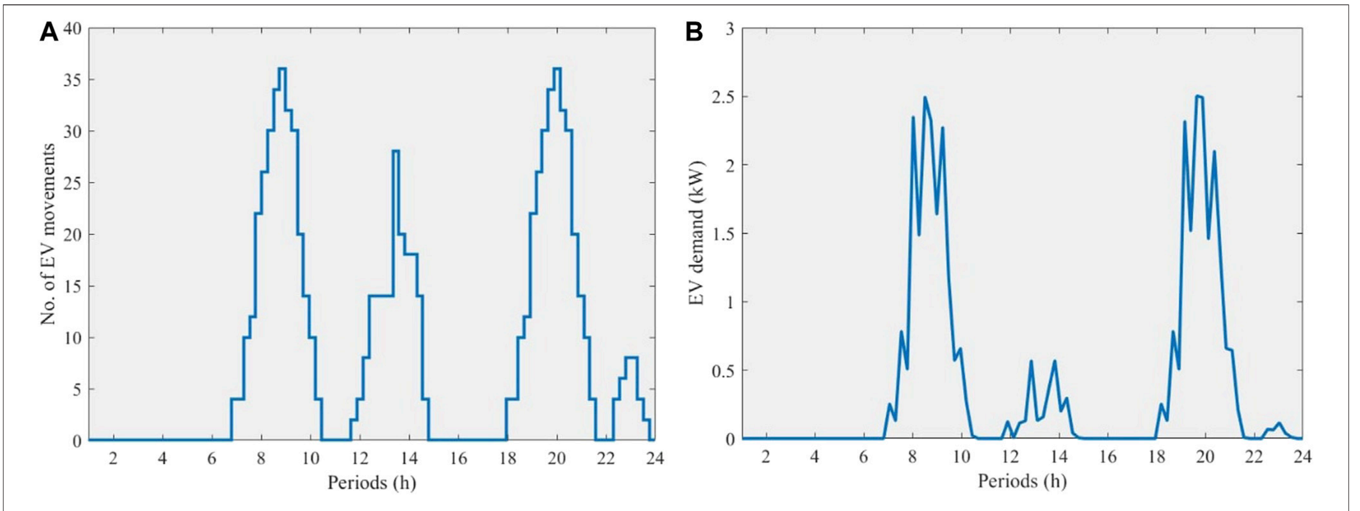

FIGURE 4 | EV profiles, **(A)** movements, and **(B)** mean consumption.

TABLE 3 | Tariffs description.

Tariff	Type	Price (€/kWh)		Contracted power (kVA)	Fixed costs (€/day)	No		
		Off-peak	Peak			Prosumer	EV	Total
Buy	ToU	0.0923	0.1833	4.60	0.3251	12	8	20
		0.0924	0.1834	5.75	0.3847	10	0	10
		0.0924	0.1836	6.90	0.4448	21	2	23
		0.0922	0.1829	10.35	0.6209	7	14	21
		0.0926	0.1838	13.80	0.8022	0	16	16
Sell	Feed-in tariff (*fit*)	0.0450		50% of buy limit	0.0000	50	0	50

TABLE 4 | Optimization results (€).

Scenario		Centralized[a]		Decentralized	
		No P2V market	P2V market	No P2V market	P2V market
		A	B	A	B
Mean cost	Prosumers	2.10	2.10	2.10	2.06
	EV	4.62	4.37	4.62	4.44
Sum of costs	Prosumers	104.84	104.96	104.84	102.82
	EV	184.85	174.95	184.85	177.52
Total costs		289.69	279.92	289.69	280.34
Reduction (%)		3.37		3.23	

[a]*Considering model presented in reference (Faia, et al., 2021b).*

load and generation data are obtained through forecasts. Two different scenarios are considered to enable the comparison: scenario A for the possibility of transacting electricity with retailers and the option of exporting to the grid, and scenario B for the possibility of transacting electricity with retailers, the option of exporting to the grid, and transacting electricity in the P2V market. **Table 4** presents the optimization results for a centralized approach and the decentralized approach proposed in this work.

Table 4 presents the optimization results for the same case study with two different variants (with and without P2V market) and for two different implementations (centralized and decentralized). It was found that the results are the same when the P2V market is not available; however, as expected, the centralized method provides slightly better total costs for the P2V market variant. The only difference is the implementation, which has disadvantages considering the privacy issues. Comparing the two different implementations when the P2V

TABLE 5 | Optimization time results (seconds).

Iteration	Centralized		Decentralized	
	No P2V market	P2V market	No P2V market	P2V market
1	9.74	1,118.57	1.78	1.64
2	–	–	–	1.34
3	–	–	–	1.59
4	–	–	–	1.58
5	–	–	–	1.58
Total	9.74	1,118.57	1.78	7.73
Total (minutes)	0.16	18.64	0.03	0.13

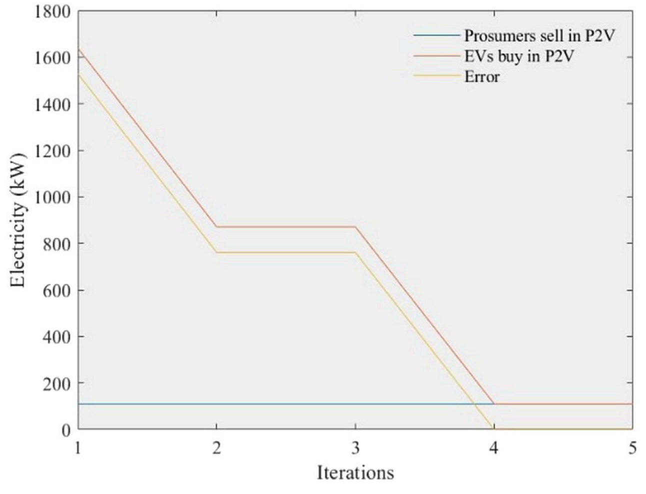

FIGURE 5 | Process convergence.

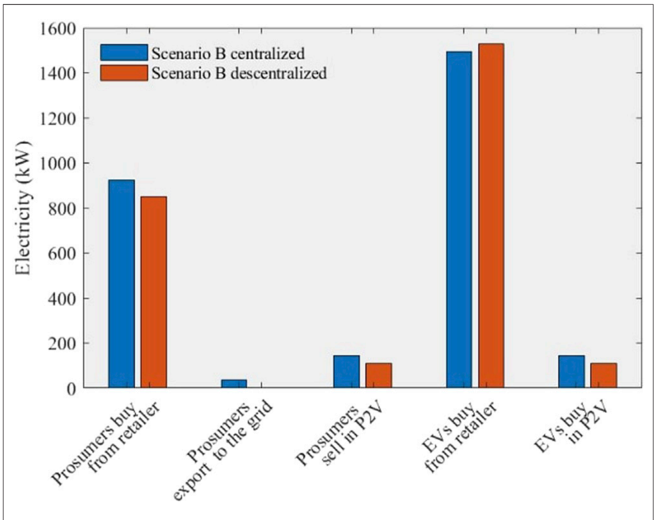

FIGURE 6 | Buys and sells of scenario B.

market is available, the centralized implementation has better results with a minimal difference (0.15% comparing the total costs). Analyzing other indicators' results, different values are presented when considering scenario B in the two different implementations. In the decentralized option, the values of mean prosumer cost decreases (2.04%) and the mean EV costs increase (1.45%). Since each player is trying to make the most advantageous transaction for itself, which leads to a suboptimal cost. On the other hand, in a centralized implementation, the community profit is maximized.

Table 5 presents the optimization time results for both implementation scenarios. In the decentralized implementation, the time presented in each iteration corresponds to the maximum resolution time in the set of all players. Execution times in the decentralized implementation for both scenarios A and B are lower than the times required by the centralized implementation. The big difference and the advantage of the decentralized implementation are verified when the resolution times for scenario B are presented. As can be seen, when the centralized implementation is considered, the resolution time is 144 times greater than the decentralized implementation.

Figure 5 shows the convergence of the optimization process. Three different variables are presented in **Figure 5**, the error

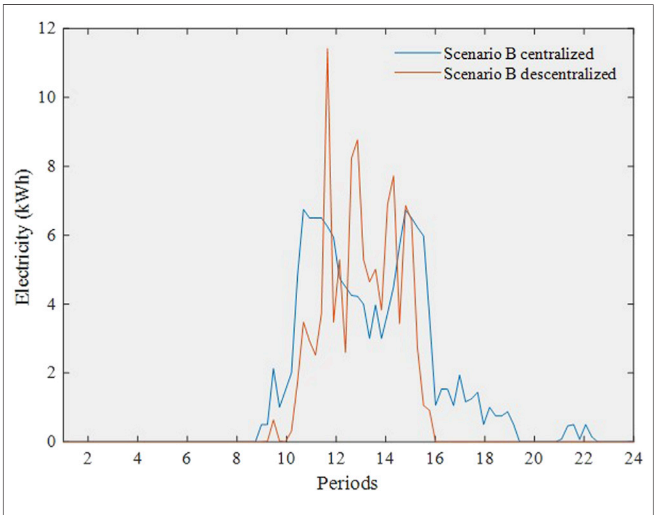

FIGURE 7 | Buys and sells of scenario B.

(obtained by **Eq. 34**), the value of prosumers sells in P2V, and the EV buys in P2V. The sales and buys should have the same value. In the first iteration of **Figure 5**, the EVs are buying more units of

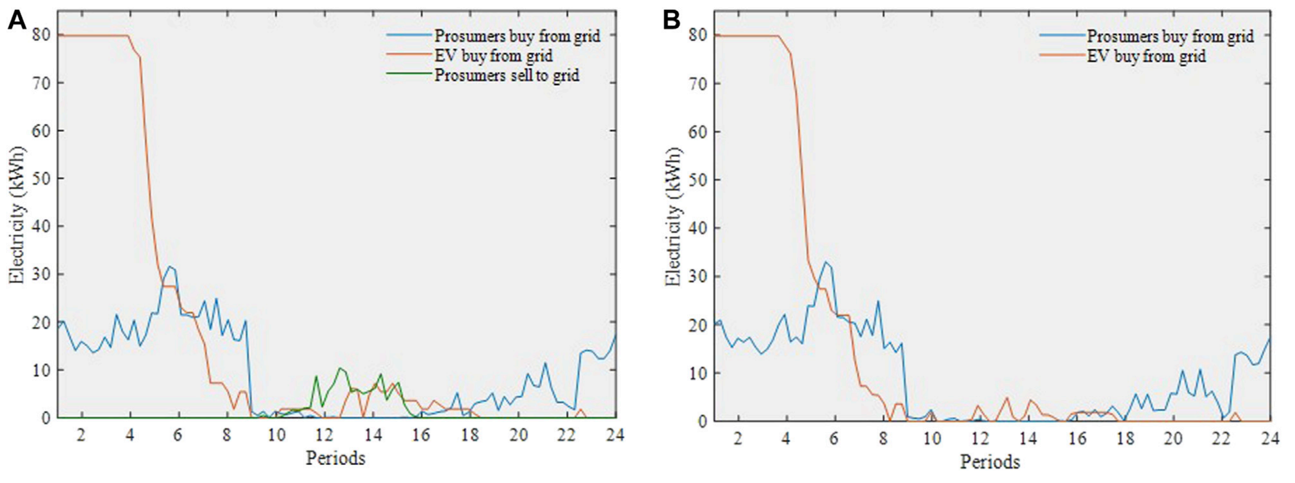

FIGURE 8 | Transactions on grid for decentralized **(A)** scenario A and **(B)** scenario B.

electricity than the amount available on the market, corresponding to the prosumers' selling. The electricity sold by the prosumers in the P2V market remains constant in all iterations. However, in the end, the EVs adjust their purchased electricity with what is sold by the prosumers. Throughout the iterations, the amount of purchase of EVs decreases as a result of the application of the rules created, leading the error to zero. In this case, the EVs adapt their actions to the behavior of the prosumers. This is because the amount of electricity available on the part of the prosumers is less than that required by the EVs.

Figure 6 presents the electricity transaction of scenario B in centralized and decentralized implementations. The presented results are very similar, although there are differences, mainly in the electricity exported to the grid. Electricity is exported in the centralized implementation, while it is not exported in the decentralized approach. One of the important aspects observed is the value of electricity traded in the P2V market, which is superior to decentralized implementation. **Figure 7** presents the transaction on P2V electricity market considering the centralized and decentralized implementation.

As can be seen in **Figure 7**, the transactions of P2V for the centralized and decentralized solutions have differences. The main difference is related to the period of transaction: in the centralized approach, the transactions occur between 9:00 h and 19:00 h and also between 21:00 and 22.30 h. In the case of decentralized resolution, the transactions occur during 9:00 h to 16:00 h, which corresponds to the PV prosumers' production hours. **Figure 8** presents the electricity transaction on grid for the decentralized approach.

Both **Figures 8A** and **B** present results for the decentralized resolution, **Figure 8A** for scenario A, where P2V market is not available, and **Figure 8B** for scenario B where P2V market is available. The big difference presented in the figures is related to the prosumers' sell to grid values. In the case of scenario A, there are sells to the grid made by prosumers, while in scenario B, all the electricity units available to be sold is sold in the P2V market. **Figure 9** presents the mean costs for prosumers and EV of scenario B.

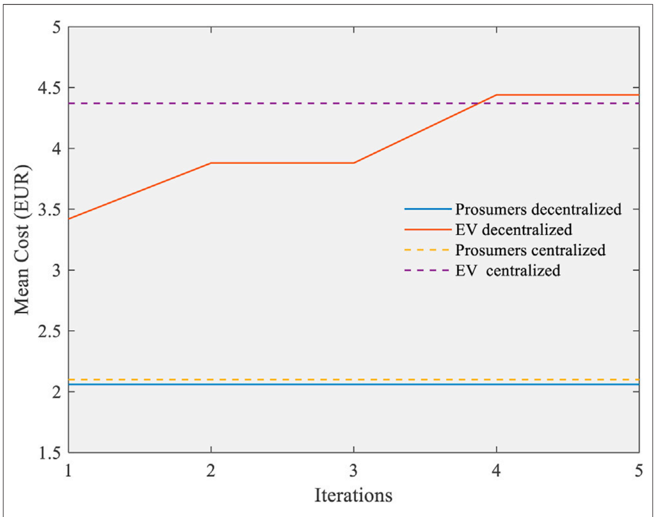

FIGURE 9 | Mean costs of Scenario B.

The mean costs for prosumers and EVs regarding the iterations are presented in **Figure 9**. The mean values for decentralized implementation vary in the case of EV, but in prosumers' case, the value is constant. The mean value of EV increases throughout interactions. In the fifth iteration, the value is higher than the value of the first iteration because they decrease the value of electricity bought in the P2V market, which has a better price for EVs. As the liquidity of electricity is not sufficient for the amount needed by the EVs, they have to buy from the retailer and pay a higher price. Buying at the retailer rates increases the average of electricity costs.

CONCLUSION AND FUTURE WORKS

This study presented a decentralized approach for a prosumer-to-vehicle (P2V) market at a local energy community composed of 90 players [50 prosumers and 40 electric vehicles (EVs)]. The results using the P2V market mechanism show a reduction in the total energy costs and the average costs of each player's type. Comparing the results of centralized with decentralized implementations, the difference in total costs is minimal, but the optimization time difference is significantly higher. Other issues may arise regarding the centralized implementation, such as data privacy. In the case of decentralized implementation, players perform their optimization and only share the values referring to the P2V market. Cyberattacks can also be an important aspect of decentralized implementation. In the centralized implementation, if a cyberattack occurs, the operation of the system can be stopped, leaving users without service. In the case of decentralized systems, as distributed by the various users, an attack will only affect the targeted user, while others remain safe.

The influence of the P2V market depends on the quantity of energy available from the prosumers' side. As can be seen, by using rules created, the EV adapts the electricity bought in the P2V market to the electricity sold to the prosumers in the same market. Most of them have PV installations, and it is possible to assume that enough amount will be available in future. The use of small thermoelectric generation units can be a solution to increase the supply capacity for the P2V market. Still, the higher production costs of those units can be a barrier.

The P2V market allows prosumers to benefit the local distribution grid and the energy community. As a future work, the authors intend to compare this approach with other decentralized methods available in the literature. The authors are considering the possibility to implement the ADMM technique, although the application of this technique involves proof of concepts that sometimes are not possible to obtain and fully prove the convergence of the implementation. Considering dynamic pricing in the P2V market is another relevant aspect worthy to be explored in the future. The inclusion of dynamic pricing in the P2V market can encourage the users to participate in local energy transaction. Participating in such markets could lead to higher benefits for prosumers and the EV owners. In this case, the idea would be to vary the price of electricity in the P2V market with the amount of electricity offered and required. An important aspect that serves as a subject for future work is the study of the vulnerabilities that the system presents in terms of cyber security and the effective mechanisms and measure to protect the users.

DATA AVAILABILITY STATEMENT

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: http://doi.org/10.5281/zenodo.4737293.

AUTHOR CONTRIBUTIONS

JS and RF developed the concept and decentralized optimization model; JS wrote the article and supervised the work; RF wrote the article, implemented the model in TOMLAB, and conducted the experiments; MG wrote the literature review and reviewed the article; JF reviewed the optimization model and rewrote sections of the work; JS, MG, JF, and ZV reviewed the article, ZV and JS supervised the work and the fund acquisition.

FUNDING

This work has received funding from FEDER Funds through COMPETE program and from National Funds through (FCT) under the projects CENERGETIC (PTDC/EEI-EEE/28983/2017), CEECIND/02814/2017 (JS grant), SFRH/BD/133086/2017 (RF PhD grant). We also acknowledge the work facilities and equipment provided by GECAD research center (UIDB/00760/2020) to the project team. Brazilian Federal Agency for Support and Evaluation of Graduate Education (CAPES), in the scope of the Program CAPES-PrInt, process number 88887.310463/2018-00, International Cooperation Project number 5-P2-1479.

ACKNOWLEDGMENTS

We thank our funders and RF for collaborating for CENERGETIC in the scope of pursuing his PhD.

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Conflict of Interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Core Publication V

Ricardo Faia, Tiago Pinto, Zita Vale, and Juan M. Corchado, "Portfolio optimization of electricity markets participation using forecasting error in risk formulation," International Journal Electric Power Energy Systems, vol. 129, 2021, doi: 10.1016/j.ijepes.2020.106739. **(2020 Impact Factor: 4.63)**;

Resumen

Los cambios recientes en el sector de la energía están aumentando la importancia de la optimización de la cartera de clientes para la participación en el mercado. Aunque el problema de optimización de cartera es más popular en finanzas y economía, solo recientemente está siendo objeto de estudio y aplicación en los mercados de electricidad. Sin embargo, el modelado de riesgos en este dominio se está abordando como en el clásico problema de optimización de carteras, donde la diversidad de inversiones es la medida adoptada para mitigar el riesgo. La creciente imprevisibilidad de los precios de mercado como reflejo de la variabilidad de la generación renovable trae una nueva dimensión a la formulación del riesgo, ya que el riesgo de participación en el mercado debe considerar la variación de precios en cada mercado. Este artículo propone así un nuevo modelo de optimización de cartera, considerando un nuevo enfoque para la gestión de riesgos. El problema de asignación de electricidad entre diferentes mercados se formula como un problema clásico de optimización de cartera considerando el error de pronóstico de los precios de mercado como parte del activo de riesgo. Tratar con un problema multiobjetivo conlleva una gran carga computacional y, por esta razón, se aplica un método basado en la optimización de enjambre de partículas (particle swarm optimization en inglés). Un estudio de caso basado en datos reales del mercado eléctrico ibérico demuestra las ventajas del enfoque propuesto para aumentar las ganancias de los actores del mercado y minimizar el riesgo de participación en el mercado.

Core Publication VI

Ricardo Faia, Tiago Pinto, Zita Vale, and Juan M. Corchado, "Prosumer Community Portfolio Optimization via Aggregator: The Case of the Iberian Electricity Market and Portuguese Retail Market," Energies, vol. 14, no. 13, p. 3747, 2021, doi: 10.3390/en14133747. **(2020 Impact Factor: 3.004)**;

Resumen

La participación de los prosumidores domésticos en los mercados mayoristas de electricidad es muy limitada, considerando el límite mínimo de participación impuesto por la mayoría de las reglas de participación en el mercado. La capacidad de generación de los hogares ha ido en aumento ya que la instalación de generación distribuida a partir de fuentes renovables en sus instalaciones aporta ventajas para ellos y para el sistema. Debido al crecimiento del autoconsumo, los operadores de red han ido dejando de lado la compra de energía eléctrica a los hogares, y se ha producido una reducción del precio de estas transacciones. Este artículo propone un modelo innovador que utiliza la agregación de hogares para alcanzar los límites mínimos de volumen de electricidad necesarios para participar en el mercado mayorista. De esta forma, el agregador representa a la comunidad de hogares en las compras y ventas del mercado. Se propone un modelo de optimización de cartera de transacciones de electricidad para permitir que el agregador tome decisiones sobre en qué mercados participar para maximizar los resultados de negociación de estos, considerando el mercado diario, el mercado intradiario y el mercado minorista. Se presenta un caso de estudio considerando el mercado eléctrico mayorista ibérico y el mercado minorista portugués. Para la realización de los experimentos se utiliza una comunidad de 50 prosumidores equipados con generadores fotovoltaicos y sistemas de almacenamiento individual. El enfoque logra una reducción de costos del 6 al 11 % cuando la comunidad de hogares compra y vende electricidad en el mercado mayorista a través del agregador.

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Prosumer Community Portfolio Optimization via Aggregator: The Case of the Iberian Electricity Market and Portuguese Retail Market

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Abstract: The participation of household prosumers in wholesale electricity markets is very limited, considering the minimum participation limit imposed by most market participation rules. The generation capacity of households has been increasing since the installation of distributed generation from renewable sources in their facilities brings advantages for themselves and the system. Due to the growth of self-consumption, network operators have been putting aside the purchase of electricity from households, and there has been a reduction in the price of these transactions. This paper proposes an innovative model that uses the aggregation of households to reach the minimum limits of electricity volume needed to participate in the wholesale market. In this way, the Aggregator represents the community of households in market sales and purchases. An electricity transactions portfolio optimization model is proposed to enable the Aggregator reaching the decisions on which markets to participate to maximize the market negotiation outcomes, considering the day-ahead market, intra-day market, and retail market. A case study is presented, considering the Iberian wholesale electricity market and the Portuguese retail market. A community of 50 prosumers equipped with photovoltaic generators and individual storage systems is used to carry out the experiments. A cost reduction of 6–11% is achieved when the community of households buys and sells electricity in the wholesale market through the Aggregator.

Keywords: aggregator; Iberian electricity market; portfolio optimization; prosumer; Portuguese retail market

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Citation: Faia, R.; Pinto, T.; Vale, Z.; Corchado, J.M. Prosumer Community Portfolio Optimization via Aggregator: The Case of the Iberian Electricity Market and Portuguese Retail Market. *Energies* **2021**, *14*, 3747. https://doi.org/10.3390/en14133747

Academic Editor: Yuji Yamada

Received: 24 May 2021
Accepted: 20 June 2021
Published: 22 June 2021

1. Introduction

Considering the targets imposed by the European Commission [1] about greenhouse gas emission reductions, the installation of distributed generators (DG) based on renewable energy sources (RES) can make a positive contribution to the cause. The successful implementation of national energy policies can contribute also for a global economic growth (one average of 3.4% by 2040) [2]. DG based on RES includes small-scale generation units connected essentiality to distribution grids in low or medium voltage. They can provide challenges and opportunities to the users and participants of the distribution system (utilities, end-users, operators, and retailers) [3]. The use of distributed energy resources (DER) based on RES or non-RES from the costumers side, can improve local dependability, and reduce costs with energy supply [4], from the grid side can minimize the operation costs [5] or help to avoid some expensive investments in planning actions [6]. Due to the price reduction of photovoltaic (PV) systems, the global installed capacity increased from 23 GW

(2009) to 627 GW (2019) [7]. The growth of installed PV systems as DER in households has been supported by various policies, such as feed-in tariffs (FIT), renewable electricity standards, net metering, and auctions [8]. In Portugal, installing PV panels in households has been mainly incentivized through FIT approaches and installation incentives. FITs are experiencing a downward trend in Portugal, in 2015 the FIT was fixed at 0.095 EUR/kWh [9] and 0.045 EUR/kWh in 2020 [10], which correspond to a reduction of 53%. The reduction of FITs can cause uncertainty regarding the installation of PV systems by Portuguese households, and the targets imposed for greenhouse gas emissions may be compromised [11]. On the other hand, reducing FITs can also increase the levels of self-consumption, since the amount received for the export to the national grid does not bring profits [12]. Around the world, the trade war caused the trend of deglobalization to be much more important, influencing energy demand, knowledge and technology commerce, and financial capital flows [13]. These effects can reduce the installation of technologies that make it possible to generate clean energy.

The installation of small or medium-sized DG in Portugal must consider the Portuguese legislation "Decreto-Lei n.º153/2014, 2014" [14] where two different facility types were defined: UPP dedicated to the generation for grid export, and UPAC dedicated for self-consumption. Some challenges are arising for these facilities considering the Portuguese legal framework. In the UPP, the FIT (export grid tariff) has been experiencing a downgrade trend, as identified above, resulting in a reduction in profits of electricity exported to the grid, leading to the consideration of different alternatives to export electricity. In the UPAC, the surplus electricity of self-consumption is exported to the grid without costs 0.00 EUR/kWh. Therefore, no payment is received for the exported electricity. In this case, different options for exporting the surplus electricity should be considered, as well as Portuguese legislation suggests the use of market facilitators to transact electricity in wholesale electricity markets.

The participation in wholesale electricity markets is restricted to players with a great volume to trade, e.g., in the MIBEL electricity market, a minimum value of 1 MW is required to submit any bid (buy or sell). Solutions like virtual power producers (VPP) [15] represent small aggregate DGs to achieve the minimum bidding quantity in the Wholesale electricity markets. Based on the same approach of VPP, the Aggregator entity has emerged with greater popularization with the association with demand response (DR) actions [16]. The term VPP was used to represent small generators in wholesale markets, thus enabling their participation, as it was impossible in isolation. The Aggregator performs the same functions as the VPP although currently it can perform energy service provider functions, where in addition to wholesale market participation it can also provide DR services and also battery system management. Considering the DR capabilities of households, the Aggregator can manage flexible loads, reducing household energy costs [17].

Participation in the wholesale market via Aggregator is not a new concept [16,18–24] however they usually only consider one asset. Works [16,21] use the well-known DR asset to participate in the market. Reference [18] uses heat pumps as an asset for flexibility acquisition to participate in the EPEX market (Netherlands). Electrical vehicles (EV) are used in [19] by an Aggregator to participate in ancillary services in Quito, Ecuador. Another application involving EVs and their aggregation is presented in [22], in this work the flexibility of EVs to participate in reserve markets is used. In [20], an aggregated model of RES is used to participate in a real-time market. At industrial level the aggregator can also perform some services, such as this approach [23] where its services are used to facilitate industrial demand response. In reference [24], the authors propose a framework for comprehensive market participation of DER Aggregators. Different kind aggregators are modelled by the DSO, including energy storage aggregators, dispatchable distributed generation aggregators, electric vehicle charging stations, and demand response aggregators. The presented work has the same purpose as this work, but the Aggregator uses the household as a hold to participate in the wholesale market. On the other hand, the model proposed in this work does not combine just one asset but a set of them (PV production, energy storage system, and flexibility). Another relevant issue of this work is its application in a real setting, like in [18]. References [25–27] presented the wholesale market's participation in the Electricity Iberian Market (Mibel) as also presented in this work. The presented paper compared with [26,27] describes an innovation, which considers the day-ahead spot market and the intraday sessions. Ref. [25] uses a non-deterministic resolution to solve the problem, which can compromise the results and provoke losses for the user. The model proposed in the current paper solves this problem using a deterministic method that guarantees the optimal global best result. Aggregators' activities in the electricity system and electricity markets have been widely explored, showing positive results in theoretical applications but also real simulations. The study [28] concludes that more guidance is needed for convergence on a more harmonized approach.

Considering this study's aim, the Aggregator represents the market's facilitator (enunciated by Portuguese legislation), finding the best opportunity to export the surplus electricity. This paper offers an optimization model to minimize the energy costs of an energy community, considering the possibility of buying or selling electricity in the wholesale electricity market via an Aggregator. The model also allows the management of PV-battery systems to take the most advantages of them. Figure 1 presents a scheme of the proposed approach.

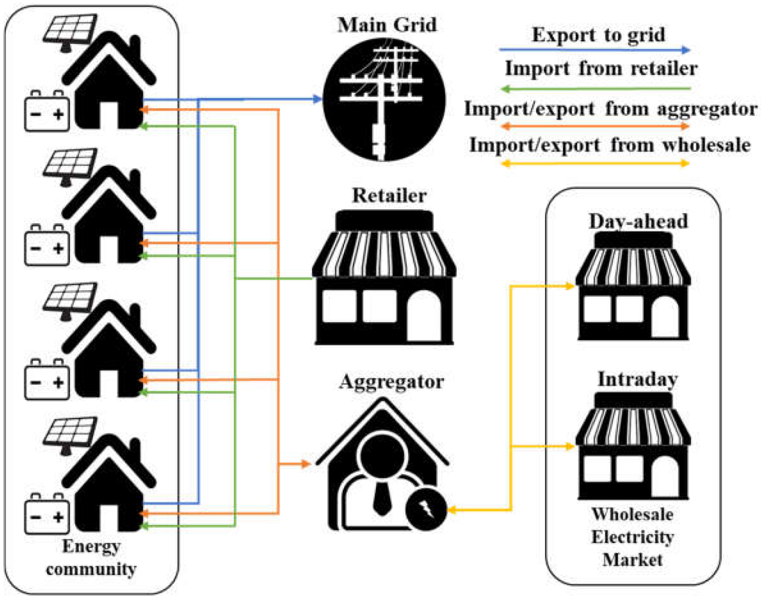


Figure 1. Proposed approach.

As can be seen in Figure 1 the proposed approach considers an energy community, a retailer and wholesale electricity market, an Aggregator, and the main grid. Prosumers constitute the energy community, and each of them can be equipped with PV panels and storage units. Prosumers can purchase electricity in the retail market and wholesale market, and also sell its electricity to the main grid and, also in the wholesale market. To participate in the wholesale market, a minimum quantity of participation is needed, to overcome this issue, an Aggregator represents the energy community in the wholesale market. The Aggregator's business is to buy and sell electricity in the wholesale market, receiving each prosumer's fee. As main contributions of this work, the following aspects are highlighted:

- An optimization model that jointly solves the minimization of the operating costs (energy usage) of an energy community and the optimal participation of an Aggregator in the Spot market and intraday sessions.
- A real scenario (prices and condition of participation) is modeled considering the Portuguese retail market and MIBEL wholesale electricity market.

- A thorough analysis of different case studies, demonstrating interesting insights on the importance of Aggregator participating in the wholesale electricity market.
- A consumer-centric approach that can bring empowerment of small electricity end-users in the power systems.

The rest of the paper is organized into five different sections. Section 2 presents the participation conditions in the MIBEL wholesale market and Portuguese distributed generation installation options. The mathematical formulation of the model is explained in Section 3. In Section 4, the case studies and respective characterization are presented. The achieved results using the proposed model in the case studies are presented in Section 5. Finally, conclusions and future works are drawn in Section 6.

2. Legal Framework

This section presents the legal framework to participate in the wholesale market and rules imposed by the Portuguese legislation to install distributed generation in end-consumers facilities.

2.1. MIBEL Operation

As most wholesale electricity markets in Europe, MIBEL is divided into day-ahead and intraday sessions. MIBEL also has a particularity for trading electricity in future markets. The asset (electricity) may not require physical delivery, and the negotiation is considered for a later date.

Considering the day-ahead spot market, the players should submit their bids until the gate close (12:00 of day d), after that they cannot modify their bids. Two different types of bids are available, one from the demand side and the other from the generation side, each of these types of bids is comprised of a price and energy volume for a specific hour. The equilibrium between the demand curve and generation curves determines the price and the volume transacted in each hour of the day ahead spot market. Figure 2 presents the negotiation options in the MIBEL market. The day-ahead spot market is available for 24 h. The MIBEL market option in intraday has six different sessions, represented in Figure 2.

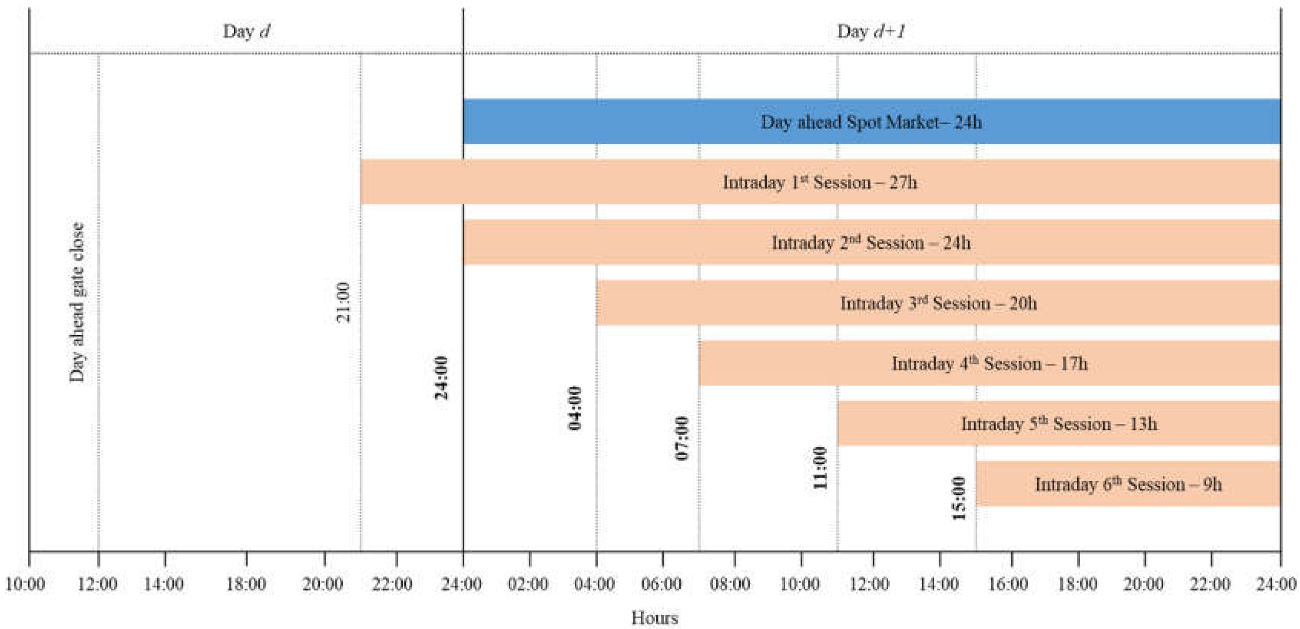


Figure 2. Negotiation options in the MIBEL market.

The intraday sessions have the same day-ahead operation mode, but the bids process submissions have different times. In the six different sessions, presented in the Figure 2, the agents can adjust their generation and consumption schedules to adapt to the new forecasts or unpredicted events.

The MIBEL wholesale market contains two different operators, the OMIE and OMIP. OMIE represents the market operator for the management of day-ahead and intraday electricity markets of the Iberian Peninsula. OMIP corresponds to the market operator for the derivatives exchange energy market, namely, futures, forwards, swap and options. The stock associated with these contracts is electricity and natural gas. In the MIBEL market, only physical agents located in Portugal and Spain can participate. Due to the physical restrictions of interconnection between the two countries, there may be a separation from the wholesale market, and each country can have a different electricity price.

2.2. Distributed Generation in Portugal

According to the Decreto-Lei n.º153/2014, 2014 [14] (Portuguese regulation) there are two types of distributed generation in consumers facilities the UPP (Portuguese acronym for units of small generation) and UPAC (Portuguese acronym for units of small generation for self-consumption). UPP facilities are dedicated to electricity generation from renewable sources using only one generation technology, where the connection to the main grid is equal to or less than 250 kW. All the electricity generated must be sold in full to the main grid, but must be equal to or less than 50% of the consumer's electricity consumption. Figure 3 presents typical UPP connection schemes.

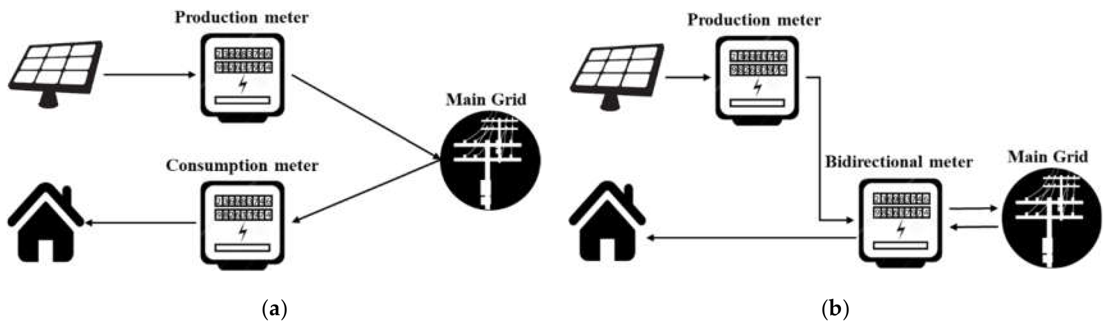


Figure 3. UPP schemes, (**a**) Two unidirectional meters, and (**b**) One unidirectional and one bidirectional meter.

Figure 3a meters only accepted unidirectional power flows, the production has a meter, and the consumption has another. Figure 3b has two meters, but one of them is only for production, the other is bidirectional and allows the power flow in both directions. Three different categories of UPP are available. Category I consists of producers that install a small generation unit, category II comprises producers with a small generation unit and an electric vehicle charging station, and category III represents producers with a small generation unit and solar thermal accumulator. Portaria n.º 80/2020 [10] defines 45 EUR/MW (0.045 EUR/kW) as the reference tariff that corresponds to the payment that producers receive from each unit of electricity exported to the grid.

UPAC is defined as being electricity generation facilities from renewable and non-renewable sources used primarily for self-consumption, with the possibility of connection to the grid for sale. The surplus energy from self-consumption can be traded in the wholesale market with the help of an Aggregator. Figure 4 presents typical UPAC connection schemes.

In Figure 4a there are two different meters, and the generation power installed is greater than 1.5 kW. When the generation power installed is equal to or less than 1.5 kW the facility only needs a single meter as seen in Figure 4b where there is no possibility of exporting electricity to the grid.

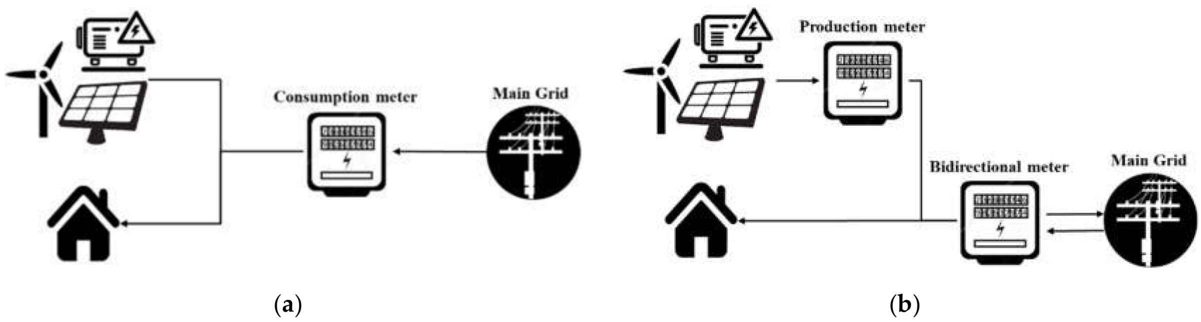


Figure 4. UPAC schemes, (**a**) One unidirectional meter, and (**b**) One unidirectional meter and one bidirectional meter.

3. Proposed Model

3.1. Model Overview

The proposed model considers an energy community that intends to minimize the costs of electricity usage, and able community members to buy and sell electricity in different markets. The model considers the Aggregator operation, which is responsible for representing the energy community in the wholesale market (day-ahead and intraday sessions) and also for determining the best scheduling the usage of the battery storage system installed in each household. The retail market is used by households as a backup where they can purchase electricity when needed, or when wholesale market participation is not advantageous. The public network is responsible for absorbing the feed-in electricity provided by each household when the Aggregator cannot sell in the wholesale market.

The considered wholesale market refers to the MIBEL operator which is divided into day-ahead and 6 intraday sessions. The Aggregator is responsible for complying with the rules imposed for participation in the wholesale market. The presented model considers that a minimum value of electricity is required to participle in the wholesale market, according to MIBEL participation rules. For the energy community in the study, the minimum can be reduced. The Aggregator has other methods to obtain more electricity for participation when it is required. The rule imposed by the market operator regarding the participation in intraday sessions is only valid if the participation in the wholesale market, is not considered in this model, however, the Aggregator has to comply with this rule.

3.2. Formulation

Equation (1) presents the objective function of the problem. The objective function minimizes the sum of the total operating costs of all energy community members.

$$minimize\ obf = SM_{costs} + IDS_{costs} + R_{costs} + AGG_{income} \tag{1}$$

where, SM_{costs} represents the spot market costs, IDS_{costs} represents the intraday sessions costs, R_{costs} represents the retailer's costs and AGG_{income} represents Aggregator income. Equation (2) presents the calculation of the cost for the spot market.

$$SM_{costs} = \sum_{i=1}^{Ni} \sum_{t=1}^{Nt} \left(\left(p_{i,t}^{SM\ buy} - p_{i,t}^{SM\ sell} \right) \times \pi_{i,t}^{SM} \right) \tag{2}$$

where, $p_{i,t}^{SM\ buy}$ represents the electricity purchased in the spot market, $p_{i,t}^{SM\ sell}$ represents the electricity sold in the spot market, $\pi_{i,t}^{SM}$ corresponds to the price of electricity in the spot market, i is the respective player, t the respective period, Ni the numbers of players, and Nt the numbers of periods. Only one option of sell or buy can be applied at the same time. Equation (3) presents the calculation of the costs in intraday sessions.

$$IDS_{costs} = \sum_{i=1}^{Ni} \sum_{t=1}^{Nt} \sum_{s=1}^{Ns} \left(\left(p_{i,t,s}^{IDS\ buy} - p_{i,t,s}^{ISD\ sell} \right) \times \pi_{i,t,s}^{IDS} \right) \tag{3}$$

where, $p_{i,t,s}^{IDS\ buy}$ represents the electricity purchased in intraday sessions, $p_{i,t,s}^{ISD\ sell}$ represents the electricity sold in the intraday session, $\pi_{i,t,s}^{IDS}$ corresponds to the price of electricity in intraday session, s is the respective session and Ns represents the number of intraday sessions. Equation (4) presents the costs in the retailer market.

$$R_{costs} = \sum_{i=1}^{Ni} \sum_{t=1}^{Nt} \left(p_{i,t}^{R\ buy} \times \pi_{i,t}^{TOU} - p_{i,t}^{Grid\ sell} \times \pi_{i,t}^{FIT} \right) + FixedCosts_i \tag{4}$$

where, $p_{i,t}^{R\ buy}$ represents the electricity purchased in the retail market, $\pi_{i,t}^{TOU}$ is the price of purchased electricity denominated as time of use tariff, $p_{i,t}^{Grid\ sell}$ represents the electricity sells in the grid, $\pi_{i,t}^{FIT}$ is the price of selling electricity to the grid denominated the feed-in tariff and $FixedCosts_i$ represents the fixed costs that users should pay to retailers for the supply guarantees. Equation (5) presents the Aggregator income calculation.

$$AGG_{income} = \sum_{i=1}^{Ni} \sum_{t=1}^{Nt} \left(p_{i,t}^{SM\ buy} + p_{i,t}^{SM\ sell} + p_{i,t,s}^{IDS\ buy} + p_{i,t,s}^{ISD\ sell} \right) \times Fee^{AGG} \tag{5}$$

where, Fee^{AGG} represents the fee in EUR per Kilowatt that the Aggregator charges for the aggregated user participation in the spot market and intraday sessions. Equation (6) presents the balanced equation for each user.

$$\begin{gathered} p_{i,t}^{gen} + p_{i,t}^{dch} + p_{i,t}^{SM\ buy} + \sum_{s=1}^{Ns} p_{i,t,s}^{IDS\ buy} + p_{i,t}^{R\ buy} = \\ p_{i,t}^{load} + p_{i,t}^{ch} + p_{i,t}^{SM\ sell} + \sum_{s=1}^{Ns} p_{i,t,s}^{IDS\ sell} + p_{i,t}^{Grid\ sell}, \\ \forall i \in Ni,\ \forall t \in Nt \end{gathered} \tag{6}$$

where, $p_{i,t}^{gen}$ represents the electricity generated, $p_{i,t}^{dch}$ represents the electricity discharged from the battery, $p_{i,t}^{load}$ represents the load of each end-user, and $p_{i,t}^{ch}$ is the electricity that charges the battery. Equations (7)–(9) represent the constraints applied to the spot market for each user.

$$p_{i,t}^{SM\ buy} \le x_{i,t}^{SM\ buy} \times p_{i,t}^{SM\ max\ buy}, \forall i \in Ni,\ \forall t \in Nt \tag{7}$$

$$p_{i,t}^{SM\ sell} \le x_{i,t}^{SM\ sell} \times p_{i,t}^{SM\ max\ sell}, \forall i \in Ni,\ \forall t \in Nt \tag{8}$$

$$x_{i,t}^{SM\ buy} + x_{i,t}^{SM\ sell} \le 1, \forall i \in Ni,\ \forall t \in Nt \tag{9}$$

where, $x_{i,t}^{SM\ buy}$ represents a binary variable for the individual spot market buy action, $p_{i,t}^{SM\ max\ buy}$ represent the maximum individual limit for each user to buy electricity in the spot market, $x_{i,t}^{SM\ sell}$ represents a binary variable for the individual spot market sell action and $p_{i,t}^{SM\ max\ sell}$ represents the maximum individual limit for each user sell electricity in the spot market. Equation (9) imposes that it is only possible to buy or sell in the spot market. Equations (10) and (11) represent global constraints for participation in the spot market.

$$L^{SM\ buy} \le \sum_{i=1}^{Ni} p_{i,t}^{SM\ buy} \times X_t^{SM\ buy} + L^{SM\ buy} \times \left(1 - X_t^{SM\ buy}\right), \forall t \in Nt \tag{10}$$

$$L^{SM\ sell} \le \sum_{i=1}^{Ni} p_{i,t}^{SM\ sell} \times X_t^{SM\ sell} + L^{SM\ sell} \times \left(1 - X_t^{SM\ sell}\right), \forall t \in Nt \tag{11}$$

where, $L^{SM\ buy}$ represents the minimum amount of electricity necessary to purchase electricity in the spot market, $X_t^{SM\ buy}$ represents the global binary variable to participate in the spot market, $L^{SM\ sell}$ represents the minimum amount of electricity necessary to sell electricity in the spot market and $X_t^{SM\ sell}$ represents the global binary variable to participate in the spot market. Equations (10) and (11) allows that when each binary variable $X_t^{SM\ buy}$ and $X_t^{SM\ sell}$ is active, the minimum amount should be respected. In the other case, the constraint is also satisfied. Equations (12)–(14) represent the constraints applied to the intraday sessions for each user.

$$p_{i,t,s}^{IDS\ buy} \leq x_{i,t,s}^{IDS\ buy} \times p_{i,t,s}^{IDS\ max\ buy} \times A_{t,s}^{IDS}, \forall i \in Ni,\ \forall t \in Nt,\ \forall s \in Ns \tag{12}$$

$$p_{i,t,s}^{IDS\ sell} \leq x_{i,t,s}^{IDS\ sell} \times p_{i,t,s}^{IDS\ max\ sell} \times A_{t,s}^{IDS}, \forall i \in Ni,\ \forall t \in Nt,\ \forall s \in Ns \tag{13}$$

$$x_{i,t,s}^{IDS\ buy} + x_{i,t,s}^{IDS\ sell} \leq 1, \forall i \in Ni,\ \forall t \in Nt,\ \forall s \in Ns \tag{14}$$

where, $x_{i,t,s}^{IDS\ buy}$ represent the binary variable for the individual intraday session buy action, $p_{i,t,s}^{IDS\ max\ buy}$ represents the maximum electricity amount limit to buy in intraday sessions, $A_{t,s}^{IDS}$ is an input binary parameter that indicates the availability of each intraday session, $x_{i,t,s}^{IDS\ sell}$ represent the binary variable for the individual intraday session sell action and $p_{i,t,s}^{IDS\ max\ sell}$ represents the maximum electricity amount limit to sell in intraday sessions. Equation (14) imposes that it is only possible to buy or sell in the intraday session. Equations (15)–(18) represent global constraints for participation in intraday sessions.

$$L_s^{IDS\ buy} \leq \sum_{i=1}^{Ni} p_{i,t,s}^{IDS\ buy} \times X_{t,s}^{IDS\ buy} + L_s^{IDS\ buy} \times \left(1 - X_{t,s}^{IDS\ buy}\right), \forall t \in Nt,\ \forall s \in Ns \tag{15}$$

$$L_s^{IDS\ sell} \leq \sum_{i=1}^{Ni} p_{i,t,s}^{IDS\ sell} \times X_{t,s}^{IDS\ sell} + L_s^{IDS\ sell} \times \left(1 - X_{t,s}^{IDS\ sell}\right), \forall t \in Nt,\ \forall s \in Ns \tag{16}$$

$$\sum_{s=1}^{Ns} X_{t,s}^{IDS\ buy} \leq 1,\ \forall t \in Nt \tag{17}$$

$$\sum_{s=1}^{Ns} X_{t,s}^{IDS\ sell} \leq 1,\ \forall t \in Nt \tag{18}$$

where, $L_s^{IDS\ buy}$ represents the minimum amount of electricity needed to purchase electricity in intraday sessions, $X_{t,s}^{IDS\ buy}$ represents the global binary variable to participate in the intraday session to purchase electricity, $L_s^{IDS\ sell}$ represents the minimum amount of electricity necessary to sell in intraday sessions, $X_{t,s}^{IDS\ sell}$ represents the global binary variable to participate to sell in the intraday session. Equations (15) and (16) performs the same process of Equations (10) and (11). Equations (17) and (18) allow the sale or purchase of electricity in one of the intraday sessions. Equations (19)–(21) represent the constraints applied to the retail market for each user.

$$p_{i,t}^{R\ buy} \leq x_{i,t}^{R\ buy} \times p_{i,t}^{R\ max\ buy}, \forall i \in Ni,\ \forall t \in Nt \tag{19}$$

$$p_{i,t}^{Gird\ sell} \leq x_{i,t}^{Grid\ sell} \times p_{i,t}^{Grid\ max\ sell}, \forall i \in Ni,\ \forall t \in Nt \tag{20}$$

$$x_{i,t}^{R\ buy} + x_{i,t}^{Grid\ sell} \leq 1, \forall i \in Ni,\ \forall t \in Nt \tag{21}$$

where, $x_{i,t}^{R\ buy}$ represents the individual variable for the retailer by action, $p_{i,t}^{R\ max\ buy}$ represents the maximum limit to purchase electricity from a retailer, $x_{i,t}^{Grid\ sell}$ represents the individual variable to sell electricity in the grid, $p_{i,t}^{Grid\ max\ sell}$ represents the maximum quantity to sell electricity in the grid. Equation (21) imposes that it is only possible to buy in the retail market or sell to the grid. Equation (22) represents the constraints applied to buying and selling electricity in different markets in the same period.

$$x_{i,t}^{SM\ buy} + \sum_{s=1}^{Ns} x_{i,t,s}^{IDS\ sell} \leq 1, \forall i \in Ni,\ \forall t \in Nt \tag{22}$$

$$x_{i,t}^{SM\ buy} + x_{i,t}^{Grid\ sell} \leq 1, \forall i \in Ni,\ \forall t \in Nt \tag{23}$$

$$\sum_{s=1}^{Ns} x_{i,t,s}^{IDS\ buy} + x_{i,t}^{Grid\ sell} \leq 1, \forall i \in Ni,\ \forall t \in Nt \tag{24}$$

$$\sum_{s=1}^{Ns} x_{i,t,s}^{IDS\ buy} + x_{i,t}^{SM\ sell} \leq 1, \forall i \in Ni,\ \forall t \in Nt \tag{25}$$

$$x_{i,t}^{R\ buy} + \sum_{s=1}^{Ns} x_{i,t,s}^{IDS\ sell} \leq 1, \forall i \in Ni,\ \forall t \in Nt \tag{26}$$

$$x_{i,t}^{R\ buy} + x_{i,t}^{SM\ sell} \leq 1, \forall i \in Ni,\ \forall t \in Nt \tag{27}$$

Equation (28) represents the energy storage system balance.

$$p_{i,t}^{Bat} = p_{i,t-1}^{Bat} + p_{i,t}^{ch} \times \eta_i^{ch} - p_{i,t}^{dch} \times \frac{1}{\eta_i^{dch}}, \forall i \in Ni,\ \forall t \in Nt \tag{28}$$

where, $p_{i,t}^{Bat}$ represents the status of the battery, η_i^{ch} represents the efficiency of a charge action, and η_i^{dch} represents the efficiency of the discharge action. Equations (29)–(31) present constraints applied to the battery charge and discharge actions.

$$p_{i,t}^{ch} \leq p_{i,t}^{ch\ max} \times x_{i,t}^{ch}, \forall i \in Ni,\ \forall t \in Nt \tag{29}$$

$$p_{i,t}^{dch} \leq p_{i,t}^{dch\ max} \times x_{i,t}^{dch}, \forall i \in Ni,\ \forall t \in Nt \tag{30}$$

$$x_{i,t}^{ch} + x_{i,t}^{dch} \leq 1, \forall i \in Ni,\ \forall t \in Nt \tag{31}$$

where, $p_{i,t}^{ch\ max}$ represents the maximum value for charge action, $x_{i,t}^{ch}$ represents the binary variable for the charge action, $p_{i,t}^{dch\ max}$ represents the maximum value for the discharge action and $x_{i,t}^{dch}$ represents the binary variable for the discharge action. Equation (31) presents the constraints applied to control the charge and discharge of the batteries in the same period, Equations (32)–(40) present the limits for the continuous variables of the problem.

$$0 \leq p_{i,t}^{SM\ buy} \leq p_{i,t}^{SM\ max\ buy}, \forall i \in Ni,\ \forall t \in Nt \tag{32}$$

$$0 \leq p_{i,t}^{SM\ sell} \leq p_{i,t}^{SM\ max\ sell}, \forall i \in Ni,\ \forall t \in Nt \tag{33}$$

$$0 \leq p_{i,t,s}^{IDS\ buy} \leq p_{i,t,s}^{IDS\ max\ buy}, \forall i \in Ni,\ \forall t \in Nt,\ \forall s \in Ns \tag{34}$$

$$0 \leq p_{i,t,s}^{IDS\ sell} \leq p_{i,t,s}^{IDS\ max\ sell}, \forall i \in Ni,\ \forall t \in Nt,\ \forall s \in Ns \tag{35}$$

$$0 \leq p_{i,t}^{R\ buy} \leq p_{i,t}^{R\ max\ buy}, \forall i \in Ni,\ \forall t \in Nt \tag{36}$$

$$0 \leq p_{i,t}^{Grid\ sell} \leq p_{i,t}^{Grid\ max\ sell}, \forall i \in Ni,\ \forall t \in Nt \tag{37}$$

$$0 \leq p_{i,t}^{dch} \leq p_{i,t}^{dch\ max}, \forall i \in Ni,\ \forall t \in Nt \tag{38}$$

$$0 \leq p_{i,t}^{ch} \leq p_{i,t}^{ch\ max}, \forall i \in Ni,\ \forall t \in Nt \tag{39}$$

$$p_{i,t}^{Bat\ min} \leq p_{i,t}^{Bat} \leq p_{i,t}^{Bat\ max}, \forall i \in Ni,\ \forall t \in Nt \tag{40}$$

where, $p_{i,t}^{Bat\ min}$ represents the minimum possible limit for the battery level and $p_{i,t}^{Bat\ max}$ represents the maximum possible limit for the battery level. Equations (41)–(52) represent the minimum and maximum limit for the binary variables.

$$0 \le x_{i,t}^{SM\ buy} \le 1, \forall i \in Ni,\ \forall t \in Nt \tag{41}$$

$$0 \le x_{i,t}^{SM\ sell} \le 1, \forall i \in Ni,\ \forall t \in Nt \tag{42}$$

$$0 \le X_{t}^{SM\ buy} \le 1, \forall t \in Nt \tag{43}$$

$$0 \le X_{t}^{SM\ sell} \le 1, \forall t \in Nt \tag{44}$$

$$0 \le x_{i,t,s}^{IDS\ buy} \le 1, \forall i \in Ni,\ \forall t \in Nt,\ \forall s \in Ns \tag{45}$$

$$0 \le x_{i,t,s}^{IDS\ sell} \le 1, \forall i \in Ni,\ \forall t \in Nt,\ \forall s \in Ns \tag{46}$$

$$0 \le X_{t,s}^{IDS\ buy} \le 1, \forall t \in Nt,\ \forall s \in Ns \tag{47}$$

$$0 \le X_{t,s}^{IDS\ sell} \le 1, \forall t \in Nt,\ \forall s \in Ns \tag{48}$$

$$0 \le x_{i,t}^{R\ buy} \le 1, \forall i \in Ni,\ \forall t \in Nt \tag{49}$$

$$0 \le x_{i,t}^{Grid\ sell} \le 1, \forall i \in Ni,\ \forall t \in Nt \tag{50}$$

$$0 \le x_{i,t}^{ch} \le 1, \forall i \in Ni,\ \forall t \in Nt \tag{51}$$

$$0 \le x_{i,t}^{dch} \le 1, \forall i \in Ni,\ \forall t \in Nt \tag{52}$$

4. Case Study

Three different case studies are created to evaluate the application of the proposed model. The objective is to compare the market participation results of prosumers when considering an all-encompassing approach (case study 1 (CS1)) that includes the market opportunities for an installation without considering the rules imposed to both UPP and UPAC, the UPP—case study 2 (CS2)) and UPAC—case study 3 (CS3), according to the Portuguese regulation; and. Table 1 presents an overview of the considered case studies.

Table 1. Case study conditions overview.

				CS 1	CS 2	CS 3
					UPP	UPAC
Scenario 1	Buy		Retailer	Yes	Yes	Yes
	Sell		RESP *	Yes	All	No
		Self-consumption		Yes	No	Yes
Scenario 2	Buy	Retailer		Yes	Yes	Yes
		MIBEL via AGG	Spot	Yes	Yes	Yes
			Intra-Day	Yes	Yes	Yes
	Sell	RESP *		Yes	Yes	No
		MIBEL via AGG	Spot	Yes	No	Yes
			Intra-Day	Yes	No	Yes
		Self-consumption		Yes	No	Yes

* public electricity network.

As seen in Table 1 the case studies are CS1, CS2, and CS3, in all case study two different scenarios are implemented, one considering the normal operation without the possibility of trading electricity in the wholesale market (basis approach), and one considering the use of an Aggregator to trade electricity in the wholesale market (proposed approach). The UPP and UPAC case studies comply with the Portuguese legislation in both scenarios (basis and proposed approach). Thereby, in total, six different scenarios are simulated.

The all-encompassing case (CS1) considers the formulation presented in Section 3.2, in which there are no restrictions related to UPP or UPAC for trading electricity. The specificities of UPP (CS2) and UPAC (CS3) conditions require some modifications in the formulation, as follows.

In CS2, the UPP conditions explained in Section 2.2 are simulated. To model the UPP conditions, Equation (6) must be modified. Equations (53) and (54) replace Equation (6).

$$p_{i,t}^{dch} + p_{i,t}^{SM\ buy} + \sum_{s=1}^{Ns} p_{i,t,s}^{IDS\ buy} + p_{i,t}^{R\ buy} = p_{i,t}^{load} + p_{i,t}^{ch}, \forall i \in Ni,\ \forall t \in Nt \tag{53}$$

Equation (53) is very similar to Equation (6), but as UPP must inject into the grid all generated electricity the power generated $p_{i,t}^{gen}$ and $p_{i,t}^{Grid\ sell}$ don't take part of the energy balance. Equation (54) imposes the condition that all electricity generated should be injected into the grid.

$$p_{i,t}^{gen} = p_{i,t}^{Grid\ sell},\ \forall i \in Ni,\ \forall t \in Nt \tag{54}$$

In the case of UPAC (CS3) the electricity should be used for self-consumption or can be sold in a wholesale market considering an aggregated entity. Equation (55) replaces Equation (6) of the generic formulation.

$$\begin{gathered} p_{i,t}^{gen} + p_{i,t}^{dch} + p_{i,t}^{SM\ buy} + \sum_{s=1}^{Ns} p_{i,t,s}^{IDS\ buy} + p_{i,t}^{R\ buy} = \\ p_{i,t}^{load} + p_{i,t}^{ch} + p_{i,t}^{SM\ sell} + \sum_{s=1}^{Ns} p_{i,t,s}^{IDS\ sell}, \forall i \in Ni,\ \forall t \in Nt \end{gathered} \tag{55}$$

Equation (55) represents the energy balance for a UPAC facility where the $p_{i,t}^{Grid\ sell}$ variable withdrawn, and the electricity sales are only allowed in the spot market or intraday sessions.

An energy community with 50 prosumers is considered in the case study. It is important to note that the minimum amount required to participate in the MIBEL market has been reduced to 200 kW, as the legally required amount of 1000 kW (1 MW) would be impossible to obtain with the 50 prosumers. Figure 5 presents the accumulated consumption and generation of total energy community members, the values are randomly generated using the database used in [29].

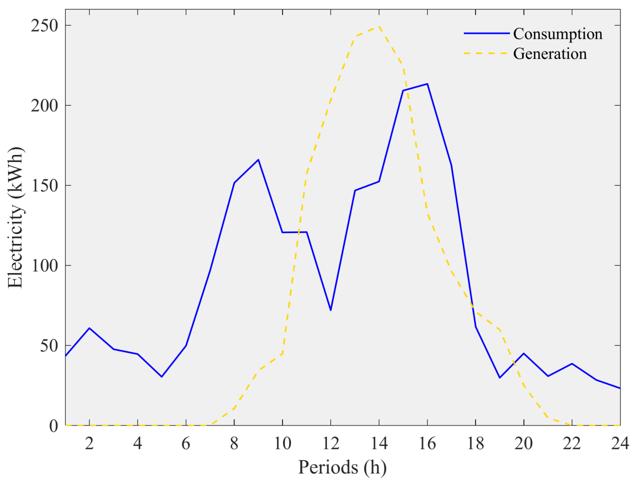
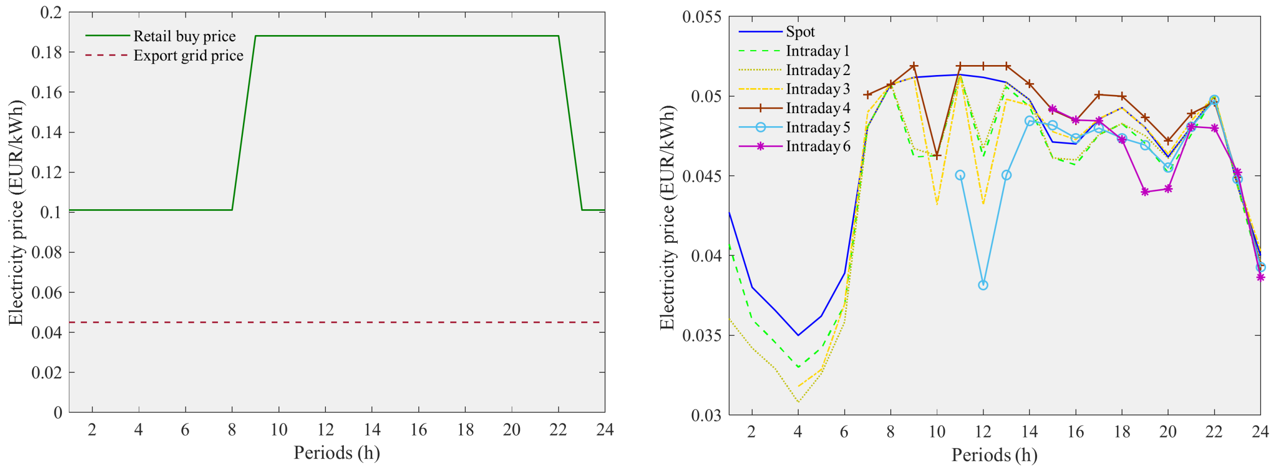


Figure 5. Consumption and generation profile of the energy community.

The total consumption for the referred periods is 2145.59 kWh per day, which corresponds to an average of 89 kWh per hour. The energy community has installed 261 kWp of PV generations and is generated 1556.59 kWh per day in the 24 periods, an average of 64 kWh per hour. It was verified two different peaks of consumption, in the morning (09:00 h) and the afternoon (17:00 h). Figure 6 presents the electricity prices used in the simulations.



(**a**) (**b**)

Figure 6. Electricity prices, (**a**) retail market, and (**b**) wholesale market.

Figure 6a presents the retailer's electricity price provided by the EDP retailer and the export grid price considering the Portuguese legislation. A bi-horary tariff with two different periods and days is used, the period off-peak (23.00 to 08.00) and peak (09.00 to 22.00). Figure 6b presents the wholesale market price for the spot market and in the six intraday sessions, corresponding to real prices of September 01 of 2020 obtained with online access to the OMIE website [30]. In the wholesale market, the price has high variability. Figure 7 presents contracted power and battery characteristics used by the prosumers.

Figure 7a presents the contracted power limits for the community member, the contracted power limits are established by the retailer and selected by the consumers. The community members use five different contracting powers. Export power limits correspond to the limit available to inject electricity into the grid. This limit also available in Figure 7a is imposed by Portuguese legislation [10] and corresponds to half of the contracted power. Figure 7b presents the batteries' characteristics and represents the battery capacity and charge/discharge capacity. Five different batteries are used in the case study and were randomly distributed among community members, the efficiency of charge and discharge actions is considered 90%.

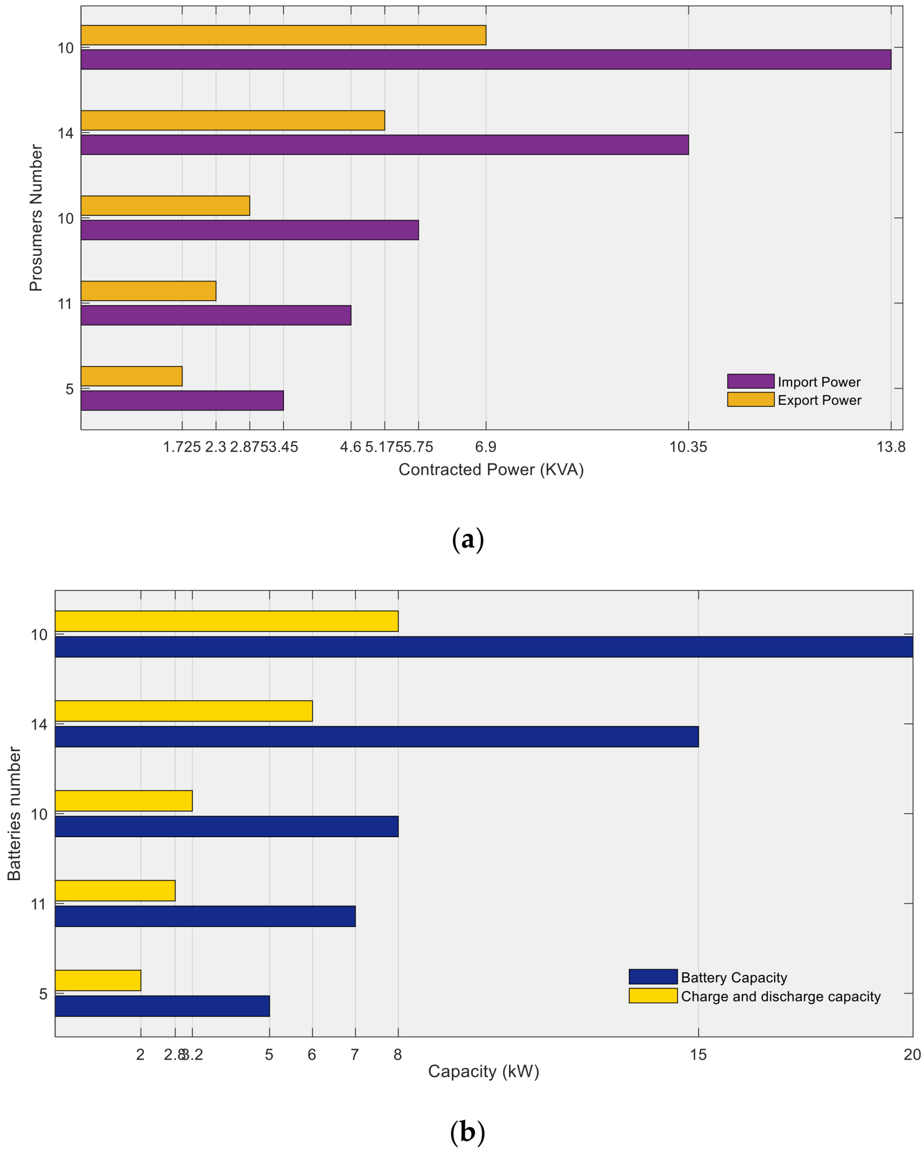


Figure 7. Prosumers characteristics, (**a**) Contracted power limits and (**b**) batteries characteristics.

5. Results

This section presented the results of the proposed methodology. The simulations were carried out on a computer with an Intel Xeon(R) E5-2620v2@2.1 GHz processor with 16 GB of RAM running Windows 10. To implement the optimization problem, a MATLAB2018a with TOMLAB optimization toolbox is used. CPLEX is the solver used to optimize the problem. Six different variants are constructed considering the possibility of transacting electricity in the wholesale market via Aggregator. A list of variants is presented below:

- Scen1-CS1—All-encompassing, without the possibility of transacting electricity in the wholesale market.
- Scen1-CS2—UPP without the possibility of transacting electricity in the wholesale market.
- Scen1-CS3—UPAC without the possibility of transacting electricity in the wholesale market.
- Scen2-CS1—All-encompassing, with the possibility of transacting electricity in the wholesale market.
- Scen2-CS2—UPP with the possibility of transacting electricity in the wholesale market.
- Scen2-CS3—UPAC with the possibility of transacting electricity in the wholesale market.

In variants Scen1-CS1, CS2 and CS3, the Aggregator only does the management of the battery systems. Scen1-CS1, CS2, and CS3 the Aggregator can transact electricity in the wholesale market, buying electricity to supply the needs of the energy community or selling surplus electricity. In all scenarios, the FIT (export grid price) is established at 0.045 EUR/kWh, according to the Portuguese legislation [10]. Table 2 presents the comparison of the results of operation costs, considering the scenarios defined previously.

Table 2. Optimization Results.

Variants		Type	Wholesale Market	Total Costs (EUR)	Average Costs (EUR)	Time (s)
Scen1	CS1	All-encompassing	No	117.41	2.15	2.34
	CS2	UPP	No	278.48	5.57	1.93
	CS3	UPAC	No	130.50	2.61	2.18
Scen2	CS1	All-encompassing	Yes	104.66	2.09	225.19
	CS2	UPP	Yes	262.80	5.26	10.68
	CS3	UPAC	Yes	117.76	2.36	583.23

Table 2 presents all results for the six scenarios implemented, the scenario of the group presents the scenario where the possibility of transacting electricity in the wholesale market is unavailable. In variants of Scen2, the possibility of transacting electricity in the wholesale market is available. Scen1-CS1 presents a reduction of 58% and 10% compared with Scen1-CS2 and Scen1-CS3, respectively. Scen1-CS3, where the facility uses the generation only for self-supply, presents a reduction of 53% in total costs when compared with Scen1-CS2. Considering scenario 2 (wholesale transactions available) the same tendency of scenario 1 is verified, the best variant is Scen2-CS1, the following is Scen2-CS3, and in last Scen2-CS2. A reduction of 60% (compared with Scen2-CS2) and 10% (compared with Scen2-CS2) is verified for Scen2-CS3. A reduction of 55% is verified for Scen2-CS3 when compared to In Scen2-CS2 (UPP). Comparing the results between the variants of the two scenarios, Scen2-CS1 presents a reduction of 11% compared with Scen1-CS1. Scen2-CS2 compared with Scen1-CS2 presents a reduction of 6% in total costs, and Scen2-CS3 with Scen1-CS3 obtain a 10% reduction in total costs. As can be seen by the comparison showed above, the scenarios where the wholesale transactions are available present reductions between 6% and 11% compared with the same scenarios but without wholesale market transactions. In the variants considered, Scen2-CS2 presents the best results, and Scen1-CS2 the worst result for total costs. Attending to the optimization time, it can be seen a great increment in variants of scenario 2, which is explained by the fact that the optimization problem incorporates more variables due to the wholesale market transactions. Figure 8 presents the costs and revenues in each different variant.

As can be seen in Figure 8, the costs are the positive values, and the revenues are negative. For Scen1-CS1, Scen1-CS2, and Scen1-CS3 the costs or revenues associated with the wholesale market do not exist. Scen1-CS2 presents higher costs for buying electricity in retailer market and presents a higher revenue to sell electricity in the grid. Scen1-CS3 doesn't present revenues for the sale of electricity on-grid because the type of facility (UPAC) does not allow it. The revenues and costs of wholesale transactions only appeared in Scen2-CS1, Scen2-CS2, and Scen2-CS3. UPP facility (Scen1-CS2 and Scen2-CS2) is buying a great amount of electricity in a retailer compared to the other variants. The fixed costs are always the same in all scenarios defined. The sales revenues in the wholesale market are not presented, because no electricity is sold (minimum limit required not reached). Figure 9 presents the electricity transactions in each period considering Scen1-CS1, Scen1-CS2, and Scen1-CS3, where the wholesale transaction is not available.

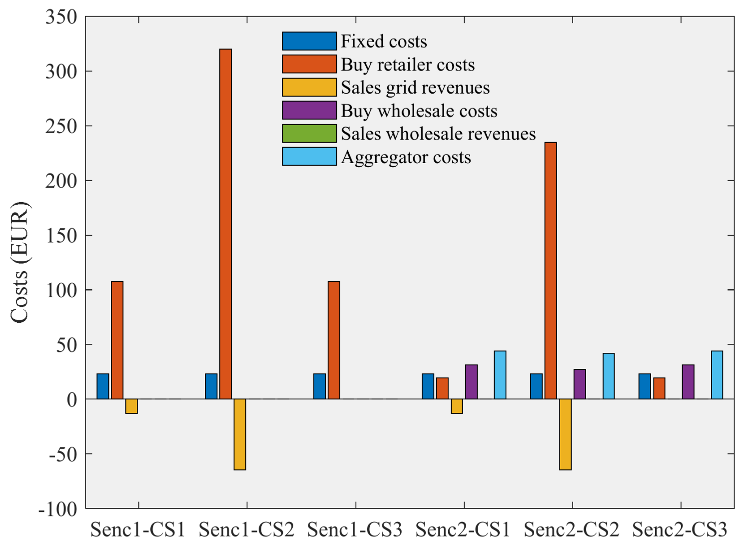


Figure 8. Energy costs comparison for all scenarios.

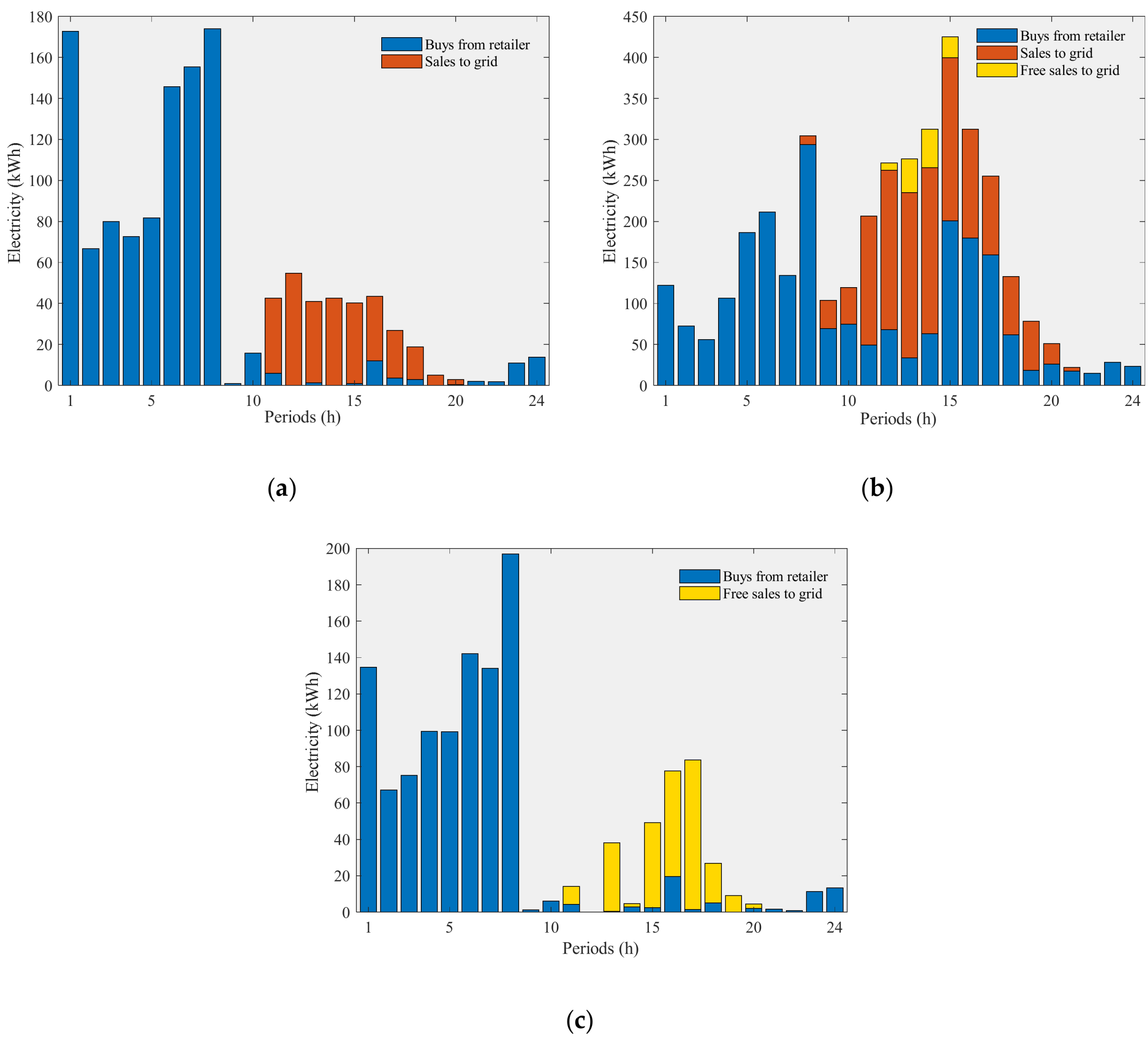


Figure 9. Electricity transactions without wholesale participation, (**a**) Scen1-CS1, (**b**) Scen1-CS2, and (**c**) Scen1-CS3.

Figure 9b,c have presented the free sales to the grid as the sale of electricity on the grid is limited to half the contracted power and at certain periods the excess electricity cannot be stored in the batteries and must be injected into the network but at zero cost. Only in scenarios covered by Portuguese legislation do free sales to the grid. Scen1-CS2 presents 122.53 kW, and Scen1-CS3 has 270.03 kW. It can also be seen that free sales occur in the periods that photovoltaic generation exists. Scen1-CS2 shows almost twice as much electricity bought at the retail market as the electricity produced which is obligatorily all injected into the grid. Figure 10 presents the electricity trading in each period for Scen2-CS1, Scen2-CS2, and Scen3-CS3, where the wholesale transaction is available.

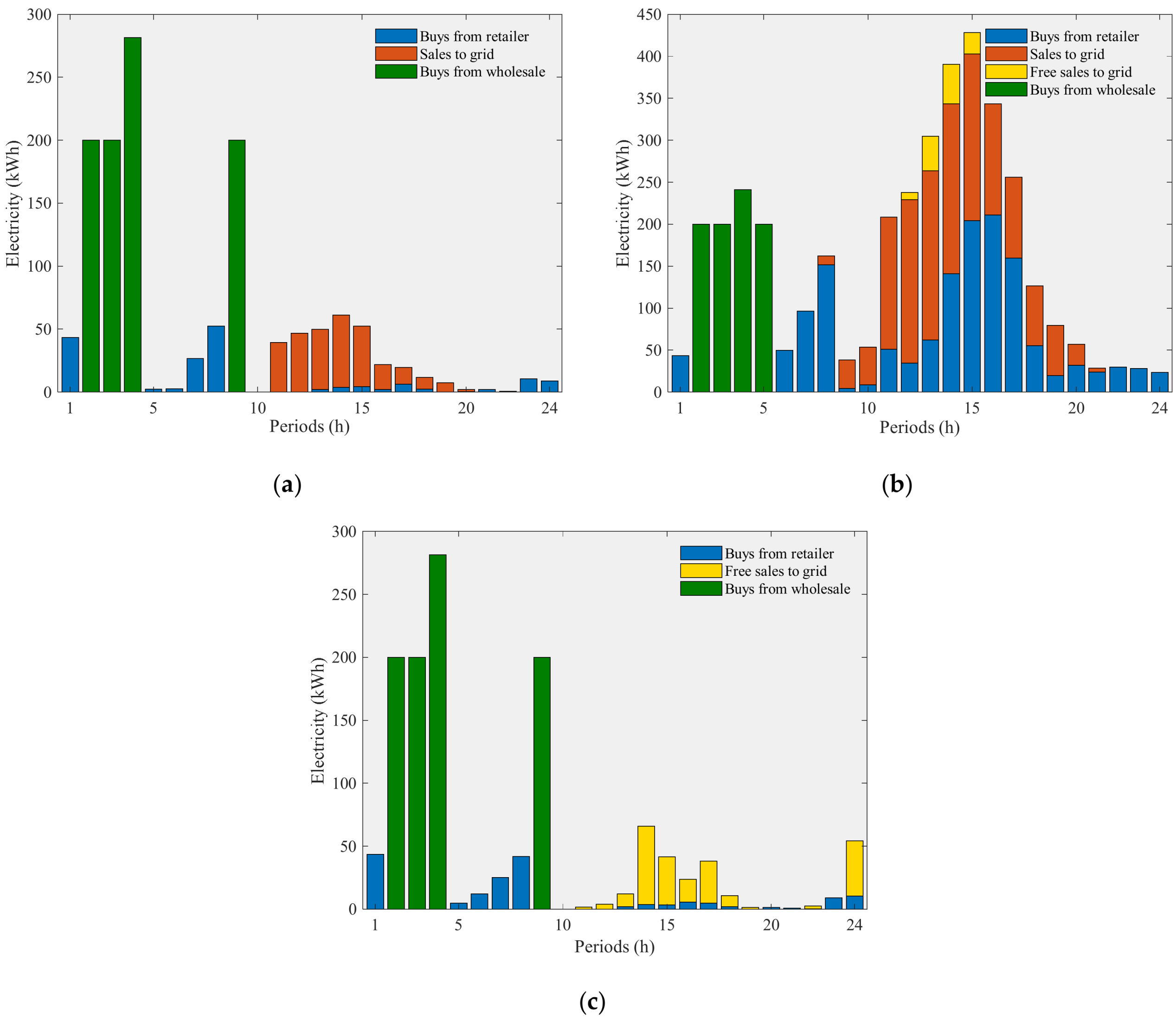
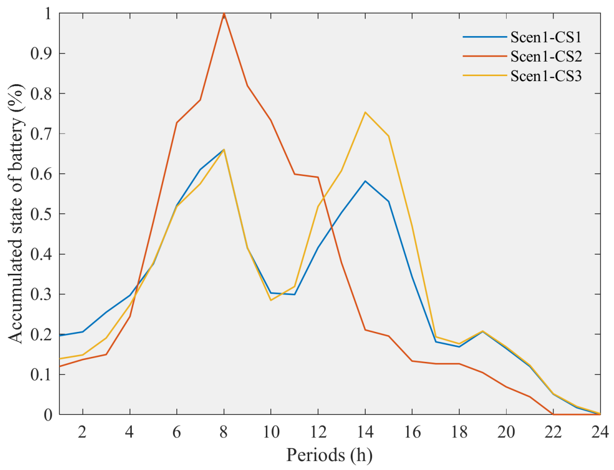
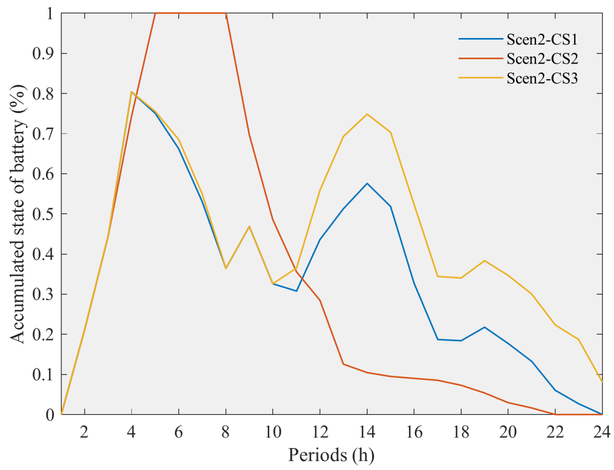


Figure 10. Electricity transactions with wholesale participation, (**a**) Scen2-CS1, (**b**) Scen-CS2, and (**c**) Scen2-CS3.

In all of the representations of Figure 10, it is presented the purchases made from the wholesale market. Considering Scen2-CS1, the purchases from retailers decrease 83% when compared with Scen1-CS1. Scen2-CS2 the purchases on the retail market also decrease by 37% compared with Scen1-CS2. Comparing the buy-in retailer market of Scen1-CS3 with Scen2-CS3, the decrease is about 83%, in the same scenarios but comparing the free sales on the grid in Scen2-CS3 we have a decrease of 17%. Scen2-CS1 and Scen2-CS3 present the same value for electricity purchases from the wholesale market, however, Scen2-CS2 presents a small value (minus 5%). Figure 11 presents the accumulated state of the battery for all variants tested.



(a)



(b)

Figure 11. Accumulated state of the battery, (**a**) without wholesale participation and (**b**) with wholesale participation.

In Scen1-CS2 at 8:00, the community members have the batteries at the maximum level of capacity, the same happens in Scen2-CS2 for periods 5:00 to 8:00. The identified scenarios are both UPP facilities. Figure 11b presents the state of the batteries but considering the possibility of the wholesale transaction and in the case of Scen2-CS2 the full state of batteries is obtained when the purchases in the wholesale market occur (Figure 11b). Considering the comparison of Scen2-CS1 and Scen2-CS2 Scen1-CS1 and Scen1-CS3, the state of battery increases when wholesale market purchases occur. Table 3 the portfolio of electricity transactions in all scenarios tested.

Table 3. Portfolio of Electricity transactions in different markets for the energy community.

Accumulated Transactions (kWh)		**Variants**					
		Scen1-CS1	**Scen1-CS2**	**Scen1-CS3**	**Scen2-CS1**	**Scen2-CS2**	**Scen2-CS3**
Buys from retailer		1020.83	2270.57	1020.83	170.24	1429.44	170.24
Sales to grid		291.14	1434.06	-	291.14	1434.06	-
Free sales to the grid		0	122.53	270.05	0	122.53	223.43
Buys from wholesale	Spot	-	_-	-	0	0	0
	Intraday sessions	-	-	-	881.43	841.13	881.43
Sales to wholesale	Spot	-	-	-	0	0	0
	Intraday sessions	-	-	-	0	0	0

The transaction's portfolio in Scen1-CS1, Scen1-CS2, and Scen1-CS3 are divided into purchases from the retail market and sales to the grid. In Scen2-CS1, Scen2-CS2, and Scen2-CS3 the portfolio of transaction increases considering the wholesale availability. Considering the wholesale transactions, there are the spot market and the intraday sessions, considering the results only traded in intraday sessions. The sales in the wholesale market are not used due to the minimum amount not reached. Figure 12 presents the electricity transacted in different options of the wholesale market.

With Figure 12 it is possible to identify the intraday sessions where the electricity transactions are made. Scen2-CS1 uses intraday session 1 and session 2 to buy electricity in the wholesale market, the same happens for Scen2-CS3. Considering Scen2-CS2, only on intraday session 2 it is used to buy electricity from the wholesale market. The representation of wholesale market sales is not presented as it is not registered.

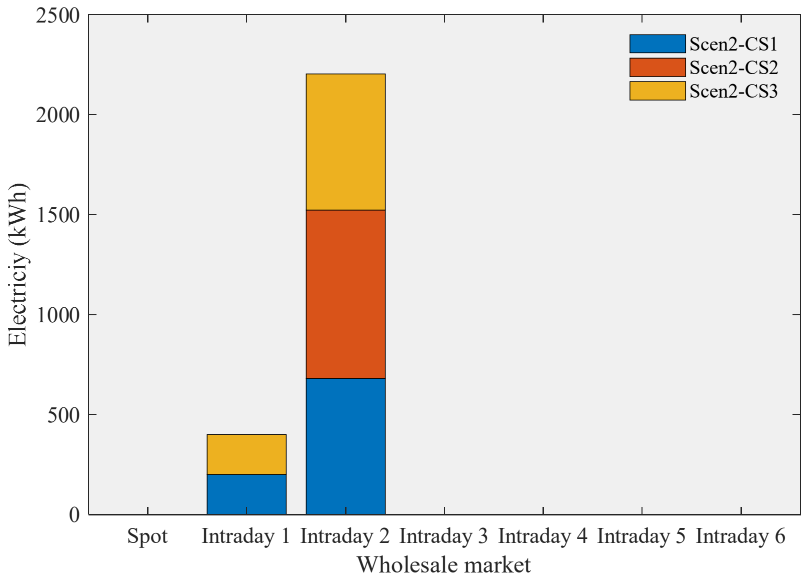


Figure 12. Accumulated electricity buy from the wholesale market.

6. Conclusions

The participation of household prosumers in the wholesale market is limited to the minimum amount transacted, approaches using aggregators have been used to overcome this particularity. Using energy management systems, aggregators can focus on the ideal periods for buying and selling electricity in the wholesale market, taking advantage of the price differences observed over time. The case study presented where the possible scenarios used by Portuguese households (UPP and UPAC) are used, and it is possible to demonstrate that the best option is UPAC, where self-consumption is prioritized. Comparing the UPP and UPAC scenarios where there is the possibility of transacting electricity in wholesale markets, there is a 55% reduction in operating costs when opting for UPAC, considering the proposed methodology. By using managing the batteries and market opportunities appropriately, the prosumers can reduce the consumption costs significantly. In view of the proposed methodology using the Aggregator to transact electricity in the wholesale market, there is a reduction in the total operating costs of the community. The all-encompassing scenario is the one that presents the best results considering or not the participation in the wholesale market, demonstrating that, despite not being legally possible in Portugal, the prosumers participation in the wholesale market via Aggregators brings significant advantages for the whole energy community. As future work, we intend to increase the community's resources by increasing the number of prosumers to obtain greater participation in the wholesale market. It is also intended to carry out a robust optimization to study the influence of the price variability of the wholesale market.

Author Contributions: Conceptualization, R.F. and T.P.; methodology, R.F., T.P. and Z.V.; software, R.F.; validation, T.P., Z.V. and J.M.C.; formal analysis, Z.V.; investigation, R.F., T.P., Z.V. and J.M.C.; resources, Z.V.; data curation, R.F.; writing—original draft preparation, R.F. and T.P.; writing—review and editing, Z.V. and J.M.C.; visualization, R.F.; supervision, T.P., Z.V. and J.M.C.; project administration, Z.V.; funding acquisition, T.P. and Z.V. All authors have read and agreed to the published version of the manuscript.

Funding: This work has received funding from the European Union's Horizon 2020 research and innovation program under project TradeRES (grant agreement No 864276) and from FEDER Funds through COMPETE program and from National Funds through FCT under projects CEECIND/01811/2017 and UID/EEA/00760/2019.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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Core Publication VII

Ricardo Faia, Tiago Pinto, Zita Vale, and Juan M. Corchado, "A Local Electricity Market Model for DSO Flexibility Trading," in International Conference on the European Energy Market, EEM, 2019, vol. 2019-September.

Resumen

La necesidad de la participación del usuario final en los sistemas de energía se ha convertido en una realidad en los últimos tiempos. Una de las soluciones a este compromiso es la creación de mercados energéticos locales. Los operadores de sistemas de distribución se ven obligados a investigar y optimizar su costo de inversión de activos en el refuerzo de las redes mediante la introducción de funcionalidades de redes inteligentes para evitar inversiones. La gestión de la congestión es una de las estrategias más prometedoras para hacer frente a los problemas de la red. Este artículo presenta un mercado eléctrico local o negociación de flexibilidad como una estrategia para ayudar al operador del sistema de distribución en la gestión de la congestión. El mercado local se realiza considerando un modelo de actuación asimétrico y es coordinado por un agregador. Se presenta un caso de estudio considerando una simulación que utiliza una red de baja tensión con 17 buses, que incluye 9 consumidores y 3 prosumidores, todos usuarios domésticos. Los resultados muestran que, utilizando el modelo de mercado propuesto, se evita la congestión de la red aprovechando la flexibilidad comercial de los consumidores.

Appendix B. Preprints

Preprint I

Ricardo Faia, Fernando Lezama, Tiago Pinto, Pedro Faria, Zita Vale, José Terras, Susete Albuquerque. (2022). A Simulation of Market-based Non-Frequency Local Ancillary Services Procurement Based on Demand Flexibility, doi: 10.13140/RG.2.2.18549.45280.

Resumen

La flexibilidad de la demanda se puede utilizar para proporcionar servicios que respalden el control y la operación del sistema de energía. Esto incluye los servicios auxiliares con o sin frecuencia. Este artículo propone un mecanismo innovador para la provisión de servicios auxiliares de no frecuencia por parte de consumidores conectados a redes de baja tensión. El método propuesto para la negociación de AS permite a los consumidores establecer el precio y la cantidad a negociar, considerando un mercado local asimétrico basado en un pool. Este mecanismo de negociación está diseñado de acuerdo con el reciente marco regulatorio de la Unión Europea, que promueve la participación activa de los consumidores. Se utiliza un estudio de caso con 98 consumidores para ilustrar el enfoque de adquisición de servicios auxiliares que no son de frecuencia basado en el mercado propuesto. Se implementaron y evaluaron tres estrategias diferentes de participación de los consumidores en una red real de baja tensión con topología radial. Los consumidores obtienen ganancias por la venta de su flexibilidad, contribuyendo a la reducción de pérdidas ya mantener el voltaje y la corriente dentro de límites predefinidos.

A Simulation of Market-based Non-Frequency Local Ancillary Services Procurement Based on Demand Flexibility

Ricardo Faia, Fernando Lezama, Tiago Pinto, Pedro Faria, Zita Vale, José Manuel Terras, Susete Albuquerque

***Abstract*—This paper proposes a novel mechanism for the provision of non-frequency ancillary services (AS) by consumers connected to low-voltage distribution networks. The proposed method considers an asymmetric pool-based local market for AS negotiation, allowing consumers to set the flexibility quantity and desired price to trade. A case study with 98 consumers is used to illustrate the proposed market-based non-frequency AS provision approach. Also, three different strategies of consumers' participation were implemented and tested in a real low voltage network with radial topology. It is shown that consumers can make a profit from the sale of their flexibility while contributing to keeping the network power losses, voltage, and current within pre-defined limits. Ultimately, the results demonstrate the value of AS coming directly from end-users.**

***Index Terms*— Demand Flexibility, Local Electricity Markets, Ancillary Services.**

I. Introduction

NOWADAYS, the renewable energy sources (RES) connected to the distribution network are changing the system operation towards a decentralized and market-based paradigm. At the same time, the stochastic nature of RES production, which is often higher in periods of low consumption, is increasing the reserve requirements of power and energy systems, usually guaranteed by ancillary services (AS) provision. This situation results in new opportunities for the implementation of flexibility services, for instance, those related to the trading of available energy into local electricity markets (LEM) [1], [2].

Directive 2012/27/EU (48, Art. 2) [3] defines AS as essentials for the operation of transmission and distribution systems, including frequency (frequency regulation) and non-frequency (e.g., voltage control, black start capabilities and reactive power compensation) services. Furthermore, the definition of AS has been moving forward, also including balancing [3] and congestion management [4] services. In other words, AS can be defined as services that support network operators to keep the electric power system into levels that guarantee a secure operation mode.

Several initiatives are currently searching for innovative means of exploiting the flexibility of end-users, focusing on the development of full-scale demonstrators that take advantage of smart grid technologies [5], [6] and the flexibility of consumers at the local level of the distribution grid [7], [8]. In the case of Europe, financial support is currently given to projects aiming at the development of the European electricity grid through the program H2020-EU.3.3.4 - A single, smart European electricity grid [9]. In fact, taking into account current regulation provided by public authorities in Europe in context of AS, we identified the following aspects as a motivation for this work: (1) The Strategic Energy Technology Plan from the European Commission (EC) [10] stating that the energy consumers (and not aggregators) are envisioned at the center of the future energy power system; (2) The Directive of the European Parliament and the Council on the internal market for electricity (recast) [11] proposing rules for TSO and DSO procurement of AS considering demand response (DR) providers and independent aggregators, in a non-discriminatory way; and (3) The 2030 framework for climate and energy policies from the EC [12] targeting a reduction of 40% of greenhouse gases and

This work has received funding from the EU Horizon 2020 research and innovation program under project DOMINOES (grant agreement No 771066) and from FEDER Funds through COMPETE program and from National Funds through FCT under projects UID/EEA/00760/2019 and CEECIND/01811/2017. Ricardo Faia was supported by the PhD grant SFRH/BD/133086/2017.

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a 27% increase of shared RES efficiency by 2030. Also, the large penetration of IoT devices in the electrical system provides network operators with a more suitable perception of the resources available in the network. While several AS are currently adopted at the transmission level for an effective operation of the system [13], market approaches at the distribution level are rather limited, usually leading to unfair contracting conditions for the end-users.

Thus, new market approaches need to be developed to make possible a competitive and fair acquisition of flexibility resources at the distribution level. In this work, we propose a local non-frequency AS market mechanism to support network operators (i.e., DSOs), keeping bus voltages and line currents within acceptable levels for the proper grid operation. We assume that the DSO (as the network operator of a distribution grid) procures non-frequency AS from consumers. An aggregator acting as a local market operator is still in place, but consumers can actively participate in the market putting flexibility offers according to their own interests. To this end, an asymmetric pool auction model is used for non-frequency AS negotiation considering consumers' flexibility offers. The article also explores different market participation strategies of consumers in the newly defined AS marketplace. The main contributions of this article are as follows:

- A non-frequency AS marketplace for small consumers and prosumers where they can actively participate offering their flexibility. The aggregator plays the role of the market operator, gathering the flexibility offers without the limitations of the amount offered;
- A mechanism directed to the DSO aiming at keeping voltage and current grid limits within acceptable levels of operation using AS and a market-based approach;
- Definition of three innovative market participation strategies for consumers and prosumers in the AS market;
- Validation of the non-frequency AS market through simulation considering network constraints and a case study with 96 end-users (consumers and prosumers) connected to a low voltage distribution network.

The article is organized into six sections as follows: After the introduction in Section 1, Section 2 presents a literature review of related work. Section 3 presents the proposed methodology and the mathematical formulation. Section 4 provides the details of the case study used in this work. Section 5 presents the main results and discussion of the findings. Finally, Section 6 draws the main conclusions of the work.

II. Background and Literature Review

In traditional and vertically integrated power systems, large-size central power plants generally provide the AS necessary to maintain the power system security and stability. Network operators should have AS reserves for providing additional generation to meet the demand during contingencies. The rapid growth of distributed generation (DG) with intermittent characteristics brings new challenges to such operation model. Therefore, this section presents an overview of different AS acquisition methods at the distribution level.

As pointed in [14], the term distributed AS refers to AS delivered by local resources in a distributed way. Thus, the imbalance between generation and demand can be mitigated at the distribution level (i.e., the distribution network) with distributed AS. This prevents the spread of issues to upstream power networks, ensuring the system's control and stability [15].

The AS acquisition option considering the aggregator as a market operator and not in a central role is also in line with the motivations behind this work. Since the DSO procures AS from users connected to the distribution network, it is assumed that those end-users are equipped with the required technologies to execute demand-side management [16], [17]. DSO can use the AS for its own purpose and with different objectives. For instance, [18] considers the use of AS by the DSO for the control and operation of a micro-network. In [19], ASs are used from the supply side combining wind/battery power plant operation. Unlike the above works, we propose the use of demand-side as the main provider of AS. This attribute is in line with the future research directions of AS acquisitions and it is an initiative that empowers end-users.

Also, the resources used for AS participation vary depending on the context and applications. For instance, buildings participation in AS markets is proposed in [20], using the AS to reduce the overall energy building costs. The use of heating and ventilation air conditioning (HVAC) system as flexibility resource is explored in [21]–[23]. AS provision by storage systems is proposed in [14], [24]–[26] while the utilization of electric vehicles (EV) for supporting network operation is proposed in [25]. The works [26], [27] also considers EV for AS provision, but including battery degradation cost and estimating the safe amount of power that EVs can supply. In references [24], [28], PV generation is explored as a resource for AS. The PV inverters in [28] are used for reactive power and harmonic current compensation based on different control strategies applied to single-phase and three-phase PV inverters. Similarly, wind generation is used as a base for AS provision in [19], [29]. References [21], [28], [30] also consider the acquisition of AS at a domestic level using a specific appliance, (e.g., a fridge-freezer). An island operation capability AS implementation is presented in [31]. In this work, the authors consider the modification of network topology, allowing the energy supply from distribution energy resources (DERs). This kind of approach required installing advanced smart grid technologies, which are generally not included in conventional networks, requiring large investments to implement the solutions into practice.

Considering the literature analysis, we can classify the AS negotiation into pre-qualified auctions [20], [21], [24], incentive-based [25], [26], [30], penalized tariff as an incentive [14], voluntary participation [32], and price signal-based [27]. Considering the voltage and current control, the following relevant works can be found in the literature [33]–[36]. A voltage regulation strategy with thermostatically controlled loads is presented in [33]; in this work, it is assumed that the aggregator directly controls the specific loads installed in the houses. This type of approach can present problems from the point of view of cybersecurity (in contrast, the presented approach does not allow direct control of any user's asset). In fact, analyzing the works covered, almost none of the methods consider a local market or similar approach to carry out the control of current.

Addressing the problem at the distribution level makes the proposed work more attractive for the participation of users, as it gives them greater freedom of participation. From the literature review, we can identify a gap related to the lack of models for implementing competitive markets localized at consumers level to trade AS. The purpose of this work is to provide a contribution to overcome the identified gap.

TABLE I presents a list of works related to AS acquisition classifying the asset used to provide AS, the AS product, the AS type, the AS variable, and the AS negotiated type. References [14], [19], [24]–[29] consider DERs as an asset for AS provision. On the other hand, [15], [32], [37] provide AS from the ideal operation of the system as a whole. The AS product can be divided into two major categories: the Frequency Restoration Reserve (FRR) and Non-Frequency. The FRR product can have two subcategories: the automatic (aFRR) and manual (mFRR) [38].

TABLE I
AS ACQUISITION ON THE LOCAL LEVEL

Ref	Asset	Product	Type	Variable	Neg. Type
[20]	Commercial building	aFRR	SCR	Frequency	Pre-qualified actions
[24]	Distributed solar batteries	FRR	PCR	Frequency	Pre-qualified actions
[25]	EV	aFRR	PCR, SCR, TCR	Frequency	Incentives
[37]	DC community	Non-Frequency	-	Reactive power	-
[28]	PV inverters	Non-Frequency	-	Reactive power, harmonic current compensation	-
[21]	HVAC systems	FRR	SCR	Frequency	Pre-qualified actions
[30]	Domestic fridge-freezer	Non-Frequency	-	Spinning reserve	Incentives
[32]	MG optimal scheduling	Non-Frequency, FRR	-	Ramping support, frequency regulation	Voluntary
[29]	Wind farms	FRR	-	Frequency	-
[22]	HVAC systems	FRR	-	Frequency	-
[14]	Battery storage systems	Non-Frequency, FRR	-	Power factor, voltage profile frequency	Penalized tariff
[15]	AC meshed MG	Non-Frequency, FRR	-	Frequency voltage control	-
[23]	Air-conditioning	FRR	PCR	Frequency	-
[26]	EV	FRR	-	Frequency	Incentives
[27]	EV smart charging			-	Price signals
[19]	Wind and Battery power plants	FRR	-	Frequency	-
[31]	Network reconfiguration	Non-Frequency	-	Generation reserve	-
[33]	Thermostatically controlled loads	Non-Frequency		Voltage control	-

TABLE I presents twelve applications for AS FRR products and ten for the AS non-frequency products. The AS related to control reserve is classified as primary control reserve (PCR), secondary control reserve (SCR), and tertiary control reserve (TCR). This classification is not consensual among the market operators, so each can use its own. However, the classification is directly related to the time of operation and the order of reserves activation. With the analysis of the respective column in TABLE I, three works are identified as PCR and SCR and one as TCR. The AS variable column identifies the system variable controlled with the use of AS. The work classified with FRR in column AS product must have a frequency as AS variable. Twelve works have a frequency as AS variable and also have reactive control [28], voltage control [14], [15], [33], [34] ramping support [32] and spinning reserve [30]. Regarding the AS negotiation, the literature analysis considers four different mechanisms based on pre-qualified action, incentives, voluntary, and penalized tariff.

III. Propose Methodology

This section presents the proposed methodology that focuses on using the local non-frequency AS market, considering the coordination between DSO and an Aggregator. The DSO will use non-frequency AS to operate the distribution network within rated parameters, acting as a network operator. Issues can appear in the network operation where the operation parameters overreach the limits; in this case, we consider a violation of the network operation parameters. The aggregator is responsible for organizing the selection of resources (consumers providing demand response) in the non-frequency AS procurement process. Two different algorithms, representing different processes, are presented in this section. Algorithm 1 consists of a day-ahead analysis and non-frequency AS procurement, which consists of selecting potential consumers to reduce their consumption, according to the forecasted operation parameters. Algorithm 2 describes the process of real-time non-frequency AS activation, where the selected consumers are notified to reduce their consumption. Thus, Algorithm 1 is a process repeated each day.

Algorithm 1 Day-ahead analyses and non-frequency AS procurement

```
1:  Available forecasts of energy consumption
    for the next 24h
2:  DSO, based on forecasts, runs power flow of
    the network (Equation (11))
3:  DSO check control parameters (Equation (9)
    and (10))
4:  IF Control parameters are unbounded THEN
5:     Request the pre-acquisition of non-
       frequency AS in the market
6:     Aggregator performs auction qualifications
       for each necessary period
7:     PROCEDURE Asymmetric Pool Auction
       (Equation (6))
8:        Connected users submit offers of
          flexibility
9:        Accepted offers determine non-frequency
          response
10:    Aggregator communicates to DSO the results
       of the pre-auction
11: ELSE
12:    Request is not performed
```

Algorithm 1 starts with the forecast for the next 24 hours, which can be performed by DSO, or contracted to other entity. With the forecasts of demand and generation, DSO performs the power flow analysis for each period of the next 24 hours (step 2). Considering the power flow results, the DSO identifies the periods where problems with the control parameters can occur (step 3). For each period when it is identified violations, the DSO requests the pre-acquisition of non-frequency DSO in the market (step 5). The Aggregator (working as market operator) selects the offers according to an asymmetric pool auction procedure (step 7).

When the non-frequency AS providers present their offers, each offer is composed of an amount of amount flexibility (for energy reduction in context of demand response) and a price. The Aggregator (the entity responsible for the process with non-discriminatory functioning) organizes the bids using a merit order procedure, starting with the lowest price and moving up. The non-frequency AS providers reveal their offers to set up the reduction in their consumption. Once the Aggregator knows the request from the DSO, it accepts as many offer bids as needed to fulfil the request, starting from the lowest price. After the pre-acquisition process, the Aggregator will communicate the offers selection results to the DSO.

This process is repeated each day for the 24 hours of the following day Algorithm 2. Algorithm 2 is executed period by period and starts with the updating forecasts (step 1). This process is necessary due to the accuracy of the forecasting methods. Forecasting errors can influence the activation of the non-frequency AS, as they can create a variation in load and production that was initially expected. DSO re-executes the power flow analyses and checks the control parameters of the system (step 2).

Algorithm 2 Real-time non-frequency AS activation

```
1:  Updated forecasts for next period
2:  In real-time DSO re-execute power flow
    analysis (Equation (11))
3:  IF Control variables are unbounded THEN
    (Equation (9) and (10))
4:     DSO send the activation non-frequency AS
       signal to the Aggregator
5:     Aggregator active the non-frequency AS
6:     Providers delivered the non-frequency AS
7:  ELSE
8:     Non-frequency AS is not activated
9:  Aggregator notify DSO about availability and
    provision of non-frequency AS
```

If the violations persist, the DSO sends the activation signal to the Aggregator who activates the non-frequency AS among providers (step 4). In a later stage, the Aggregator notifies the DSO about the availability and provision of non-frequency AS to proceed with the payment of services (step 9).

Equation (1) represents the operation costs for DSO.

$$OC^{DSO} = \sum_{t=1}^{T} (LC_t + LMC_t) \tag{1}$$

where OC^{DSO} represents the total cost (EUR) of operation for the DSO, LC_t represents the cost of losses in period t and LMC_t represents the local market costs (acquisition of non-frequency AS) in period t. Equation (2) represents the calculation of losses cost:

$$LC_t = \sum_{l=1}^{L} \left(WL_{l,t} \times Cp_l\right), \forall\, t \in T \tag{2}$$

where $WL_{l,t}$ are the energy losses (kWh), Cp_l is the per kilowatt-hour cost of power losses (EUR/kWh). Equation (3) represents the local market costs for period t:

$$LMC_t = FlexC_t + AggC_t + BonusC_t, \forall\, t \in T \tag{3}$$

where $FlexC_t$ represents the costs with the demand flexibility, $AggC_t$ represents the cost with the payment to the aggregator and $BonusC_t$ corresponds to the costs of bonus paid to the consumers with accepted offers, all correspond to the period t. Equation (4) represents the cost of the pool market.

$$FlexC_t = \sum_{c=1}^{C} \left(Offer_{c,t}^{W} \times Clearing_t^{price} \times Offer_{c,t}^{bin}\right), \forall\, t \in T \tag{4}$$

where $Offer_{c,t}^{W}$ is the energy cut (kWh) of offer c at period t, $Clearing_t^{price}$ is the clearing price of cut (EUR/kWh) at period t, $Offer_{c,t}^{bin}$ is a binary variable of offer c at period t and C is the total number of customers.

The term $Offer_{c,t}^{W}$ and $Offer_{c,t}^{P}$ are considered inputs for the problem while $Offer_{c,t}^{bin}$ are decision variables. The decision variables are presented in equation (5), and are composed by a binary operator indicating the acceptance of a offer:

$$Offer_{c,t}^{bin} = \begin{cases} 1, & If\ the\ offer\ is\ selected \\ 0, & otherwise \end{cases}, \forall\, c \in C, \forall\, t \in T \tag{5}$$

where $Offer_{c,t}^{bin} = 1$ means that offer c in period t is selected for DSO and $Offer_{c,t}^{bin} = 0$ if the offer is not selected.

Variables $Offer_{c,t}^{bin}$ and $Clearing_t^{price}$ are obtained using the function presented in equation (6). The Asymmetric pool model is one of the pool models applied in market trading (different to the symmetric model). In the case of the asymmetric model, only offers (i.e., players' demand) are received and there is only one buyer with a defined quantity without a defined price.

$$\left(Clearing_t^{price}, Offer_{c,t}^{bin}\right) = \mathbf{Auction}\left(Offer_{c,t}^{W}, Offer_{c,t}^{P}\right) \tag{6}$$

where **Auction** is a function that returns the $Clearing_t^{price}$ and $Offer_{c,t}^{bin}$ represents the price and the offers accepted and rejected considering the asymmetric pool model. The results obtained from the function described in equation (6) have a direct impact in the corresponding values of operational costs (calculated with equation (1)). The inputs for this function are offers with energy and price information. With this information, it is possible to obtain the flexibility amount available in each customer and new values for customers' load are available. This function ($\mathbf{Auction}(.)$) receives the inputs and returns as outputs the clearing price and the corresponding accepted offers. In a first step, the offers are sorted in ascending considering the price, and the accumulated quantity of electricity is added. When the accumulated quantity equals the requested quantity, the clearing price is determined by the price of the offer that matched the requested quantity, and all orders below this quantity are accepted. In this particular case, the required quantity is determined iteratively until the restrictions are met.

Equation (7) represents the remuneration of the aggregator.

$$AggC_t = 0.05 \times FlexC_t, \forall t \in T \tag{7}$$

With Equation (7) the remuneration for the aggregator corresponds to the percentage of the total amount paid considering the offers accepted.

$$BonusC_t = 0.5^{\frac{\alpha}{6}} \times C(PG), \forall t \in T \quad (8)$$

where α corresponds to the number of accepted offers and $C(PG)$, corresponds to the thermometric generator's production cost to generate the equivalent energy to aggregator request. The bonus calculation equation is an additional mechanism to encourage players to make better offers. The total bonus amount is obtained depending on the number of offers accepted and the greater the number of offers accepted, the lower the bonus amount. So, this mechanism can lead players to perform better offers with the intention of receiving a larger amount in this component.

The local market mechanism is used if the conditions of equations (9) and (10) are violated. Equation (9) represents the conditions imposing bus voltage magnitude limits, and equation (10) represents the condition that imposes the maximum admissible current of lines:

$$V_{min} \leq V_{b,t} \leq V_{max}, \forall b \in B, \forall t \in T \quad (9)$$

$$I_{l,t} \leq I_{max}, \forall l \in L, \forall t \in T \quad (10)$$

where V_{min} and V_{max} are respectively the minimum and maximum magnitude voltage limit in p.u., $V_{b,t}$ is the voltage magnitude of bus b at period t and B represents the total number of buses. $I_{l,t}$ is the current, in p.u., in l at time t, I_{max} is the maximum current limit in p.u., and L represents the total number of lines.

To verify the conditions imposed, it is necessary to obtain the $\Omega_V = [V_{b,t}]$ and $\Omega_I = [I_{l,t}]$. For this, the forecast of customers load is updated considering the accepted offer, after applying equation (11). We assume that a power flow function is available to validate at any moment the network state (i.e., network constraints). Therefore, a power flow function is defined as [39]:

$$(\Omega_V, \Omega_I, \Omega_P) = \mathbf{PF}(\cdot) \quad (11)$$

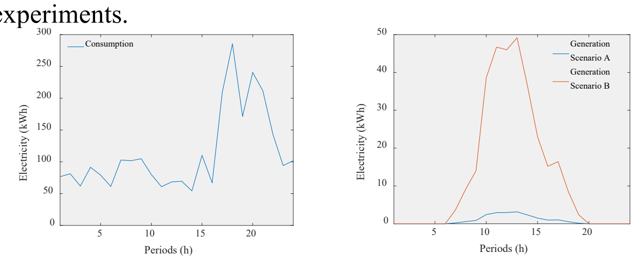
where $\mathbf{PF}(\cdot)$ is a function that receives the information of load consumption and grid information (lines, buses, transformers, generators), and returns the voltage status of buses $\Omega_V = [V_{1,t}, V_{2,t}, \dots, V_{B,t}]$, the current status of lines $\Omega_I = [I_{1,t}, I_{2,t}, \dots, I_{I,t}]$, and the power losses in lines $\Omega_P = [P_{1,t}, P_{2,t}, \dots, P_{L,t}]$. This function is used to validate the network status at each time $\forall t \in T$. With the information returned by the power flow function, equation (9) and equation (10) can be validated. To run the PF(·) function, *pandapower.runpp* module from the *pandapower* package installed in the Python software is used. The *pandapower* package can be installed and used on every platform with an installation of Python 2.7 or higher. The *pandapower.runpp* model allows to obtain a balanced AC power flow with different algorithms. For this work, the "bfsw" backward/forward sweep algorithm was used since it is recommended for distribution networks. For instance, the work [40] also uses *pandapower* to obtain power flow results and validating results.

IV. Case Study

In the simulation process, we consider 24 periods with 1 hour of duration, the voltage limits are set to $V_{min} = 0.95$ and $V_{max} = 1.05$, I_{max} is specific for each line and the Cp_l is 0.02 EUR/kWh. We consider consumers (households) complying with the actual Portuguese legislation, which allows a small amount of generation (consumers with local generation) to be used for their own energy needs and bring excess energy to the grid. Each one of the consumers is equipped with controllable loads that can be used to reduce the total energy consumption when needed. According to the actual EU targets [12] regarding the increase in electricity production by renewable sources, we decide to create two different scenarios:

- Scenario A - corresponds to the simulation considering the real configuration of the network with 2 DG;
- Scenario B – corresponds to the same network configuration of scenario A, but considering the inclusion of more 31 DG, which corresponds to 33 DG units based on PV generation.

These scenarios are used to test the influence of DG in the presence of a violation of network operation limits. While the location of DG has an impact in the operational costs, the optimal location of DGs is out of the scope of this work and open an interesting line for future research. Fig. 1 presents the accumulated consumption and generation profiles used in the experiments.



a) b)

Fig. 1. Consumption and generation, (a) accumulated consumption and (b) accumulated generation

In Fig. 1 (a) the consumption profile presents a peak of 285 kWh at 18:00 h. Fig. 1 (b) presents two different electricity profiles generated, one for scenario A and other for scenario B. The increment of generation is visible in the figure when scenario B is used to perform the simulations.

A. *Grid Configuration*

The proposed methodology is simulated using data from a real low-voltage network presented in [41]. The network is connected to a medium voltage network, rated 50 Hz of frequency, operating in radial topology.

The network contains 237 buses in total, from which 236 are in low-voltage level (0.4 kV) and 1 in medium voltage level (20 kV). All 98 loads in low-voltage level are considered resistive loads. The network also has 2 distributed generators located at buses 79 and 226, based on PV technology. The number of lines is 235 (with a total of 3146 m). The transformer presented between bus 0 and bus 1 is rated 0.4 MVA, 20 kV/0.4 kV. We consider the external source bus 0 as the reference for simulation tests.

B. *Offers Definition*

The consumer offers used for participating in the local non-frequency AS provision are composed by the amount of load reduction (kWh) and a price (€/kWh). We consider that each consumer connected to the distribution network can reduce 30% of their total consumption in each hour. To create the amount of reduction for each consumer equation (12) is used.

$$Offer_{c,t}^{W} = X \sim \text{unif}(Min^{Red}, Max^{Red}), \forall\, c \in C, \forall\, t \in T \quad (12)$$

where $X \sim \text{unif}(Min^{Red}, Max^{Red})$, represents a uniform distribution between Min^{Red} (minimum load reduction), and Max^{Red} (maximum load reduction). In the creation of the offer, we consider for $Min^{Red} = 0$ and for $Max^{Red} = 0.3$ of the referred consumption.

Regarding the price, three different strategies are considered. These strategies aim to simulate the behavior of the consumer regarding the available amount of consumption reduction, as follows:

1) Random *based (strategy 1)*

This strategy considers a random creation. The consumer does not react to the energy reduction amount. The offer prices are simulated considering a uniform distribution presented in equation (13):

$$Offer_{c,t}^{P} = X \sim \text{unif}(Min^{Price}, Max^{Price}), \forall\, c \in C, \forall\, t \in T \quad (13)$$

where Min^{Price} and Max^{Price} correspond to the minimum and maximum price consider for offer reductions, respectively. The values for Min^{Price} is 0 EUR/kWh and for Max^{Price} is 0.02239[1] EUR/kWh.

2) Linear *reduction dependent (strategy 2)*

This strategy considers a consumer reaction to the amount proposed for reduction. It is considered that a higher reduction causes a higher impact on the comfort, and the reduction price should be increased. Equation (14) represents the offer price definition of strategy 2.

$$Offer_{c,t}^{P} = m \times Offer_{c,t}^{W} + b, \forall\, c \in C, \forall\, t \in T \quad (14)$$

where m is the slope of the linear expression and is given according to equation (15) and b is the is the intersection with the Y-axis and is given by the Min^{Price}

$$m = \frac{Max^{Price} - Min^{Price}}{Max^{Red} - Min^{Red}} \quad (15)$$

3) Intelligent *price reaction (strategy 3)*

The last strategy provides an improvement based on strategy 2. This strategy also considers a comfort impact reaction, but the consumers adapt their offer price according to their behavior. Two different behaviors are considered: the consumer accepts a reduction of the offer price (anxious), and the consumer increases the offer price (ambitious). To model this strategy, Equation (16) is considered.

$$Offer_{c,t}^{W} = \left(m \times Offer_{c,t}^{W} + b\right) \times r_{c,t}, \forall\, c \in C, \forall\, t \in T \quad (16)$$

where $r_{c,t}$ models the consumer behavior and is obtained considering equation (17).

$$r_{c,t} = \begin{cases} X \sim \text{unif}(r^{Min}, 1) & if\ c\ is\ anxious \\ X \sim \text{unif}(1, r^{Max}) & if\ c\ is\ ambitious \end{cases}, \forall\, c \in C, \forall\, t \in T \quad (17)$$

where r^{Min} represents the minimum value for reducing the offer price and r^{Max} represents the maximum value for increasing the offer price. For r^{Min} and r^{Max} we chose 0.7 and 1.10.

[1] The value corresponds to the mean day price of MIBEL spot market in 06/05/2020

V. Results

To organize better the results, Section 5.A presents the results of the day-ahead network analysis where the periods with violations are identified, and the procurement of non-frequency AS is made; Section 5.B presents the results of the non-frequency AS activation in real-time and the influence of non-frequency AS activation is analyzed; Section 5.C presents a discussion of the results using the proposed methodology.

A. Day-ahead analyses and non-frequency AS procurement results

The results of the day-ahead analysis considering the forecast for the day ahead are presented in this section. TABLE II presents a summary of the power flow analysis considering all 24 periods and the two scenarios.

TABLE II
ENERGY SHARE RESULTS

Scenario		Losses	External	DG	Total Load	Load (Average)
A	Active (kWh)	88.32	2797.18	19.7	2728.56	27,84
	Reactive (KVArh)	70.07	70.07	0	0	0
	Apparent (kVAh)	112.74	2798.05	19.7	2728.56	27,84
B	Active (kWh)	82.93	2502.11	309.38	2728.56	27,84
	Reactive (KVArh)	62.85	62.85	0	0	0
	Apparent (kVAh)	104.05	2502.9	309.38	2728.56	27,84
Difference		8,69	295.16	289.68	0	0

TABLE II presents the active component, the reactive component and the apparent energy for the losses, external supply, DG production and total load. As can be seen, all reactive power injected into the network in both scenarios is used to cover the reactive losses in the lines. In scenario B the reactive power is lower than in scenario A, due to the influence of DG production. We assume that loads have only active component, which results in active energy consumption in both scenarios with equal values. The average load presented in the Table 2 is done over the 98 loads. If we consider the total number of periods presented in the case study, each load has an average consumption of 1,16 kWh per period.

Checking the network status according to the results of power flow, the condition of equation (9) is violated 17 times in period 18th for scenario A, considering scenario B the same condition is violating 16 times in the same period. Since only one period is identified with magnitude buses with violations in both scenarios. On the other hand, no violations were found considering the condition of equation (10) for maximum current limits. Considering the results of equation (9) verification $V_{min} = 0.95\,p.u.$ and $V_{max} = 1.05\,p.u.$ for scenario A in period 18th, the buses with magnitude violation are: 215, 218, 220, 223, 224, 225, 226, 227, 228, 229, 230, 231, 232, 233, 234, 235 and 236. Considering the scenario B in period 18th are presented the same buses excluding the bus 215. In buses identified with violations, seven constitute buses where loads are connected (buses: 223, 224, 226, 231, 233, 234 and 236).

TABLE IV presents the summary results in the group of buses identified violations for period 18th.

TABLE III
SUMMARY RESULTS OF THE VIOLATED BUS GROUP

	Scenario A	Scenario B
Maximum	0.9496	0.9480
Minimum	0.9380	0.9401
Average	0.9411	0.9426

Once the periods with violations have been identified, the DSO requests non-frequency AS pre-acquisition in the market. The Aggregator is responsible for carrying out the offers selection process. This section presents the results for offers selection considering the different strategies to create the offers. TABLE IV presents the results of the asymmetric pool results for the pre-acquisition of non-frequency AS.

TABLE IV
PRE-SELECTION OFFERS COMPARISON RESULTS FOR THE 18TH PERIOD.

Scenario	A			B		
Strategy	1	2	3	1	2	3
Total offers	98	98	98	98	98	98
Total offer amount (kWh)	55.75	55.75	55.75	54.25	54.25	54.25
Offers accepted	69	75	68	67	56	56
Amount selected (kWh)	39.14	39.10	32.65	36.80	26.27	25.21
Clearing price (EUR/kWh)	0.013	0.015	0.014	0.012	0.013	0.013
Offers costs (EUR)	0.513	0.579	0.471	0.459	0.332	0.322

TABLE IV shows the results for scenario A and scenario B, considering all acting strategies. In both scenarios, all strategies present 98 offers. The total amount of energy offered in scenario A is 55.75 kWh, and in scenario B is 54.25 kWh. The difference in values between scenarios is related to the total load consumed in each scenario. In both scenarios, the offers bid amount is equal in terms of percentage. Moreover, the offer amount in kWh is different because in scenario B, with inclusion the higher value of DG, the load of some consumers decreases.

The offers consist of a reduction amount and a price as shown in the figure. Depending on the pricing strategies, the amount is always the same, and the price varies depending on the strategy used. Considering scenario A, the number of accepted offers is different for the different strategies adopted. Strategy 2 presents the higher value of offers accepted, but it presents the smallest selected amount with 39.10 kWh, while presenting the higher clearing price and the higher costs. In this case, strategy 2 presents the bids with comfort affect when the higher value of offer amounts presents higher values of offer prices. The higher offers prices cause an increment in the clearing price. Comparing the strategy 3 with strategy 2, a small number of accepted offers and amount selected are verified. As it was explained, in strategy 3 the offer prices suffer a change, when in this case, the buses with violations adopt a benevolent behavior. With the benevolent behavior, the prices of these buses decreased, and they were accepted making lower clearing price and selected amount. In this scenario, the use of strategy 3 brings benefits for the DSO, reducing the offers costs used for acquisition the non-frequency AS.

In scenario B, the differences between strategy 2 and strategy 3 are more reduced. In this scenario, the tendency between strategies does not repeat. Strategy 1 presents higher values in all sub-categories. Comparing the strategy 2 and strategy 3 presents the same number of accepted offers, although accepted offers are different sets. It is found that the sets are different because the offer amount accepted is different, and if the sets were equal, they would require having the same offer amount accepted. In the amount of the offers, accepted strategy 3 presents a value slightly lower than strategy 2. The clearing price (strategy 2 and strategy 3) in TABLE IV is equal, but the values have a small difference (1.34E-04). Considering the offer costs, strategy 3 also presents (as in scenario A) the smallest value.

In Fig. 2 the graphical results from the asymmetric pool market are presented. Fig. 2(a) and Fig. 2(d) represent the strategies where the offer prices are randomly created, bringing the prices close to zero.

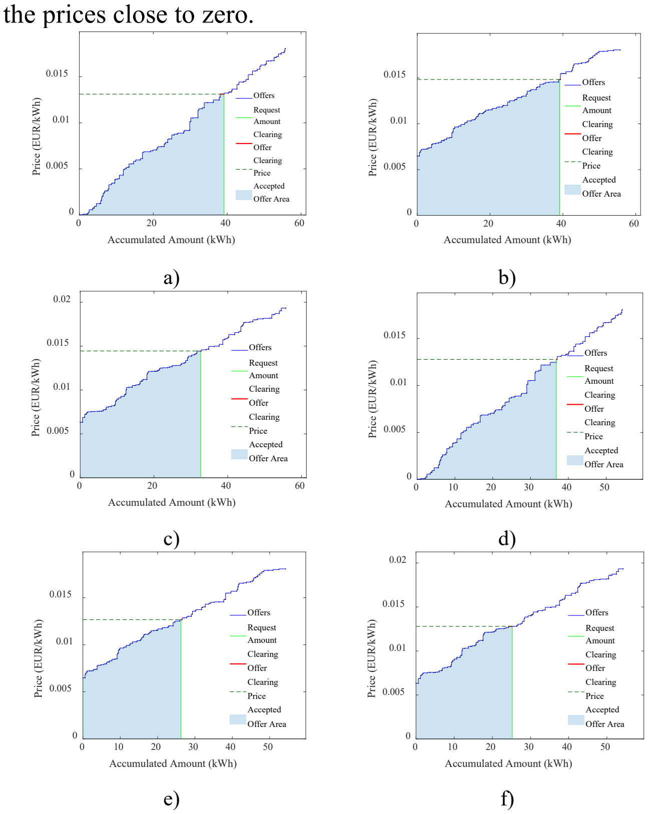


Fig. 2. Asymmetric Pool Results, Scenario A: (a) –strategy 1, (b) – strategy 2, (c) – strategy 3 and Scenario B: (d) –strategy 1, (e) – strategy 2, (f) – strategy 3

B. Real-time non-frequency AS activation results

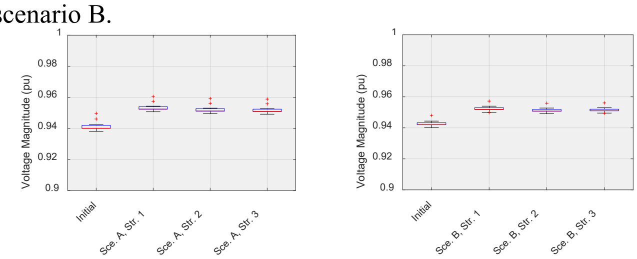
This section presents the results of non-frequency AS activation in real-time. The results presented are obtained for each hour and shown for all periods together. As it was stated in Algorithm 2, in step 1 the forecast is updated at each hour and DSO re-execute the power flow analysis for testing the control variables. In the simulations executed was verified a total consumption average error of 0,350 kWh considering the 24 periods. For the total generation in scenario A an average error of 0,038 kWh was verified and in scenario B the average error was 0,008 kWh. Considering the resulting power flow analyses, the DSO actives the AS already selected (presented in the previous section). TABLE V presents a costs comparison between the different scenario and different strategies, the table also presents the results for the initial analyses for each scenario.

TABLE V
COSTS COMPARISON (EUR)

Scenario	A				B			
Strategy	Init	1	2	3	Init	1	2	3
Losses Costs	2.29	2.18	2.19	2.20	2.13	2.04	2.06	2.07
Flex Costs	0	0.51	0.57	0.47	0	0.45	0.33	0.32
Agg Costs	0	0.02	0.02	0.02	0	0.02	0.01	0.01
Bonus Costs	0	0.0025	0.0011	0.0026	0	0.0032	0.0121	0.0124
Operational Costs	2.29	2.72	2.80	2.70	2.14	2.53	2.43	2.42
Difference		0.44	0.51	0.41		0.36	0.29	0.28

The column with initial in TABLE V presents the initial operation costs with violations in period 18^{th} as was presented in section 5.A. TABLE V presents the different components of operational costs (Losses, Flexibility acquisition, Aggregator and Bonus). Notice that the operational costs presented by the different strategies are both larger than those initially presented. However, this increase in cost is justified since the solution now presents no violations. The initial losses costs were also higher than those presented by the different strategies in both scenarios, but this only reflects a different transit of power in the network. Considering the results of flexibility acquisition was already comment in section 5.A. The aggregator costs have a direct relationship with the amount of energy selected, so if more energy is selected a greater fee, he will receive. The bonus should be divided into the consumers with offers accepted. Strategy 3 is the strategies that get a greater value of the bonus. This strategy is characterized by the adjustment of the offer prices, considering the behavior adopted by the consumer. When the consumers located in buses with violations adopt the benevolent strategy, their offers have higher acceptance possibility. The system resolves the problems with less costs and the consumers receive a great value of the bonus. Both strategies in both scenarios can solve the problem, but as can be seen by the TABLE V the strategy 3 presents the smallest operating costs and the smallest difference with the operation costs of initial analyses with violations.

Fig. 3 presents the boxplot analysis for the set of buses with voltage problems in the period 18^{th} identified in Section 5.1.Fig. 5 presents the boxplot of magnitude voltage for buses with violations. Fig. 3 (a) related scenario A and Fig. 3 (b) if for scenario B.



a) b)

Fig. 3. Magnitude voltage comparison for the 18th period, (a) scenario A and (b) scenario B.

The figure presents the distribution of magnitude voltage values on considering minimum, first quartile, median, third quartile and maximum. Boxplot with label "Initial" represents the distribution of magnitude voltage considering the network's initial state in both scenarios. As can be seen in Fig. 3, all values are below the minimum limit of magnitude voltage (0.95 p.u.). Fig. 3 shows that the use of the different strategies in both scenarios, the violations can be avoided, all the minimum limits are above the 0.95 p.u. Considering the strategy 1, where the greater offer amount is selected, the improvements in the voltage magnitudes are more visible, yet is spent more costs for the AS acquisition.

C. *Discussion*

Considering the different offers strategies used to simulate the consumers behavior, for strategy 1, although the network violations were avoided, and the results were the worst. Strategy 2 creates the prices of the offers considering a linear expression. The use of linear expression tries to simulate the comfort influence felt by the consumer. In this strategy, the consumers with small offer amounts also have small offer prices. Strategy 3 tries to simulate the intelligent behavior of the consumers; thus, when the consumers are located in busses with problems, they reduce their offer prices with the intention that these will be accepted before the others. The created case study envisages the participation of consumers, reducing their load consumption when the Aggregator requests flexibility. Two different scenarios have been explored in order to study the influence of DG production. As results showed, the number of accepted offers decreases with this strategy, making an increment in the bonus. The final results showed that violations can be avoided by using the non-frequency AS provided by consumers. Comparing the results of period 18th (the period where the non-frequency AS were activated), the initial costs were lower than the costs when violations are avoided.

VI. CONCLUSION

The acquisition of non-frequency AS in low voltage level has been explored as a solution to solve issues that may arise in distribution networks. In this paper, a methodology for non-frequency AS acquisition in low voltage networks was presented, and three different strategies for offer prices creation were implemented and compared. The simulation was performed using real attributes of a distribution network located in Portugal. The use of non-frequency AS by DSO brings advantages to the quality of operation as well as payments for consumers due to the non-frequency AS provision. Considering the DSO role for operating the distribution networks with control variables between limits, the simulation demonstrated that marker-based non-frequency AS at the local level are a good option for enabling active participation of consumers and guarantee a smooth grid operation. This work opens different lines of research that are worth to follow as future work. For instance, it is interesting to study the different market structures that allow the participation of final consumers to discover suitable market structure for the benefits of all participants. Another relevant line of research is related to the optimal location of DG to minimize the voltage and lines violations. Finally, the consideration of different asset in the grid and distributed resources (e.g., electrical vehicles and store systems) and their impact in operational costs under the proposed framework is another venue of research.

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Preprint II

Ricardo Faia, Hugo Morais, Tiago Pinto, Fernando Lezama, Zita Vale. (2022). Indoor Temperature Evolution Modelling Through Computational Intelligence, doi: 10.13140/RG.2.2.31971.22560.

Resumen

Un modelo preciso de la temperatura interior de los edificios es crucial para mejorar el confort térmico mientras se gestiona de manera eficiente el consumo de energía de calefacción y refrigeración del edificio. Este artículo propone un método para modelar la evolución de la temperatura interior a lo largo del tiempo en edificios con múltiples oficinas. El nuevo modelo se obtiene considerando los modelos térmicos teóricos con dos modificaciones para maximizar la precisión del modelo. Este tipo de modelo es especialmente útil cuando se combina con sistemas de gestión energética de edificios, con el objetivo de controlar la energía utilizada por los sistemas de calefacción/refrigeración, minimizando costes y garantizando el confort térmico de los usuarios. El modelo propuesto mejora los resultados de los modelos térmicos teóricos mediante el uso de algoritmos basados en inteligencia computacional, a saber, optimización de enjambre de partículas, evolución diferencial, evolución diferencial adaptativa híbrida con función de decaimiento y algoritmo de búsqueda de vórtice. Se utilizan tres tipos de datos de entrada para configurar un modelo predictivo: i) datos de temperatura obtenidos de los sensores instalados en el edificio; ii) consumo de calefacción, ventilación y aire acondicionado de los analizadores de energía y, iii) atributos físicos del edificio, es decir, materiales de construcción. Los datos reales de la temperatura real dentro de un edificio se utilizan para probar el rendimiento del modelo. Los resultados muestran una mejora de hasta un 81 % en la precisión de la temperatura interior prevista cuando el modelo utiliza los coeficientes determinados por los algoritmos de inteligencia computacional.

Indoor Temperature Evolution Modelling Through Computational Intelligence

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ABSTRACT

An accurate model of buildings' indoor temperature is crucial to improve thermal comfort while efficiently managing the building heating and cooling energy consumption. This paper proposes a method to model the indoor temperature evolution along time in buildings with multiple offices. The new model is obtained considering the theoretical thermal models with two modifications in order to maximize the model accuracy. This type of model is especially useful when combined with building energy management systems, with the aim to control the energy used by heating/cooling systems, minimizing costs, and guaranteeing users' thermal comfort. The proposed model improves the results of theoretical thermal models by using algorithms based on computational intelligence, namely particle swarm optimization, differential evolution, hybrid-adaptive differential evolution with decay function, and vortex search algorithm. Three types of input data are used to set up a predictive model: *i)* temperature data obtained from sensors installed in the building; *ii)* heating, ventilating, and air conditioning consumption from power analysers and, *iii)* physical building attributes, i.e., building materials. Real data for the actual indoor temperature of a building is used to test the model performance. Results show an improvement of up to 81% in the predicted indoor temperature accuracy when the model uses the coefficients determined by the computational intelligence algorithms.

KEYWORDS: Buildings, Computational intelligence; Indoor temperature; Temperature modelling; User thermal comfort.

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1. Introduction

The buildings sector is one of the major consuming sectors in the world. In Europe it represents around 40% of the total energy consumption, taking into account the households and service buildings [1,2]. Due to this high energy consumption, it is important to develop strategies for energy conservation and energy management in buildings. In [3,4] authors point out that building energy management models have a key relevance in modeling and controlling the energy demand. Building energy management systems must be able to manage and use energy efficiently and intelligently, ensuring indoor comfort for buildings occupants [5,6]. It is known that people perform their activities better and more effectively if comfort is guaranteed and there are no negative factors (e.g., cold, heat, low light, noise, poor air quality) that can disturb them [7]. Modelling such factors efficiently is therefore crucial to enable suitable energy management decisions [8].

Modelling indoor temperature in buildings is a widely studied topic. However, the existing models can be extremely complex or highly simplified depending on the number of variables the user wants to consider [3,9–15]. This work builds on previous studies found in the literature. In specific, [13] has built a model based on the building's physical processes but results reported an error of 6ºC in their records. In work [14], the authors use a less complex model and adapt it to the building by training the model with historical data. The model presented in [11] also presents great complexity in terms of the physical components considered in the building. The drawback of such complex models where a high number of variables is considered is mainly related to the quality of results obtained. Additionally, the simpler models obtain similar results and are easier to implement due to the fewest number of included variables.

Departing from the work already done in this domain, this paper presents a mathematical model that allows, through the analysis of heat exchanges and thermal gains of buildings, calculating the instantaneous temperature in different rooms. The proposed model can be incorporated into buildings' energy management systems, enabling a suitable temperature control.

The proposed model considers physical variables (thermal conductivity of materials and area) of the building, as proposed by [14]. In order to improve the performance of the model, two adjusting coefficients are added to the formulation. These coefficients are adjusted using computational intelligence algorithms to minimize the modeling error, resulting in an improved model performance. By doing so, the model can be applied straightforwardly to different rooms in the same building with different heating performance and profiles.

It should be noted that the proposed model takes into account the influence that adjacent rooms have on each particular room. Thus, to obtain the best values for coefficients added to the modified model, four different algorithms are implemented and compared, namely Particle Swarm Optimization (PSO) [16], Differential Evolution (DE) [17], Hybrid-adaptive differential evolution with decay function (HyDE-DF) [18], and Vortex Search algorithm [19] (VS).

This paper presents a case study considering a real building for which the proposed model is applied to eleven different rooms, allowing to evaluate the model performance for rooms with distinct characteristics. The obtained results demonstrate the capabilities of the used algorithms of achieving higher levels of accuracy, in the order of up to 80%, when compared to previous works. The following points are enunciated to highlight the contributions of this work:

- Design and development of a generalized indoor temperature model, which can be used in different case studies;
- Computational implementation of the proposed model;
- Use of 4 different computational intelligence algorithms to obtain a more robust training;
- Application of the proposed model to 11 different room of a real office building., using real data.

The paper is divided into 4 different sections. After this introductory section presents the proposed methodology (section 2), which is divided into three different subsections. Section 3.2 presents the proposed model based on literature works, section 2.2 presents the computational intelligence algorithms used to refine the model in order to obtain a minimal error, and section 2.3, a brief description of the optimization process is presented. The physical characteristics of the building used for experiments, the results from the model validation, and coefficients identification are presented in section 3. Finally, the main conclusions from this work are drawn in the last section of the paper (section 4).

2. Proposed Methodology

This section presents the proposed methodology, namely describing thermal heating model and the modification the algorithms used to refine the coefficient values. It also presents the metrics used in this paper to evaluate the performance of the thermal heating models.

2.1.Proposed model

The conceptual model proposed in this paper is based on the principle of energy conservation and is presented in Fig. 1, in which the model is illustrated for a specific illustrative room (Room A). As can be seen in Fig. 1, Room A considers different heat gains and losses. Room A has heat gains from equipment (Q_{eq}), occupants (Q_{ocu}), HVAC systems (Q_{hvac}), lights (Q_{light}), and from adjacent room B (Q_{ind}). On the contrary, room A has losses of energy to the exterior of the building (Q_{ext}).

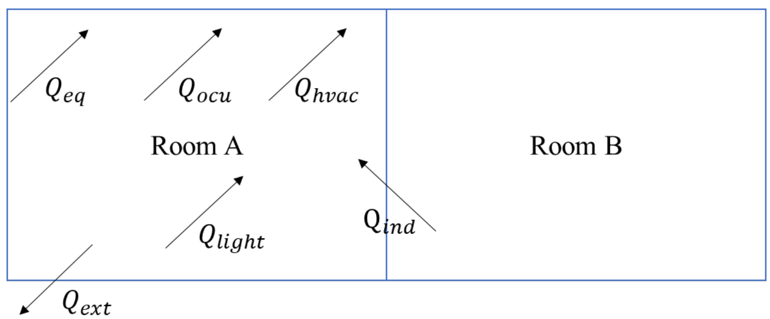


Fig. 1**.** Different heat gains and losses (illustrative example)

The Q_{ext} parameter representing the heat exchange with the exterior and can be obtained considering equation (1) [20].

$$Q_{ext} = A_{ext}^{wall} \times U_{ext}^{wall} \times (T_{ext} - T_{in}) + A_{ext}^{window} \times U_{ext}^{window} \times (T_{ext} - T_{in}) \quad (1)$$

where A_{ext}^{wall} and A_{ext}^{window} are the wall and window areas respectively, U_{ext}^{wall} and U_{ext}^{window} are the global heat transference coefficients of wall and window, and T_{ext} and T_{in} represent the exterior and interior temperatures.

The heat exchange over the indoor wall is represented by Q_{ind} and is obtained considering equation (2) [20].

$$Q_{ind} = A_{ind}^{wall} \times U_{ind}^{wall} \times \left(T_{in}^{adjacent} - T_{in}\right) + A_{ind}^{window} \times U_{ind}^{window} \times \left(T_{in}^{adjacent} - T_{in}\right) \quad (2)$$

where A_{ind}^{wall} and A_{ind}^{window} represent the areas of wall and window, U_{ind}^{wall} and U_{ind}^{window} are the global heat transference coefficients of indoor wall and window, and $T_{in}^{adjacent}$ represents the temperature of adjacent areas.

Equation (3) regards the heat gains from HVAC systems [20].

$$Q_{HVAC} = P_{HVAC} \times ON_{HVAC} \tag{3}$$

where Q_{HVAC} represents the heat gain from a HVAC system considering the heating function, P_{HVAC} corresponds to the HVAC power supply, and ON_{HVAC} represents the HVAC state (1=ON , 0=OFF).

The heat gains from occupants can be obtained using (4) [20].

$$Q_{Ocu} = N_{ocu} \times q_{sensible} \tag{4}$$

where Q_{Ocu} represents the heat gain from occupants, N_{ocu} represents the number of occupants, and $q_{sensible}$ represents the heat exchanged by a body.

Heat gain from equipment's is given by equation (5) [20].

$$Q_{Eq} = N_{eq} \times q_{eq} \tag{5}$$

Where Q_{Eq} represents the heat gain considering the internal equipment, N_{eq} represents the number of equipment, and q_{eq} is the heat released by equipment (e.g., computers).

Equation (6) represents the heat gains from lightning [20].

$$Q_{light} = N_{light} \times q_{light} \tag{6}$$

where Q_{light} represents the heat gain by lighting, N_{light} is the number of lights, and q_{light} represents the heat released by lighting equipment.

Considering all enunciated gains and losses, the energy balance can be expressed using equation (7).

$$\frac{dU_{vc}}{dt} = +Q_{ext} + Q_{ind} + Q_{HVAC} + Q_{Ocu} + Q_{Eq} + Q_{light} + Q_{rad} \tag{7}$$

Considering a constant mass in the control volume, the left-side term of the energy balance, which describes the variation of internal energy in the room, can be considered as equation (8) shows.

$$\frac{dU_{vc}}{dt} = M_{vc}C_v\frac{dT_{in}}{dt} \tag{8}$$

Applying the substitution of equation (7) into equation (8), we obtain equation (9).

$$M_{vc}C_v\frac{dT_{in}}{dt} = \begin{matrix} A_{ext}^{wall} \times U_{ext}^{wall} \times (T_{ext} - T_{in}) + A_{ext}^{window} \times U_{ext}^{window} \times (T_{ext} - T_{in}) \\ +A_{ind}^{wall} \times U_{ind}^{wall} \times \left(T_{in}^{adjacent} - T_{in}\right) + A_{ind}^{window} \times U_{ind}^{window} \times \left(T_{in}^{adjacent} - T_{in}\right) \\ +N_{eq} \times q_{eq} \\ +P_{HVAC} \times ON_{hvac} \\ +N_{ocu} \times q_{sensible} \\ +N_{light} \times q_{light} \end{matrix} \tag{9}$$

Modifying equation (9) by placing all temperatures in evidence leads to equation (10).

$$\begin{aligned} M_{vc}C_v\frac{dT_{in}}{dt} &+ T_{in}\left(A_{ext}^{wall} \times U_{ext}^{wall} + A_{ext}^{window} \times U_{ext}^{window} + A_{ind}^{wall} \times U_{ind}^{wall} + A_{ind}^{window} \times U_{ind}^{window}\right) \\ &= T_{ext}\left(A_{ext}^{wall} \times U_{ext}^{wall} + A_{ext}^{window} \times U_{ext}^{window}\right) \\ &+ T_{in}^{adjacent}\left(A_{ind}^{wall} \times U_{ind}^{wall} + A_{ind}^{window} \times U_{ind}^{window}\right) + N_{eq} \times q_{eq} \\ &+ P_{HVAC} \times ON_{hvac} + N_{ocu} \times q_{sensible} + N_{light} \times q_{light} \end{aligned} \tag{10}$$

Indoor temperature evolution with t (equation (11)) can be obtained by solving the differential non-homogeneous equation (10).

$$T_{in}^{t+1} = \frac{(T_{in}^{t} \times B + C) \times e^{B \times \Delta t} - C}{B} \tag{11}$$

where T_{in}^{t+1} represents the indoor temperature for the following period, T_{in}^{t} is the temperature at period t, Δt corresponds to the time interval between T_{in}^{t} and T_{in}^{t+1}, parameter B is obtained by equation (12), and C by equation (13).

$$B = -\frac{A_{ext}^{wall} \times U_{ext}^{wall} + A_{ext}^{window} \times U_{ext}^{window} + A_{ind}^{wall} \times U_{ind}^{wall} + A_{ind}^{window} \times U_{ind}^{window}}{M_{vc}C_v} \tag{12}$$

$$C = \begin{pmatrix} T_{ext}\left(A_{ext}^{wall} \times U_{ext}^{wall} + A_{ext}^{window} \times U_{ext}^{window}\right) + \\ T_{in}^{adjacent}\left(A_{ind}^{wall} \times U_{ind}^{wall} + A_{ind}^{window} \times U_{ind}^{window}\right) + \\ N_{eq} \times q_{eq} + P_{HVAC} \times ON_{hvac} + \\ N_{\mathrm{ocu}} \times q_{sensible} + N_{light} \times q_{light} \end{pmatrix} \times \frac{1}{M_{vc}C_v} \tag{13}$$

Initial experiments, from which results for one of the rooms under study are presented in Fig. 2, show that the model presented in equation (11) with six physical parameters (i.e., external wall conductivity, internal all conductivity, equipment number, HVAC power consumption, occupants number and number of light) is not able to model the indoor temperature satisfactorily compared with real measurements. As can be seen in Fig. 2, the actual room temperature and the room temperature obtained with equation (11) for one specific room (room 107 in the case of results presented in Fig. 2), present a notorious difference (e.g., a difference of 4ºC in some periods), thus not being able to model the indoor room temperature correctly. Therefore, it is clear that adjustments are needed.

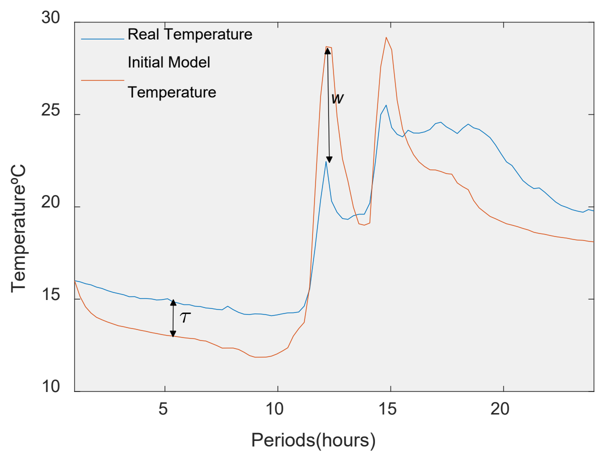


Fig. 2**.** Initial experiments

In order to keep the model simple considering the enunciated coefficients while increasing the modeling accuracy as much as possible, two additional coefficients, w, and τ have been included in the model. These coefficients are used to capture the degradation of HVAC efficiency and the lack of modeled factors that provide loss or gain of heating (loss/gain ratios when the door is opened). Thus, the model is modified according to equations (14) and (15).

$$T_{in}^{t+1} = \frac{(T_{in}^{t} \times B + C) \times e^{B \times \Delta t} - C}{B} + \boldsymbol{\tau} \tag{14}$$

$$C = \begin{pmatrix} T_{ext}\left(A_{ext}^{wall} \times U_{ext}^{wall} + A_{ext}^{window} \times U_{ext}^{window}\right) + \\ T_{in}^{adjacent}\left(A_{ind}^{wall} \times U_{ind}^{wall} + A_{ind}^{window} \times U_{ind}^{window}\right) + \\ N_{eq} \times q_{eq} + (P_{HVAC} \times \boldsymbol{w}) \times ON_{hvac} + \\ N_{\text{ocu}} \times q_{sensible} + N_{light} \times q_{light} \end{pmatrix} \times \frac{1}{M_{vc} C_v} \tag{15}$$

As can be seen in (14) and (15), the two coefficients w and τ are added to the model. w influences the heating generated by the HVAC and τ affects the overall room temperature. The rationale for the introduction of these two coefficients can be explained using a practical example. Analyzing Fig. 2 in further detail, one can detect two different contexts in which with an additional coefficient is possible to improve the accuracy of the model. The first context is when the HVAC is off (1:00h to 10:00h and 18:00 to 24:00). The other context is when HVAC is on (10:00 to 18:00). In order to deal with the periods when the HVAC is on, a coefficient w is added, which directly multiplies the HVAC power, simulating the HVAC system efficiency deterioration over time. For the periods when the HVAC is off, the coefficient τ compensates positively (up) or negatively (down) the temperature. This is done since the model may not gather all the necessary components and there must be an increase in the estimated temperature, or in some cases, the existing ones are above the real values with an increase in the estimated values and it is necessary to reduce it. In this sense, the value of τ, single in each building part that is intended to be modeled, can assume a negative or positive value.

2.2. Computational intelligence algorithms

This section presents the computational intelligence algorithms used to optimize the values of coefficients w and τ. To compare the results with large robustness, four different algorithms are used, namely Particle Swarm Optimization (PSO) [16], Differential Evolution

(DE) [17], Hybrid-adaptive differential evolution with decay function (HyDE-DF) [18], and Vortex Search algorithm [19] (VS). Each of the algorithms will look for the best set of coefficients according to equation (18) that minimizes equation (19).

$$\vec{x} = [\tau^1, \tau^2, \tau^3, \dots, \tau^{Nr}; w^1, w^2, w^3, \dots, w^{Nr}] \tag{16}$$

$$\text{minimize: } f(x) = \sum_{r=1}^{Nr} (Error^r) \tag{17}$$

where, $\vec{x}$ represents the vector of the decision variables containing two different coefficients for each room, resulting in a dimension of $D = (2 * Nr) = 2 * 10 = 20$. Equation (17) represents the objective function considering the minimization of the total errors. Notice that it is possible to select the error metric, $Error^r$, between the Mean Absolute Error (MAE) equation (18) or Root Mean Squared Error (RMSE) equation (19).

MAE and RMSE measure the difference between the values obtained with the proposed model and the real values. Equation (16) and (17) are used to obtain the MAE and RMSE values, respectively.

$$\text{MAE} = \frac{\sum_{t=1}^{Nt} |T_{in}^t - Real\ T_{in}^t|}{Nt} \tag{18}$$

$$\text{RMSE} = \sqrt{\frac{1}{Nt} \sum_{t=1}^{Nt} (T_{in}^t - Real\ T_{in}^t)^2} \tag{19}$$

where T_{in}^t is the value obtained considering the model, $Real\ T_{in}^t$ is the real value measured and Nt is the total number of periods.

- Particle Swarm Optimization

PSO is an optimization algorithm that iteratively searches the improvement of solutions regarding a given fitness function. It contains a population of possible solutions, here called particles, and move these particles around the search-space according to equation (20) (describing the particles position) and equation (21) (describing how the velocity of particles is updated).

$$\vec{x}_{i+1}^{j} = \vec{v}_{i+1}^{j} + \vec{x}_{i}^{j} \tag{20}$$

$$\vec{v}_{i+1}^{j} = w_i^j \times \vec{v}_i^j + c1_i^j \times r1_i^j \times \left(P_{best}^{j} - \vec{x}_i^j\right) + c2_i^j \times r2_i^j \times \left(G_{best} - \vec{x}_i^j\right) \tag{21}$$

where $\vec{x}_i^j$ represents the position vector of particle j for n variables at iteration i, $\vec{v}_i^j$ represents the velocity vector, w_i^j represents the inertia weight obtained through equation (22), $c1_i^j$ and $c2_i^j$ are acceleration coefficients obtained by equations (23) and (24) respectively, and $r1_i^j$ and $r2_i^j$ are two uniformly distributed random numbers independently generated within [0,1] for the *n*-dimensional search space.

$$w_i^j = w^{max} - \left(\frac{w^{max} - w^{min}}{i^{max}}\right) \times i \tag{22}$$

where w^{max} is the maximum value for the inertia weight, w^{min} is the minimum value for the inertia weight, and i^{max} represents the maximum number of iterations.

$$c1_i^j = c_1^{max} - \left(\frac{c_1^{max} - c_1^{min}}{i^{max}}\right) \times i \tag{23}$$

$$c2_i^j = c_2^{min} + \left(\frac{c_2^{max} - c_2^{min}}{i^{max}}\right) \times i \tag{24}$$

- Differential evolution

DE is also an iterative algorithm that searches for a solution considering a fitness function. In the standard form of DE, the so-called DE/rand/1 algorithm, new solutions are created applying a mutation and recombination operator defined by:

$$\vec{m}_{i,G} = \vec{x}_{r1,G} + F\left(\vec{x}_{r2,G} - \vec{x}_{r3,G}\right) \tag{25}$$

$$\vec{t}_{j,i,G} = \begin{cases} \vec{m}_{i,G} & \text{if } \left(\text{rand}_{i,j}[0,1] < \text{Cr} \ \vee (j = \text{Rnd})\right) \\ \vec{x}_{j,i,G} & otherwise \end{cases}, \tag{26}$$

where, $\vec{x}_{r1,G}$, $\vec{x}_{r2,G}$ and $\vec{x}_{r3,G}$ are three random individuals from the population, mutually different from each other. F and Cr are the mutation and recombination parameters of DE, usually set in the range $[0,1]$. An elitist selection procedure is applied in DE by replacing solution with worse performance than the new generated ones.

- HyDE-DF

HyDE-DF is an improved version of HyDE [21], and HyDE is a new self-adaptive version of DE proposed in [22]. The main difference in its operation is the incorporation of a decay function as can be seen in equation (27):

$$\vec{m}_{i,G} = \vec{x}_{i,G} + \delta_G \cdot \left[F_i^1\left(\epsilon \cdot \vec{x}_{best} - \vec{x}_{i,G}\right)\right] + F_i^2\left(\vec{x}_{r1,G} - \vec{x}_{r2,G}\right) \tag{27}$$

where δ_G is a decreasing function (from 1→0) that gradually mitigates the importance around $\vec{x}_{best}$. The decay factor at each generation G is calculated considering equation (28):

$$\delta_G = e^{1-\frac{1}{a^2}}, \text{ with } \quad a = \frac{(GEN-G)}{GEN} \tag{28}$$

δ_G parameter controls the premature convergence effect around $\vec{x}_{best}$ (best individual). This process allows an increased exploration process in the initial stages of search and contributes to a higher exploitation in final stages of the optimization process.

- Vortex Search

VS is a single-solution-based algorithm, to obtain a good balance between the exploration and the exploitation, the search process of the vortex search algorithm is modeled as a vortex model. In each iteration, a number N of neighbor solutions are created using a Gaussian distribution considering the initial solution using equation (29):

$$p(\vec{m}/\mu, \Sigma) = \frac{1}{\sqrt{(2\pi)^d |\Sigma|}} \exp\left\{-\frac{1}{2}(\vec{x} - \mu)^G \Sigma^{-1} (\vec{x} - \mu)\right\} \tag{29}$$

where d represents the dimension, $\vec{x}$ is the vector of a random variable, μ is the vector of sample mean (center), and Σ is the covariance matrix.

2.3. Optimization process

Fig. 3 presents the general diagram of the optimization process using a metaheuristic algorithm.

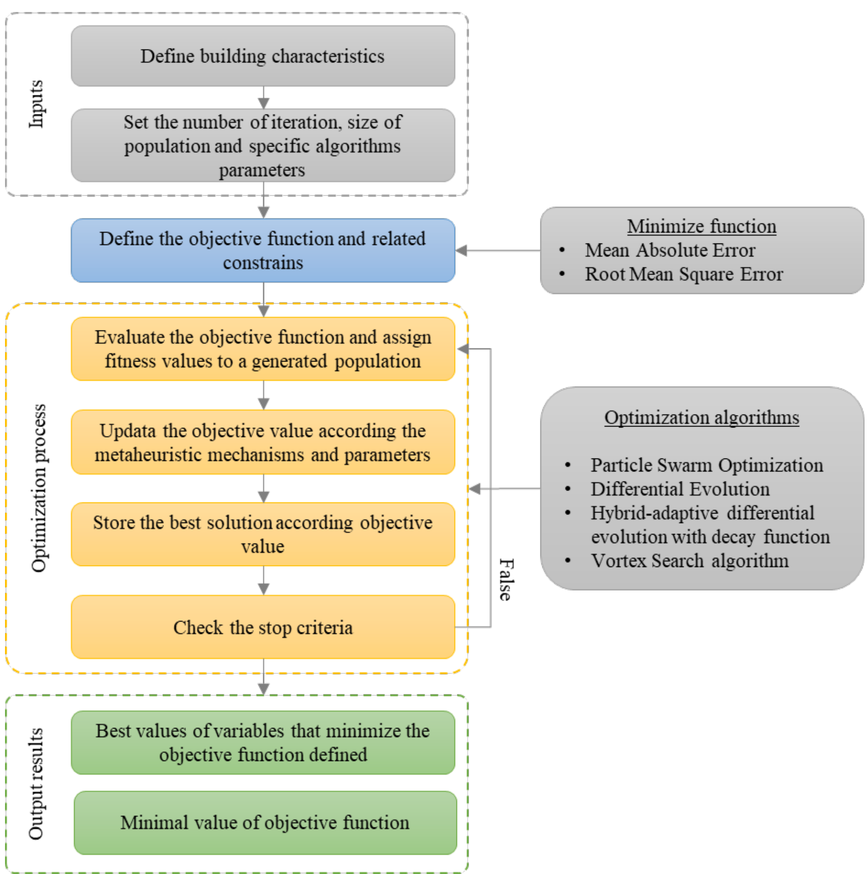


Fig. 3. Optimization process diagram.

In the "Inputs" phase, the characteristics of buildings should be defined (areas, the conductivity of materials, among others) and the number of iterations, population size, and specific parameters that each algorithm needs to work. After the previous phase, the objective function and related constraints should be defined. As explained before, MAE or RMSE can apply as objective functions. In the "Optimization process" process, a solution should be founded considering specific steps. Therefore, the solution found should minimize the value of the error metric, obtaining the best values for the coefficients (w and τ) of the proposed thermal heating model. PSO, DE, HyDE, and VS can be used to realize the optimization process. In "Output results," the results are obtained when the process reaches the maximum number of iterations, defined as the stopping criteria for all algorithms. As a result, the algorithms return the best value for the objective function and the best value for each variable, representing the value for each coefficient of the proposed model.

3. Case studies

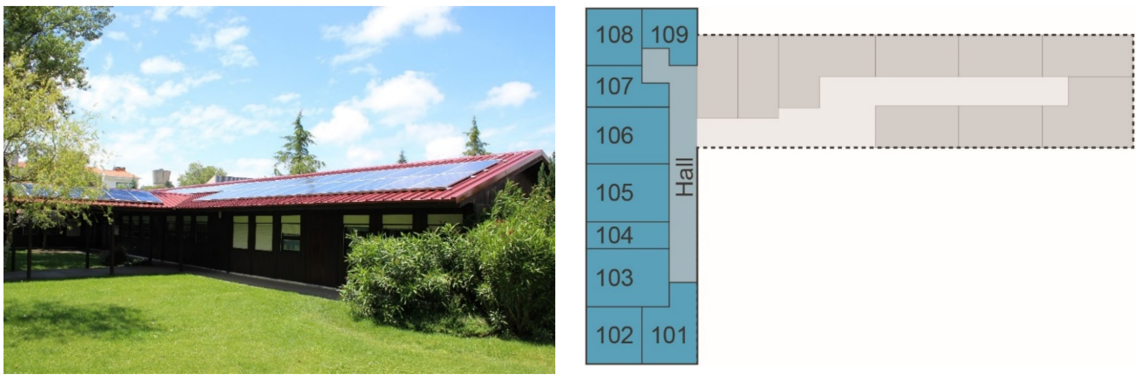
This section describes the characteristics of the building considered in the experiments, presents the obtained results, and the outcome of the analysis regarding the proposed model performance. The experiments have been conducted using MATLAB2018a in a computer with Intel Xeon(R) E5-2620v2@2.1 GHz processor with 16GB of RAM running Windows 10. The experimental study considered the following cases:

- Baseline - thermal heating model without redefined coefficients (equation (11));
- Case 1 - thermal heating model with redefined coefficients considering MAE as the Error (equation (18)) in the objective function of equation (17);
- Case 2 - thermal heating model with redefined coefficients considering RMSE

(equation (19)) as the Error in the objective function of equation (17).

3.1. Building characteristics

The building used in the case study is located in Porto and has the following GPS coordinates (41°10'45.8"N 8°36'31.2"W). As aspect of the building is shown in Fig. 4.



a) b)

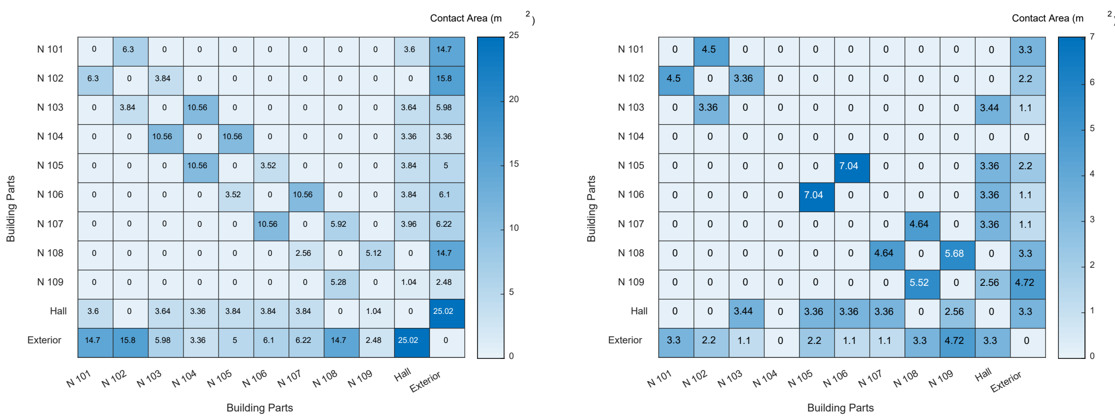
Fig. 4. Test building, a) exterior building view and b) floorplan.

Fig. 4b) presents the floorplan of the building. As can be seen, the building has 20 different parts, corresponding to 11 office rooms, 3 halls, 2 bathrooms, 2 server rooms, 1 kitchen, and 1 meeting room. For the experiments, we have considered 7 office rooms, 1 server room (N104), 1 meeting room (N101) and 1 hall. The considered parts are highlighted in blue in Fig.4 b). TABLE I presents the physical characteristics of the building.

TABLE I. BUILDING PHYSICAL CHARACTERISTICS

Building Parts		Contact - exterior				Contact - interior			
		Area (m^2)		Coefficient ($W/m^{2o}C$)		Area (m^2)		Coefficient ($W/m^{2o}C$)	
		Wall	Glass	Wall	Glass	Wall	Glass	Wall	Glass
Rooms	N101	14.7	3.3	1.31	2.85	13.5	4.5	2.31	1.71
	N102	15.8	2.2			12.24	5.76		
	N103	5.98	1.1			20.76	7.44		
	N104	3.36	0			24.48	0		
	N105	5	2.2			17.92	10.4		
	N106	6.1	1.1			17.92	10.4		
	N107	6.22	1.1			20.44	8		
	N108	14.7	3.3			7.68	10.32		
	N109	6.1	1.1			17.26	11.34		
Hall		25.02	3.3			23.16	16.08		

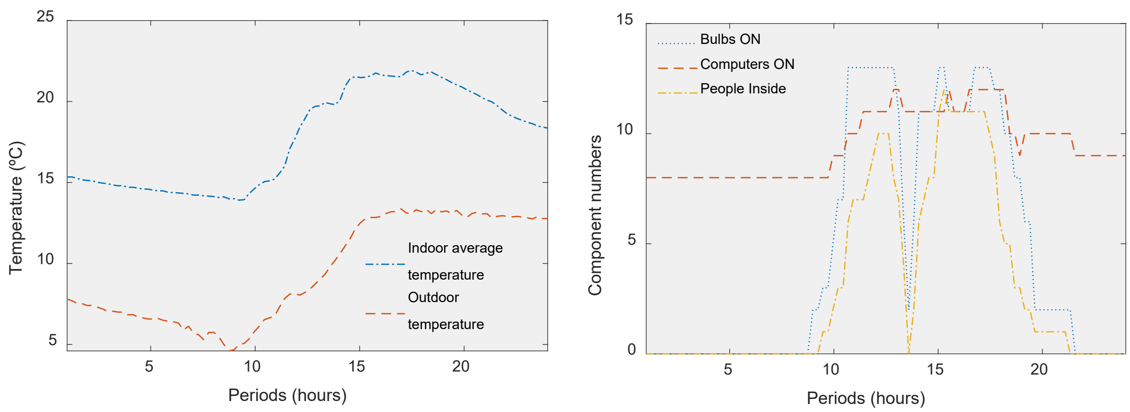
For each space considered in the experiments, TABLE I presents wall and glass windows areas in contact with the exterior and with other indoor parts. The heat transfer coefficients represent the rate of heat transfer between two different surfaces per unit surface area and per unit temperature difference. Analyzing the coefficients values listed in the table, there are two different groups of walls and two different groups of glass windows: the group in contact with the exterior and the group in contact with indoor parts. Fig. 5 shows the information of contact between different sections of the building considered in the case study.



a) b)

Fig. **5.** Contact area matrix, a) building parts and b) windows

Comparing Fig. 5 a) and b) with Fig. 4 b), it is possible to see which rooms are in contact with each other. Fig. 5a) presents the contact wall area of each part of the building. For instance, room N101 has a contact area of 6.3m^2 with room N102, 3.5m^2 with the Hall, and 14.7m^2 with the Exterior. Analyzing Fig. 5 b), it is also possible to see the glass area (i.e., the windows) that separated the building parts. For instance, room N102 has shared windows areas of 4.5m^2, 3.36m^2, and 2.2m^2 with room N101, room N103, and the exterior, respectively. A value of 0 in Fig. 5 represents no contact between the parts (e.g., room N101 is not in contact with the room N104). Fig. 6 shows the data regarding indoor and outdoor temperature and number of components in the building for a winter day, specifically on 13th January 2020. Fig. 6 a) presents the mean indoor temperature of the building and outdoor temperature, and Fig. 6 b) displays the input components considered in the presented model (number of lights on, number of computers on and number of people inside the building). These components are presented only for the building parts in study and are used to capture the heat transfer gathered from such elements.



a) b)

Fig. 6. Building data for 13th January 2020, a) Outdoor and indoor temperature, b) number of lights turned on, computers turned on and people inside the building

As can be seen in Fig. 6 a), the mean indoor temperature of the entire building has a similar behavior to the outdoor temperature, despite being always higher. This indicates that the building is drastically affected by changes in the outdoor temperature. The indoor temperature reaches its minimum value around 9 am (around 14°C) and its maximum around 6 pm (22°C). The used data sample regards a normal working day in the building before the start of the Covid 19 pandemic in Portugal. Fig. 6 b) presents three different input components: the number of lights on, the number of computers on, and the numbers of people inside the building. As can be seen in the figure, the number of lights on has a maximum of 13 in three moments, the number of computers on vary from 8 to 12, and the maximum number of people inside the building in study was registered at 15:00 with 12 people. Fig. 7 presents the comparison between the total electricity consumption of the building parts involved in the case study and the total HVAC consumption in these parts. The consumptions presented in Fig. 7 are for the same day as Fig. 6 a) and b).

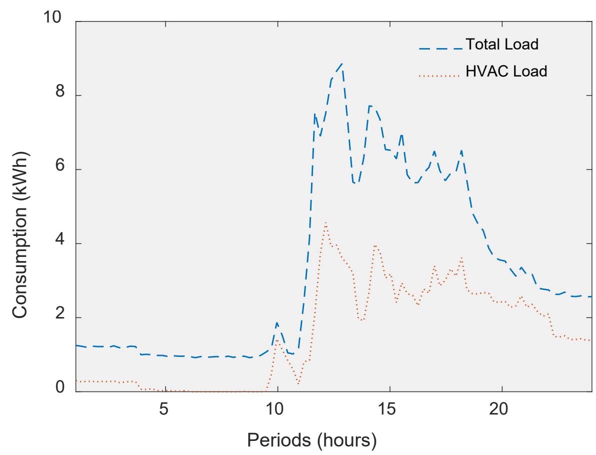


Fig. 7**.** Electricity consumption for 13th January 2020

As can be seen in Fig. 7, the HVAC load has a direct influence on the total load. HVAC load represents around 46% of the total load, and each building space considered in the case study has an HVAC average consumption of 3.6 kWh per day. At the end of the day, the total load presents a cumulative value of 79.75 kWh.

3.2. Results

In order to obtain more robust solutions, 30 different runs were executed for each algorithm. The comparison between the results obtained with the base case (without the two coefficients and the respective optimization) and the proposed model with coefficients optimized, is presented in TABLE II.

TABLE II presents two different results, the best-of-run value obtained for the 30 runs, and the mean and standard deviation values obtained over the set of 30 performed runs. Analyzing these results, it is possible to see a reduction of error values in both metrics for all the proposed models compared with the baseline case. Considering the results for Case 1 (MAE as optimization evaluation metric), the best algorithm is the DE, presenting a slight difference of 6.43E-05 compared with the second best, the HyDE-DF.

TABLE II. OPTIMIZATION RESULTS

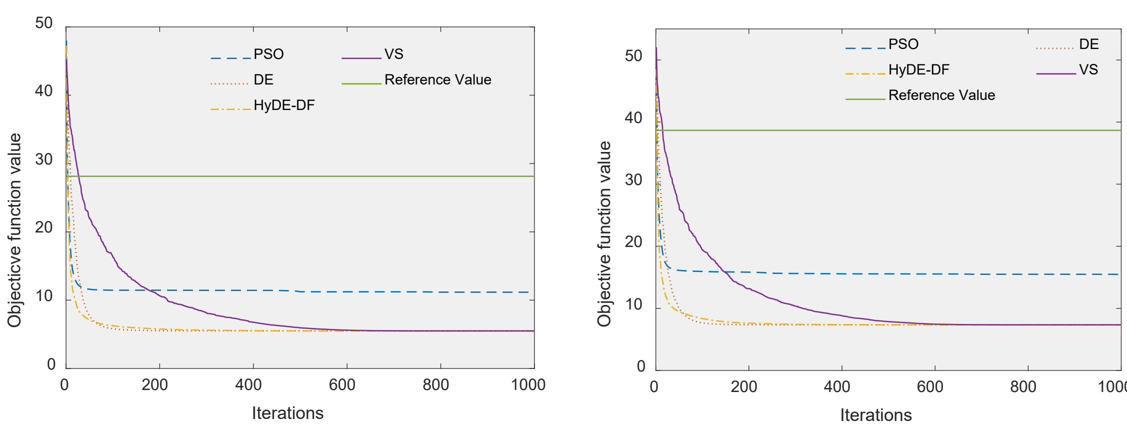
Scenario	Model	Best-of-run value			Mean and standard deviation over 30 runs		Execution time(s)
		$f(x)$	$\sum$^(MAE)	$\sum(RMSE)$	mean$\big(f(x)\big)$	std$\big(f(x)\big)$	
Base Case*		-	28.132	38.664	-	-	-
Case 1 - MAE	PSO	6.938	6.938	10.122	11.165	3.582	540.321
	DE	5.479	5.479	7.503	5.514	0.113	536.746
	HyDE-DF	5.479	5.479	7.502	5.479	6.29E-05	540.268
	VS	5.480	5.480	7.505	5.497	0.019	522.263
Case 2 - RMSE	PSO	9.000	6.516	9.000	15.446	4.565	517.635
	DE	7.334	5.637	7.334	7.345	0.024	515.940
	HyDE-DF	7.334	5.637	7.334	7.334	6.05E-07	515.717
	VS	7.335	5.634	7.335	7.351	0.026	513.666

*The case-base uses the model shown in Equation 11 and therefore optimization is not required

Looking at the mean values and standard deviation of the 30 runs, HyDE-DF presents the lowest values of the group of used algorithms. This feature is an indicator that HyDE-DF gives solutions that are more robust and less sensitive to variability for this test, allowing a reduction on the number of runs due to its low variability. PSO presents the worst performance within the group of algorithms tested in Case 1 in both indicators.

Considering the results of Case 2 (using RMSE), the same trend is observed with DE obtaining the minimum value with a difference of only 4.54E-06 concerning the second best, the HyDE-DF. Again, HyDE-DF presents the best results in terms of mean and standard deviation values. Comparing the results of Case 1 and Case 2, it can be seen that for Case 1, where the MAE is evaluated as error metric, the RMSE metric does not present a better value than the one obtained in Case 2 (where the RMSE is the error metric optimized), and vice versa (notice that in Case 2 the calculated MAE never has a smaller value than the one in Case 1). It thus can be concluded by the results that besides enabling better results, the use of RMSE metric has a positive impact in the execution time. On average, a run with RMSE takes less than 20 seconds than using MAE. The runtime values shown are the mean values over the set of 30 runs.

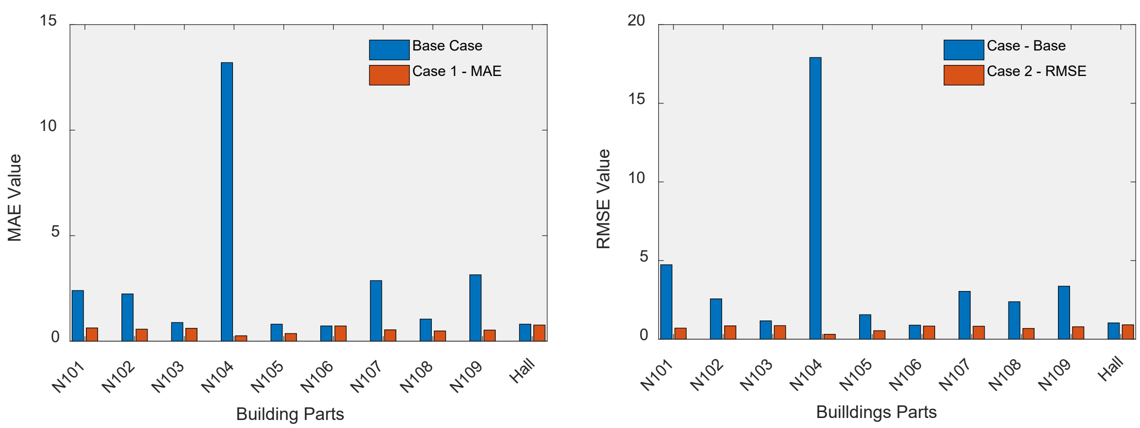
Fig. 8 presents the objective function value for the undertaken iterations, considering MAE and RMSE, in Fig. 8a) and in Fig 8b), respectively. Fig. 8a) and b) present the mean results over the 30 runs at each iteration for all models tested. The reference value presented in both figures corresponds to the value of the Base Case presented in TABLE II for both error metrics. The performance of DE and HyDE-DF are very similar, finding a good solution within the first 100 iterations. Notice that PSO presents a similar performance, but the final solution achieved has a higher value. On the other hand, VS achieves a similar final solution compared with DE and HyDE-DF, but the convergence behavior is different. As can be seen in the figures, the value of objective function stabilizes at 550 iterations, achieving a final value near to the one obtained by DE and HyDE-DF. It can be concluded that VS can avoid a premature convergence of solutions scaping from local optimal solutions in spite of not showing the best results when analyzing the evolution of the objective function. Fig. 9 presents the errors obtained in the simulations for simulations considering MAE and for simulations considering RMSE, in Fig 9a) and Fig. 9b), respectively.



a) b)

Fig. 8. Objective function value, a) using MAE and b) using RMSE

Comparing the values of MAE and RMSE for the Base Case, it can be seen that the maximum MAE value regards room 104 both for MAE and RMSE. Analyzing Fig. 9a) and Fig 9b), it can be noticed that the error for the base case is very high for room N104. This can be explained since room 104 is the room where the computer servers are located and has very particular characteristics. For instance, the HVAC is set so that the temperature in that never exceeds 18ºC and, therefore, there is an automatic system that turns on the HVAC system whenever that situation occurs. Due to the results achieved with the error metrics for the Base Case, the proposed model includes a multiplicative coefficient to the HVAC power in the thermal model. As can be seen from the results for both MAE and RMSE, the proposed models lead to a decrease of 98% in the error for Room N104, compared with the error of the Base Case. Overall, a decrease in the respective error is verified for all rooms. Room N106 in Case 1 presented a smallest decrease (0.15%). Room N106 also presents the smallest decrease in Case 2, around 6%.



a) b)

Fig. 9**.** Errors per building part, a) using MAE error, and b) using RMSE value

TABLE III presents the values of each coefficient for each building space corresponding to the solution with the minimum achieved value (i.e., the solution found by the DE algorithm).

TABLE III. COEFFICIENTS' VALUE OPTIMIZED.

Building Parts		Coefficients			
		w		τ	
		Case 1	Case 2	Case 1	Case 2
Rooms	N101	0.151	0.153	0.042	0.021
	N102	0.143	0.128	0.795	0.879
	N103	0.353	0.406	-0.169	-0.104
	N104	0.207	0.207	0.122	0.137
	N105	0.128	0.166	-0.201	-0.194
	N106	0.735	0.227	-0.035	-0.115
	N107	0.741	0.781	1.532	1.442
	N108	0.034	0.031	-0.094	-0.157
	N109	0.604	0.563	1.651	1.638
Hall		0.574	0.112	-0.086	-0.206

By analyzing the results presented in TABLE III, it can be observed that the values in both cases follow the same trend of positive or negative numbers. Values for w in Case 1 have a mean value of 0.367, and in Case 2, a mean value of 0.277. Considering the case of τ, in Case 1, a mean of 0.356 is obtained, and in Case 2 the mean is 0.334. Comparing the values for each room in the different cases, they are quite similar, except for room N106 for which the values are very different. The w in Case 1 is greater than the one obtained in Case 2; for the value of τ, the opposite happens.

Fig. 10 presents the temperature values obtained for room N102. The coefficient τ in this room will cause the values obtained by the Base Case model to rise at each instant to values closer to the real value (note that τ is a unique value applied to all periods). The coefficient w will only have an influence when the HVAC starts operating, as this is directly multiplied by the HVAC power. In this specific case, it will allow a drop in the value obtained by the model in the Case Base, getting closer to the real value. Room N102 in the Base Case has a MAE of 2.24 and a RMSE of 2.57, while for Case 1 the MAE is 0.57 (reduction of 75%) and for Case 2 the RMSE is 0.85 (reduction of 67%). Looking at the reported values, the use of coefficients τ and w in the proposed models enables a significant improvement of the thermal heating model.

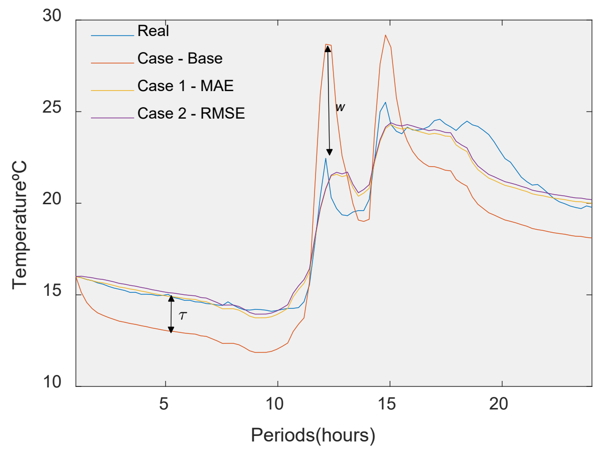


Fig. 10**.** Temperatures values for Room N102

4. Conclusion

This work presents the conception, design, and refinement of a model to estimate the indoor temperature in different of rooms building. The refinement process adapts the model in a way that it is fitted to a specific part of the building. Real measured data acquired from each building space has been utilized in the model performance analysis. Based on the simulations and on the best result achieved by the proposed models, the average MAE and RMSE during the considered 24 hours, divided in 96 periods of 15 minutes each was 5.5ºC and 7.3 ºC respectively. The achieved results show a significant improvement when compared to the Base Case, which represents the baseline indoor temperature model from the literature and presents a MAE of 28.13 ºC and RMSE of 38.66 ºC.

In addition, the use of different computational algorithms brings more robustness to the results. Results demonstrate an acceptable accuracy for the various building parts of the case study. Generalizing the model structure allows implementing and adapting the model to the other rooms or to other buildings.

Declaration of Competing Interest

The authors declare that they have no conflicts of interest.

Funding

This article is a result of the project RETINA (NORTE-01-0145-FEDER-000062), supported by Norte Portugal Regional Operational Program (NORTE 2020), under the PORTUGAL 2020 Partnership Agreement, through the European Regional Development Fund (ERDF). The authors acknowledge the work facilities and equipment provided by GECAD research center (UIDB/00760/2020) to the project team.

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Preprint III

Ricardo Faia, Fernando Lezama, Zita Vale, João Soares, Tiago Pinto, Juan Manuel Corchado. (2022). Local Electricity Markets – Review, doi: 10.13140/RG.2.2.15194.00961.

Resumen

Los mercados eléctricos locales se perfilan como una solución natural para superar los retos que plantea la penetración masiva de la generación renovable distribuida, y la consiguiente necesidad de situar a los consumidores como actores centrales del sistema, con un papel activo y dinámico. Si bien existe una literatura significativa que aborda el tema de los mercados eléctricos locales, este sigue siendo un tema bastante nuevo y emergente. Por lo tanto, este documento proporciona una visión general de este dominio y brinda una perspectiva sobre las necesidades futuras y los desafíos que deben abordarse. Esta revisión presenta los conceptos más importantes en el dominio del mercado eléctrico local, brinda un análisis sobre los diferentes marcos regulatorios y de políticas, expone las iniciativas mundiales más relevantes relacionadas con la implementación de campo de los mercados eléctricos locales y analiza los modelos alternativos de mercado local propuestos en la literatura. La discusión presenta los principales beneficios y barreras de los modelos de mercado local actualmente propuestos, y el impacto esperado de su implementación generalizada. La revisión se concluye con la recapitulación y discusión sobre los caminos más relevantes para futuras investigaciones y desarrollos en este campo de estudio.

Local Electricity Markets – Review

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ABSTRACT

Local electricity markets are emerging as a natural solution to overcome the challenges brought by the massive penetration of distributed renewable generation, and the consequent need to put consumers as central players in the system, with an active and dynamic role. Although there is significant literature addressing the topic of local electricity markets, this is still a rather new and emerging topic. Hence, this paper provides an overall view on this domain and provides a perspective on future needs and challenges that need to be addressed. This review introduces the most important concepts in the local electricity market domain, provides an analysis on the different policy and regulatory framework, exposes the most relevant worldwide initiatives related to the field implementation of local electricity markets, and scrutinizes the alternative local market models proposed in the literature. The discussion puts forth the main benefits and barriers of the currently proposed local market models, and the expected impact of their widespread implementation. The review is concluded with the wrap-up and discussion on the most relevant paths for future research and development in this field of study.

Keywords: Local Electricity Markets, Peer-to-Peer, Prosumers, Structure of Local Electricity Markets, Worldwide Initiatives

Contents

1. Introduction

This paper explores the concept of local electricity markets (LEM), which comprises the electricity transactions and negotiations at the distribution level. The emergence of LEM aims at making the energy system more sustainable, reliable, and accessible by different stakeholders [1]–[3]. To attain these goals, system management should no longer be restricted to top-down approaches, and should accommodate bottom-up approaches with greater involvement of local grid operators and the active participation of end-users [4].

In energy markets trade shoud be beneficial to all the respective contractors and different players contribute to bring increased competition. Electrical energy negotiation is still a complicated process, directed to large players, which until today prevents small and medium end users to benefit from a competitive market model. Due to current regulatory frameworks, consumers are still only allowed to establish simple contracts with energy retailers, which guarantee the energy supply under certain conditions. Currently, with the development of the Internet of Things technologies, which in turn gave rise to the so-called transactive energy (TE) concept [5], [6], the development of end user-centric electricity market structures is facilitated [7]. However, the widespread implementation of these new local market structures, will only be possible with the involvement and commitment of the end users. For that, these must be aware of the possibilities and benefits that market participation bring to them and have the required conditions to participate. Nowadays a significant number of end-users have their own distributed generation sources, namely rooftop photovoltaic panels, acting as small-scale electricity producers. This enables them to trade electricity in an autonomous way in the LEM structures [8] given that the right conditions are ensured.

This paper presents a review that identifies and discusses the different proposed approaches regarding LEM structures. For this, a survey of projects and publications that address the LEM structures is carried out. The existing regulation that from our point of view encourages the creation of the LEM and that will possibly regulate the LEM is also reviewed and discussed. Another relevant contribution of the paper is the proposed classification for the LEM structures. This classification is based on the works found in the literature, which have been carefully selected, and are classified according to the analysis made in this review.

The literature reviewed in the following sections highlights research on EU energy regulation to incentivize LEM adoption, the worldwide initiatives, including projects and real pilots, research publications, benefits and main barriers identifications for LEM implementations, and future research paths that LEM can follow. The key topics found in the literature reviewed in this work are summarized in Figure 1.

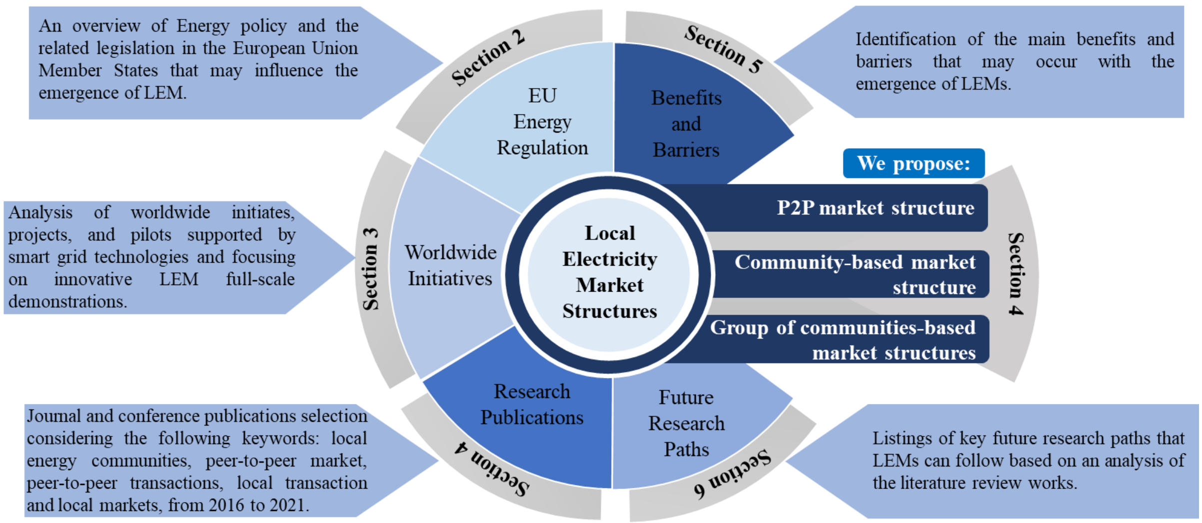

Figure 1 – Concepts reviewed in this work

The key topics appearing around the figure are distributed within the sections of the paper. Considering the EU energy regulation, energy policy and the related legislation are analyzed. From worldwide initiatives, a list of research projects, a description of three platforms, and one open framework are presented. This work's main topic consists of exploring and analyzing research publications to find the possible LEM structures. The benefits and barriers are identified according to their similarities presented within the research publication. Finally, the future research paths are identified and explored. All these topics are briefly explained and referenced in this work.

The paper is organized into six different sections. The first divided into two different sections, introduces the addressed topics, identify the motivations and contributions, contextualizes LEM and presents the related most relevant concepts. The second section presents an overview of most important EU regulation that has a relation to the LEM implementation and operation. Section three presents a list of worldwide initiatives relevant to LEM, including an overview of EU projects related with the implementation of LEM and considering transaction of energy and services. Section four presents a detailed description of LEM along with three different structures for LEM implementation. Section five presents a discussion related with the implementation of LEM including the main identified benefits and barriers. Finally, in section six the conclusions of the work are drawn, and the envisaged future directions are presented.

1.1. Motivations and Contributions

The directive on the European electricity market 96/92 EC [9] takes strong steps towards the liberalization of the electricity markets and had significant impact on the 27 member states. One of the important aspects in this directive is the non-discriminatory access to the electricity grid for third parties, thus enabling energy-free trade and boosting competition. Currently, the electricity market comprises the wholesale market and the retail market.

While the wholesale market regards the transaction of large quantities of energy, supporting transactions between large generators and other large players, the retail market is targeted at smaller consumers. Currently, in most retail markets, the consumer can freely choose any retailer operating in the respective geographic area, thus enabling market competition among the different retailers [10].

The share of renewable energy installed in final electricity end-users has increased considerably in recent years. The European Commission Energy Roadmap 2050 specifies that 75% of the gross final energy consumed in 2050 should be ensured by renewable sources [11]. A large part of the renewable facilities is decentralized and small scale. At the same time, micro-generation at home has great potential and enables consumers to gain control over their energy bill and actively participate in electricity markets.

A significant part of renewable-based generation of electricity uses primary energy sources that are intermittent, such as the sun and wind, and, in many cases, energy generation becomes highly geographically distributed, with a significant share of small-scale generation. This creates a whole new level of challenges for power systems requiring a paradigm change, where the traditional approach of large-scale generation units being dispatched based on current load is no longer suitable [12]. Smart grids (SG) create opportunities for short-term actions as they provide users with real-time information on the supply, demand, and operation of the grid. SGs are therefore an important enabler for the transition of the European energy system based on renewable energies.

Energy communities are also gaining interest and value, according to REScoop.eu [13], in annual report 2021 [14], their network has 1900 energy cooperative in Europe. According to the EC, the interest in LEM for local energy communities is a consequence of the current trend towards the carbonization of the European electricity system that is occurring through the propagation of renewable energy sources [15]. Energy cooperatives can be a contribution to mitigate the existing monopolies in the energy domain, as these cooperatives can provide the kind of services that end-users need [16]. By 2050, it is expected that in the European electrical system there will be millions of prosumers, electric vehicles, and distributed storage systems with the capacity to provide energy and flexibility. Reference [17] presents a perspective considering a wholesale market coexisting with multiple local markets geographically distributed. Moreover, the creation of LEM can overcome to some of the economic and efficiency challenges that energy cooperatives face.

Based on the literature analysis it is clear that electrical power systems are facing major changes and require a different approach on the consumption and production of electricity [18]. The new approaches should consider end-users with active participation and essential roles in the new electricity markets models. In references [19],

[20], the authors mention that the key to innovation in the energy sector is to develop consumer-centric business models and to define demand-side management programs carefully.

LEM focus on local production and consumption [21]–[23] and aim to address relevant issues in the current electricity markets, by considering the local context [7]. The creation of new business models for local power supply has the potential to establish the necessary conditions for small community generators [24]. Local energy trade significantly contributes to the autonomy of micro-grids, reducing their demand and dependence from the main grid [25]. Local markets can also be beneficial for the grid [26]. Some grid investments can be avoided by using local flexibility sources, as the additional capacity would only be used for a few hours a year. The need for additional grid capacity can be overcome if the DSOs locally contract flexibility sources as part of their planning activities [27].

Table 1 presents the different motivations for the emergence of local electricity markets, based on [4], [25], [28]–[34].

Table 1 – Motivations for LEM emergence

Area	Motivation	Purpose	Ref.
Economic	Competitiveness	*"it is important to consider the effect of actor roles and responsibilities for managing the electric flexibility from resources locally in the regulatory context of energy retail competition."*	[31]
	Job creation	"*Thus, the use of renewable energies has significant potential to create value-added and employment effects throughout Germany*"	[32]
	Grid investment deferral	"*If the DSO actively contracts flexibility as part of grid planning activities, then it can be said that investment deferral is a purpose of using local contracting*"	[4]
Energy security	Energy independence	"*Whilst a distributed energy future would mean a high proportion of energy is generated locally, this was not shown to lead to energy independence, even with the high levels of demand reduction"*	[33]
Energy policy	Adequate market model	*"New rules making the EU's electricity market fit for the future and putting the consumer at the center of the energy transition have been signed off by the European Parliament today"*	[34]
	Social Cohesion	"*a more bottom-up approach is required with a larger involvement of the regional (local) grid operators and the proactive end users*"	[4]
Environmental	Carbon emissions reduction	"*less electricity will be generated by conventional generators leading to less greenhouse gas emissions.*"	[25]

As shown by Table 1, most LEM related works are motivated in their majority by economic and energy policy drivers, highlighting the competitiveness as an important factor that can motivate the electricity end-user to switch their interest to the LEM applications. The existing works in this domain have already been reviewed by some dedicated studies. Table 2 presents a summary of review papers found in the literature related with LEM, TE and pear-to-peer (P2P) subjects. In total twelve publications are presented. This table was built considering the main topic of the publication and, more specifically, the matters on which the works are focused. With the analysis of these works and their focus, the gap which this paper addresses are identified.

Table 2 – Published Local Electricity Markets Literature Review Papers

Ref.	Year	Main Topic	Address:
[35]	2016	Electricity markets	Prosumers markets models
[36]	2017	Peer-to-Peer	Peer-to-Peer energy trading projects identification
[5]	2017	Peer-to-Peer	Challenges reviews
[1]	2017	Local Energy Markets	Market designs, Biding strategies
[37]	2018	Local Energy Markets	Designs models, Clearing approaches
[38]	2018	Peer-to-Peer	Energy trading architectures, DR optimization methods, Power Routing
[39]	2019	Peer-to-Peer	Practical implementation
[6]	2019	Transactive Energy	ICT technologies
[40]	2019	Transactive Energy	ICT technologies
[41]	2020	Transactive Energy	ICT technologies, Architecture
[42]	2021	Local Markets	Practical implementations review
[43]	2021	Local Electricity Markets	Challenges Review, Practical implementation
This paper		Local Electricity Markets	Theoretical models, Projects identification, Regulation identification

Table 2 shows that there are three big terms related to LEM: P2P, LEM and TE. A review focused on ICT technologies is usually the approach when addressing the topic of TE [6], [40], [41]. Regarding the peer-to-peer [5], [36], [38], [39] and local electricity markets [1], [37], [42], [43] focused reviews, the studies address different aspects, as Table 2 shows. From the analysis of these reviews, the authors identify a significant gap in the classification and categorization of markets at the local level. Therefore, the authors decide to consider these as the main aspects related to LEM addressed by this research. Evolving from [36], projects related to LEM implementation are identified and discussed in this study. The regulation analysis is also a gap that the authors intend to answer with the identification of the main EU energy regulation, with direct influence on the future development of LEM. Finally, the comparison of practical and theoretical implementations of LEM is undertaken and discussed.

1.2. Local Electricity Market Concept

Currently, there is no consensus regarding the local electricity market definition and there are different opinions regarding on how local markets should operate. However, there is a common idea in the literature that local electricity should facilitate energy transactions at the local level. A market can generally be defined as an environment where potential consumers and sellers of a given economic product engage in trade [27]. The EU Strategy Energy Technology Plan [44] states that the energy end-users are envisioned to be at the center of the future energy system. This requires to ensure that consumers are better informed and better protected, which is progressing along with new proposals for local markets and TE systems [15]. The following definition is adopted in this paper to characterize the terms of LEM [45].

Definition 1. "*as a market, a physical or virtual space (in this case local), in which the transactions between the actors are carried out taking into account the rules defined for the exchange of products or services in agreed* *temporal horizons. Being that the main market elements are: actors, territory, transactions, market rules, product, services, physical or virtual space"*

LEMs have the potential to evolve with the restructuring of electric power system and to integrate small producers and prosumers with renewable generation into the energy supply system, as well as any other consumers without local generation. According to [1], LEM arise from the need to create suitable and adaptable markets to negotiate the energy needs of prosumers. According to [2], this type of market makes use of and combines smart grid technologies with the intention of coordinating the operations between grid, prosumers, distributed generation, connected to the distribution network, and consumers. LEM may include many sources of uncertainty and flexibility, such as renewable distributed generation, flexible demand, and storage [3].

LEM are relevant for microgrid structures [46] as they enable the implementation of market rules at the medium and low voltage levels of the system. Microgrids can take the form of energy communities with prosumers and consumers of various types as well as with storage facilities belonging to community members [47]. A community-based LEM will engage all its members and those who share the community interest in a range of business activities, thus serving to create a better and more sustainable energy environment for all stakeholders [16]. A similar concept is described in [48], using the term micro-market, which is described as an environment that allows all participants (consumers, producers, and prosumers) to share their energy in a competitive regime. In the same publication, the author presents the day-ahead micro-market. This market aims to organize local resources using market-based rules to participate in the wholesale market on the following day.

LEMs provide energy-related exchanges that are usually combined with other community-adjusted services and products. LEMs can support flexibility services, aggregation support, energy efficiency measures, storage, financing, generation efficiency aid, installation services, and maintenance programs [16]. However, LEMs are not restricted to those services and they may support specific services for certain customers [16]. The provision of these services, as well as avoiding violations of network stability limits or energy stability issues, can be obtained through coordinated distributed energy resources usage. This coordination can be attained using appropriate price signals [49]. By using local consumption and generation, LEMs can reduce the price of electricity for end-users and also reduce transmission losses as presented in reference [23].

The distribution system operator can contract flexibility services in the scope of a LEM. In this way, considering the spatial specifications, the LEM can be considered as a new submarket for flexibility [27]. A market of local flexibility is a market of electricity trading to sell and buy flexibility, which is usually established in geographically limited areas. A local market for flexibility with a platform that support participants' flexibility negotiations is presented in [35]. This platform is also useful for sending information and scheduling actions. The Smart Energy Service Provider (SESP) is responsible for managing that platform and performs aggregator functions. In this way, the end-users submit their value of flexibility to the platform and SESP bids these offers on the wholesale market.

The concept of P2P appeared with the evolution of the Internet, where it presented advantages over traditional hierarchies. P2P electricity trading has recently emerged and is gaining increased importance [50]. In the case of electricity markets, the P2P concept refers to the scenario in which all points of the distributed power system have equal responsibility and play an active role in the production and/or consumption of electricity. This paradigm is based on the possibility that all the consumers in the network can make their produced energy available for trade, becoming prosumers. Consumers thus take an active part in the electric power system [5]. The concept of P2P requires that new business models are created to be applied in the context of LEM. However natural distributed configuration of the distribution grid can facilitates the implementation of this market models which have as their main characteristic the decentralization [22].

2. EU energy regulation in the Local Electricity Markets context

Energy policy and the related legislation in the European Union Member States are guided by EU directives, thus affecting the political energy decisions of every EU member state. The climate change, security of supply and affordability/competitiveness has been referred as the energy policy trilemma in the EU [51]. This section outlooks the current regulation that will drive the implementation of LEM in the future.

The EU energy policy is defined in article 194 (1) of treaty on the functioning of the European Union (TFEU) which obligates EU member states to make political decisions that [52]:

1. Ensure a competitive Electricity market;
2. Contribute to the security of supply;
3. Promote energy efficiency, energy savings and new forms of renewable energy;
4. Promote interconnected electricity networks.

In this direction, EU began the preparation of three energy packages and an agenda focused on the sustainability and climate change. Those energy packages are also driving the implementation of LEM.

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Table 2 summarizes the main EU directives and policies that will motivate the implementation and proposal of new structures of LEMs. The 2020 climate & energy package also known as the “20-20-20 targets” were established by EU leaders in 2007 and came finally into legislation in 2009. This package had the goal of tackling important climate change and sustainability issues of carbon emissions, renewable energy, and energy efficiency for smart, sustainable and inclusive growth [53]. Later, in October 2014, under preparation for the 2015 Conference of the Parties summit, the European Council agreed on the 2030 climate and energy framework [54]. This framework is a follow-up of the previous package but aims to provide further requirements to achieve more ambitious decarbonization targets and to address the issue of affordability/competitiveness and security of supply. The 2030 targets include: at least 40% cuts in greenhouse gas emissions (from 1990 levels), at least 27% share for renewable energy, and at least 27% improvement in energy efficiency. Unlike 2020 goals, specific national targets were not set to allow more flexibility for each country.

Table 3 – European Union regulation and directives driving the implementation of LEMs

Ref.	Name of regulation/directive	Scope	Contribution to Local electricity markets	Year
[53]	2020 climate & energy package	Goals by 2020: 20% reduction of GHG, 20% of increase in RES share in energy mix, 20% energy efficiency increase from 1990	Targets still relevant for consensus among EU states; LEMs can help to improve RES use and reduce GHG emissions.	2009
[52]	Consolidated Treaty	General treaty of EU (includes energy scope)	The treaty includes to ensure a competitive electricity market. LEM are another option to foster this competition at the local level and increase security of supply	2012
[54]	2030 climate and energy policy framework was developed	Reformed ETS emissions trade, reduction of 40% GHG by 2030, efficiency increase of 27% and 27% share RES by 2030	In line with previous directives this brings strong ambitious and opens the line for LEMs contribution to achieve those targets by 2030	2014
[55]	Framework strategy for an energy union	Focus of the framework is energy security (of gas especially), to be addressed mainly through improved coordination through the Internal Energy Market.	A unified energy framework would create more conditions for the internal electricity market and consequently easy the path towards LEMs	2015
[56]	Summer package	European Commission’s vision for a new market design. Higher cross-border integration of electricity markets and regional coordination in market design and policy making	Market design changes start to emerge in this set of legislative proposals.	2015
[15]	Winter package	Increased horizontal integration among Member States (in market transactions and in regulatory/industry cooperation) and increased the vertical integration of wholesale and retail markets	Market design changes proposed to increase flexibility and responsiveness of short-term markets and remuneration for flexibility services and consumers demand offer. Therefore, motivating the implementation of LEMs.	2016
[57]	Clean energy for all Europeans	The package’s overarching goal is to facilitate the transition to a more stable, more competitive, and more sustainable European Union (EU) energy sector	Access to retail, local and wholesale markets should be enabled to increase liquidity. The concept can allow local market and wholesale market structures to work in union, thus not restricting competition.	2019
[58]	Directive 2019/944	Directive on common rules for the internal market for electricity and amending directive 2012/27/EU	The directive promotes the consumer empowerment refereed as citizen energy communities	2019
[59]	Delivering the European Green Deal	Objective is to make Europe the first climate-neutral continent in the world. By 2050, all 27 of the EU's member states pledged to make the	Reduce emissions and external energy dependency can be greatly achieved by	2021

		EU the world's first climate-neutral continent. In addition, lower emissions by at least 55% by 2030 compared to 1990 levels.	the development and implementation of LEMs.	

More recently, efforts have been made to create a framework to shift from national regulatory frameworks into a unified one [55]. This framework is refereed as the energy union package that identifies several aspects required for greater flexibility, energy security, sustainability and competitiveness.

The summer package [56] and the winter package [57] are a set of legislative proposals set to introduce new market design proposals and create the foundations in EU for a unified and internal electricity market. Overall, the changes in this set of packages aim at increased horizontal integration among the Member States, i.e. integrated market transactions and more regulatory and industry cooperation. In addition, these packages seek for increased vertical integration of wholesale and retail markets, e.g. via demand participation and cooperation between distribution and transmission system operators. In this sense, this set of packages clearly aim at engaging consumer participation. The "Clean Energy for all Europeans" package [57] from 2019, provides an updated view of the EC's desired "measures to keep the European Union competitive, as the clean energy transition is changing global energy markets", encouraging the development of solutions that enable energy consumers to produce and sell their own electricity. LEMs and TE implementation contribute to these EU recommendation to put consumers as an important player of the electricity markets and thus ensuring that they are empowered and better protected [15].

Specific legal and regulatory framework for the implementation of the LEMs does not exist in EU member states. Nevertheless, pilot projects of LEMs are being implemented, e.g. [60] and [61]. Legislation is a key factor for the successful implementation of LEMs [62]. Sustainable business models for LEMs need to be developed to ensure that there is a successfully shift from current pilot projects and concepts to commercial solutions.

3. Worldwide Initiatives

Worldwide initiatives are currently focusing on the research, development and full-scale demonstration of smart grid technologies. In particular, efforts in the EU have been spread into financial support to projects concerning the development of the European electricity grid through the program H2020-EU.3.3.4 - A single, smart European electricity grid. Since the scope of this paper is to analyze LEM architectures, we provide here a general overview of recent (and some already finalized) European projects under the umbrella of the H2020 programme that address issues related to the development of LEM and smart grids. Additionally, some demonstrators and real implementations are also revised.

3.1. H2020 EU Projects

Table 4 presents some selected European H2020 projects related to the design and implementation of local electricity markets. The Table provides a general scope of such projects, as well as the project status that can be devised according to the duration dates. Most of the listed projects aim at enabling higher flexibility and efficiency of energy grids. This is tightly related with empowering end-users in market activities using DR programs. It is expected that different stakeholders will be engaged in the new local market activities. Therefore, interactions and linked activities among stakeholders should be carefully analyzed to provide stability and resilience in the network.

Table 4 – European H2020 projects related with local electricity markets

Ref	Project Name	Scope	Start/End
[63]	ENERGISE	Efficient deployment of smart grid solutions by offering a toolkit that supports decision-making process as regards the use of telecommunication infrastructure for existing or projected business cases; Target group includes telecommunication providers, industry associations, utility sectors, energy suppliers, national regulatory agencies, and other players being active in the relevant fields; The ENERGISE toolkit addresses: Smart grid solutions, telecommunication infrastructure, and specific cases or business models, where shared infrastructure use is beneficial.	01-01-15/ 31-03-17
[64]	P2P-SmarTest	Investigate and demonstrate a smarter electricity distribution system integrated with advanced ICT, regional markets and innovative business models; Employ Peer-to-Peer (P2P) approaches to ensure the integration of demand side flexibility and the optimum operation of DER while maintaining power balance and the quality and security of the supply; Built upon experience ICT for the Energy Sector, Smart Grids including DER integration, Microgrids, CELLs, VPPs, power system economics, electricity markets and business models, etc	01-01-15/ 31-12-17
[65]	IndustRE	Identify and implement business models for supplying variable renewable electricity (e.g., on and off-site renewable energy production) to industrial users with flexibility in their demand; Business models adapted to 5 industrial sectors (Chemicals, non-ferrous metals, cold storage, steel, and water treatment) and 6 target countries (Belgium, France, Germany, Italy, Spain and UK). Methodology will be transferred to third parties and will be applied in 6 case studies covering all target sectors and countries. Use of a sophisticated power system model and detailed analysis will provide reliable data on the impact the policy recommendations could have	01-01-15/ 31-12-17
[66]	ERANet SmartGridPlus	Organize the learning down to regional Smart Grids stakeholders, beyond the demonstration phase towards implementation from local trials to a European knowledge community; Support knowledge sharing between regional and European Smart Grids initiatives by financing 15-20 transnational projects on applied research, piloting and demonstration in the field of Smart Grids; Taking a next step in Smart Grids development building on the knowledge base, R&D initiatives as well as research and demonstration facilities already in place at regional, national and European level.	31-01-15/ 29-01-20
[67]	Flex4Grid	Create a framework for "prosumer" flexibility management; Create a system for new market players offering aggregation and data analytic services directed to DSO.	01-01-15/ 31-03-18
[68]	EMPOWER	Investigate electricity LMs to promote the "prosumer" role in SG; Develop and verify a local marketplace and business models to exploit the flexibility created by "prosumers"; The smart energy service provider (SESP) role was proposed to handle the operation coordination of participants in the market.	01-01-15/ 30-04-18

Ref	Project Name	Scope	Start/End
[69]	NOBEL GRID	Deploying and evaluating ICT services and tools to enable active consumers participation in LMs; The developed tools allow DSOs to mitigate management and maintenance costs; One of the most innovative aspects of the project was the development of the smart low-cost advanced meter, that empower prosumers and consumers.	01-01-15/ 30-06-18
[70]	FLEXICIENCY	Demonstrate that an open European Market Place for standardized interactions among electricity stakeholders (market players) can accelerate the deployment of flexibility services, advanced monitoring, and local energy control; Assessment of economic models of these new services based on five demonstrations and a variety of use cases.	01-02-15/ 31-01-19
[71]	Smartnet	Propose solutions and architecture for optimized interaction between TSOs and DSO; Explore monitoring and acquisition of ancillary services (e.g., reserve and balancing, voltage regulation, congestion management) from resources in the distribution segment (DG and flexible loads) for both local needs and for the whole system.	01-01-16/ 31-12-18
[72]	DR-BOB	Demonstrate the economic and environmental benefits of demand response in blocks of buildings for the different key actors; Integration of existing technologies for energy management and the demonstration of such solutions in 4 sites with different conditions (UK, France, Italy and Romania); Validate method of assessing technology readiness, identify revenues with at least 5% profit margin to developed business models, and engage with companies involved in the supply chain for DR in buildings across the EU.	01-03-16/ 31-08-19
[73]	FHP	Provide services to DSOs and RES producers using heat pumps, large thermal stores and building thermal inertia; To test practical prototypes representing the European power grid; The expected services include, algorithms for heating systems management, tools supporting grid operators to solve local problems using flexible resources, grid flexible heat pump, and model-free building thermal characterization.	01-11-16/ 31-10-19
[74]	GOFLEX	Develop and demonstrate a group of electricity smart-grid technologies, enabling the cost-effective use of DR in distribution grids and supporting an increasing share of renewables; Enabling active use of distributed sources of load flexibility to provide services for grid operators, balance electricity demand and supply, and optimize energy consumption and production at the local level of electricity trading and distribution systems; Building on top of existing technologies for capturing and exploiting distributed flexibility using automatic trading of general, localized, device-specific energy as well as flexibility in trading aggregated prosumer energy; Three use-cases, covering a diverse range of structural and operational distribution grid conditions in three European countries, are used to demonstrate the proposed solution.	01-11-16/ 31-10-19
[75]	Interflex	Empower DSOs towards a flexible local energy system; 18 use cases will be tested including diverse resources to provide flexibility such as: energy storage technologies (electricity, heat, cooling), DR schemes with two coupling of networks (electricity and gas, electricity and heat/cooling), integration of EVs, and automation of grid operations including contributions of microgrids.	01-01-17/ 31-12-19
[76]	FLEXCoop	Propose an end-to-end DR framework allowing energy cooperatives to participate in LMs under the role of aggregator; Innovative and effective tools for microgrids and VPPs as balancing and ancillary assets for grid stability; The project considers local generation, demand and storage flexibility, and EVs integration.	01-10-17/ 30-09-20
[77]	DOMINOES	Develop new DR, aggregation, grid management and peer-to-peer trading services for a scalable LM; Deliver new business models for DR and VPP operations; Propose tools to validate DR services based on smart metering, methods to utilize VPP and microgrids as active balancing assets (flexibility), and secure data handling procedures in LMs.	01-10-17/ 31-03-21
[78]	Magnitude	Identify potential flexibility options coming from synergies between the electricity, heating, cooling and gas networks; Simulate the multi-energy system to optimize its operation maximizing the provision of flexibility services; Propose improved market designs and evaluate their performance; Quantify the benefit of pooling flexibilities coming from the multi-energy system in LMs through an aggregation platform.	01-10-17/ 31-03-21

Ref	Project Name	Scope	Start/End
[79]	FLEXITRANSTORE	Propose a technical basis to support flexibility services enhancing the existing European internal electricity market; Strategic objectives include to accelerate the integration of renewables and to increase cross-border electricity flows across Europe; Resources include state-of-the-art ICT technologies, control improvements and exploring the enhancement of the existing infrastructure by integrating storage and DR management.	01-11-17/ 31-10-21
[80]	EU-SysFlex	Ensure services to facilitate a share of renewables while maintaining the level of resilience that consumers expect from the European electricity system; Design of a new electricity market, considering the need for new regulations; Stakeholders and roles include: generation and flexibility providers, TSOs, DSOs, and regulators at different system levels (e.g., interconnected system, national transmission and distribution sub-systems and consumers).	01-11-17/ 31-10-21
[81]	eDREAM	Develop tools for DR, including early detection of flexibility potential based on data fusion and big data techniques; Design optimal DSO-driven DR management, including applications of blockchain technology for secure energy transactions, market-based microgrid control and near real-time closed loop DR verification.	01-01-18/ 31-12-20
[82]	DELTA	Propose an aggregator management platform distributing its task into lower layers of intelligence to establish a more easily manageable and computationally efficient DR solution. Propose and implements novel multi-agent based, self-learning algorithms to enable aggregation, segmentation and coordination of supply/demand clusters; Facilitate real-time DR flexibility activation between prosumers to satisfy the aggregator's portfolio self-balancing needs and deliver services to market or grid-related stakeholders.	01-05-18/ 30-04-21

From the scope of these projects, we can devise some significant drivers in the context of LEM, namely: (i) taking advantage of the penetration of distributed generation and renewables to support efficient smart grid solutions; ii) flexibility management using flexible resources; (iii) flexibility services directed to DSO; and (iv) DR programs taking advantage of the flexibility. Moreover, LEM approaches need to ensure the integration of variable distributed generation (renewables) and demand-side flexibility while guaranteeing a secure supply of energy and power balance. Flexibility resources include different types of storage systems, EVs integration, heating, and cooling management, and DR programs (that involve the participation of end-users).

Projects proposed in the earlies 2010s [63], [64], [66], [83], [84] were more focused on the adoption of renewables and distributed generation at the local level, as well as addressing the challenges (variability of generation, infrastructure and ICT required to control distributed resources, interoperability) and opportunities (small consumer participation, efficient use of active supply and demand at the local level, reduction of environmental impact) that such adoption would bring to the electric power system. Follow-up of these projects was given, for instance in projects [67], [69], [73], [75], focusing on the development of services directed to the DSO for local flexibility management. Such services can span different options like aggregation and data analytics services [67], ICT technologies for reduction of management and maintenance costs [69], and energy management systems to support DSO activities through the use of flexible resources [73], [75]. DR programs using flexibility will be explored practically in all the proposed projects, emphasizing the importance of the involvement of end-users in LEM activities. In particular, projects [76], [77] consider a LEM in which DR is provided taking into account the role of aggregators. Moreover, VPP, energy communities and microgrids are also devised as crucial participants of this new LEM, and business models directed to these entities are explored as well. Finally, projects [71], [79], [80] also study in some degree the interactions between DSO and LEMs with external markets, for instance examining the interactions between DSO-TSO and the use of flexibility for ancillary services.

3.2. Online platforms for local energy trading

One of the fundamental parts to enable the implementation of LEMs relates to the capacity (including infrastructure and platforms) of performing P2P local transactions in a transparent and reliable manner. Trials on local energy trading have been carried out in recent years. In this section we provide an overview of open platforms and frameworks currently used for the development of LEMs. These initiates can serve as a basis for the implementation of business models related to the use of flexibility or can be accessed by consumers (and prosumers) to perform energy transactions (sell and buy) locally.

Piclo is an online platform developed in the UK in 2015 [85]. The platform can be used for P2P energy local trading between consumers with generation capabilities. Basic functionalities are used to provide data visualization and analytics to customers that perform the trading. A matching algorithm is used to guarantee a balance between generation and consumption locally. The platform allows consumers to choose the seller from who they want to buy energy in the local market. Advanced metering technologies are used to perform local balance between supply and demand in a half hour span.

Vandebron [86], developed in The Netherlands, is another online platform for local energy trade where energy consumers can buy electricity directly from independent producers (e.g., farmers with wind turbines or PV generation). Vandebron therefore takes the role of an energy supplier with the particularity of providing incentives for consumers and generators to exchange energy. Prosumers who inject surplus energy to Vandebron platform can purchase energy from the platform at a lower price comparing to other suppliers.

The sonnenCommunity [87] integrates sonnenBatterie owners (sonnenBatterie is a battery storage manufacturer in Germany) who desire to share self-produced energy with other members in the community. The idea behind sonnenCommunity is to use a virtual energy pool of batteries, where PV generation can be stored and shared between the members, taking advantage of the differences in renewable generation from diverse locations. The idea is similar to Piclo and Vandebron, with a special emphasis in storage technologies. A centralized approach (software-based) is used to monitor and control the generation and storage capacity of sonnenCommunity members, guaranteeing the balance of supply and demand. This program is available in Germany, Austria, Switzerland and Italy, providing benefits to its members for a monthly fee of around 20 EUR. The benefits for members include ten years guarantee on sonnenBatteries, energy from 23 cent, software updates for all existing functions, free weather forecast updates and energy usage optimization. Remote maintenance and monitoring, as well as intelligent usage control, are also provided.

3.3. Open framework

The universal smart grid energy framework (USEF) [12], developed by the USEF Foundation, has the purpose of delivering one common standard on which smart energy products and services can be created. The USEF Foundation consists of a partnership of seven worldwide leader organizations in all areas of the energy industry, including ABB, Alliander, DNV GL, Essent, IBM, ICT Automation and Stedin. Particularly, USEF is intended to unlock the value of flexibility, defining the market structures, rules and tools required to make possible the trading of flexibility as a commodity. USEF positions the aggregator in a central role of the flexibility market. Therefore, in the USEF framework aggregators have the target of accumulating the flexibility obtained from DR programs at different levels of the energy demand (i.e., industrial, commercial and residential level), and offering such flexibility as a reliable product to different stakeholders for different purposes. Examples of such products and services, and the stakeholders that might be interested in such commodity embrace all different roles present in the LEM such as retailers, DSOs, BRPs, and even TSOs. Finally, USEF fits on top of current electricity market models and can be used to extend existing processes and propose new business models. Besides, the information of the framework is accessible to anyone through the documentation provided by the USEF foundation, so that it represents a solid initial step for researchers and companies interested in the implementation of LEM and the use of flexibility as an asset.

4. Local Electricity Markets Structures

In this section a review of published articles is realized considering the LEM scope. The characteristics and objectives of market participants are essential features to be considered in the definition of LEM [7]. The LEMs concept should encompass different services, such as: flexibility services, aggregation support, energy efficiency measures, storage, and generation assistance. All these services are ensured by contracts made between end-users and retailers [16]. In fact, LEM might have the participation of different actors, for instance, sellers (distributed generators, prosumers, storage units), buyers (consumers, prosumers, and storage units), energy service companies (ESCo), aggregators, DSO or Distribution Network Operator (DNO) [88]. Some LEM attributes and rules directly related to the characteristics of market participants, such as the degree of competition, the negotiation horizon, or dispatch intervals, are addressed in [23]. On the other hand, the market rules determining the restrictions of bidding, acceptance of the bids, price determination, and settlement rules are described in [89]. Overall, the design of LEM depends on existing grid conditions, on the arrangement of loads and generation, and also on the consideration of future developments [2]. Millions of DGs supplying variable energy, dependent on solar and wind energy, require different control schemes compared to the existing ones [90]. This situation has motivated the development of LEM, contributing to better integrating the prosumers generation. Thus, LEMs will need to consider the trading of energy between end-users, with or without an intermediary between them. In this regards, the direct trading among end-users (prosumers and consumers) can be advantageous as it enables, for instance, avoiding the costs associated with retailers and at the same time reducing transmission line losses due to the decreased energy transmission ranges [2], [91].

LEM structures in which the market clearing is centralized are characterized by supervisory nodes in a higher layer, thus reducing the conflicts between the lower layers requiring a smaller number of iterations. On the other hand, decentralized market clearing structures are considered more flexible and allowing the system connections at lower levels, where each node has only local information. When the size of the system is considered, the centralized systems may not be able to calculate the ideal dispatch without all the local information [92]. Notice that both types of structures, centralized and decentralized, need to have central accounting and registration nodes, but the differences between the two approaches is the way the clearing is performed.

From the analyzed literature presented in Table 5, we conclude that LEM structures are converged to the following: P2P market structure (Figure 2), Community-based market structure (Figure 3) and Group of community-based market structure (Figure 4). The main difference of these structures is related to their typology and the degree of decentralization. These concepts are, however, not consensual, and several divergent statements can be found in the literature, for instance: "*This is not a P2P mechanism in the strictest sense (trades that are negotiated bilaterally) but in the broader sense that it incentivizes and remunerates power sharing between peers*." [93]. Such statements make the definition of P2P markets blurry, referring to the term P2P as long as there is electricity sharing between peers. Given such contradictions, the authors consider that a clearer distinction between the P2P and community-based markets is needed.

In P2P markets like those depicted in Figure 2, decentralization is the most significant feature, enabling the markets to be more autonomous and flexible. This type of architecture mostly follows a bottom-up approach with a high number of agents and contractual relationships. The implementation of P2P markets can be done based on models such as the ones followed by companies such as Airbnb or Uber, taking the notion of shared economy and translating this to an electricity market level. Thus, in such P2P market structure, a P2P platform enables electricity producers and consumers to directly sell and buy electricity and other energy-related services without the support of a central entity.

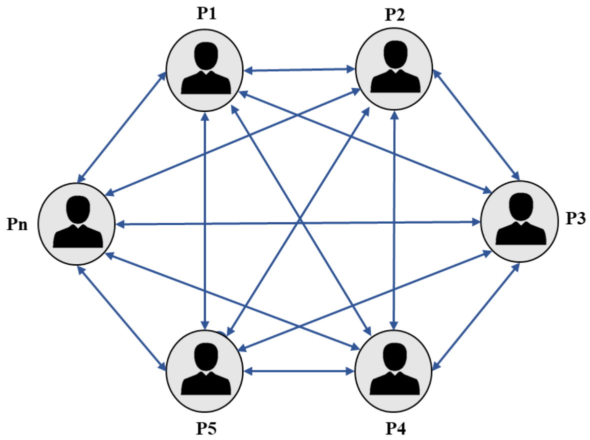

Figure 2 – P2P market structure

The term P2P is usually associated with decentralized market structures lacking a central authority, as can be seen in references [1], [2], [7], [94]. P2P and peer-to-platform terms are assigned to the decentralized structures in reference [94]. Two different terms are assigned to the decentralized structure, the peer-to-retailer, and peer-to-wholesale models [95], [96]. TE terms, also aligns with this type of market structure [97], it is related to the coordinated operation of a vast number of actively involved DERs based on value-based information in the smart grid [3]. In general, decentralized systems within liberalized electricity markets can reduce market effectiveness, because agents are self-interested [23].

To study and implement the P2P markets structures different techniques can be used, game theory approaches was implemented to find optimal solutions in decentralized LEM [8]. Other methods based on game theory as Stackelberg game and Non-cooperative game, was applied to the LEM [7], [8]. References [98], [99] present also methods that use game-theory approaches not directly addressing the concept of LEM but used for electricity transactions in microgrids. The agent simulation-based solution is also proposed as a different approach to simulate environments in LEM [8], [100], techniques like reinforcement learning and Q-learning can be techniques applied to agents for trading electricity into LEM according to [7]. This structure can use a decentralized market clearing, for which multi-agent systems can be used to simulate the direct negotiations (bilateral contracts). In this case, each peer is simulated by an agent, and when the negotiation takes place, there must be an interaction among the agents. If the agents determine the price directly between them, the market clearing is performed in a decentralized way.

Figure 3 depicts a community-based market structure where a local market operator is considered the central entity controlling the clearing of the market. In [101] the aggregator participates in the energy trading and also provides services for the users of the distribution grid. Reference [7] introduces a local grid controller managing the interactions between the local electricity resources and the aggregator. It is also responsible for managing the demand side response, optimizing and transferring the locally generated energy with the main grid or another local grid by means of an aggregator. In [48], a micro market operator similar to the market operator in the wholesale market, is presented with the role of executing the clearing algorithm and supervising the operation of the market.

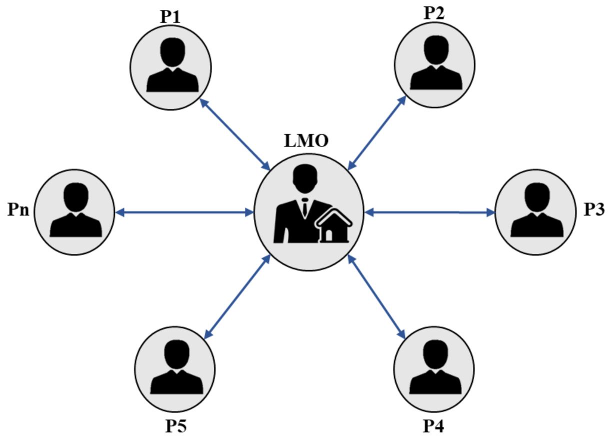

Figure 3 – Community-based market structure

Considering community-based structure, the system can operate in connection to the main grid or in an island model with no grid connection, presenting different incentives for users according to the connection. When a system is connected to the main grid, there is an incentive for users to generate as much electricity as possible because the excess of generation can be sold to the main grid. Thus, the local market operator has the goal of maximizing the profits of the community where the LEM is taking place. DSOs are becoming active system managers with local markets operators responsibilities where the flexibility is fundamental for the functioning of the system [102]. The other possibility is when the system operates in island mode, and the user services need to be optimized at the microgrid level. According to reference [23], the LEM must be configured and operated by the DSO or by a LEM operator acting as an aggregator. [23] also proposes an interesting idea related to prosumers acting as market operators, a possibility that might increase the robustness of the control. In general, the LEM operator can be considered as an entity of the LEM since the decentralized approaches will eventually have control of the system. According to [103], DR approaches are also considered centralized approaches when an aggregator (DR operator) serves as an intermediary between generation and demand.

Centralized structures usually use optimization techniques, such as convex, stochastic, or swarm optimization [7], [8]. In [104], a market structure between two island mode microgrids is presented and a convex optimization problem is formulated to minimize the overall cost. The auction format is recommended to be used in the centralized approach of LEM design according to reference [102]. As a rule, symmetrical double auctions require buy and sale orders submitted to a block order. These orders are then matched either continuously or at discrete market closing times [105]. A continuous double action to trade energy between multiple consumers and prosumers is presented in [106] and [48], the match between the generators offers and the consumer's bids determines the price for the electricity in auction market. Another double auction mechanism applied at local level is presented in [99] where distributed storage units trade energy in the smart grid.

The group of communities-based market structure, as depicted in Figure 4, lays between the previous two presented models in terms of structure and scale. It is based on the concept of community, where each local market operator represents a community and can negotiate with other communities.

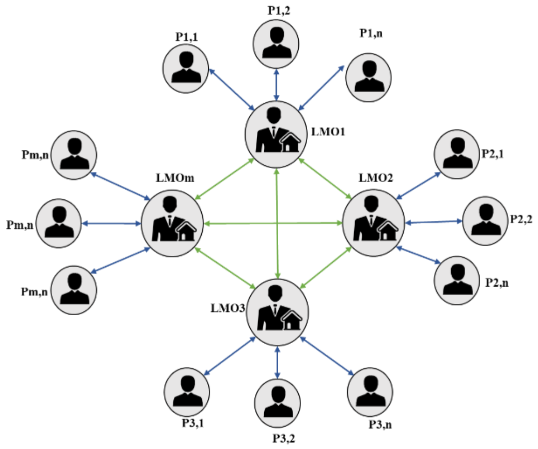

Figure 4 – Group of communities-based market structures

This type of model is usually presented in smart grid environments, enabling opportunities for local organizations, neighborhoods, or communities, allowing to manage energy needs efficiently and dynamically with the use of local balancing resources. Peer-to-platform approaches found in the literature fit with a group of communities-based market structures and presents some advantages for flexibility negotiation compared to P2P markets. Such as, standard flexibility services are required by larger entities such as BRPs, DSOs, or TSOs, and P2P markets could lead to prosumers having low negotiation energy. The production potential of each prosumer can also be an obstacle to P2P trading in the wholesale market since there are requirements on the minimum quantities of energy for participation [94]. Incentives that enable end-users to become prosumers facilitate the creation of community-based initiatives that in turn stimulate local management of supply and demand. Theoretically, communities and local authorities can use their resources to generate revenue for themselves.

Similar to traditional companies operating in the electricity system, new small and medium-sized companies may operate at the local level performing aggregation functions or providing distribution and energy services.

In both group of communities-based market and community-based market structures, aggregator can be responsible for the decision making and can perform centra supervision. Thus, the aggregator as controller has a full and complete overview of the market status and can make decisions for the benefit of the local energy community as a group and not taking into account each participant individually. However, LEMs used to provide flexibility to upper levels of the energy chain might present disadvantages in some specific situations. For instance, in the case of prosumers with thermal flexibility, this flexibility can be activated by the aggregator frequently, which can bring a loss of comfort and result in a decline of acceptance by the final user. To overcome this situation, higher rewards should be paid to the prosumer to achieve participation in the LEM and compensate for the discomfort to their daily environment [94].

To summarize our analysis, Table 5 presents a review of the works regarding LEM structures. The first column identifies the publication with the respectively reference. The second column presents a characterization of each work according to the categories proposed in this section. In the third column, it is identified the type of market clearing realized and in fourth column the type of objective function is identified. Fifth column presents the central entity that coordinates the LEM or not. The sixth column identifies the scope of the LEM, referring essentially to a what service the LEM is designed for. The seventh column presents the available resources that are used by LEM users, for instance, active supply and demand (DR) and DGs. Eighth column are identified the number of involved players to perform the simulations. In the nineth column, titled comments and additional information provided by the authors of the studies is presented. Finally, in tenth the publication year is presented.

Table 5 – Summary of the publications analyzed considering LEM approaches

Ref	Structure	Market Clearing	Objective Function	Central entity	Scope	Available resources	Number of involved players	Comments	Year
[16]	Community-based market	Centralized	Cooperative	Smart energy service provider	Electricity, Flexibility and other services	ESS, Active supply and demand	-	Different contexts: island mode, and direct or indirect relation with the wholesale market	2016
[31]	Community-based market	Centralized	Cooperative	Aggregator	Flexibility trading	ESS	-	Framework for flexibility services	2016
[107]	Community-based market	Centralized	Cooperative	Micro market operator	Electricity trading	PV, ESS	-	The storage unit is controlled by the micro market operator	2016
[107]	Community-based market	Centralized	Cooperative	Aggregator	Flexibility trading	PV, ESS	40	Augmented power consumption management mode is proposed.	2016
[108]	Group of communities-based market	Decentralized	Competitive	Microgrid operator	Electricity trading	ESS, Active supply and demand	3 MG	Incentive mechanism using the Nash bargaining solution	2016
[1]	P2P market	Centralized	Competitive	-	Electricity trading	Active supply and demand	-	Agent-based Simulation	2017
[2]	Community-based market	Centralized	Competitive	DNO	Electricity trading	-	16	For numerical analysis, a 22-Buses UK medium voltage distribution system is considered	2017
[4]	Community-based market	Centralized	Competitive	-	Flexibility trading	-	-	DSO seeks to procure flexibility to resolve grid	2017
[25]	Community-based market	Centralized	Competitive	Supplier	Electricity trading	Active supply and demand	2	Double action trading mechanism	2017
[48]	Group of communities-based market	Centralized	Competitive	Manager agent	Electricity trading	ESS, Active supply and demand	4 MG	The market is divided into two level the intra-market and inter-market	2017
[90]	Community-based market	Centralized	Cooperative	Aggregator	Electricity trading	ESS, Active supply and demand	21	Clustering Power System Approach	2017
[3]	Community-based market	Centralized	Competitive	Energy Brokers	Electricity trading	Active supply and demand	6	A two-stage market decision-making process is implemented	2017
[109]	Community-based market	Centralized	Competitive	LEM operator	Electricity and Hydrogen trading	ESS, EV, HV	100	The inclusion of hydrogen storage systems in a local energy market	2017
[110]	Group of communities-based market	Centralized	Competitive	Aggregator	Electricity trading	ESS, Active supply and demand	8	The interaction between the aggregators in the market as a Potluck game-theoretic problem	2017
[22]	P2P market, Community-based market	Centralized	Cooperative	-	Electricity trading	ESS, Active supply and demand	4	Two distinct market designs are implemented the Flexi User and Pool Hub.	2018
[94]	Community-based market	Centralized	Cooperative	Aggregator	Flexibility trading	Active supply and demand	-	The aggregator manages the flexible loads to provide services to DSO and BRPs	2018
[97]	Community-based market	Centralized	Cooperative	Smart energy service provider	Flexibility trading	ESS	4	A case study was present with four different households	2018

Ref	Structure	Market Clearing	Objective Function	Central entity	Scope	Available resources	Number of involved players	Comments	Year
[111]	P2P market	Centralized	Cooperative	P2P Energy Sharing Coordinator	Energy sharing	ESS, PV	100	An aggregator controls the many small-scale batteries	2018
[112]	Community-based market	Centralized	Competitive	-	Electricity trading	PV, ESS	10	Designed a platform Elecbay for P2P energy trading	2018
[113]	Community-based market	Centralized	Cooperative	ESCO	Electricity trading	PV, ESS	90	Inclusion of flexible residential loads	2019
[114]	Community-based market	Decentralized	Competitive	Market controller	Electricity trading	-	-	Behaviours of both risk-neutral and risk-averse agents are tested	2019
[115]	P2P market	Centralized	Cooperative	Market operator	Electricity trading	PV, EV	22	Model incorporating both energy trading and uncertainty trading	2019
[116]	P2P market	Decentralized	Competitive	Central coordination	Electricity trading	PV, EV	15	A dual decomposition method is proposed	2019
[117]	Community-based market	Centralized	Competitive	Energy Sharing Coordinator	Electricity trading	PV, ESS	10	Three pricing models: Double Auction, Mid-Market Rate and Supply and Demand Ratio	2019
[118]	Group of communities-based market	Centralized	Competitive	DisCo	Electricity trading	-	3	Proposing an iterative algorithm for exchange energy within a distribution network	2019
[119]	P2P market	Decentralized	Competitive	Distribution Network Operator	Electricity trading	PV, ESS	6	Distributed storage system	2020
[120]	P2P market	Centralized	Competitive	-	Electricity trading	PV, ESS	37	Blockchain-based platform is implemented	2020
[121]	Community-based market	Centralized	Competitive	Central Market Operator	Electricity trading	PV, ESS, EV	10	Uses bid dependencies possibilities	2020
[122]	P2P market	Decentralized	Competitive	-	Electricity trading	PV	12	Implementation of general nash equilibrium and variational equilibrium	2020
[123]	Community-based market	Centralized	Competitive	Auctioneer	Electricity trading	PV	36	Continuous double auction	2020
[124]	P2P market	Centralized	Competitive	Community Manager	Electricity trading	PV	11	Cooperative and non-cooperative gaming concepts are employed for efficient trading	2020
[125]	Community-based market	Centralized	Cooperative	Aggregator	Electricity trading	-	-	Integration with Pan-European Wholesale Electricity Market Model	2020
[126]	Community-based market	Decentralized	Competitive	-	Electricity trading	PV	372	Decentralized autonomous area agent simulation framework	2020
[127]	Community-based market	Centralized	Competitive	LEM operator	Electricity trading	PV	57	Chance-constrained optimization algorithm	2020
[128]	Community-based market	Centralized	Cooperative	-	Electricity trading	PV	55	IEEE European LV Test Feeder grid is used	2020
[129]	P2P market	Centralized	Cooperative	Aggregator	Electricity trading	ESS, EV, DER	5	Uses a game-theoretic framework to analyse a local trading mechanism	2021
[130]	P2P market	Centralized	Competitive	Virtual agent	Electricity trading	PV, ESS	60	Continuous doble action market	2021
[131]	Community-based market	Centralized	Competitive	Community Manager	Electricity and heat trading	DER, ESS, HSS	4	Different allocation schemes: uniform pricing, Vickrey-Clarke-Groves, Shapley value, and nucleolus.	2021

Ref	Structure	Market Clearing	Objective Function	Central entity	Scope	Available resources	Number of involved players	Comments	Year
[132]	P2P market	Centralized	Competitive	-	Flexibility trading	PV, ESS	1 (office building 6800 m2)	Blockchain-based decentralized energy flexibility market	2021
[93]	P2P market	Centralized	Competitive	Microgrid coordinator	Electricity trading	PV, EV	50	Inclusion of V2X possibilities	2021
[133]	P2P market	Centralized	Competitive	Local Market Operator	Energy and flexibility trading	PV	10	Designing a 2-stage hierarchical model	2021
[134]	Community-based market	Centralized	Competitive	Aggregator	Electricity trading	PV	30	Bi-level optimization model	2021
[135]	Community-based market	Centralized	Competitive	-	Electricity trading	PV, ESS	11	Simulation in a blockchain platform	2021
[136]	P2P market	Centralized	Cooperative	-	Electricity trading	PV, EV	5	Shaded storage option	2021
[137]	Community-based market	Centralized	Competitive	DSO	Flexibility trading	PV	410	Three-stage market clearing method	2021
[138]	P2P market	Centralized	Cooperative	Aggregator	Electricity trading	PV, ESS	20	Model that determines the best P2P energy transactions	2021
[139]	P2P market	Centralized	Competitive	Aggregator	Electricity trading	DER, ESS	6	Market clearing method for the non-cooperative electricity market	2021
[140]	Community-based market	Centralized	Cooperative	Aggregator	Electricity trading	ESS	48	Contract-based distributed algorithm for electricity trading	2021
[141]	Community-based market	Centralized	Competitive	Community Manager	Electricity trading	PV, ESS	10	ADMM-based clearing process	2021

From the analysis of Table 5 is possible to create Figure 5 in order to analyze the proportion of analyzed works studying different structure types.

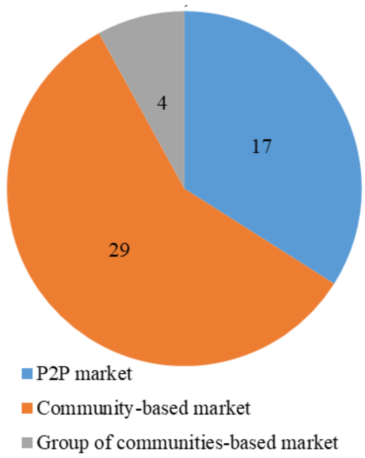

Figure 5 – Structures classification results

Figure 5 shows that 29 present a Community-based market structure, 17 a P2P market structure, and only 4 cover the Group of communities-based market. On the other hand, Figure 6 b) shows that 79% of the analyzed works (38 out of 48) used a central entity in the implemented market. In fact, by making a cross reference from these two classifications, we noticed that structures classified as Community-based market typically consider a central entity. Contrarily, when a P2P market structure is considered, the presence of central entities is not necessary. There is also a relation between the market clearing and studies considering a centralized entity since structures considering a market clearing procedure will require a local market operator. However, as identified in Table 5, there are many approaches classified as community-based market structures where auction methods are applied for determining the price of electricity. In this way, we can conclude that this market structure has a competitive objective function, but the market is carried out in a centralized way where all users make their bids to buy and sell electricity.

From Table 5 we can identify two main categories of works related to the market clearing procedure and the objective function. Figure 6 presents the comparison of the number of analyzed papers separated by these categories. The analyzed works have been classified into two types, market clearing and objective function (a classification previously defined in [43]).

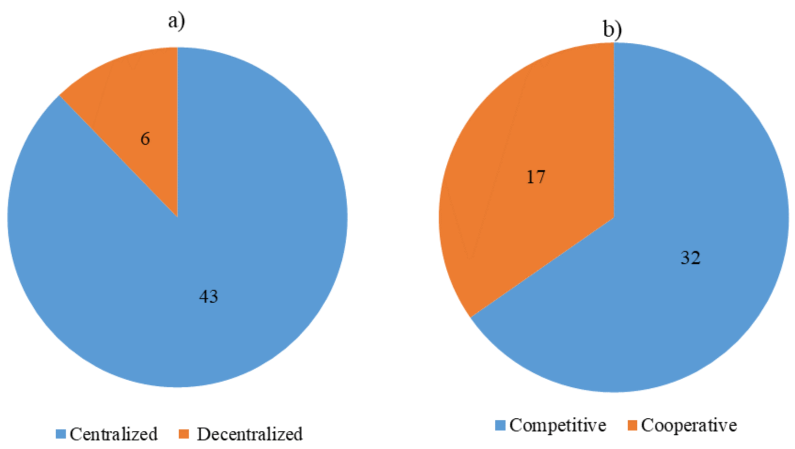

Figure 6 – Results: a) Market clearing and b) Objective function

In [8], a description of the two types of clearing price (centralized and decentralized) is presented. For instance, when an energy trading organization is configured to have only one user or central controller that can dictate its decisions to a group of users, it is considered a centralized market clearing. On the other hand, the market clearing is considered decentralized when several interacting users try to optimize their resources independently of others [8]. Figure 6 a) shows the distribution of works considering centralized and decentralized market clearing types. It can be seen that the majority of work is focused on centralized models (43 out of 49 analyzed articles). Thus, it is clear that less decentralized market clearing models have been implemented or studied in the literature, with only 12% of the total of analyzed works. In fact, most of the analyzed works apply auction methods considering a central market clearing to define the market clearing price. Now looking at Figure 6 b), it can be seen that objective functions considering competitive approaches represent about 65% (32 works out of 49) compared to the 35% studying cooperative approaches. This is a more balanced comparison, yet, it highlights the need for studies focusing on cooperative approaches.

We also show graphically in Figure 7 the works that consider the central entity and the scope of work. Notice that the sum of the inner circles in Figure 7 might exceed the number of the analyzed sample (i.e., 49 articles), which means that a given article can fit into more than one topic within the classification.

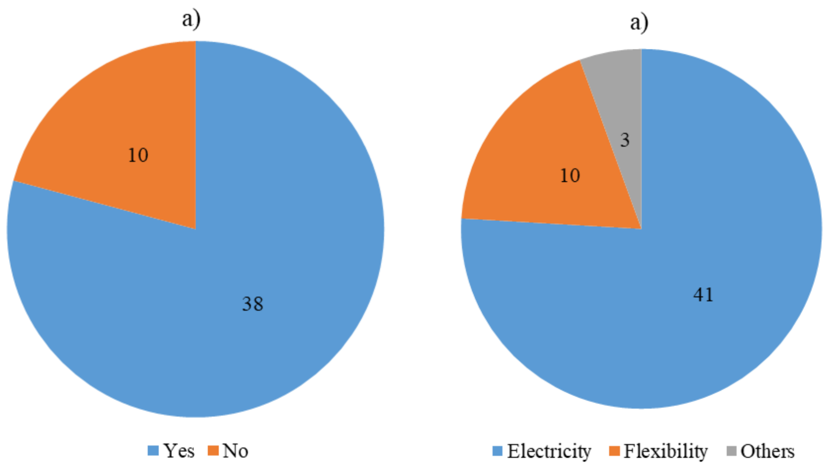

Figure 7 – Results: a) Central entity and b) scope of work

Considering Figure 7 a) is possible to count the number of works that 38 works consider central entity and 10 do not consider. Figure 7 b) shows that 41 works lay within the scope of electricity trading, while only 10 articles address flexibility trading and 3 present other types of trading (e.g., hydrogen).

Finally, Figure 8 presents the proportion and number of works for the categories of scope, and number of players involved.

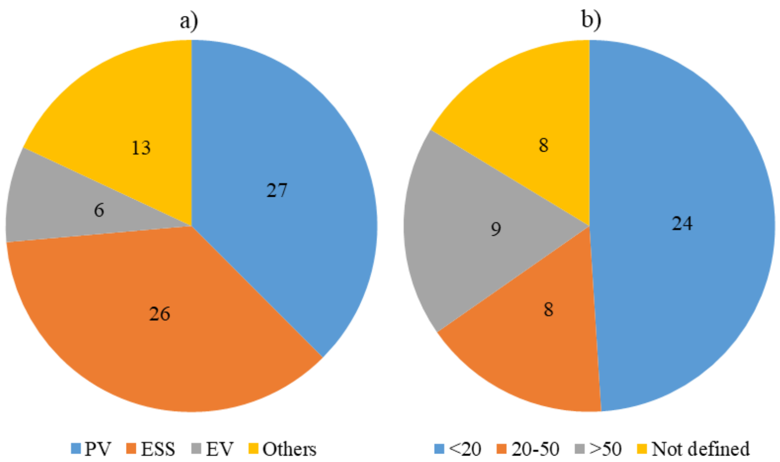

Figure 8 – Results: a) Available resources and b) number of involved players

Figure 8 a) groups the works according to the types of available resources considered, with 27 articles focusing on PV; 26 on ESS; 6 considering EVs; and 13 considering other resources (such as: hydrogen storage systems and DER). It is relevant the use of renewable energy sources, particularly PV generation, and the use of ESS as the main drivers for LEM implementation. Finally, Figure 8 b) presents the analysis regarding the number of involved players into the simulations/implementations. Nearly half of the works (24 articles) perform simulations with less than 20 players; 8 articles consider 20 to 50 players; only 9 works present a number of players greater than 50; and 8 do not specify how many players are involved in the market. It is noteworthy to highlight the low number of involved players in most of the works related to LEM, which reflects the state of maturity of this topic. In fact, many of the analyzed works are still theoretical, addressing the market models and mechanisms and neglecting the actual impact of such implementations when it comes to scalability and practical applications of such models.

5. Discussion

This section discusses the analyzed LEM structures as well as the main benefits and barriers that these new markets present. One of the most notable aspects within the energy sector that enables the appearance of the LEM is the transformation of consumers into prosumers. LEM operations in distribution networks can become essential for avoiding additional investments. For instance, LEM devoted to the use of flexible resources (also called flexibility markets) can be used to compensate the local energy consumption deviations caused by the forecast errors [97].

Also, DR programs, make possible to transfer the consumption of periods of high demand to periods with lower demand. Such modification provides very useful flexibility for the network operator, making them potential stakeholders interested in the development of LEM.

Currently, one way to shift electricity consumption from end-users is based on incentives related to the electricity prices. Assuming that end-users are rational and have some generation capabilities, they will react to a variable electricity price so that their respective revenues are maximized, or their energy bill is minimized. Therefore, system operators need to take into account end-users' behaviors to be able of defining the price of electricity to control demand and supply at any given moment and maximize the utility of the energy system [91]. This type of solution has been applied commonly to large energy consumers. Thus, similar approaches can be applied in the context of LEMs as a solution that network operators can use to get a more efficient load response from end-users.

The increasing penetration of DERs and renewable energy is another significant factor in the implementation of LEM structures. While renewable energy production can be predicted with a good level of accuracy (85% - 95%) for large producers [142], it is much more difficult to forecast DERs from prosumers at a lower level. This is also related to different variations of consumption habits related to human behavior, leading to deviations that may cause network problems. LEM can designed to mitigate these deviations, allowing prosumers to generate additional revenues by selling their output to individual consumers [1].

The power system is forced to evolve due to several factors: the increasing penetration of DER, the new consumers (prosumers) roles and new electric loads, such as electric vehicles. In the past, the centralized generation that was dispatchable and predictable offered flexibility at the transmission level and was used to find the balance between generation and demand. At present, the large number of installed DERs (including renewables) are transforming the generation component into a more variable and intermittent energy source. This characteristic in generation is calling for different and more efficient management approaches (e.g., distributed optimization might be considered in many cases). On the demand side, the LEM can be the solution for adequate management of the flexibility available from end-users overcoming the problems of intermittencies of the renewable DERs.

Consideration of combined markets, as discussed in [109], [143], will also boost the appearance of the LEM. By default, these types of structures combine two or more energy sources, like electricity and hydrogen. For instance, an hydrogen distribution market can serve as a fuel for cars and at the same time be used for the commercialization of electricity [109]. Thus, the combination of two forms of energy that can be traded locally can contribute to a more significant expansion of local market structures. With the inclusion of combined markets, LEM are not restricted only to the trade of electricity, and other assets can be negotiated (e.g., hydrogen).

Currently in the electric power system, a significant number of tasks, including design, planning, operation, and control, cannot be performed without the assistance of computer software and modeling based on simulations [103]. Thus, it can be inferred that LEM will suffer from the same situation and simulations and decision making tools will be essential to evaluate and anticipate changes and achieve good functioning of the system.

Considering presented LEM structures, end-users can increase their participation in the electricity markets since, for now, direct participation of end users in the electricity market is limited, having to contract a tariff with retailers in order to receive electricity. With LEM, end-users will be able to conduct direct negotiations with peers and interact with different players in the market [23]. The LEM gives energy independence to the communities, providing the possibility of direct electricity trading within communities, and increasing the reliability and resilience of each member of the community as well. In fact, LEM promote local generation with the consideration of local sellers in the system [144]. If sellers use renewable DER, they will also contribute to the goals imposed by the EU [54]. As competition will increase, it is expected better services from traditional power industry actors, benefiting the needs of customers and giving them access to a more competitive market with better prices [145].

Concerning network operators, a minimization of the network investments costs can be seen as a benefit. Usually, these investments are made to prevent possible networks issues. LEM structures can also be used to avoid such costs [27]. The increase of local energy producers located in the community will decrease the flow of energy from the generation utilities which in turn can reduce network losses [97]. In addition, the fact that local production is closer to the point of consumption brings benefits to power quality and reliability in distribution networks [24]. Moreover, the emergence of LEMs will enable new business models due to the technology required for LEMs to be implemented [144]. Such approaches are in line with the roadmap defined by the EU, in which the electricity consumer should be at the center of the system and have an active participation on it [34].

Table 6 presents a summary of the benefits presented in the literature review for LEM. The classification is performed considering the contribution of analyzed articles addressing each benefit. After analyzing 26 articles, we have determined qualitative levels of merit for each of the identified benefits and barriers. A "weak", "moderate", and "strong" level is assigned to a benefit reflecting the degree of importance that it has in the context of LEM. These levels were defined considering the percentage of articles that address a given topic, namely a "weak" level is assigned to a benefit/barrier if it is addressed by 0-to-3 works, a "moderate" level if it is addressed by 4-to-6 works, and a "strong" level if it is addressed by 7 or more works.

Table 6 – LEM benefits classification.

Benefits	LEM impact	Work reference
Consumer on centric approaches	Strong	[1], [4], [16], [34], [46], [48], [90], [109], [107]
Benefits to power quality and reliability of distribution networks	Strong	[23], [146], [97], [109], [108], [24], [112]
More offers available	Moderate	[1], [146], [3], [103], [147]
RES increment	Moderate	[94], [90], [54], [91], [148]
Decrease the network costs	Moderate	[1], [94], [27], [97], [149]
New business models appearance	Moderate	[22] ,[30], [31], [144]
Better response from tradition power industry	Weak	[7], [145]

The implementation and operation of LEM, presented in section 4.2, may encounter barriers that hinder their emergence. For instance, the increase in penetration of variable resources as renewables will require technical maturity of some DER, which poses a barrier concerning their installation and in turn will also affect the implementation of LEM [146]. Smart meters are a key part of the implementation of LEM structures, as it will be from them that the information will emerge. Despite the various measures taken by political entities, the installation of smart meters in every home of energy users is far from being achieved [150]. Due to the information flow and access points that the implementation of LEM frameworks requires, guarantee data privacy is seen as a barrier that needs to be overcome by LEM, and it is certainly a good challenge in cybersecurity [151]. Trading platforms that include LEMs will need to be created so that users can access them effortlessly. At present, such platforms exist in reduced number and with restricted access, thus constituting also a barrier [86]. Negotiating of flexibility between DSOs and small end-users is a relevant aspect of LEM implementation. The lack of legislation and regulation in this DSO activity constitutes a barrier adjacent to the implementation of the LEM [145]. LEM structures will be created and dimensioned considering low voltage networks, because it is where small end-users are connected. The operation of these networks can constitute also a barrier since their current operation is essentially performed without considering a bidirectional flow, contrary to LEM in which bidirectional flows of electricity and information are a must [7]. LEM structures will have to use distribution grids for electricity transactions to take place. As a rule, distribution networks are exclusive to DSO, thus imposing another barrier due to conflicts that may occur between market participants [145]. Currently, it is on-going work from standardization bodies and policy makers to clearly define new concepts that arise in LEM, yet the fact that these works are still in progress represents a barrier that limits the emergence of the LEM [151]. LEMs are based on energy end-users, so there are gaps in business models capable of promoting these interests. In fact, most of today's business models are focused on the large users of power system [30]. Economically, the implementation costs of technology for end-user's participation on LEM can be high due to technology immaturity. This also constitutes a barrier to the development of LEM [145]. In addition, successful implementation of LEM requires the full involvement of end-users, which in many cases adopt a position of resistance to change due to distrust or simply lack of knowledge, constituting another barrier that depends on user-behavior and have more societal implications [151]. Table 7 presents the barriers classification for LEM found in the literature, the classification is performed considering the barriers impact in each structure. We perform the same qualitative assessment done for **Table** 6.

Table 7 – LEM barriers classifications

Barriers	Impact on LEM	Work reference
ICT technologies (smart meters, data privacy and trading platforms)	Strong	[1], [7], [150], [23], [25], [30], [94], [86], [3], [148], [152], [151]
Standardization bodies and policy makers	Moderate	[90], [148], [147], [112], [145]
DSO distribution networks exclusivities	Moderate	[7], [153], [145], [151]
Absent regulation and legislation on the flexibility negotiation	Weak	[4], [31], [94]
Lack of business models capable of promoting the interests of end-consumers	Weak	[30], [109]
Implementation costs	Weak	[152], [145]
Maturity of some DERs	Weak	[146]
Resistance to change	Weak	[151]

6. Conclusion

Structuring and modifying the electric power systems for the implementation of the LEM models can bring benefits to customers, particularly to residential and commercial end-users. LEM can also influence DR, making it more attractive because users will be able to perform DR for incentives while opening the opportunity to trade the saved electricity consumption to interested parties. LEM may also influence the installation of more distributed production technology. In fact, since there will be the possibility of selling electricity in LEM at a more attractive price than selling to the network, users will be interested on more means of production to increase their profits. However, the actual implementation of LEM structures can only be achieved if government entities (e.g., the EU) can recognize and support their implementations. LEM can be differentiated by the services and roles for which they are intended. Despite the current implementations and studies on the basic forms of LEM (showed throughout this work), the electrical system will require a more significant effort from researchers, suppliers, policymakers, and industry so that an effective implementation of LEM can become a reality.

If well-structured, LEM will allow a greater involvement of end-users in the electricity markets. In this regard, the concept of prosumer is one of the main drivers that is making possible the participation of end-users in the electricity markets, and in turn is promoting the emergence of LEM structures. Also, electricity trading at the local level can open a window of opportunity for local energy service companies. For instance, energy service companies can be suppliers of hardware and software for the implementations and operation of LEM. The implementations of LEM structures can also support the development of new businesses and agreements between stakeholders, adding private and shared resources to the benefit of individuals, communities, and society.

LEM can offer a better balance in general for energy negotiation, as they will allow more energy sellers to enter the system, promoting competition and reducing prices for the consumers. For instance, PV technology suppliers will benefit from successful implementation of LEM since they will promote the use PV panels increasing their sales. This increase in sales is explained for the possibility of selling energy by end-user and the willingness of increasing local production. Considering the joining concept of Internet of Things and residential automation systems, new modus operandi for energy management can be created to bring more active users and replacing gradually centralized management approaches. The resistance to change as a human characteristic can be sometimes difficult to overcome, but considering the LEM benefits presented in this study, it is expected a gradually transition from the users to this new paradigm of local electricity transactions.

Based on the contents of this article, some suggestions on future research paths are as follow:

- LEM design and structure of: Despite the development that market structures have had over the years with the market reform, concepts related to LEM still need to be further defined and standardized. The actual structure of energy power system should include specified regulation to incentive the participations of DER in the markets. New regulations should be created considering the needs to specify the roles of both new players and traditional players.
- Coordination of ancillary services with LEM: The ancillary services are considered an important mechanism which guarantees the security of the system. These types of mechanisms are typically used for regulating the power system variables, like frequency or voltage. LEM can be a good solution for ancillary services mechanisms at the local level. Therefore, new coordination approaches need to be designed and implemented to enable ancillary services at the local level.

- The use of distributed approaches: The use of distributed approaches in power systems is not a novelty and can be also applied into LEM. Since it is expected that the number of agents acting in the LEM increases significantly, the computational burden and scalability of the methods will be crucial for an efficient implementation. Thus, scalability of the distributed methods should be a topic for research enabling operation in a shorter periods of time and reducing the computational burden.
- Human dimension modelling: Decision support systems are needed to assist players in market participation. New decision support systems should be designed considering the rules and factors needed for participation in LEM mechanisms. The strategic behavior of the LEM agents should be an important issue to explore. In fact, a key feature of LEM consists in finding ways to optimally express consumers preferences and evaluate the impact of such preferences on the markets.
- LEM design considering the physical network: Players of LEM will use the traditional grid to make the energy transactions. Therefore, LEM should consider this during its designs. With the possibility of obtaining profits locally, or reducing energy bills, it is predictable that the participation of users in LEM will increase. In this way, it is possible that the limits of the traditional network can be exceeded. Thus, adequate network fees for LEM transactions should be designed.
- Communication system for interactions in LEM: In the negotiations of market players, a communications structure is fundamental for a correct information flow within each player. For instance, if players are not aware in real-time of the energy availability of each other player, transactions may not happen. Future developments of LEM should include new designs of communication and feasible information exchanges between players.
- Cyber-security in LEM structures: As LEM is mostly a market for end-users' participation, the number of connections in the systems will increase, and with more connections, more points of vulnerability in the system can be detected. This feature makes the system fragile to suffer cyber-attacks, damaging the power system and reaching the users. Cyber-security issues are therefore a critical topic that deserves further and continuous research to ensure reliable LEM structures.

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Appendix C. Conclusions in Spanish / Conclusiones en Castellano

Conclusiones Principales y Contribuciones

La integración a gran escala de fuentes de energía renovables (RES por sus siglas en inglés), como la solar y la eólica, impulsada como medio para minimizar la huella de carbono, ha llevado a un cambio en la operación y control de los sistemas de energía y potencia (PES por sus siglas en inglés) en todo el mundo. Este cambio ha llevado a la adopción de enfoques para controlar la demanda, minimizando el desequilibrio entre la generación y la demanda provocado por la fluctuación de la producción de RES. Directrices recientes de la comisión europea (EC por sus siglas en inglés) sugieren una participación significativa de los usuarios finales de electricidad (consumidores y prosumidores) en los PES. Para ello, deben participar en la gestión y planificación del sistema eléctrico y desempeñar un papel activo en los mercados eléctricos. La aparición del "agregador" permitió a los usuarios finales de electricidad beneficiarse de ventajas que antes no tenían, como la participación en los mercados mayoristas. De esta forma, el agregador permite que los usuarios finales de electricidad tengan mayor importancia, ya que, a través de un intermediario, pasan a poder participar activamente en el sistema. En el ámbito de los mercados eléctricos (EM), también se están produciendo cambios para introducir un comportamiento competitivo en el mercado mayorista de electricidad y, más recientemente, la liberalización del mercado minorista. Traer pequeños participantes al mercado está allanando el camino para el surgimiento de mercados eléctricos locales (LEM por sus siglas en inglés). Los enfoques LEM actuales que se encuentran en la literatura han tenido mucho éxito y están comenzando a aparecer en la práctica, lo que lleva a los usuarios finales de electricidad a una mayor participación en el sistema. Permiten a los usuarios finales de electricidad realizar transacciones de su propia electricidad localmente y también negociar servicios que los operadores de red pueden usar para operar el sistema.

En este contexto, con las nuevas posibilidades de participación activa de los usuarios finales de electricidad en el sistema, se necesitan nuevos modelos de simulación y soporte de decisiones para hacer frente a los nuevos desafíos. Este trabajo de tesis contribuyó con la propuesta de nuevos modelos y métodos enfocados en las dificultades referidas, orientados a apoyar las decisiones de los usuarios finales en las actividades futuras que brindan los nuevos modelos EM y en la posible participación activa en la gestión de los PES. Como contribución central, este trabajo se centró en el estudio de modelos orientados a agregadores para impulsar la participación activa de los usuarios finales de electricidad (prosumidores y consumidores) en futuros PES. Por tanto, se dirigió a los consumidores o prosumidores como ente central de las actividades.

Se han abordado cuatro contribuciones clave, incluida la gestión del lado de la demanda, los mercados eléctricos locales, la gestión de la cartera de electricidad y los servicios auxiliares locales. Además, se pueden destacar otras contribuciones específicas, como el uso de técnicas matemáticas para resolver modelos lineales, y metaheurísticas para optimización no lineal y compleja, y la creación de diferentes casos de estudio para evaluar los modelos propuestos.

Aunque el concepto LEM es considerablemente nuevo, la literatura relacionada con él está aumentando significativamente. Una contribución adicional relevante de este Ph.D. se relaciona con el concepto LEM en sí, desarrollando dos trabajos de revisión de literatura. Uno de estos trabajos, que ya está publicado, ha proporcionado una revisión de las implementaciones prácticas de LEM. El otro, proporcionado como preimpresión en esta tesis, presenta un análisis sobre las estructuras LEM actualmente propuestas, los proyectos que incluyen LEM y la legislación para fomentar la aparición de LEM. Se evidenció que se debe adoptar una definición y descripción común de LEM, por ejemplo, algunos autores consideran P2P como el nombre para el comercio local de electricidad y otros LEM. Otro tema identificado son las estructuras que pueden existir dentro de este segmento de mercado y las diversas propuestas para su organización.

Las aportaciones de este trabajo se basan en diferentes modelos dirigidos principalmente al consumidor y prosumidores a través del agregador. Desde el lado del consumidor y prosumidor, se han abordado diferentes aspectos, como la inclusión de generación fotovoltaica, sistemas de almacenamiento de energía (ESS por sus siglas en inglés) y vehículos eléctricos. Algunos de los modelos desarrollados también consideran la inclusión de pequeñas unidades de combinación de calor y potencia (CHP por sus siglas en inglés) como una entidad individual para producir electricidad para ser transaccionada en LEM. Sin embargo, algunos aspectos que surgen con la operación de CHPs son necesarios para crear o mejorar las metodologías desarrolladas. Por otro lado, el rol del agregador en los PES ha sido ampliamente discutido tanto en la literatura como en aplicaciones reales. Sin embargo, se deben desarrollar o ajustar nuevos modelos comerciales para permitir la generalización de las aplicaciones LEM en la práctica.

Este trabajo de tesis contribuyó con enfoques para ayudar al usuario final de electricidad en su empoderamiento dentro del ámbito de PES y EM. Los modelos propuestos se centran en el papel del agregador y están orientados a apoyar al usuario final de electricidad en sus actividades de PSA y EM. Los resultados de la investigación abordaron la pregunta de investigación (Q0) y las cinco preguntas de investigación (Q1 a Q5), presentadas en la sección 1.2. Se desarrolló al menos un modelo para cada una de las cuatro actividades principales identificadas. Estos modelos se construyen para abordar problemas específicos y, al mismo tiempo, posiblemente superar la brecha identificada inicialmente. Cómo tal, los artículos, *Core Paper II*, *III*, *IV*, *V* y *VI* presentan diferentes modelos que simulan actividades donde el agregador es el proveedor y los usuarios finales de electricidad son los clientes. En este sentido, se identificó la brecha, es decir, donde faltaban modelos y soluciones que ayuden al agregador en la prestación de servicios. Para la literatura, los modelos implementados y publicados también son una contribución, ya que permiten a los interesados seguirlos e implementarlos.

Los hallazgos resultantes del desarrollo de modelos y métodos, del logro de respuestas a las preguntas de investigación y del consecuente cumplimiento de todos los objetivos definidos, posibilitaron la prueba y la validación de las hipótesis identificadas. Por tanto, es posible concluir que de los varios modelos desarrollados en esta tesis pueden ser aplicados en entornos reales. Sin embargo, otros aún no pueden ya que la actividad que pretenden abordar carece de legislación y regulación alineada con las necesidades actuales y futuras para la evolución continua de los PES y los EM. El trabajo desarrollado en el ámbito de esta tesis ha resultado en la publicación de diecinueve artículos principales, diez de ellos publicados en revistas JCI, y contribuido a seis proyectos en total, de los cuales tres son nacionales y tres internacionales.