UNIVERSIDAD DE SALAMANCA

DOCTORAL THESIS

Decision Support for Smart Grid Planning and Operation Considering Reliability

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Doctor Degree in Informatics Engineering

Departamento de Informática y Automática

Facultad de Ciencias

June, 2019

This work has received funding from *FCT - Fundação para a Ciência e a Tecnologia*, through the *POCH - Programa Operacional Capital Humano*, supported by the *Fundo Social Europeu* and by the MCTES national funds.

PhD scholarship with reference SFRH/BD/110678/2015 between 2016 and 2019.

Thesis Type

This Ph.D. thesis is based on a collection of previously published works in international journals indexed at JCR and on a Springer book chapter.

The following six international journals papers and one book chapter compose the core of this Ph.D. work:

I. Bruno Canizes, João Soares, Zita Vale, Cristina Lobo, "Multi-criteria optimisation approach to increase the delivered power in radial distribution networks", IET Generation, Transmission & Distribution. 9 (2015) 2565–2574. doi:10.1049/iet-gtd.2014.1196 (**2015 Impact Factor is 1.576**);

II. Bruno Canizes, João Soares, Zita Vale, Cristina Lobo, "Optimal Approach for Reliability Assessment in Radial Distribution Networks", IEEE Systems Journal. 11 (2017) 1846–1856. doi:10.1109/JSYST.2015.2427454 (**2017 Impact Factor is 4.337**);

III. João Soares, Bruno Canizes, Mohammad Ali Fotouhi Ghazvini, Zita Vale, Ganesh Kumar Venayagamoorthy, "Two-Stage Stochastic Model Using Benders' Decomposition for Large-Scale Energy Resource Management in Smart Grids", IEEE Transactions on Industry Applications. 53 (2017) 5905–5914. doi:10.1109/TIA.2017.2723339 (**2017 Impact Factor is 2.743**);

IV. Bruno Canizes, João Soares, Mohammad Ali Fotouhi Ghazvini, Cátia Silva, Zita Vale, Juan M. Corchado, "Long-term smart grid planning under uncertainty considering reliability indexes", in: Operation, Planning, and Analysis of Energy Storage Systems in Smart Energy Hubs, 2018, Springer. doi:10.1007/978-3-319-75097-2_13;

V. Bruno Canizes, João Soares, Fernando Lezama, Cátia Silva, Zita Vale, Juan M. Corchado, "Optimal expansion planning considering storage investment and seasonal effect of demand and renewable generation", Renewable Energy. 138 (2019) 937–954. doi:10.1016/j.renene.2019.02.006 (**2018 Impact Factor is 5.439**);

VI. Bruno Canizes, João Soares, Zita Vale, Juan M. Corchado, "Optimal Distribution Grid Operation Using DLMP-based Pricing for Electric Vehicle Charging Infrastructure in a Smart City", Energies. 686 (2019) 12(4). doi:10.3390/en12040686 (**2018 Impact Factor is 2.707**);

VII. Bruno Canizes, João Soares, Angelo Costa, Tiago Pinto, Fernando Lezama, Paulo Novais, Zita Vale, "Electric Vehicles User Charging Behaviour Simulator for a Smart City", Energies. 1470 (2019) 12(8). doi:10.3390/en12081470 (**2018 Impact Factor is 2.707**).

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STATEMENT

Zita Maria Almeida do Vale, Full Professor at School of Engineering Polytechnic of Porto, authorizes that Bruno Miguel da Rocha Canizes can present his thesis using a collection of previously published works in international journals indexed at SCI and a Springer book chapter (thesis by papers).

Porto, May 20, 2019

Zita Maria Almeida do Vale

STATEMENT

Juan Manuel Corchado Rodríguez, Full Professor, Area of Computer Science and Artificial Intelligence, Department of Computer Science and Automation Control at the University of Salamanca and director of the BISITE (Bioinformatics, Intelligent Systems and Educational Technology) research group, authorizes that Bruno Miguel da Rocha Canizes can present his thesis using a collection of previously published works in international journals indexed at SCI and a Springer book chapter (thesis by papers).

Salamanca, May 13, 2019

Juan Manuel Corchado Rodríguez

"We can only see a short distance ahead, but we can see plenty there that needs to be done."

Alan Turing
— Computing Machinery and Intelligence, Mind, 1950

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Abstract

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Decision Support for Smart Grid Planning and Operation Considering Reliability

by Bruno CANIZES

This thesis provides contributions to the complementary topics of power systems and electric mobility. It proposes innovative solutions for the planning of traditional radial distribution network without or with few distributed generators units penetration, and for medium voltage distribution network long-term planning, operation, reconfiguration, and energy resource management considering high distributed energy resources penetration in the context of smart grids.

Concerns about the availability of fossil fuels and the rising climate effects caused by its widespread use in electricity generation have led to several policies and incentives to attenuate these problems. These measures contributed to considerable investments in renewable energy sources and motivated many smart grid initiatives. Although the future panorama of modern power systems looks very promising, the large-scale integration of renewable energy sources of intermittent nature, such as wind and photovoltaic poses new challenges, and limitations in the current power industry. Nowadays, the distribution network design is not correctly prepared to accommodate a high quantity of distributed renewable energy sources. Thus, the distribution system operators recognize the need to change the network design by planning, and reinforcement.

As renewable energy sources penetration is increasing an energy aggregator can provide a highly flexible generation and demand as required by the smart grid paradigm. Moreover, this entity can allow to achieve high integration of renewable energy supply and raise value for small producers and consumers that cannot negotiate directly in the wholesale market. However, the energy aggregator entity needs adequate decision support tools to overcome the complex challenges and deal with a large number of energy resources. Thus, energy resource management is crucial for the energy aggregator entity to reduce operation costs, increase profits, reduce carbon footprint, and improve system stability.

In the current world outlook, many people are moving to the cities searching for a better quality of life, contributing in this way to the continuous expansion of urban areas. Consequently, the transportation sector is playing a critical role in carbon dioxide emissions. Considering this, many environmental and economic advantages can be provided from the shifting of

internal combustion engines to electric vehicles. However, this shift will contribute to a burden on the distribution network giving place to the possibility of new situations of network congestion. Thus, to facilitate the electric vehicles charging integration in the distribution network, an electric vehicle user behavior modeling and prediction could be an essential tool. Moreover, the smart grid paradigm is challenging the conventional control and operation framework designed for passive distribution networks. Thereby, distribution network reconfiguration will be an essential and significant strategy for the distribution system operator.

A lack of adequate decision support models, strategies, and tools for medium voltage distribution networks planning, operation, and energy resource management problem in a smart grid context with high penetration of distributed energy sources were identified in the current state of the art. In this way, several research challenges arise leading to the need for the development of new and innovative models that deal with: a) the renewable energy sources and demand variability impact in the long-term expansion planning, b) the large-scale energy resource management problem, considering the demand, renewable energy sources, electric vehicles, and market price variability, c) the impact analysis of dynamic electric vehicles charging prices on the distribution network operation and the electric vehicle user behavior. Besides that, in the context of traditional radial medium voltage distribution networks, the need for innovative models to improve the reliability through the identification of new investments in the network components was also verified.

This thesis proposes innovative solutions to address these gaps and problems. For that purpose, the thesis aggregates contributions that ultimately result in an innovative decision support system – Advanced Decision Support Tool for Smart Grid Planning and Operation (*SupporGrid*). The *SupporGrid* is composed of a set of diversified models that together contribute to handling the complexity of traditional radial distribution networks planning (*PlanTGrid*), and for planning (*PlanSGrid*), operation (*OperSGrid*), and energy resource management (*ERMGrid*) optimization problems in medium voltage distribution networks under the smart grid paradigm. The *PlanTGrid* includes an expansion planning model for traditional radial distribution networks to identify the possibility of new investments at the minimum cost. The long-term expansion planning of distribution networks in a smart grid context with high penetration of distributed renewable energy sources and which deals with the uncertainty sources is solved by the *PlanSGrid*. An electric vehicle users travel simulation tool operating in conjunction with distribution locational marginal pricing based on Benders' decomposition operation and reconfiguration to understand the impact of the dynamic energy charging price on both sides: the distribution network and the EV user is included in the DSS by the *OperSGrid* module. To deal with large-scale energy resource management with demand response and energy storage systems issues as well as with the variability of demand, renewable energy sources, electric vehicles, and market price the *ERMGrid* includes a two-stage stochastic model.

The developed decision support system methodologies have been tested and validated in realistic scenarios. The promising results achieved under realistic conditions support the hypothesis that the methodologies are adequate and innovative for traditional radial distribution network planning, and for distribution network long-term planning, operation, reconfiguration, and energy resource management considering high distributed energy resources and electric vehicles penetration in the context of smart grids. In fact, this decision support system will improve the medium voltage distribution networks operation, allowing savings to the involved players.

Keywords: Benders' decomposition, distribution network operation, distribution network planning, distribution network reconfiguration, electric mobility, energy resource management, optimization, smart grid, stochastic systems.

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Resumen

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Decision Support for Smart Grid Planning and Operation Considering Reliability

por Bruno CANIZES

Esta tesis aporta contribuciones a los temas de los sistemas de energía y la movilidad eléctrica. Por lo tanto, se proponen soluciones innovadoras para la planificación de la red de distribución radial tradicional sin o con pocas unidades de recursos energéticos distribuidos, y para la planificación, operación, reconfiguración, y gestión de recursos energéticos en redes de distribución en media tensión considerando una alta penetración de los recursos energéticos distribuidos en el contexto de las redes inteligentes.

Las preocupaciones sobre la disponibilidad de combustibles fósiles y el aumento de los efectos climático causados por su uso generalizado en la generación de electricidad han llevado a varias políticas e incentivos para atenuar estos problemas. Estas medidas contribuyeron a inversiones considerables en fuentes de energía renovables y motivaron muchas iniciativas de redes inteligentes. Aunque el panorama futuro de los sistemas eléctricos modernos parece muy prometedor, la integración a gran escala de fuentes de energía renovables de naturaleza intermitente, como la eólica y la fotovoltaica, plantea nuevos desafíos y limitaciones en la industria eléctrica actual. Hoy en día, el diseño de la red de distribución no está correctamente preparado para alojar una gran cantidad de fuentes de energía renovables distribuidas. Por lo tanto, los operadores del sistema de distribución reconocen la necesidad de cambiar el diseño de la red mediante la planificación y el refuerzo.

A medida que aumenta la penetración de las fuentes de energía renovable, un agregador de energía puede proporcionar una generación y demanda altamente flexibles según lo requiere el paradigma de red inteligente. Además, esta entidad puede permitir lograr una alta integración de la oferta de energía renovable y aumentar el valor para los pequeños productores y consumidores que no pueden negociar directamente en el mercado mayorista. Sin embargo, la entidad agregadora de energía necesita herramientas adecuadas de apoyo a la decisión para superar los desafíos complejos y hacer frente a un gran número de recursos energéticos. Por lo tanto, la gestión de recursos energéticos es crucial para que la entidad agregadora de energía reduzca los costos de operación, aumente de los beneficios, reduzca la huella de carbono y mejore la estabilidad del sistema.

En la perspectiva mundial actual, muchas personas se están mudando a las ciudades en busca de una mejor calidad de vida, contribuyendo de esta manera a la continua expansión de las áreas urbanas. En consecuencia, el sector de transportes está jugando un papel crítico en las emisiones de dióxido de carbono. Teniendo en cuenta esto, muchas ventajas medioambientales y económicas pueden ser obtenidas del cambio de los motores de combustión interna a los vehículos eléctricos. Sin embargo, este cambio contribuirá a una carga en la red de distribución, dando lugar a la posibilidad de congestión de la red. Por lo tanto, para facilitar la integración de la carga de los vehículos eléctricos en la red de distribución, un modelo de predicción del comportamiento del usuario de un vehículo eléctrico pode ser una herramienta muy importante. Además, el paradigma de la red inteligente está desafiando la estructura de control y operación convencional diseñado para redes de distribución pasivas. De este modo, la reconfiguración de la red de distribución será una estrategia esencial y significativa para el operador del sistema de distribución.

En el estado del arte actual se identificó una falta de modelos, estrategias y herramientas de apoyo a la toma de decisiones adecuadas para los dominios de problemas de planificación, operación y gestión de recursos energéticos de redes de distribución en media tensión con una alta penetración de fuentes de energía distribuidas. Por lo tanto, surgen varios desafíos de investigación que llevan a la necesidad de desarrollar modelos nuevos e innovadores que aborden: a) el impacto de las fuentes de energía renovable y la variabilidad de la demanda en la planificación de la expansión a largo plazo, b) el problema de la gestión de los recursos energéticos a gran escala, teniendo en cuenta la demanda, las fuentes de energía renovables, los vehículos eléctricos y la variabilidad de los precios del mercado, c) el análisis de impacto de los precios de carga dinámicos de los vehículos eléctricos en la operación de la red de distribución y en el comportamiento del usuario del vehículo eléctrico. Además, en el contexto de la red de distribución de media tensión radial tradicional, también se verificó la necesidad de modelos innovadores para mejorar la confiabilidad a través de la identificación de nuevas inversiones en los componentes de la red.

Por lo tanto, esta tesis propone soluciones innovadoras para hacer frente a todos estos vacíos y problemas. Para ese propósito, las contribuciones de la tesis, resultan en un innovador sistema de apoyo a la decisión llamado *Advanced Decision Support Tool for Smart Grid Planning and Operation* (*SupporGrid*). El *SupporGrid* se compone de un conjunto de modelos diversificados que juntos contribuyen a manejar la complejidad de la planificación tradicional de las redes de distribución radial (*PlanTGrid*), y para la planificación (*PlanSGrid*), operación (*OperSGrid*), y los problemas de gestión de recursos energéticos (*ERMGrid*) en redes de distribución de media tensión en el paradigma de red inteligente. *PlanTGrid* incluye un modelo de planificación de expansión para redes de distribución radial tradicionales para identificar la posibilidad de nuevas inversiones al costo mínimo. La planificación de la expansión a largo plazo de las redes de distribución en un contexto de red inteligente con una alta penetración de fuentes de energía renovables distribuidas y que trata las fuentes de incertidumbre se resuelve mediante el uso *PlanSGrid*. *OperSGrid* contiene una herramienta de simulación de viajes de los usuarios de los vehículos eléctricos funcionando en conjunto con un modelo de operación y reconfiguración que utiliza descomposición de Benders y precios marginales para comprender el impacto del precio de carga de energía dinámica en ambos lados: la red de distribución y el usuario de vehículo eléctrico. Para hacer frente a la gestión de recursos energéticos a gran escala con problemas de respuesta a la demanda y sistemas de almacenamiento de energía, así como con la variabilidad de la demanda, las fuentes de energía renovable, los vehículos eléctricos y el precio de mercado, *ERMGrid* incluye un modelo estocástico de dos etapas.

Las metodologías desarrolladas para el sistema de soporte de decisiones se han probado y validado en escenarios realistas. Los resultados prometedores logrados en condiciones realistas respaldan la hipótesis de que las metodologías son adecuadas e innovadoras para la planificación de la red de distribución radial tradicional, y para la planificación, operación, reconfiguración y gestión de recursos energéticos a largo plazo de la red de distribución considerando alta penetración de recursos energéticos distribuidos y de vehículos eléctricos en el contexto de red inteligente. Los resultados prometedores logrados en condiciones realistas respaldan la hipótesis de que las metodologías son adecuadas e innovadoras para la planificación de la red de distribución radial tradicional, y para la planificación, operación, reconfiguración y gestión de recursos energéticos a largo plazo de la red de distribución considerando la alta distribución de recursos energéticos y la penetración de vehículos eléctricos. De hecho, este sistema de apoyo a la decisión mejorará el funcionamiento de las redes de distribución de media tensión, permitiendo ahorros para las partes interesadas.

Palabras clave: Descomposición de Benders, gestión de recursos energéticos, movilidad eléctrica, operación de redes de distribución, optimización, planificación de redes de distribución, reconfiguración de redes de distribución, redes inteligentes, sistemas estocásticos.

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Resumo

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Decision Support for Smart Grid Planning and Operation Considering Reliability

por Bruno CANIZES

O contributo desta tese é dado essencialmente nas áreas dos sistemas elétricos de energia e da mobilidade elétrica. São assim propostas soluções inovadoras para o planeamento de redes de distribuição tradicionais sem ou com poucas unidades de produção distribuída e também para o planeamento a longo prazo, operação, reconfiguração e gestão de recursos energéticos, considerando grande penetração de recursos energéticos distribuídos num contexto de redes inteligentes em média tensão.

A incerteza sobre a disponibilidade dos combustíveis fósseis e os crescentes efeitos climáticos causados pela sua ampla utilização na produção de energia elétrica impulsionaram diversas políticas e incentivos para atenuar esses problemas. Essas medidas contribuíram com investimentos consideráveis em fontes de energia renováveis e motivaram muitas iniciativas relacionadas com as redes inteligentes. Embora o panorama futuro para sistemas elétricos de energia modernos pareça muito promissor, a integração em grande escala de fontes de energia renovável caracterizadas pela sua intermitência (como por exemplo eólica e fotovoltaica), apresenta novos desafios, e evidencia as limitações do atual estado do setor elétrico. Atualmente, as redes de distribuição não estão corretamente preparadas para incluir uma grande quantidade de fontes distribuídas de energia renovável. Assim, os operadores do sistema de distribuição reconhecem a necessidade de alterar o atual estado das redes de distribuição por meio de planeamento e reforço.

Como a penetração de fontes de energia renovável está em franco crescimento, uma entidade agregadora será indicada para fornecer a flexibilidade necessária para a geração e procura de energia exigidas pelo paradigma das redes inteligentes. Além disso, essa entidade agregadora permitirá uma grande integração de fornecimento de energia por fontes renováveis, elevando assim os ganhos dos pequenos produtores e consumidores que não podem negociar diretamente em mercado. Para tal, a entidade agregadora necessitará de ferramentas adequadas de apoio à decisão para superar os diversos desafios e lidar com um grande número de recursos energéticos. Assim, a gestão dos recursos energéticos é crucial para que a entidade agregadora de energia reduza os custos de operação, aumente os lucros, contribua para a redução das emissões de dióxido de carbono e melhore a estabilidade do sistema.

Atualmente, um grande número de pessoas estão a deslocar-se para as cidades em busca de melhor qualidade de vida, contribuindo desta forma para uma contínua expansão das áreas urbanas. Como consequência, o setor dos transportes está a desempenhar um papel crítico nas emissões de dióxido de carbono. Tendo isto em conta, diversas vantagens ambientais e económicas poderão ser obtidas com a troca dos veículos de motores a combustão interna por veículos elétricos. No entanto, esta mudança sobrecarregará a rede de distribuição levando a um possível congestionamento da mesma. Assim, por forma a facilitar a integração dos carregamentos dos veículos elétricos na rede de distribuição, uma ferramenta de modelização e previsão comportamental dos utilizadores deste tipo de veículos poderá ser muito importante. Além disso, o paradigma de redes inteligentes tem colocado desafios à estrutura convencional de controlo e operação projetada para as redes de distribuição passivas. Como tal, a reconfiguração da rede de distribuição será uma estratégia essencial e significativa para o operador do sistema de distribuição.

Foi identificado no atual estado de arte um défice de modelos adequados de apoio à decisão, de estratégias e de ferramentas para o planeamento, operação e gestão de recursos energéticos nas redes distribuição em média tensão num contexto de redes inteligente com alta penetração de recursos distribuídos. Deste modo, novos desafios surgirão levando à necessidade do desenvolvimento de modelos inovadores que lidem com: a) o impacto da variabilidade das fontes de energia renovável e carga no planeamento a longo prazo, b) a gestão a larga escala de recursos energéticos, considerando a variabilidade das fontes de energia renovável, da carga, dos veículos elétricos e do preço de energia, c) a análise do impacto de preços dinâmicos para o carregamento dos veículos elétricos quer na operação das redes de distribuição quer no comportamento do utilizador dos veículos elétricos. Além disso, no contexto de redes tradicionais de distribuição em média tensão, foi também detetada a necessidade do desenvolvimento de modelos inovadores que identificam a necessidade de novos investimentos nos componentes da rede por forma a melhorar a fiabilidade da mesma.

Esta tese propõe soluções inovadoras para abordar todos estes problemas e lacunas. A tese agregou diversas contribuições que levaram a um sistema inovador de suporte à decisão, a *Advanced Decision Support Tool for Smart Grid Planning and Operation (SupporGrid)*. A *SupporGrid* é composta por um conjunto de modelos diversificados que juntos lidam com a complexidade do planeamento tradicional das redes de distribuição em média tensão (*PlanTGrid*), do planeamento (*PlanSGrid*), operação (*OperSGrid*) e gestão de recursos (*ERMGrid*) em redes de distribuição em média tensão num contexto de redes inteligentes. O *PlanTGrid* executa um modelo de planeamento para expansão de redes de distribuição tradicionais radiais em média tensão, onde é identificada a possibilidade de novos investimentos ao menor custo. O planeamento da expansão de redes de distribuição de média tensão com grande penetração de fontes de energia renovável distribuídas num contexto de redes inteligentes a longo prazo é resolvido pelo *PlanSGrid*. *OperSGrid* contem uma ferramenta de simulação para viagens dos veículos elétricos que permitirá simular ambientes realistas considerando aspetos comportamentais dos utilizadores de tais veículos. Essa ferramenta trabalha em conjunto com um modelo de otimização de operação, reconfiguração e de preços marginais baseado na decomposição de Benders num contexto de redes inteligentes que permitirá perceber o impacto dos preços dinâmicos de energia para o carregamento dos veículos elétricos nos pontos de vista do operador do sistema de distribuição e dos utilizadores dos veículos. Para fazer frente à gestão de recursos energéticos a larga escala com problemas relacionados com a resposta ativa da carga e dos sistemas de armazenamento de energia elétrica, assim como com a variabilidade da carga, das fontes de energia renovável, dos veículos elétricos e do preço de mercado da energia, o *ERMGrid* possui um modelo estocástico de dois estágios.

As metodologias desenvolvidas para o sistema de suporte à decisão propostas nesta tese foram testadas e validadas em cenários realistas. Os resultados promissores que foram alcançados sob condições realistas reforçam a hipótese de que as metodologias serão adequadas e inovadoras para o planeamento de redes radiais de distribuição tradicionais, planeamento a longo prazo, operação e reconfiguração de redes de distribuição, e para a gestão de recursos energéticos num contexto de redes inteligentes com grande penetração de fontes de energia renovável e de veículos elétricos. O facto é que este sistema de apoio à decisão permitirá melhorar a operação das redes de distribuição em média tensão permitindo assim também uma poupança monetária aos intervenientes.

Palavras-chave: Decomposição de Benders, gestão de recursos energéticos, mobilidade elétrica, operação de redes de distribuição, otimização, planeamento de redes de distribuição, reconfiguração de redes de distribuição, redes inteligentes, sistemas estocásticos.

Acknowledgements

I want to take this opportunity to thank and recognize the support of several persons who, during this work, collaborated directly or indirectly with the risk of committing some injustices by unintentional omission.

In the first place, I want to express my sincere gratitude to my parents and brother, who supported me several times in my life, especially in the worst ones. I recognize that they have overcome their obligations, and without them, everything would be more difficult. So, I will be eternally grateful to them.

I want to thank my supervisor, Professor Zita Vale, for her support, encouragement, availability, the rigor of her comments, suggestions, and contributions that led this work to succeed. For professional and personal growth that she gave me over more than ten years. The merit of this work belongs to her as well. I feel truly privileged to have her as a supervisor.

I would also like to thank my supervisor at the University of Salamanca, Professor Juan Corchado, who was always available and also a great ally at the university. For this, the merit of this work also belongs to him.

I want to express my gratitude to the Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD), which provided me with technical means to fulfill this Ph.D. thesis.

I would also like to thank the Synthetic Intelligence Lab (ISLab), especially to Professor Paulo Novais for the work placement opportunity.

Thanks to Professor António Machado e Moura and Professor Rubipiara Cavalcante for their availability to give their opinion about the developed work presented in the thesis, with the purpose to obtain the international doctor mention.

I want to thank Professor María Moreno García, for her availability and help regarding all questions and doubts about the Ph.D. that I addressed.

I want to dedicate this paragraph to a great friend with whom I have been sharing the good and bad moments, challenges, ideas, and work for more than ten years. His critical vision, exigency level, perfectionism, and enthusiasm were fundamental to the accomplishment of this work. The merit of this work is also yours João Soares.

A big thanks to Tiago Pinto, Fernando Lezama, Pedro Faria, Professor Sérgio Ramos, and Omid Abrishambaf for all the valuable comments and suggestions to the thesis manuscript. I would also like to thank Tiago Pinto and Professor Sérgio Ramos, for their help in some bureaucratic processes, especially in the international doctor mention.

A special thanks to my friends João Vinheiras and Daniela Vinheiras for their fantastic help and correction of the Portuguese abstract.

My special words are dedicated to my lovely girlfriend, Evelin, who had to bear with my absence for way too long. *"Antes de amarte, amor, nada era mío, vacilé por las calles y las cosas,..."*[1]

[1]Pablo Neruda, in Soneto XXV

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List of Abbreviations

AC	Alternating Current
ANN	Active Network Management
CAIDI	Customer Average Interruption Duration Index
CHP	Combined Heat and Power
CO_2	Carbon Dioxide
DER	Distributed Energy Resources
DG	Distributed Generators
DLMP	Distribution Locational Marginal Pricing
DN	Distribution Network
DNR	Distribution Network Reconfiguration
DR	Demand Response
DSO	Distribution System Operator
DSS	Decision Support System
ERM	Energy Resource Management
ESS	Energy Storage System
EU	European Union
EV	Electric Vehicle
EVPI	Expected Value of Perfect Information
FOR	Forced Outage Rate
GAMS	General Algebraic Modeling System
GECAD	Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development
GHG	GreenHouse Gas
LMP	Locational Marginal Pricing
MCS	Monte Carlo Simulation
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
NSP	Non-Supplied Power
PGC	Power Generation Curtailment
Ph.D.	Doctor of Philosophy
PSO	Particle Swarm Optimisation
PV	Photovoltaic
R&D	Research and Development
RES	Renewable Energy Sources
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
SC	Smart City
SG	Smart Grid
VPP	Virtual Power Player
VSS	Value of the Stochastic Solution

Chapter 1

Introduction

The motivation for the development of the work done in the scope of this thesis is presented in section 1.1. The presented motivation leads to the set of research questions and objectives defined in section 1.2. These research questions and objectives were the foundations for the development of this Ph.D. research work. Section 1.3 provides a brief outline of the main contributions and the related projects of this work. Optimization methods, solvers, and computational resources used during the Ph.D. work are presented in section 1.4. Finally, section 1.5 shows the organization of the thesis document.

1.1 Motivation

Nowadays, societies are highly dependent on electricity to ensure safe, reliable, and comfortable living. The electricity demand is expected to still increase in the future and is an essential requirement for economic development [1].

It is known that the highest unavailability issues of all energy supply chain occur at distribution level [2], [3]. Distribution networks (DN) are usually composed of radial feeders, where a single component failure can affect a considerable number of customers. The adequacy of these networks can be evaluated by reliability indexes using the outage parameters such as the average failure rate λ, the average outage duration r, and the annual outage duration U. The indexes values can be improved by modifying the λ and r, for instance, applying line reinforcement to enhance the λ, and increasing the operation personnel to enhance the r. In the majority of the countries, the increasing electricity needs are mostly satisfied with non-renewable energy sources like coal, oil or natural gas. However, these energy resources are scarce and bring negative consequences to the environment. The growing load trend in DN requires an upgrade of the current network [4]–[9]. This growth can be related to the consumer's new requirements, for instance, an increase in electrical based home equipment and the number of electric vehicles (EV). Furthermore, several innovative developments in power distribution systems have taken place around the world. One of them is related to the minimization of the carbon footprint using a large-scale integration of renewable energy sources (RES) such as wind and solar. The European Union (EU) renewable energy directive (2009/28/EC) [10] sets a binding target of 20% final energy consumption from renewable sources by 2020. In

December 2018, the new revised renewable energy directive (2018/2001) [11] entered into force by establishing a new binding renewable energy target for the EU for 2030 of at least 32%, with a clause for a possible upwards revision by 2023.

Despite the need of high integration of RES to meet EU targets and address environmental issues, the distributed generators based on renewable sources, such as solar, and wind, among others, carry an inherent variability that introduces several challenges to the planning and operation of distribution networks. In technical terms, the high penetration of this kind of generators may have a positive or negative impact in the normal operation of the distribution networks [12]–[15].

The adoption of smart grid (SG) enabling technologies, such as: real-time information systems, improved communication and control systems, advanced metering systems, high number of sensors, reactive power sources, advanced switching and energy storage systems (ESS) has the capability to mitigate the negative impact of large-scale RES penetration [16]–[18].

The current DN design is not prepared to integrate a large number of distributed RES units. As a result, the distribution system operators (DSO) are recognizing the needs to plan or reinforce the DN structure according to the SG paradigm [19], [20].

ESS in the DN offers technical, economic, and environmental advantages [21]. These advantages include power quality improvement, voltage deviation mitigation, frequency regulation, load shifting, load, and peak shaving, network expansion and overall cost reduction, operating reserves, and greenhouse gas (GHG) reduction [22]–[29]. Furthermore, the high penetration of RES can be facilitated by the use of ESS by absorbing and releasing power in different time horizons [30]–[33]. The problem of the optimal allocation of ESS must be carried out at the planning stage to exploit their benefits fully. This kind of problem consists in defining the type and the number of devices to be deployed, their locations, and sizes [34], [35].

DN planning and reinforcement considering the distributed energy resources (DER), mainly RES, can be classified into two categories [36]. The first one is the short-term, i.e., storage scheduling, and RES power forecast (for instance, one day before). The second one is related to the long-term (several years), where is desirable the analysis of large sets of data to indicate the behavior of RES (wind, photovoltaic (PV), among others) and demand. For long-term, these data are usually fitted to proper distribution functions, but with the uncertainty introduced by the renewable power and demand the challenge of modeling the uncertainty sources increases. For instance, the United States Department of Energy has identified the need to have robust control and predictive models to deal with the stochastic behavior and uncertainty as top research and development (R&D) priority [37]. For this, more effort is required to overcome the technical and economic challenges of the DN planning [38].

Additionally, as the RES penetration is increasing, an essential portion of the total power generation portfolio can be given by them. Thus, the entities related to the energy resources management (ERM), such as the energy aggregators [39], need adequate tools to deal with the increasing level of uncertainty. Indeed, in the last few years, significant research work has been done in this subject, delivering relevant results but also evidencing several limitations, which still require further attention. For instance, the uncertainty of wind and PV generation is usually considered, but the fluctuation of the market prices and load demand is frequently neglected. Moreover, the demand response (DR) is not considered in most of the works, and in terms of optimization problem size, the case studies are significantly small, leading to a lack of realism. Also, EVs penetration, which is expected to grow considerably in the next decade, and their related uncertainties are just considered in a few works [39], [40] but do not incorporate grid constraints. It is worth to refer that nowadays the DSO can still assume the functions of an aggregator.

Nowadays, many people move to cities in search of a better quality of life, and this contributes to the continuous expansion of urban areas, which play a significant role in modern economies. However, the urban population is responsible for most greenhouse gas emissions, and the United Nations estimates that the urban population will reach 70% of the world's total population by 2050 [41]. Consequently, it is necessary to make intelligent use of resources in urban environments, contributing to the development of smart cities [41]. SG is one of the most essential urban infrastructures to support and enable a sustainable city [42]. One of the main reasons for global warming and climate change is related to carbon dioxide (CO_2) emissions from the transportation sector [43]. It is widely acknowledged that the shift from internal combustion engines to EV has many environmental and economic advantages. However, the increasing number of EVs leads to a demand growth as well as the need of the charging infrastructure development [44] to meet the requirements of EVs operation [45]. These charging infrastructure will contribute to a burden on the distribution power grid [46]–[48], namely the high charging loads of fast EV charging stations. Also, some distribution network operating parameters are going to degrade (e.g., voltage profile and power losses).

Furthermore, a high EV penetration level may congest the distribution network. Congestion problems can be managed by the DSO using the transmission systems concept of locational marginal pricing (LMP) extended to the distribution systems [49], usually referred to as distribution locational marginal pricing (DLMP). As it is known the EVs are additional electric loads and represent mobile energy storage, generally with long resting times. Moreover, one of the main challenges to facilitate the EVs charging integration in the distribution network is the EV user behavior modeling and prediction [50]. Also, the SG features an active power architecture with a high penetration of DER, namely RES, which is challenging the conventional control and operation framework designed for passive distribution networks. Thus, distribution network reconfiguration (DNR) will be an essential and significant strategy for the DSO. DNR is known as a process to change the network topology using the remote switches such that all the network constraints are considered. In the SG context, the DNR needs to address not only the classic objectives (power losses and non-supplied power (NSP) minimization and the voltage profile improvement) [51], [52] but also the problems related to the high DER and EVs penetration [53]–[55].

This thesis focuses essentially on the topics of the planning, operation energy resource management of medium voltage (MV) distribution networks in the Smart Grid paradigm. Indeed, in the last few years, significant research works have been done in these subjects, delivering important results but also evidencing many limitations, whose still require further attention. To fully grasp the state of the art limitations in the current literature, an extensive literature review was carried out during the development of this thesis (see sections 2.2 to 2.5).

1.2 Objectives

The identified limitations in the existing state of the art refer to the lack of adequate decision support models, strategies, and tools for distribution network planning, operation, and energy resource management problems domains in a SG context with high penetration of distributed renewable energy sources. This gap brings out the need for the development of:

- New models that consider the impact of the variability of the renewable energy sources and demand in the long-term expansion planning problem of distribution networks in a smart grid context;
- New models for a large-scale energy resource management problem of aggregators in a smart grid, considering the variability of demand, renewable energy sources, electric vehicles, and market price;
- Studies to investigate if the dynamic EV charging prices can have a positive impact on the DN operation in a SG context and the EV user behavior.

Additionally, in the absence, or few distributed generators (DG) units penetration in the traditional radial distribution network, innovative multi-objective models to improve the reliability through the identification of new investments in the network components should also be developed. The minimization of the costs of those investments, the NSP costs, the power loss costs, and the costs of the optimal capacitor location and size should also be considered in the models.

The significant breakthroughs that are necessary for those domains establish the main research question of this Ph.D. thesis:

How to deal with the unpredictability of renewable energy sources and electric vehicles adequately in the planning and operation of medium voltage distribution networks in a smart grid context?

To answer this complex question, there is a need to divide the problem into smaller and focused research topics. Therefore, the following specific research questions arise:

- *How can a traditional radial distribution network be improved by new investments actions identification?*

- *How can the variability of renewable energy sources and power demand be adequately considered in a long-term distribution network planning in an SG context?*
  - *Can a stochastic optimization methodology be advantageous for long-term planning?*
  - *How can the seasonal and daily periods affect the long-term distribution network planning?*
- *Can the power generation curtailment be mitigated, and the reliability be improved by optimal ESS size and location as well as the optimal type and location of new lines or the replacement of the existent ones?*
- *How can uncertainty from EVs, market price, solar and wind power generation, be handled by the ERM problems?*
  - *How can the problem be solved with several sources of uncertainty in an integrated model and with network validation?*
  - *Can such large-scale problem be effectively and efficiently solved?*
- *Can dynamic EV charging price, have a positive impact on both, the operation of the distribution networks in a smart grid context and on EV user behavior?*
  - *Can the EV user behavior modeling facilitate the integration of EV charging in the distribution networks?*
  - *How can an operation and reconfiguration model deal efficiently and effectively with high DER and EVs penetration in the distribution networks?*

The research work carried out in the scope of this thesis focuses on achieving answers to these aforementioned specific questions using exact mathematical methods.

The conception, development, and implementation of decision support methodologies shall be directed to different approach problems, e.g., traditional radial distribution network planning, long-term distribution network planning in a SG context, ERM problems and a distribution network operation and reconfiguration in a SG context considering the EVs user behavior. The diversity of methodologies shall be integrated into a decision support system (DSS). Thus, the main expected output of this work is a DSS that incorporates capable models/methodologies to deal with the traditional radial distribution network planning, sources of uncertainty in a long-term distribution network planning and ERM problems in a SG context. Additional, this DSS also integrates a distribution network operation and reconfiguration model in a SG context and an EV user behavior simulator.

For the traditional radial distribution network planning, the model should consider the reduction in the repair times and failure rates of the distribution networks components, while minimizing the costs of those reductions and the NSP costs, losses cost, and optimal capacitor location and size cost. The model should also seek for the reliability indexes improvement, deal with the outage parameters fuzziness. Moreover, a multi-objective (to take the decision in the presence of trade-offs between conflicting objectives - minimizing costs and network improvement) AC optimization model based on mixed-integer non-linear programming (MINLP) should be used.

The long-term distribution network planning in a SG context with high RES penetration must consider a stochastic model to deal with the challenging problem of the uncertainty sources associated with the renewable generation and demand. Additionally, it should also present the optimal ESS size and location as well as the optimal type and location of new lines or the replacement of the existent ones per other types under the previous conditions. At the same time, the reliability improvement and the network radial topology should be sought.

The ERM should consider in the same model a two-stage stochastic model for a large-scale energy resource scheduling problem of aggregators and the variability of demand, renewable energy, electric vehicles, and market price variations while minimizing the total operation cost in a smart grid.

To consider the behavior aspects of the EV users and the dynamic EV charging price, an EV user behavior simulator simulates the stochastic EV user aspects, the importance of EV charging price, the importance of comfort, the slow or fast charge mode choice, and the user sensibility for the state of the battery. The simulator should also work together with a distribution network operation and reconfiguration (SG context) optimization model.

Taking into account the referred specifications, which guarantee the response to the identified research questions, the following objectives are considered, underlying the essential contributions:

1. ***Development of a methodology to deal with the expansion planning in radial distribution networks.*** To fulfill this objective, the Ph.D. work proposes:

    (a) A multi-objective AC optimization model based on mixed-integer non-linear programming considering the Pareto front technique (weighted method);

    (b) The reduction achievement in the repair times and failure rates of the distribution networks components, while minimizing the costs of those reductions and the NSP costs, losses cost, and optimal capacitor location and size cost;

    (c) A fuzzy set approach for outage parameters estimation;

    (d) Reliability indexes improvement.

2. ***Development of a two-stage stochastic model for a distribution network long-term planning in a SG context.*** For the fulfillment of this objective, the thesis proposes:

    (a) A two-stage stochastic model to deal with several sources of uncertainty associated with the renewable generation and demand;

   (b) The expansion planning associated with new lines construction for reliability indexes improvement and at the same time ensure the radial topology of the network.

3. ***Development of a stochastic model to deal with the seasonal (spring, summer, fall, and winter) and daily periods (night, morning, peak and afternoon) impact effect in the distribution networks in a smart grid context.*** To accomplish this objective, the Ph.D. work proposes:

   (a) A stochastic model to deal with seasonal and daily periods impact effect in the long-term distribution network planning;
   (b) The optimal ESS size and location as well as the optimal type and location of new lines or the replacement of the existent ones;
   (c) The reliability improvement and the optimal radial topology.

4. ***Development of a two-stage stochastic model for a large-scale energy resource management problem.*** The fulfillment of this objective is obtained by proposing:

   (a) A two-stage stochastic model to deal with the variability of demand, renewable energy, electric vehicles, and market price while minimizing the total operation cost;
   (b) The Benders decomposition approach to improving the tractability of the original model and its computational burden.

5. ***Investigate if the dynamic EV charging prices have a positive impact on the DN operation in a SG context as well as in the EV users behavior.*** To fulfill this objective, the Ph.D. thesis proposes:

   (a) The adoption of an EV user behavior simulator that can generate a realistic population, considering the network size, and EVs parking lots buildings;
   (b) A distribution network operation and reconfiguration optimization model in a SG context with high DER penetration considering the behavior aspects of the EVs users and the dynamic EV charging price considering DLMPs using the Benders decomposition method;
   (c) Understanding how and how much the dynamic EV charging prices can contribute to a positive impact in the DN operation in a SG context and the EVs users.

In general, this thesis develops crucial and innovative strategies, methods, and tools to deal with such complex decision-making processes in the MV level, namely:

- Reliability improvement cost minimization for traditional radial distribution networks without or with few DG units penetration through the identification of new investments in the network components, while minimizing the costs of those investments, minimizing the NSP cost, the power losses cost, and the cost of the optimal capacitor location and size;
- Minimizing all expenditures related to the long-term expansion planning of distribution networks in a SG context with high penetration of distributed renewable energy sources and considering their stochastic behavior;
- Minimizing the total operation cost of a large-scale energy resource management problem of aggregators in a SG, considering the challenges brought by the variability of demand, renewable energy, electric vehicles, and market price variations;
- Distribution system operator expenditure minimization in a SG context, addressing the distribution network operation and reconfiguration, high penetration of DER, EV user behavior, and dynamic EV charging price through DLMPs.

1.3 Main Contributions and Related Projects

The findings that have been achieved during the development of this work have resulted in the publication of a total of eighteen scientific papers. From these, nine have been presented and published in the proceedings of top-level conferences in the fields of power systems and computer science; two book chapters have been published in books dedicated to the related areas; and seven journal papers have been published in JCR[1] indexed journals with high impact factors. Six of these seven journal papers and one of book chapter compose the core of this thesis by covering the proposed objectives and providing the response to the research questions. The core publications are provided in Appendix A - Core Publications, and their essential contributions towards the fulfillment of this thesis' objectives are presented in chapter 3. The core publications of this Ph.D. work are the following:

I. Bruno Canizes, João Soares, Zita Vale, Cristina Lobo, "Multi-criteria optimisation approach to increase the delivered power in radial distribution networks", IET Generation, Transmission & Distribution. 9 (2015) 2565–2574. doi:10.1049/iet-gtd.2014.1196 (**2015 Impact Factor is 1.576**);

II. Bruno Canizes, João Soares, Zita Vale, Cristina Lobo, "Optimal Approach for Reliability Assessment in Radial Distribution Networks", IEEE Systems Journal. 11 (2017) 1846–1856. doi:10.1109/JSYST.2015.2427454 (**2017 Impact Factor is 4.337**);

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

III. João Soares, Bruno Canizes, Mohammad Ali Fotouhi Ghazvini, Zita Vale, Ganesh Kumar Venayagamoorthy, "Two-Stage Stochastic Model Using Benders' Decomposition for Large-Scale Energy Resource Management in Smart Grids", IEEE Transactions on Industry Applications. 53 (2017) 5905–5914. doi:10.1109/TIA.2017.2723339 (**2017 Impact Factor is 2.743**);

IV. Bruno Canizes, João Soares, Mohammad Ali Fotouhi Ghazvini, Cátia Silva, Zita Vale, Juan M. Corchado, "Long-term smart grid planning under uncertainty considering reliability indexes", in: Operation, Planning, and Analysis of Energy Storage Systems in Smart Energy Hubs, 2018, Springer. doi:10.1007/978-3-319-75097-2_13;

V. Bruno Canizes, João Soares, Fernando Lezama, Cátia Silva, Zita Vale, Juan M. Corchado, "Optimal expansion planning considering storage investment and seasonal effect of demand and renewable generation", Renewable Energy. 138 (2019) 937–954. doi:10.1016/j.renene.2019.02.006 (**2018 Impact Factor is 5.439**);

VI. Bruno Canizes, João Soares, Zita Vale, Juan M. Corchado, "Optimal Distribution Grid Operation Using DLMP-based Pricing for Electric Vehicle Charging Infrastructure in a Smart City", Energies. 686 (2019) 12(4). doi:10.3390/en12040686 (**2018 Impact Factor is 2.707**);

VII. Bruno Canizes, João Soares, Angelo Costa, Tiago Pinto, Fernando Lezama, Paulo Novais, Zita Vale, "Electric Vehicles User Charging Behaviour Simulator for a Smart City", Energies. 1470 (2019) 12(8). doi:10.3390/en12081470 (**2018 Impact Factor is 2.707**).

The combination of the contributions provided by the work developed in the scope of this Ph.D. forms a DSS - *Advanced Decision Support Tool for Smart Grid Planning and Operation (SupporGrid)* - that deals with the traditional radial distribution networks planning and with the planning, operation, and ERM of DN in SG context. *SupporGrid* integrates several modules that have been developed to answer the identified issues and to fulfill the mentioned objectives.

Figure 1.1 shows the global framework of *SupporGrid* decision support system, including the representation of its main components. Below this figure, the diagrams of each main component and a summarized explanation are depicted.

The *SupporGrid* works as the central entity of all entire DSS, which facilitate the selection of each module (*PlanTGrid*, *PlanSGrid*, *OperGrid* and *ERMGrid*).

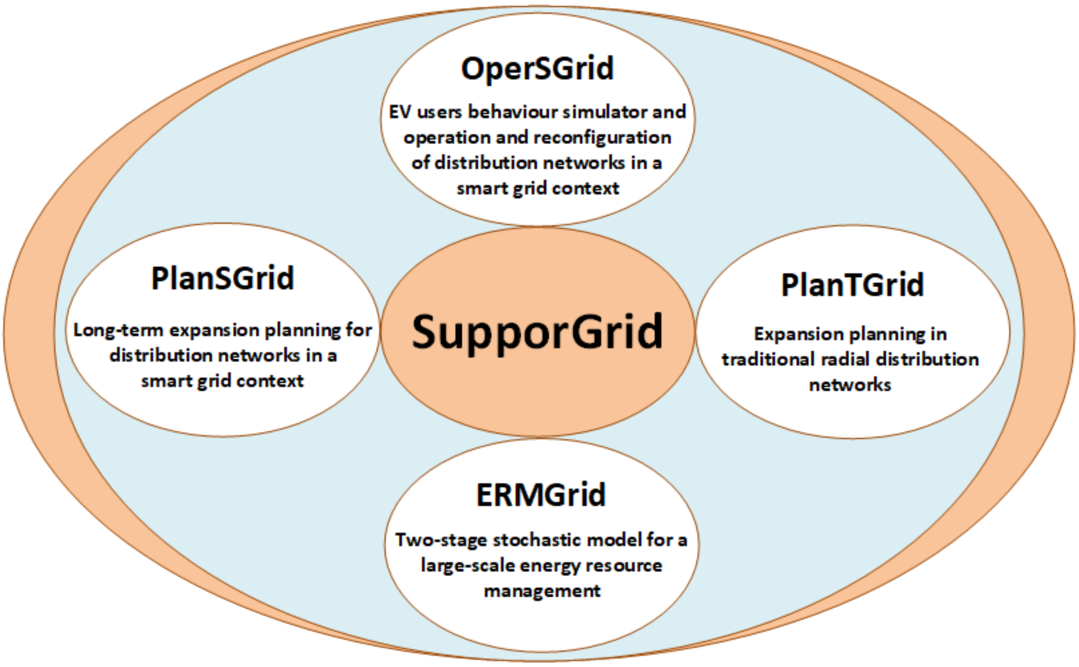

FIGURE 1.1: Overview of *SupporGrid* decision support system.

1. ***PlanTGrid*** - *Expansion planning in traditional radial distribution networks* (Figure 1.2):

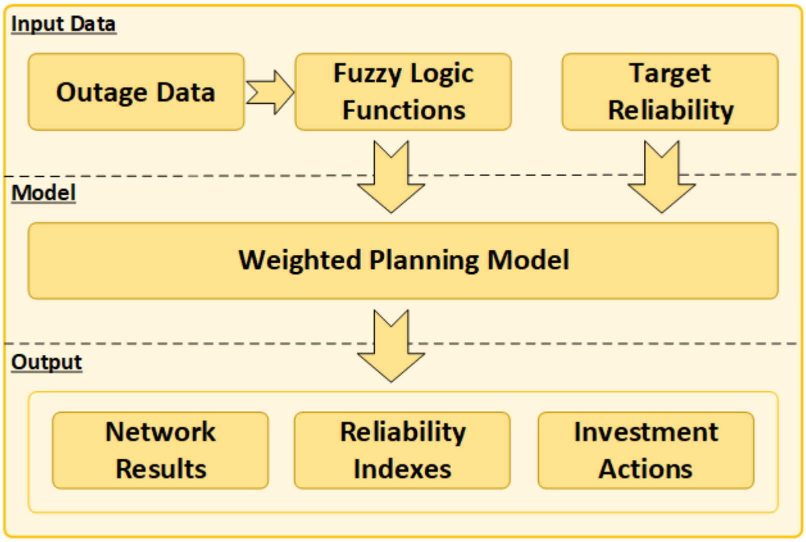

FIGURE 1.2: *PlanTGrid* diagram.

The *PlanTGrid* executes the expansion planning model for traditional radial distribution networks, which identifies the possibility of new investments to improve the average repair time (r) by minimizing the costs of that improvement as well as NSP costs. A full optimization model based on mixed-integer non-linear programming (MINLP) considering the Pareto front technique [56] is used (check core publication *I* and section 3.2). The *PlanTGrid* also evaluates the reliability in this kind of networks through the identification of new investments, not only to reduce the repair time but also to reduce the average failure rate (λ). So, a reduction of the forced outage rate (FOR) is obtained and, consequently, an increase of reliability (check core publication *II* and 3.2).

2. ***PlanSGrid*** - *Long-term expansion planning for distribution networks in a smart grid context* (Figure 1.3):

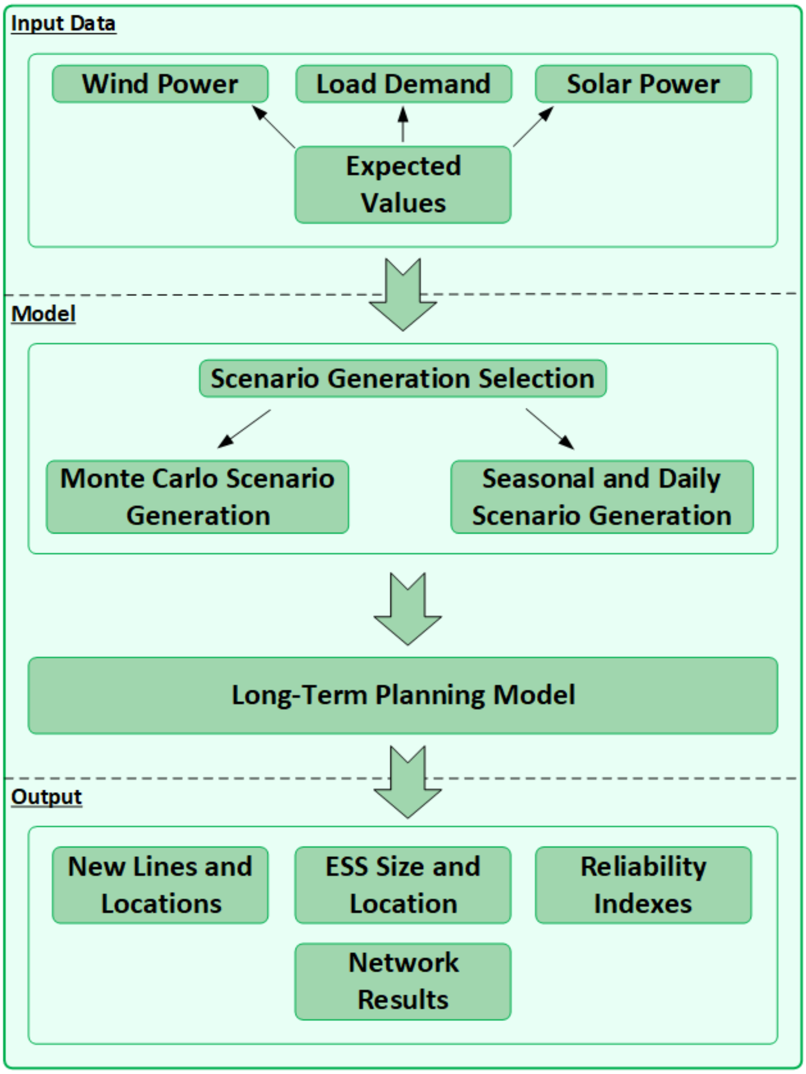

FIGURE 1.3: *PlanSGrid* diagram.

The module *PlanSGrid* can deal with the long-term expansion planning of distribution networks in a smart grid context with high penetration of distributed renewable energy sources. For this, a two-stage stochastic model is present to deal with the uncertainty sources associated with the renewable generation and demand to propose new lines construction investment. In this module, it is also considered the district heating possibility (see core publication *IV* and subsection 3.3.1). Besides that, *PlanSGrid* can also consider the seasonal and daily periods impact effect in the long-term distribution network planning, optimal ESS size and location as well as the optimal type and location of new lines or the replacement of the existent ones as well as the reliability improvement (see core publication *V* and subsection 3.3.2).

3. ***OperSGrid*** - *EV users behaviour simulator and operation and reconfiguration of distribution networks in a smart grid context* (Figure 1.4):

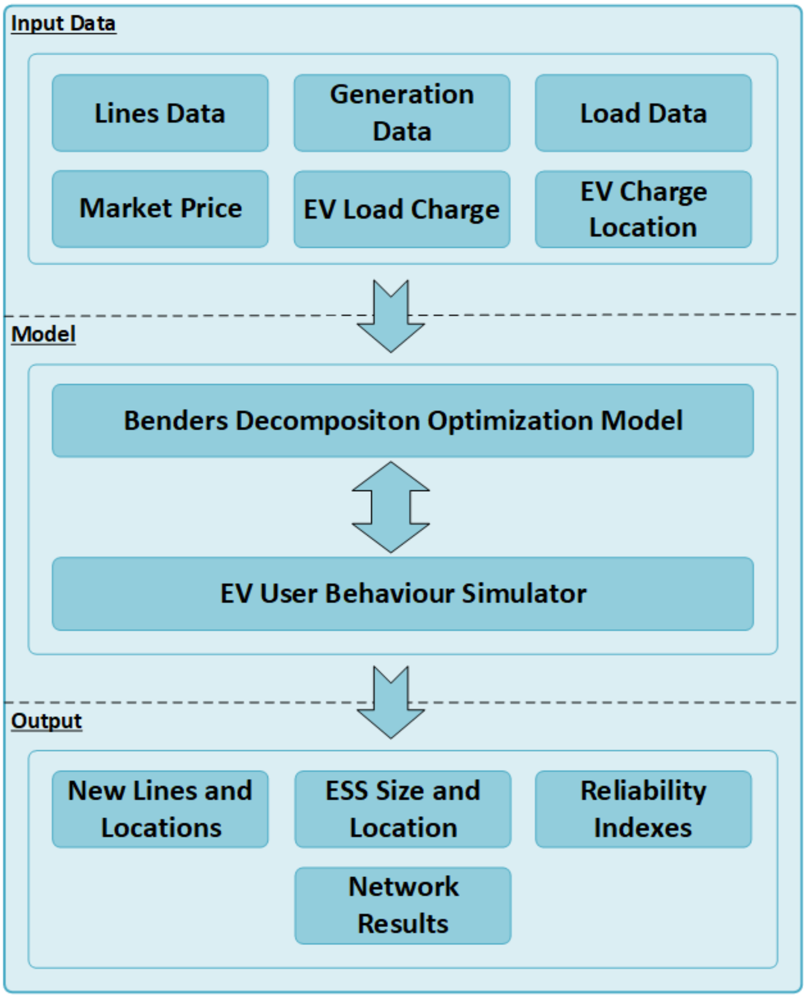

FIGURE 1.4: *OperSGrid* diagram.

The *OperSGrid* module contains a travel simulation tool for simulating real environments taking into account the behavior of realistic users (see core publication *VII* and section 3.4) which operates in conjunction with an innovative smart distribution locational marginal pricing based on operation and reconfiguration using Benders decomposition technique, for the purpose of understanding the impact of the dynamic energy pricing on both sides: the distribution network in a SG context and the EV user (see core publication *VI* and section 3.4).

4. ***ERMGrid*** - *Two-stage stochastic model for a large-scale energy resource management* (Figure 1.5):

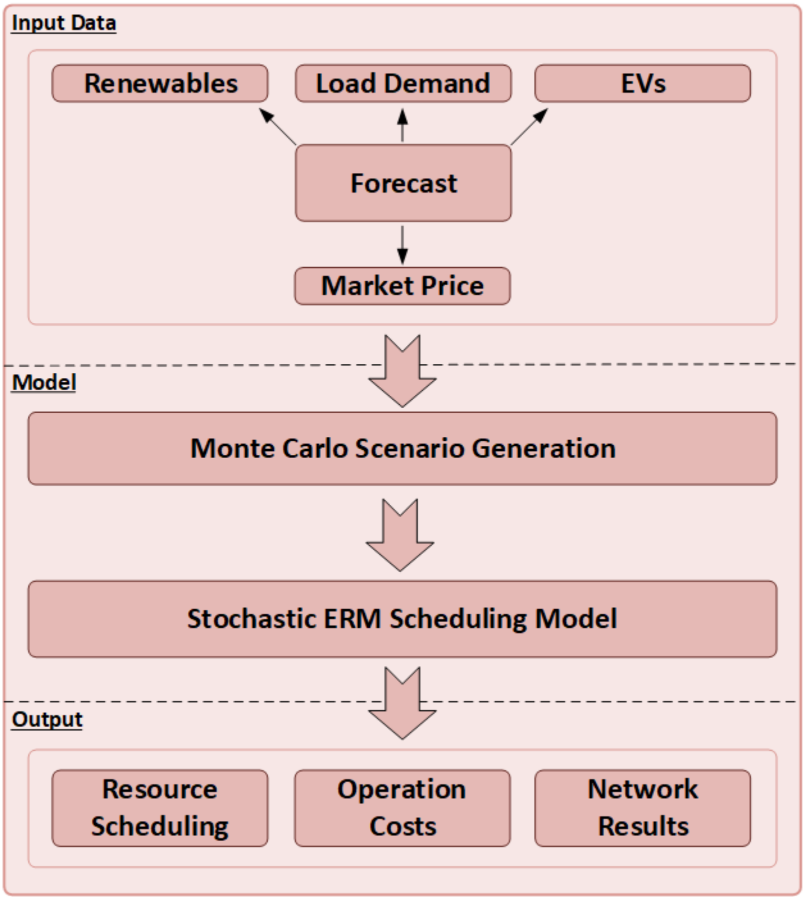

FIGURE 1.5: *ERMGrid* diagram.

A two-stage stochastic model for large-scale energy resource management considering the variability of demand, renewable energy, electric vehicles, and market price, using Benders decomposition is included in the *ERMGrid* module. Also, the two-stage stochastic model includes one DR program through direct load control and energy storage systems (check core publication *III* and section 3.5).

It is important to remark that the definition of the objectives of this work has benefited from the interaction with national and international R&D projects coordinated by or having the participation of the Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD), where this thesis has been developed. The breakthrough nature of these projects has enabled this thesis to consider innovative perspectives that have helped to enrich this work. The considered projects are:

- **DREAM-GO** – Enabling demand response for short and real-time efficient and market based smart grid operation – An intelligent and real-time simulation approach. European Union's Horizon 2020 research

and innovation programme under the Marie Sklodowska-Curie grant agreement number 641794;

- **CENERGETIC** – Coordinated energy resource management under uncertainty considering electric vehicles and demand flexibility in distribution networks, reference PTDC/EEI-EEE/29893/2017;
- **COLORS** - Contextual load flexibility remuneration strategies, reference PTDC/EEI-EEE/28967/2017;
- **DOMINOES** - Smart distribution grid: a market driven approach for the next generation of advanced operation models and services under H2020 grant agreement number. 771066;
- **GREEDi** - Plataforma Inteligente e Segura para Gestão de Recursos Energéticos em Edifícios de Grande Dimensão, reference P2020-33/SI/2015-17822

1.4 Optimization Methods, Solvers, and Computational Resources

The mathematical models developed in this Ph.D. research work are based on well-established methods, namely, MINLP, mixed-integer linear programming (MILP), multi-objective optimization, two-stage stochastic programming, and Benders decomposition technique.

The proposed optimization models were developed and implemented in GAMS[2] using CPLEX[3] and CONOPT[4] solvers, namely for the *PlanTGrid* module. For *PlanSGrid*, *OperSGrid* and *ERMGrid* MATLAB[5] and TOMLAB[6] with CPLEX and SNOP[7] solvers were used. It is worth to refer that the mentioned solvers were used with their default parameters. For the EV user behavior simulator the *R* language [57] using *RStudio* integrated development environment [58] was used.

A computer with one processor Intel Xeon E3-1225 3.20 GHz with four cores, 4 GB of random access memory (RAM), and Windows 8 Professional 64-bit operating system was used namely for core publications *I* and *II*. For the remaining core publication a computer with one Intel Xeon E5-2620 v2 processor and 16 GB of RAM running Windows 10 Pro was used.

[2] www.gams.com
[3] www.ibm.com/analytics/cplex-optimizer
[4] www.conopt.com
[5] www.mathworks.com
[6] tomopt.com/tomlab/
[7] web.stanford.edu/group/SOL/snopt.htm

1.5 Document Outline

This Ph.D. thesis' document consists of four chapters. After this introductory chapter, chapter 2 presents a background overview of the most important topics related to this Ph.D. research work, namely focusing on the planning of traditional radial distribution networks, on long-term expansion planning, operation, and reconfiguration of the distribution network in a SG context.

Chapter 3 presents the most relevant contributions of this Ph.D. research work. It also includes a description of the research questions of this Ph.D., and a discussion on how each core publication addresses those questions and how they fulfill the defined objectives. Each subsection deals with the specific research topic that is related to a particular research question.

Finally, chapter 4 presents the most relevant conclusions that have resulted from the developed research work, the main contributions, and some of the perspectives of future work.

Chapter 2

Background

This chapter presents a brief overview of the current state of the art of the traditional radial distribution network planning, and of the planning, operation, and ERM in the DN in SG context. Presenting the background overview as a whole allows reaching important conclusions on the current limitations in the field and on expected future challenges. This overview, results in the identification of the critical research topics that are addressed in this Ph.D. research work.

2.1 Introduction

The EU commission fixed two new targets for the EU for 2030: a binding renewable energy target of at least 32% and an energy efficiency target of at least 32.5% - with a possible upward revision in 2023 [11], [59]. Besides that, it confirms the 2030 interconnection target of 15%, following on from the 10% target for 2020. Thus, when these policies are fully implemented, they will lead to steeper emission reductions for the whole EU than anticipated – some 45% by 2030 relative to 1990 (compared to the current target of a 40% reduction) [11], [59]. As a consequence of these policies and of the subsequent incentives that have been put in place, huge investments have been made in renewable-based electricity generation plants and equipment in parallel with several SG initiatives to support this paradigm shift. In Europe, a total of 950 SG projects have been funded, totaling around €5 billion of investment [60]. It is currently expected that mass penetration of EVs will occur and bring more complexity to the operation and planning tasks, but also allow unique opportunities. SG enable safe integration and aggregation of more DER, namely, DG, ESS, EVs, and DR, while delivering comprehensive control, monitoring and self-healing capabilities, tailored to consumers' needs and enabling more control over consumption and electricity usage [60], [61].

Renewable generation can bring benefits to the environment by providing clean ways of getting carbon-neutral energy. However, increased renewable-based generation capacity does not directly ensure a corresponding increase in renewable-based energy use as several constraints limit not only the production but also its use. Wind and solar-based generation are dependent on natural sources and are not as dispatchable as fuel based thermal plants. Power systems, namely at medium voltage (MV) distribution level, face new challenges to deal with the integration of intermittent renewable sources [1], since the DNs have not been upgraded considerably for a long time. Besides that, the competitive electricity market and service requirements close to the technical limits of the grids have resulted in over-stressed DN operation situations [62]. The solution to overcome these issues can be the modernization of the DNs planning and reinforcement and operation strategies.

2.2 Traditional Radial Distribution Network Planning

Over the past few decades, lots of efforts have been devoted to the DN reliability assessment. Reliability is the ability to deliver electricity to all delivery points within acceptable levels of quality, in the desired amount and at the minimum cost. Obviously, these are conflicting goals, because increasing the quality and quantity of the energy provided to customers will necessarily increase the investment cost in networks [63]. Thus, network planners and operators must find adequate balance.

The importance given to the reliability problems in DN in the past was less when compared with generation and transmission. Nowadays, a large number of research works concerning the reliable and economic operation of DN are being developed [64]–[66]. Several methodologies based on analytic and simulation processes have been developed for the reliability evaluation in DN [67]–[69]. An application of genetic algorithms for reliability assessment of a distribution system is presented in [70]. The objective function considers the investment cost and the system interruption cost. The system failure rate and the average outage duration at the load point are considered as constraints. Reference [71] proposes a value-based probabilistic approach to design urban distribution systems. The proposed approach can be used to determine the optimal section length for the main feeder and the number and placement of feeder ties. In [72], a three-stage method for planning a power distribution system is proposed; the substation optimization, the number of feeders with their active route, and the node reliability optimization are included. Chang and Wu presented in [73] a technique for optimal reliability assessment of electrical distribution systems. The method is based on a polynomial-time algorithm to solve the nonlinear optimization problem. Reference [74] presents a set of composite models for distribution system reliability evaluation that can be applied to non-radial networks. In [68], comparative case studies for value-based distribution system reliability planning are made. Reference [75] presents an algorithm for the determination of the optimal interval for major maintenance actions in electrical distribution networks. Chandramohan et al. [76] proposed the minimization of radial distribution system operating cost in the regulated electricity market via reconfiguration. Arya et al. [77] proposed a methodology for reliability enhancement of radial distribution systems by determining optimal values of repair times and failure rates of each section. Reference [78] presents an analytical methodology for reliability evaluation and enhancement of distribution system having DG. When compared with [77], the main novelty is the consideration of DG. Both references present a comparison between the differential evolution, the particle swarm optimization, and the coordinated-aggregation-based particle swarm optimization approaches. Ferreira and Bretas used in [79] a nonlinear binary programming model for distribution systems reliability optimization. In addition, in this work, reliability indexes, namely the system average interruption duration index (SAIDI) and the system average interruption frequency index (SAIFI), are optimized. Canizes et al. [80] proposed a methodology that aims to increase the probability of delivering power to any load point of distribution networks by identifying new investments in distribution components to improve the failure rate and the repair time without considering the network technical constraints. This methodology uses a fuzzy set approach [81] to estimate the outage parameters, and the investments aim to reduce the components failure rates and the repair times. Unlike [77] and [78], [80] uses actions to improve the failure rate and the repair time, i.e., considering a discrete optimization. Taking into account the increasing penetration of DG and the importance of reliability of supply, [82] presented a method for DG optimum location to maximize reliability.

Although several works have been conducted on the topic of planning and reliability assessment of traditional distribution networks, there are still interesting gaps to be explored, e.g., the reliability assessment considering investments actions to reduce the repair time and the failure rate of the distribution network components, and all technical network constraints. In addition, it is well known that the major portion of power losses occurs at the distribution level [83], and the pressure of improving the efficiency of power delivery has forced the power utilities to take measures, mainly at the distribution level. So, the possibility of optimal capacitor banks location and size to supply part of the reactive power load, reducing, this way, the power loss should be considered.

2.3 Distribution Network Planning in a Smart Grid Context

The inclusion of DG units, demand variability, resources uncertainty, optimal topology or reconfiguration, and reliability issues among others make the distribution network planning further complicated. The distribution networks in a SG context will be compatible with intelligent technologies to accommodate several types of DG units and the associated components, for instance, RES units, ESS, EVs, and DR. Moreover, major power industry stakeholders are recognizing the need to address challenging issues and replan the DN according to the SG paradigm [20], [84].

Several works related to the planning of distribution network with DG penetration have been published in specialized literature. Hengsritawat et al. [5] proposed a probabilistic approach to design the PV optimal size to be used in distribution networks and the location of the PV by using a steady-state voltage stability index while minimizing the average system power loses. [6]

proposed a long-term distribution network planning under urbanity uncertainties to eliminate the harmful effects. In the end, the network is designed through the branch exchange method, which considers the embranchment points as representative to load points. Reference [7] presented a new state reduction algorithm for DG planning problems and reliability analysis by determining the minimum number of states required to represent the wind speed and solar irradiance behavior. Hemmati et al. proposed in [8] a multistage electricity generation expansion planning to minimize the planning cost and environmental pollution incorporating large-scale energy storage systems using a particle swarm optimization (PSO) algorithm. [9] proposed a long-term dynamic multi-objective planning model for distribution network expansion where two objectives are minimized, i.e., costs and emissions. The model can also determine the optimal sizing and placement of DG units and network reinforcements over the planning period. To deal with this problem, a two-stage heuristic method is used. [85] proposed a probabilistic expansion technique to minimize the new lines construction cost. A method that combines optimization and probabilistic analysis to maximize the number of wind turbines subject to the voltage stability limits, thermal limits, voltage limits, load tap changing and generator power output limits are proposed in [86]. A distribution network multiyear expansion planning is proposed in [87]. The model includes the primary feeders reinforcement as well as the location and size of DG. A binary chaotic shark smell optimization is used to solve the problem. Asensio et al. [88] proposed a bi-level model under a demand response framework for a distribution network and renewable energy expansion planning. Two problem levels are considered, an upper-level to minimize the generation and network investment cost while meeting the demand and a lower level to reduce the overall payment faced by the consumers. The problem is a MILP using the Karush Kuhn Tucker complementary constraints and is solved by branch-and-cut solvers. [89] presented a stochastic two-stage multiperiod MILP model for the optimal allocation and timing of renewable DG under uncertainty. The goal is to minimize renewable DG investment costs, substation expansion investment cost, operation and maintenance costs, power losses cost, and the costs of the power purchased from the transmission system. [90]–[92] proposed models for joint DN expansion and DG planning using a multistage stochastic linear programming. Mokryani et al. [93] presented an approach for DN planning within a distribution market environment considering multi-configuration of wind turbines and PV. A multi-configuration and multi-period market-based optimal power flow are used to maximize the social welfare considering the uncertainties associated with wind speed, solar irradiance, and load demand.

Additionally, reference [94] presented a technical literature review on optimization techniques for planning in microgrids. This review work gives some directions for innovative planning methodologies, based mainly on economic feasibility. Moreover, a few trending methods for microgrid planning are pointed out. A review of research work carried out in planning, configuration, modeling, and optimization techniques of hybrid RES for isolated / off-grid applications are shown in reference [95]. Several mathematical models developed based on objective functions, reliability, and economics studies involving design parameters are presented in this review work.

The reviewed literature indicates that there is a considerable number of works in the DN planning in a SG context. However, there is a need to consider new planning strategies from the viewpoint of DN in a SG context.

In the real world, DN planning can be considered a multi-objective, constrained, and usually a stochastic based optimization problem [94]. Moreover, the expected compromise or trade-off solutions which address conflicting objectives to satisfy multiple stakeholders makes the multi-objective planning a suitable choice for DN in a SG context [96].

Typically, planning problems focus on finding a cost-effective solution. However, objectives like reliability, power quality, environmental impact, system stability, energy efficiency, and customer satisfaction can also be considered.

It can be concluded that the traditional planning methods may not be applicable to the planning of the current DN into distribution network in a SG context [97], [98]. Furthermore, few literature references from the planning perspective of future distribution mechanisms are available. Also, for a modern DN planning, several key futures should be present, such as key enabling smart technologies, multi-objective problems as real-world planning problems, high penetration of RES and their stochastic behavior, etc.

2.4 Distribution Network Operation and Reconfiguration in a Smart Grid Context

Passive power distribution networks are being transformed into active distribution networks, the so-called SG. The main reason for this transformation is especially the need to accommodate a high number of DGs, mainly the RES. DN optimal operation in a SG context plays an essential role in delivering power in desirable quantities to the consumers, for the RES integration and economic energy management. DN operation can be divided in: *(i)* real-time operation, when actions and commands occur in short time periods and are based for instance on communication signals; *(ii)* scheduled operation, one day (or more days) ahead schedule planned based on RES power generation and demand forecast. Furthermore, the DSO is responsible for the distribution networks optimal operation in a SG context through the application of proper active network management (ANM) schemes to satisfy network constraints. The review paper of Evangelopoulos et al. [99] presents a review of the most significant papers in the area of distribution networks optimal operation in a SG context and introduces the taxonomy of models, optimization methods and ANM schemes that are applied to this kind of problems.

SCs feature an active power architecture with a high penetration of DER challenging the conventional control and operation framework designed for passive distribution networks. In this context, the loads can be supplied not only by traditional generation units at the upstream power systems but also by the DER [100]. Thus, DNR will be a crucial and significant strategy for DSO. DNR is a process that changes the network topology using the remote switches such that all the network constraints are considered. Traditionally, the DNR is associated with system power loss minimization [51], [52], however in the SG context the DNR must not only meet the classic objectives, such as power loss, minimization of power not supplied, improvement of voltage profile but also the problems related to the high DER integration and the intelligent reconfiguration related to the SG paradigm [53]–[55]. Several works considering mathematical [101]–[103], heuristics and metaheuristics [104], [105], and hybrid models [106], [107] were developed to deal with DNR and DER penetration.

Additionally, with the population increasing in urban areas, it is necessary to make intelligent use of resources in urban environments, contributing to the development of smart cities [41]. The energy infrastructure of a SC is the distribution networks in a smart grid context and is one of the essential urban infrastructures that allows creating a sustainable city [108]. To this end, it is known that the grid functionalities should be modernized. It is also known that one of the primary sources of CO_2 emissions is transportation [43]. Several authors have been analyzing the benefit of changing from traditional transportation (internal combustion engines) to EVs, in minimizing the transport sector's greenhouse gas emissions.

Consequently, high EV penetration level may congest the distribution network. The DSO can manage the congestion issues through system reinforcement (long-term planning) or market-based congestion control methods [109]. The transmission systems concept of LMP can be extended to distribution systems [49] and referred to as DLMP.

The congestion problems caused by the increasing number of EVs led several authors analyzing and proposing solutions to mitigate this issue. [110] proposed step-wise congestion management whereby the DSO predicts congestion for the next day and publishes day-ahead tariff before the clearing of the day-ahead market, while [111] solved the social welfare optimization of the distribution system considering EV aggregators as price takers in the local DSO market and demand price elasticity. Liu et al. presented in [112] a market-based mechanism taken from the DLMP concept to alleviate possible distribution system congestion caused by the integration of EVs and heat pumps. Similarly, the authors in [113] proposed a DLMP based on quadratic programming to deal with the congestion in distribution networks with high penetration of EVs and heat pumps.

As it is known, the EVs are additional electric loads and represent mobile energy storage, usually with long resting times. Several mathematical models presented in [114]–[119] also studied the impact of EV charging in the distribution networks. References [120]–[125] assessed several possibilities for demand-side management as well as better coordination of charging processes through price incentives that mitigate the impact of EV charging during peak-loads. [126]–[130] proposed an increase in EV charging flexibility, contributing to increased utilization of the highly variable renewable energy. Moreover, one of the main challenges in facilitating integrated EV charging in the distribution network is EV user behavior modeling and prediction [50]. Gan et al. [131] have proposed optimal control for allocating EV charging time and energy optimally. However, the model requires that users frequently provide the charging schedule, requiring significant effort on the part of the customer. The algorithms developed in [132] use EV random user behavior model with renewable generation for EV scheduling while [133] provided a smart charging strategy according to time-of-use price from the day-ahead forecast. The authors in [134]–[137] examined EV users' charging behavior and measured psychological variables, an analysis that can help develop new charging strategies.

Towards the era of optimal operation of DN in a SG context, the key challenge is related to the conventional distribution systems upgrade and the further integration of emerging technologies (advanced metering infrastructure, information, and communication technologies, and distribution management systems). However, most of the utilities have not fully integrated smart systems and smart equipment [99]. To facilitate the flexible operation of DGs, ESS, RES, and EVs, the utilization of cutting-edge technologies and smart systems can be the correct way. Although significant research works have been conducted in DN optimal operation under a SG paradigm, there are still interesting areas for further investigation, such as addressing the DN operation, reconfiguration, high penetration of DER, EV user behavior, and dynamic EV charging price simultaneously.

2.5 Energy Resources Management

The future power systems will require to deal with an even higher number of DER under market conditions. But some issues emerge from this inevitability. Several DER units are not able to participate in the current electricity markets due to their small size; their variability nature (wind and solar units), where the contribution to the grid operation may result in economic penalties as a result of unexpected unbalances; and different ownerships restrains the cooperation and communication between neighboring units. To mitigate the issues associated with the DER units penetration, the aggregation of those units can be considered. Such aggregation enables the same visibility, controllability, and market functionality as conventional generation [138]. A virtual power player (VPP) can be an entity that aggregates several types of energy sources, namely DG units, and it is responsible for managing them using a set of advanced tools to raise their value and competitiveness. However, VPPs require complex optimization models, control, and secure communications to run properly [139].

To allow efficient and cost-effective operation, energy aggregators, i.e., the VPPs require proper ERM tools to deal with the increasing number of resources and its underlying uncertainty, e.g., EVs and renewables [140]. The day-ahead energy scheduling is an essential part of an ERM system to obtain the expected operation cost (or profit) while providing adequate decisions one day in advance. However, energy scheduling is quite challenging due to the inherent uncertainties and the high number of resources. Adopting advanced energy management models that consider uncertainty factors is critical for successful implementation of SGs. As been said in the previous chapter, the United States Department of Energy has identified predictive models to deal with stochastic behavior and uncertainty as a top R&D priority [37].

Usually, the day-ahead problem is a combinatorial problem of large-scale nature when many DERs are considered. Due to non-linearity features of the problem, it is usually classified as MINLP. MINLP techniques require significant computer resources. The computation time needed for solving these types of problems is not compatible with the time limitations of short-term energy scheduling [141]. To overcome the computational burden issue, some approaches have been proposed in previous research. The work developed in [142] adopts Benders' decomposition approach to solve a multi-objective model in day-ahead context. The authors were able to reduce the complexity of the original MINLP scheduling problem compared to a previous formulation proposed in [141]. However, it was found later in [143] that the slave problem formulated as an hourly distribution power flow in [142] leads to suboptimal solutions, due to temporal dependencies in DERs. Therefore, the work in [143] proposes a multiperiod model to obtain better results. Furthermore, the work in [142] seems limited in the sense that it does not consider DR, renewable generation such as wind or PV, and ESS, which are increasingly important in SGs. Although the proposed works have contributed to reducing the original problem complexity, uncertainty factors have not been considered in the mentioned works [141]–[143] and many others presented in the literature [144]–[149].

Energy scheduling models that incorporate stochasticity have been studied in the literature. In [150], a dispatch scheduling approach is proposed for a wind farm using ESSs. The results indicate that the ESS can be used to perform a joint production schedule and address the forecasting errors during the real-time operation. Stochastic energy management with compressed air storage integrated with renewable generation has demonstrated to be effective in [151]. The models developed in [152], [153] focus on aggregator's market strategies and the risks associated with their portfolio optimization problems. The authors suggest that the model may be decomposable and subject of future research [153]. In [154], a stochastic model is proposed to address the ERM in hybrid ac/dc micro-grids considering DERs and uncertainty in EV demand, renewable generation, and electricity price. However, DR is not considered in work above, and it only considers a small power system (38-bus) with eight DG units. The model is adequate for small hybrid ac/dc grids, whereas the proposed model in this paper is targeted to deal with larger grids. In [155], the authors present stochastic day-ahead scheduling to address carbon emission, generation fuel costs, and uncertainties in micro-grid operation. The work does not incorporate network constraints, and the experiments are based on a small three-generator system. The work presented in [156] tackles the ERM problem of a renewable-based virtual power plant. These models consider the uncertainty in electricity prices and renewable, but the consideration of resources such as DR, EVs, and vehicle-to-grid capacity have been overlooked. The use of energy resources (e.g., ESS) can mitigate system uncertainties as demonstrated in [140], [150], [151], [156], [157]. Nevertheless, these works do not consider EVs and related uncertainties, which are expected to grow considerably in the next decade. Other works consider the EV uncertainty [39], [154] but do not incorporate grid constraints. Moreover, the review paper of Nosratabadi et al. [158] presents the DER scheduling problem works from perspectives of formulation type, objective function, solution techniques, uncertainty, reliability, reactive power, control, automation, CO_2 emission, stability, demand response, and multi-objective optimization.

In summary, although some relevant and considerable research works in the ERM have been done, when the network constraints are included in the stochastic model, it is either decoupled or only suited for a small network system with few scheduling units. Thus, models that attempt to overcome this issue should be proposed.

2.6 Chapter Conclusions

This chapter has presented a brief overview of the most relevant background and related work for the support of this Ph.D. work. Considering a proper selection of references, the most critical gaps in the literature have been identified concerning the topics of traditional radial distribution networks planning, distribution network planning, operation and energy resource management with high DG and EVs penetration. Thus, it was concluded that the need for more in-depth research work is evident to enable the development of more realistic models and studies in the SG context.

The adequate decision supports tools are necessary to enable the involved players to take full benefit from the dynamic and complex environment. The energy sector is urging for the necessary key steps to facilitate the success of SG technologies deployment, which will enable increased efficiency and greater economy in the sector. Thus, the distribution network planning, operation, and ERM play a vital role in this deployment.

The limitations of the current DSS solutions proposed in the literature have been identified. The gaps identified can be summarized as follows:

- **Traditional Radial distribution network planning**
  - *Reliability improvement considering investments actions*: Reliability improvement through investments actions to reduce the repair time and the failure rate of the distribution network components is not well developed in the literature;

  - *Cost minimization*: The minimization of the investment cost actions, the NSP cost, power losses cost, and optimal capacitor location and size cost handled in the same model is neglected in the related works;
  - *All technical network constraints*: AC optimization model based on mixed-integer non-linear programming to deal with all the network constraints is weakly referred in the literature;
  - *Fuzziness issues*: The fuzzy approaches to deal with the fuzziness associated with repair time, failure rate, and unavailability indexes are weakly explored for distribution networks planning.

- **Distribution network planning in a smart grid context**

  - *Coordinated planning*: Works considering optimal location and sizing of ESS simultaneously considered with substations and feeders' expansion/upgrade are missing in the literature;
  - *Uncertainties*: Several parameters have uncertainty, e.g., future load growth, the power of plug-in electric vehicles, market prices, future capital costs, wind power generation, and solar power generation. A lack of appropriated models and methods, e.g., stochastic optimization, to handle with these uncertainties are verified in the literature;
  - *Cost of reliability*: Reliability issues are missing in the models of DN planning in smart grid context. The successful distribution SG models have to quantify and take into account the cost of reliability, i.e., including it also as objective (multi-objective problem);
  - *Distribution utility applications*: A lack of innovative and exact models for DN planning under the SG paradigm are verified in the literature. The majority of distribution utilities still use heuristic processes and empirical rules through expert judgment and practical analysis;
  - *New loads and storage*: Weak number of studies for new components integration, such as ESS, and EV in the context of distribution SG planning;
  - *Advanced optimization methods*: The network topology optimization problem (involves continuous and discrete variables) forms an active research area of optimization methods, and it is not deserving the necessary importance in the distribution SG planning literature.

- **Distribution network operation and reconfiguration in a smart grid context considering high EVs penetration**

  - *EV user behavior aspects*: Simulate the EV user behavior aspects, such as: stochastic EV user aspects, the importance of EV charging price, the importance of comfort, chose the slow or fast charge and the user sensibility for the state of the battery, is very limited in the literature;

  - *Increasing number of EVs*: The increasing number of EVs make it necessary to develop new infrastructure for EV charging continually and this, in turn, leads to growing energy demand and consequently, congestion of the distribution SG may occur. Congestion of the distribution SG due to EVs has been not well addressed in the literature;
  - *Distribution network reconfiguration*: Distribution network reconfiguration in SG context is not well developed and requires further studies not only to meet the classic objectives, such as power loss, minimization of power not supplied, improvement of voltage profile but also the problems related to the high DER integration and the intelligent reconfiguration associated with the SG paradigm;
  - *Impact of EV user behavior aspects*: EV user behavior aspects impact in the distribution SG are not well developed in the literature;
  - *Impact of dynamic EV charging prices*: The impact of dynamic EV charging prices in the DSO and EV user is not yet addressed in the literature to the best of my knowledge;
  - *Tractability of the problem*: These kinds of problems are classified as MINLP due to its non-linear features, which leads to significant computer resources requirements. Decomposition-based techniques can improve the tractability of the problem but are weakly presented in the literature.

- **Energy resource management**
  - *Important sources of uncertainties*: The most stochastic models proposed in the literature ignore important sources of uncertainties, such as the market price and EVs behavior while not incorporating demand response;
  - *Limited scalability*: The optimization techniques available to solve ERM problems have limited scalability;
  - *Network constraints*: When the grid is included in the stochastic models, it is either decoupled or only suited for a small network system with few scheduling units. Moreover, when EV uncertainty is considered the network constraints are not incorporated;
  - *Performance improvement*: Decomposition based techniques to improve ERM problems performance are not well developed in the literature.

The work developed in the scope of this Ph.D. thesis tackles some of the most relevant and crucial issues, which have been properly identified in the presented literature review. The contributions of this work focus on the development and proposal of innovative decision support methodologies that allow DSO to take better and adequate decisions. The limitations in the literature pointed out previously for each of the four areas (traditional radial distribution network planning, distribution network planning in a SG context, distribution network operation in a SG context considering high EVs penetration and energy resource management) are addressed in this thesis.

Traditional radial distribution network planning

The initial studies were made for traditional radial distribution networks. It was developed a multi-objective AC optimization model based on mixed-integer non-linear programming considering the Pareto front technique to achieve a reduction in the repair times and failure rates of the distribution network components while minimizing the costs of those reductions and the NSP costs, losses cost, and optimal capacitor location and size cost. Moreover, the improvement of reliability indexes, such as SAIDI, SAIFI, customer average interruption duration index (CAIDI), and NSP are ensured. Additionally, a fuzzy set approach is used for outage parameters estimation.

Distribution network planning in a smart grid context

For DN planning in a SG context, a two-stage stochastic model for long-term planning was developed and implemented to deal with several sources of uncertainty associated with the renewable generation and demand and, at the same time, propose new lines construction for reliability indexes improvement maintaining the radial topology of the network. Additionally, a stochastic model to deal with the seasonal (spring, summer, fall, and winter) and daily periods (night, morning, peak and afternoon) impact effect was also developed and implemented. Also, the goal to obtain the optimal ESS size and location, as well as the optimal type and location of new lines or the replacement of the existent ones, is sought out. Furthermore, the optimal radial topology and reliability improvement are also ensured.

Distribution network operation and reconfiguration in a smart grid context

In this context, a model for DN operation and reconfiguration was developed to consider high DER penetration concerning the behavior aspects of the EVs users, the dynamic EV charging price (by DLMPs) and the congestion issues created by EVs. The Benders' decomposition technique was used to deal with the issue of computational burden and at the same time, improve the tractability of the model and the scalability of the problem. As support, an EV user behavior simulator was created to generate a realistic population, considering the DN size, and EVs parking lot buildings. Thus, it is possible to understand how and how much the dynamic EV charging prices can contribute to a positive impact in the DN operation and the EVs users.

Energy resource management

Several limitations in ERM models are addressed in this thesis by considering a two-stage stochastic model for large-scale energy resource management considering network constraints. This model takes into account the variability of demand, renewable energy, electric vehicles, and market price while minimizing the total operation cost and ensuring the scalability and tractability of the problem using advanced decomposition method (Benders' decomposition technique).

In this Ph.D., all the proposed models are tested and validated in several realistic scenarios. In this way, it is possible to demonstrate that the models are suitable for their specific purposes, solving the identified gaps, but also allowing to explore other issues related with planning and operation of distribution networks in a SG context which would be otherwise difficult using previous research approaches. The efforts made during this Ph.D. work finally result in a joint contribution to the fields of power systems and electric mobility.

In this context, the next chapter introduces the main contribution of this work, addressing how each core publication answers the research questions and fulfill the objectives.

Chapter 3

Contributions

This chapter presents the main contributions of the developed work and discusses how each of the core publications of this Ph.D. thesis addresses the related research questions. The accomplishment of the objectives as a result of the several key contributions are also described.

3.1 Introduction

The solicitations on the DNs are becoming more complex due to the ever-increasing use of electricity, the impact of RES and DG, the evolution of electricity markets, among others. Thus, improving the DN performance, namely, reliability, is a challenging problem. Moreover, due to the SG context, the planning and operation of DN are also further complicated. Consequently, an adequate DSS in the fields of DN planning and operation, including the new smart grid paradigm, is essential to provide the DSO substantial monetary savings. Using such DSS solutions, the DSO can apply attractive investments, correct operation decisions and, if it is the case, apply helpful ERM actions, contributing for efficient and cost-effective actions as well as end costumers satisfaction. The current gap in the literature regarding this type of DSS including the planning and operation of distribution networks in SG context have led to the research questions presented in the introductory section and to the consequent definition of the objectives for this Ph.D. work.

The development of the *SupporGrid* DSS, as a result of this Ph.D. research work, provides the crucial breakthrough that is required to overcome several limitations in the fields. The achieved findings contribute to the advance in the current state of the art by providing answers to the research questions that have been identified as protuberant to enable such advance.

Table 3.1 presents the coverage of each publication to the key contributions of this thesis. The key contributions are also associated with related objectives. Core publications[1] *I* to *VII* [159]–[165] represent the core publication of this Ph.D. work, which have been introduced in section 1.3. The *Other* publications refer to additional papers that have also been published in the scope of this research and that present complementary cover studies.

As can be seen in Table 3.1, all key contributions are addressed by several core publications. Additionally, some other publications resulting from this Ph.D. research work help to complement the studies of a particular research

[1]The core publications articles can be found in Appendix A

TABLE 3.1: Contributions and core publications

Key contribution	**Related Objective and Section**	**Core Publications** *I*	*II*	*III*	*IV*	*V*	*VI*	*VII*	**Other**
New investments identification in traditional radial DN	1 (see section 3.2)	X	X						[166]
Optimal capacitor location and size	1 (see section 3.2)		X						[166]
New lines construction or reinforcement	1, 2 and 3 (see sections 3.2, 3.3.1, and 3.3.2)		X		X	X			
Reliability indexes improvement	1, 2 and 3 (see sections 3.2, 3.3.1, and 3.3.2)	X	X		X	X			
Two-stage stochastic for SG long-term planning	2 (see section 3.3.1)				X	X			
Uncertainty sources	2, 3 and 4 (see sections 3.3.1, 3.3.2, and 3.5)			X	X	X			
Optimal radial topology in SG	2, 3 and 5 (see sections 3.3.1, 3.3.2, and 3.4)				X	X	X		[166] [167]
Seasonal and daily periods impact effect on SG	3 (see section 3.3.2)					X			
Optimal ESS location and size	3 (see section 3.3.2)					X			
Two-stage stochastic for large-scale ERM	4 (see section 3.5)			X					[143] [168] [169] [170]
EV user behaviour simulator	5 (see section 3.4)						X	X	
Reconfiguration in SG	5 (see section 3.4)						X	X	[166]
DLMP for EV dynamic charging prices	5 (see section 3.4)						X	X	
Impact of EV dynamic charging prices in SG and EV users	5 (see section 3.4)						X	X	

topic. Each key contribution is related to the answer of one research question and the complete or partial fulfillment of one or more objectives of the Ph.D. work. This chapter describes each research question, its relevance to the work done and briefs on how it has been answered by the papers produced as part of this Ph.D. work.

3.2 Expansion Planning Model in a Traditional Radial Distribution Network

Through the core publications *I* and *II*, this section answers the following research question and accomplishes the first objective of this Ph.D. work.

How can a traditional radial distribution network be improved by new investments actions identification?

Electric power distribution systems present the highest unavailability in the whole electrical supply chain that affects the customer's supply [2], [3]. The enhancement of distribution planning and management methods and practices can represent a significant contribution to the overall quality of the electric system service. Reliability assessment and optimization are two critical components of whole predictive performances studies for distribution networks.

DNs are generally composed of radial feeders, unlike transmission systems, which are looped. One of the most important consequences of using radial feeders is that many customers can be affected by the failure of a single component. Reliability indices can assess the adequacy of distribution networks through the following outage parameters: the average failure rate λ, the average outage duration r, and the annual outage duration U.

The average outage duration and the average failure rate can be reduced by adequate choices concerning network configuration, substation location, and feeder length and by preventive and corrective maintenance measures. These measures aim at modifying the failure rate and the repair time of each segment and thus improving the reliability indices. Repair time and failure rate modifications may require additional efforts, which are associated with other expenditures.

The considered actions for this research that the DSO can apply to reduce the repair time are as follows:

- Increasing the operation personnel;
- Automation system upgrade;
- Communications upgrade.

The considered actions for this research that the DSO can apply to reduce the failure rate are as follows:

- Reinforcing a line;
- Placing a new line in parallel with an existing one;
- Redesign link layout.

The model scheme to answer this research question and to aim the related objectives are depicted in Figure 3.1. The model includes four main aspects:

1. *Database*: An exhaustive statistical analysis of all available historical data and consistent database creation of all available information such as repair times, number of failures, and number of repairs are undertaken as the basis for the model;

2. *Target Reliability Values*: The DSO defines target values for the reliability indexes. To achieve the new reliability values (SAIDI, SAIFI, CAIDI, and NSP), the DSO should improve the repair times and the failure rates of network components;

3. *Fuzzy Membership Functions*: Several effects such as weather conditions, environmental, and operational conditions are challenging to distinguish precisely on the outage data of individual components using a probability model since there are little or any statistics available. Usually, utilities do not have enough statistical records of outage parameters. As a result, the fuzzy set approach allows obtaining adequate models;

4. *Weighted AC Optimization Using Mixed-Integer Non-linear Programming*: Based on the weighted Pareto front method, mixed-integer non-linear programming is developed and applied to identify the distribution network components (e.g., lines/cables), in which investments allow improving the reliability indexes of the network. The weighted technique is used to obtain non-dominated solutions. In this technique, a set of weights is randomly generated in order to put up a set of feasible optimization problems.

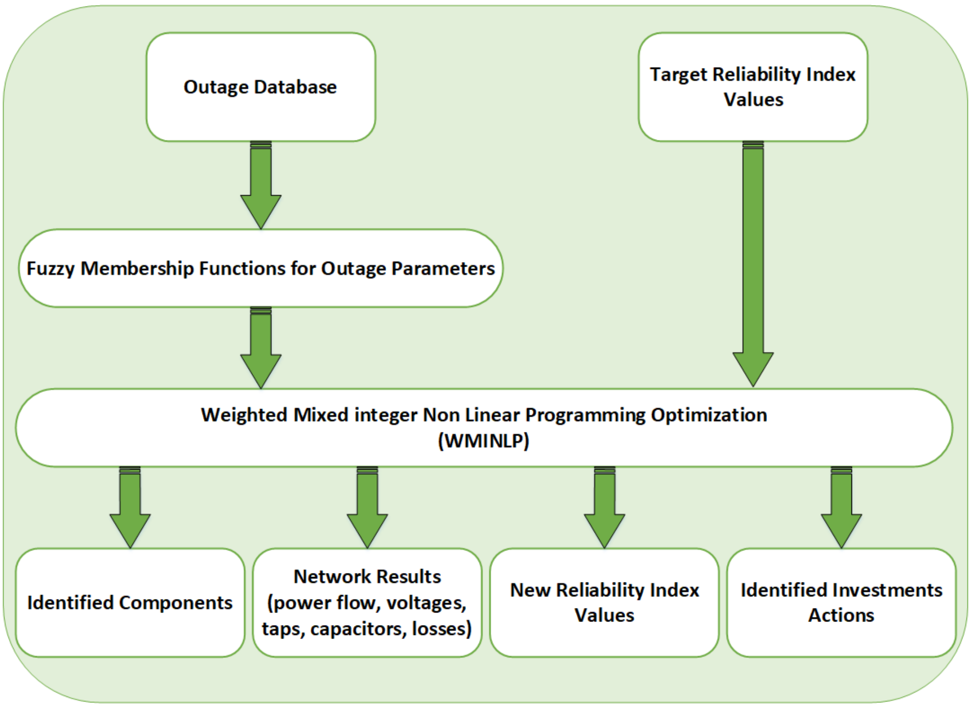

FIGURE 3.1: Diagram of *PlanTGrid* methodology (core publication *II*) [160].

To start answer to the research question in this section, the publication *I* proposes a new and innovative model for increasing the delivered power to any load point of the distribution network, by identifying new investments in distribution components, while minimising the costs of those investments, as well as the cost of the NSP (multi-objective problem). The investments aim to reduce the components repair time. The proposed methodology is a weighted AC optimization model based on MINLP using the Pareto front technique [56], [171]. A case study based on 33-bus distribution test network [172] with two DG units and with the possibility to have capacitor banks (four capacitors sizes with 150, 300, 450, and 600 kvar) in bus 5 and 10, is used to demonstrate the proposed model.

As a result, twenty-nine non-dominated solution or plans were obtained by the proposed model, as can be seen in Figure 3.2. The fuzzy satisfying decision method [173]–[175] is used to select the preferred solution among non-dominated solutions obtained in the optimization stage. Thus, this method proposes the plan number one.

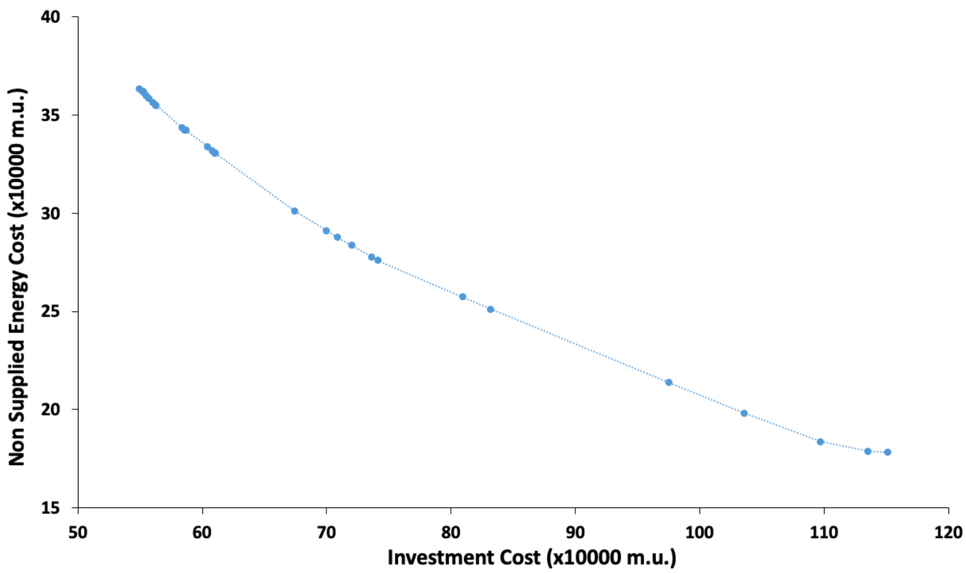

FIGURE 3.2: Non-dominated solutions or plans (core publication *I*) [159].

In this core publication, it was concluded that for the considered investment plan a 36% of the reduction in the NSP is achieved (corresponding a 790,082.00 m.u.[2] of savings and one 600 kvar capacitor bank selected for bus 5). The proposed investment plan presents a payback value of 7.96 years and 14.38% of the internal rate of return for a 10 years lifetime project. Furthermore, through the obtained results, the proposed model proves to be adequate to support the DSO to plan future network investment actions.

Additionally, further research was made to propose upgrades to the model presented in the core publication *I*, and in this way reach the answer to the

[2]monetary units

research question that motivates the topic of the planning of radial distribution networks and its corresponding objectives. Thus, core publication *II* proposes a model for reliability evaluation of radial distribution networks through the identification of new investments in radial distribution network components, while minimizing the costs of those investments, maximizing the reliability by minimizing the NSP cost, the power losses cost, and the cost of the optimal capacitor location and size (multi-objective problem). The investments aim to reduce the repair time and the failure rate of distribution network components. This new model has been tested in the same network of previous core publication but with 15 possible capacitor sizes (varying between 150kvar and 2250 kvar). The main upgrades are:

- The inclusion of optimal capacitor location and size (all bus can receive capacitors);
- Besides investment in repair times reduction, the possibility to reduce the failure rate is also included;
- Power losses minimization;
- SAIDI, SAIFI and CAIDI reliability indexes improvement.

The model obtained a total of 223 non-dominated solutions (corresponding to 223 investment plans). The fuzzy satisfying decision method [173]–[175] is also used to select the preferred solution among non-dominated solutions. It was concluded that for the considered plan given by the fuzzy satisfying decision method the operator has 119,908.00 m.u. of benefit with 8.1 years and 12.04% of payback and internal rate of return, respectively. Also, it was verified a high reduction in NSP (69%) and CAIDI (63%). Reductions for SAIDI, SAIFI, and power loss were 32%, 13%, and 36%, respectively. Moreover, a total of three capacitor banks were proposed by the model (900 kvar, 150 kvar and 1200 kvar for bus 2, 6 and 20, respectively), leading to 2250 kvar installed in the network. This upgraded model also proved to be adequate to support the distribution network operator for planning future network investment actions.

Subsection Conclusions

The contribution of this part to the Ph.D. work is a model for radial distribution networks without or with few DG units (consisting of a set of two core publications, *I*, and *II*) that has a multi-objective AC optimization methodology based on mixed-integer non-linear programming developed considering the Pareto front technique as a key contribution.

This multi-objective model was developed to achieve a reduction in repair times and failure rate of the distribution networks components while minimizing the costs of those reductions and the NSE costs, losses cost, and optimal capacitor location and size cost. The proposed method identifies the components in which the DSO should invest at minimum cost, as well as the actions to be taken. The developed optimization model considers the distribution network technical constraints and can choose the size and location of capacitor banks. For outage parameters estimation, a fuzzy set approach was used. Through the investment cost, the NSP costs, the losses cost, and the capacitor banks location and size cost, the network operator can perform an analysis to choose a solution preference. This research publications set have several advantages but also some disadvantages. Thus, the main advantages are: New failure rates and repair times in the distribution networks are obtained by a discrete optimization considering actions to be applied to the network components; all technical networks constraints are considered in the optimization model; a fuzzy approach is used for the failure rate, repair time, and unavailability in order to deal with the fuzziness associated with these parameters; minimization of the investment cost associated with the actions, NSP costs, losses costs, and optimal capacitor location and size costs. The main disadvantages are: the scalability of the problem; to obtain the reduction values associated to each action selected by the operator, some studies and analysis should be made.

Thus, with all the subjects dealt in this core publications set, the answer to the pointed out a research question, and the full accomplishment of the first objective of this Ph.D. work is achieved.

3.3 Long-term Distribution Network Planning in a Smart Grid Context Under Uncertainty

This section answers the following research question and accomplishes the second and third objective, taking into account two sub-research questions.

How can the variability of renewable energy sources and power demand be adequately considered in a long-term distribution network planning in an SG context?

3.3.1 Two-Stage Stochastic Distribution Network Planning in a Smart Grid Context

The answer to the sub-research question below is presented in this subsection as well as the accomplishment to the second objective of this Ph.D. work.

- *Can a stochastic optimization methodology be advantageous for the long term planning?*

Non-renewable energy sources like coal or natural gas can bring negative consequences to the environment. In this way, there is a necessity to find new alternatives to, at least, reduce their use. Environmental and techno-economic factors have motivated the widespread adoption of DG technologies in distribution networks [176]. Therefore, the portion of DG based generated electricity is increasing as a consequence and will play an important role in distribution network systems. Nevertheless, DG based on renewable sources such as solar and wind and therefore carry an inherent variability [39].

The expansion and planning problems of DN in a SG context can be modeled as deterministic or stochastic problems. Usually, the planners have considered this problem as a deterministic model, i.e., they considered parameters and inputs based on the assumption that the data for the problem is known accurately. The inputs of the expansion model must be estimated, such as the load demand and renewable penetration in the project lifespan, which is usually a decade at least. The high deviations in the estimations can have a substantial impact on the economic and technical aspects of daily grid operation. Therefore, the recent advances in expansion planning models are moving from deterministic to stochastic approaches to incorporate the uncertainty in projections for the future in the planning models [143], [177]. To capture the underlying uncertainty in the problem data, a sophisticated distribution network in a SG context planning model is developed in this core publication. The goal is to find a solution that is feasible for all the supplied scenarios while minimizing the objective function, e.g., the expected investment cost.

Core publication *IV* presents a two-stage stochastic model for distribution network long-term planning in a SG context to solve the challenging problem of considering several sources of uncertainty associated with the renewable generation and demand considering the network technical constraints. Besides power demand, this work also includes heat demand and seek the reliability indexes (SAIDI and SAIFI) improvement and the radial topology at minimum costs. Thus, objective function reflects the energy loss cost, the NSP cost, and the cost related to the investments, which in this case will be in the construction of new lines.

Figure 3.3 presents the scheme of the proposed methodology. The proposed model has five main steps:

1. *Input data*: The first step is to prepare all the input data to be considered in the model. Data like generation and load points, lines and new lines option characteristics, and reliability data. The data regarding the predicted values for solar power and wind power, load and heat demand and the number of consumers as well as their standard deviation values are also considered;

2. *Scenarios generation*: In this step, a set of scenarios is generated using Monte Carlo simulation (MCS) following a normal distribution. The predicted and standard deviation values referred above are used as inputs for the MCS, which is implemented in MATLAB software;

3. *Scenarios reduction*: The standard scenario reduction techniques developed in [178] is used. These scenario reduction algorithms exclude the

scenarios with low probabilities and combine those that are close to each other in terms of statistic metrics [178]. They determine a scenario subset of the prescribed cardinality and probability, which is closest to the initial distribution in terms of a probability metric [179]. The main purpose of scenario reduction is to reduce the size of the problem. GAMS with SCENRED [3] toolbox considering the fast backward/forward method is used to deal with the scenarios reduction;

4. *Long-term planning model using a two-stage stochastic method*: This optimization model has as outputs the decision variables regarding the investment in new lines, power losses and expected energy not supplied costs, as well as the SAIDI, SAIFI reliability indexes and the radial topology. The total expected planning cost corresponds to first stage planning cost (lines investment costs) plus the second stage planning cost NSP cost, power loss cost and power generation curtailment (PGC) cost subjected to the network constraints;

5. *Evaluation metrics*: The indices, such as the expected value of perfect information (EVPI) and the value of the stochastic solution (VSS) are used to evaluate the benefits of the stochastic programming [180]. The EVPI represents the amount that the decision maker is not able to gain due to the presence of imperfect information, e.g., forecasts. It is useful to evaluate how uncertainty factors affect the evaluated optimal problem. Regarding VSS, it represents the advantage of using stochastic programming over a deterministic approach [180].

A 13-bus MV distribution network under a SG paradigm with prediction data of power and heat demand, solar and wind power as well as the number of consumers for the year 2050 was used as a test system. On the other hand, four case studies are also considered to show the impact of using ESS units and the district heating in the distribution network planning in a SG context problem.

- *Case A*: ESS and combined heat and power (CHP) are not considered;
- *Case B*: ESS is considered and CHP is not;
- *Case C*: CHP is considered and ESS is not;
- *Case D*: ESS and CHP are considered.

With this core publication, it was verified that the two-stage stochastic model presents considerable advantages in terms of final costs for DSO when compared with the deterministic model. The higher costs are obtained in the deterministic model for case A and C. This is due to the existence of PGC and the non-existence of ESS. Results suggest that ESS contributes to avoiding a higher cost when the deterministic model is used and shows the two-stage

[3] www.gams.com/latest/docs/T_SCENRED2.html

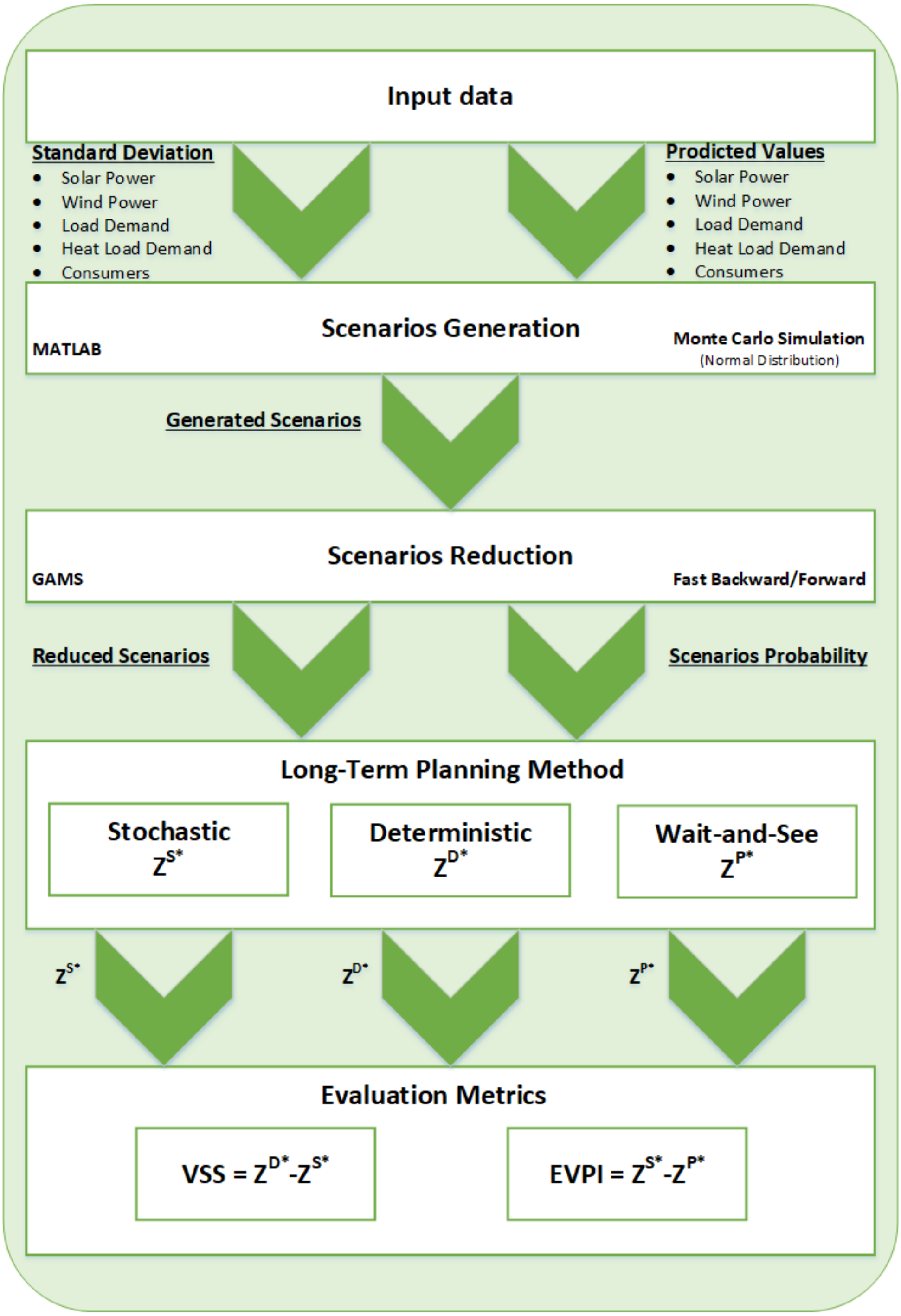

FIGURE 3.3: Model diagram of the long-them planning method under uncertainties (core publication *IV*) [162].

stochastic method advantage (even without ESS the power generation excess is zero).

Case A and case C are good proofs of the previous statement, presenting higher VSS values, which means that without ESS, the stochastic model is more important to achieve lower expected costs mitigating the uncertainty. These high VSS values for cases A and C are related to the existence of power generation excess.

The obtained results showed that the two-stochastic model presents a considerable total cost reduction compared with the deterministic model, being 64%, 11%, 69%, and 22% for the four case studies, respectively.

Subsection Conclusions

The contribution of this publication to this Ph.D. work is a two-stage stochastic model for a distribution network long-term planning in a SG context to solve the challenging problem of considering several sources of uncertainty associated with the renewable generation and power and heat demand considering the network technical constraints.

The results reveal that ESS can mitigate the increasing levels of uncertainty. Also, it was demonstrated that CHP units, besides, contributing to supply the district heating demand, also contribute to network reliability by reducing expected energy supplied and power losses costs avoiding the need to invest in new power lines for the considered lifetime project. Furthermore, it was verified that the two-stage stochastic model could be advantageous for distribution network long-term planning in a SG context, presenting lower costs when compared with the deterministic model.

The achieved results in core publication *IV* lead to a positive answer to the sub-research question as well as the fulfillment of the objective two of this Ph.D. research work.

3.3.2 Long-term Distribution Network Planning in a Smart Grid Context Considering Storage Investment and Seasonal Effect

This sub-subsection accomplishes the third objective of this Ph.D. work and answers to the following research question.

Can the power generation curtailment be mitigated, and the reliability be improved by optimal ESS size and location as well as the optimal type and location of new lines or the replacement of the existent ones?

The second sub-research question mentioned at the begin of the section 3.3 is the following:

- *How can the seasonal and daily periods affect the long-term distribution network planning?*

The answer to this sub-research question is also presented in this subsection.

A new era of cleaner distributed generators, like wind and solar, dispersed along the distribution network are gaining great importance and contributing to the environment and political goals. However, the variability and intermittency of those generators pose new complexities and challenges to network planning. Thus, taking this opportunity, the core publication *V* proposes an innovative stochastic MILP methodology to deal with the expansion planning of distribution networks in a smart grid context with high penetration of distributed renewable energy sources and considering the daily and seasonal impact. Also, new power lines locations and types, the size and the location of energy storage systems are considered in the optimization. The model is based on DC optimal power flow to deal with the expansion planning, in only one period of investment (year 0). The main target is to minimize all the expenditures.

To demonstrate the application of the proposed model, a part of the distribution network with 180 buses located at Leiria District in Portugal considering high RES penetration (with pre-defined locations) is used. As a base case, the proposed stochastic method is applied to the actual network without any investment alternatives, i.e., without new lines possibility and ESS. Also, a comparison between the stochastic model and the deterministic model was undertaken to show how much improvement can be achieved by the stochastic solution.

In this research work, it was considered a set of 16 scenarios corresponding to the combination of the four annual seasons (i.e., spring, summer, fall, and winter) and four daily periods (i.e., night, morning, peak and afternoon). Figure 3.4 shows all the considered 16 scenarios.

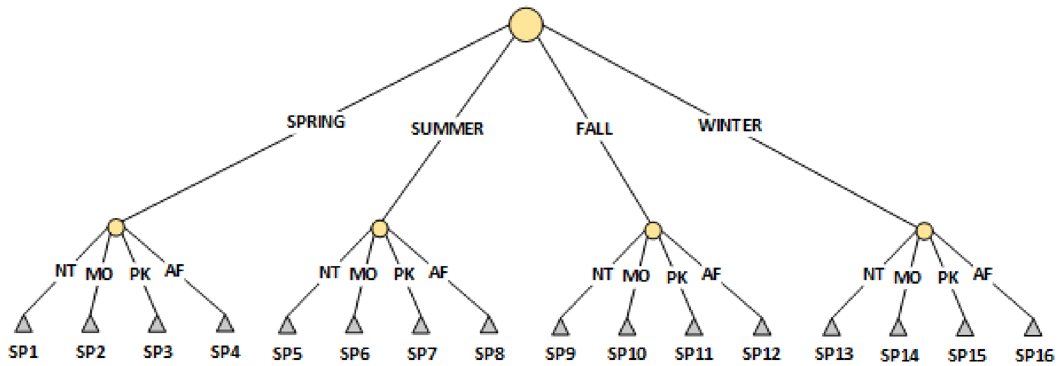

FIGURE 3.4: Probability tree diagram for a set of 16 scenarios, where SP represents the scenario probability, NT - Night, MO - Morning, PK - Peak and AF - Afternoon (core publication *V*) [163].

The method is dependent on the characteristics of the region considered. The number of days in each season where the methodology is applied as well as the number of hours in each daily period are needed to determine the probability of each scenario.

Figure 3.5 presents a diagram that illustrates the scenarios created for renewable generation and power demand. After the scenarios probability determination, the expected wind power and PV power, as well as the projected power demand for each combination of four annual seasons and four daily periods, are multiplied by the respective probability.

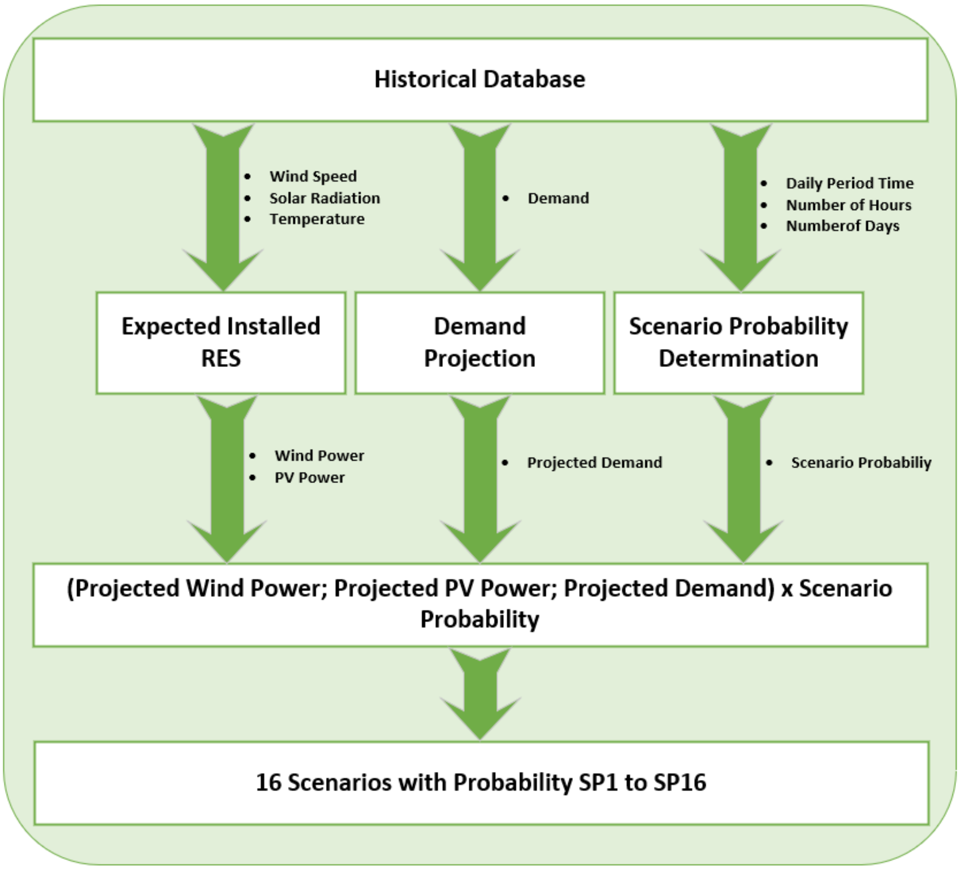

FIGURE 3.5: Scenarios diagram creation (core publication *V*) [163].

Furthermore, the next six steps summarize how to obtain the probability of each scenario.

1. A real hourly database regarding wind speed, solar irradiance, temperature, and demand was considered;

2. The data must be arranged by seasons (spring, summer, fall, and winter) and daily periods (night, morning, peak and afternoon);

3. For each season and daily periods values, the PV generation power and Wind power are calculated. The PV and wind generators units' types and locations are already previously defined in the distribution network. For the load demand it is considered the typical annual demand profile for the considered network region taking into account the projected change by *EU Reference Scenario 2016: Energy, Transport and GHG emissions trends to 2050* [181] for Portugal in 2050;

4. After the previous step, the mean value of each season and the daily period is obtained;

5. The probabilities of each scenario (each daily period in each season) are obtained following the method used in the example shown in this subsection;

6. After steps 4 and 5, it is possible to determine the probabilities of projected wind power, projected PV power, and projected demand for each daily period in each season.

The optimization model of this research work presents the following outputs variables:

- New lines and feeders types and their locations;
- New lines investment cost and feeders investment cost (including transformer cost);
- Location of ESS and its type;
- Energy storage systems investment cost;
- Power losses and its cost;
- Expected energy not supplied value and its cost;
- Power generation curtailment value and its cost;
- Optimal radial topology;
- Power flow;
- Reliability system indexes, such as the SAIFI and SAIDI.

The model in this core publication is a two-stage stochastic, which includes the new lines and feeders investment cost, the maintenance cost of all lines, the investment in ESSs and their maintenance cost as first-stage terms and the costs associated with the expected energy not supplied, power losses, power generation curtailment and load curtailment as second-stage terms.

It was verified that the proposed stochastic model presents a reduction of around 13.6 M€ of the total cost (35.54% reduction) compared with the deterministic approach. Also, the considered economic indexes, i.e., payback, internal rate of return (IRR), and net present value (NPV), have been improved by 59.90%, 170.62%, and 43.85%, respectively with the proposed stochastic model. It was verified that the PGC cost, which accounts for the generation power excess penalty of RES, has a significant influence on the total cost. The investment in new lines and ESS are important to mitigate this cost.

Subsection Conclusions

This part of the research work proposes a new stochastic methodology considering the seasonal impact to deal with the expansion planning problem of large DN in a smart grid context with high DG penetration. The main features can be summarized as follows: a) seasonal and daily periods impact effect in the long-term DN planning; b) optimal ESS size and location as well as the optimal type and location of new lines or the replacement of the existent ones; c) reliability improvement and the optimal radial topology.

The proposed stochastic methodology was tested using a case study of a real distribution network located in Portugal and compared with a traditional method (deterministic) to demonstrate the advantage of the former.

It was verified through the results that new strategies to deal with PGC cost must be sought to avoid the excessive cost in the final costumer's bill and also unnecessary investments in the network. The results also suggest that the stochastic approach can be used as an efficient approach to deal with the inherent variability of the RES during the seasons of the year and the differences registered in daily periods.

The core publication presented in this section answers the research questions stated at the begin of the section and also fulfill the objective number four of this Ph.D. work.

3.4 Distribution Network Operation and Reconfiguration in a Smart Grid Context Using Dynamic-Based Electric Vehicle Charging Price

Core publications *VI* and *VII* answer to the following main and sub-research questions and also the fulfillment of the fifth objective of this Ph.D. work.

Can dynamic EV charging price, have a positive impact on both, the distribution and on EV user behavior?

- *Can the EV user behavior modeling facilitate the integration of EV charging in the distribution network?*

- *How can an operation and reconfiguration model deal efficiently and effectively with high DER and EVs penetration in the distribution network?*

The use of EVs is growing in popularity each year. As a result, considerable demand increase is expected in the DN. Additionally, the uncertainty of EV user behavior is high, making it urgent to understand its impact on the network. Core publication *VII* presents an EV user behavior simulator (Figure 3.6).

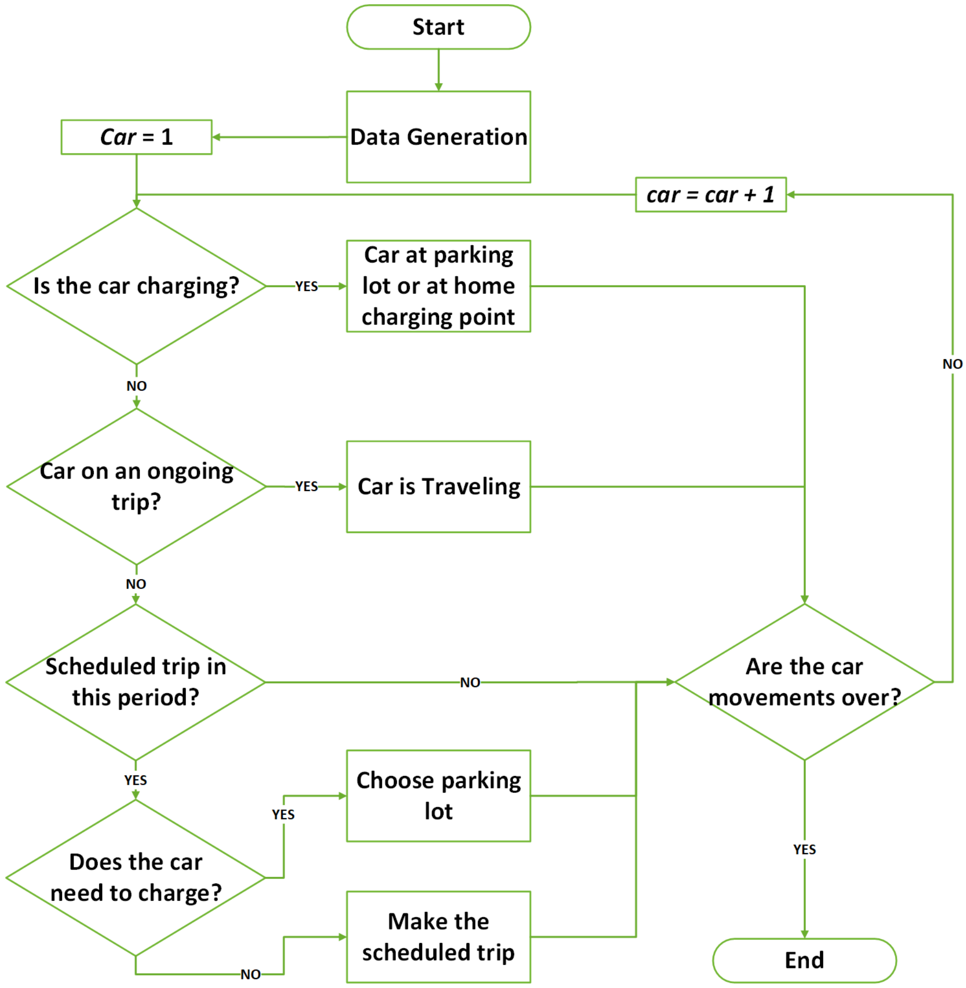

FIGURE 3.6: Flowchart for EV users behavior simulator (core publications *VI* and *VII*) [164], [165].

The simulator takes into account realistic behaviors of EV users to simulate their trips from the origin place (e.g., house or workplace) to multiple destinations, and back. The simulator also considers different types of users and vehicles, thus allowing them to create personalized profiles, destinations, and schedules. Moreover, the simulator enables defining the position of the EVs in the DN continuously throughout time. The proposed tool simulates a realistic environment, with trips and charging stations (parking lot buildings) and the users make their decisions regarding the charging process, i.e., if they charge their vehicles or not at each time. An intelligent decision EV charging is simulated considering variables such as distance and the charging price of each parking lot building. Thus, it is possible to test the impact of incentives on EV users' behavior.

Core publication *VI* presents the EV user behavior simulator operating in conjunction with an innovative smart distribution locational marginal pricing based on operation and reconfiguration, to understand the impact of the dynamic energy pricing on both sides: the grid and the user. The main goal, besides the DSO expenditure minimization, is to understand how and to what extent can dynamic pricing of energy for EV charging positively affect the operation of the smart grid and the EV charging cost. A smart city with a 13 bus medium voltage DN and high penetration of DER is used to demonstrate the application of the proposed models.

This kind of problem is classified as MINLP due to its non-linear features significant computer resources are required. To deal with the issue of computational burden and at the same time, improve the tractability of the model, the Benders decomposition method is used. The optimization model seeks:

- Minimize power loss;
- Minimize power not supplied;
- Minimize line congestion;
- Minimize the power generation curtailment;
- Minimize the power from external suppliers;
- Distribution network radial topology.

Figure 3.7 presents the description of the adopted model. The EV user behavior simulator module can generate a realistic population, considering the size of the network and the parking lots buildings. After receiving the necessary information from the optimization model, i.e., the DLMP in each bus of the network, the simulator loops for every individual car to perform the next period's decision (i.e., 15 minutes). There are only two possible types of decisions; the decision to travel to a destination or a charging decision.

According to each user preferences and behavior, decisions will be affected by the price and distance to the parking lot building. Since, in a realistic scenario, some prefer extra comfort even if they pay more, e.g., choosing a fast charge or closer parking lot building, the simulator allows defining this range of preferences for each car. These preferences will affect the efficacy of the dynamic EV charging prices since individual behaviors may neglect lower prices. Nevertheless, our case study provides a different range of behavioral aspects to provide an accurate research outcome in this research contribution.

The DLMPs are obtained by the distribution operation and reconfiguration model and are defined through Lagrangian multipliers of the corresponding constraints (power balance) of the optimization problem, whose goal is to minimize the DSO expenditures. The distribution network operation and reconfiguration problem in a SG context with high DER penetration concerning the behavior aspects of the EVs users and dynamic EV charging price considering DLMPs is classified as MINLP due to the non-linearity features. To solve complex problems like this, Benders decomposition is an adequate technique [182].

In this research work, thirty different case studies are performed. Table 3.2 summarizes the characteristics of those studies. They have been divided into two types of EV user preferences scenarios, namely the price preference scenario and distance preference scenario. For each of those scenarios, we

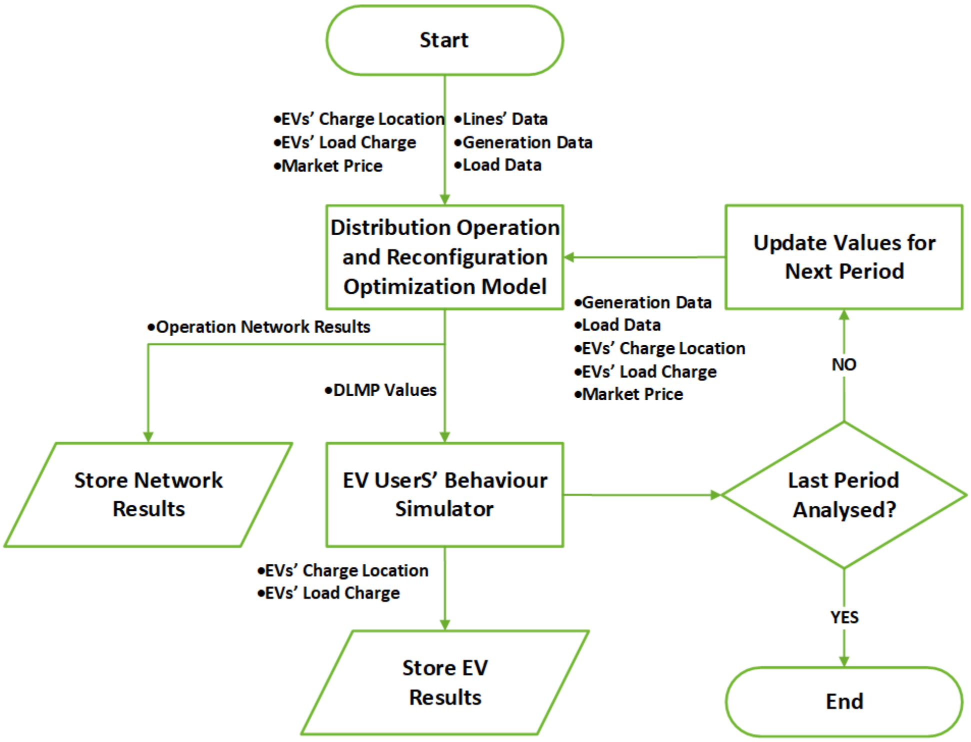

FIGURE 3.7: Flowchart for DN operation and reconfiguration with dynamic-base EV charging price (core publication *VI*) [164].

consider DG, EV, ESS, dynamic EV charging price, and fixed prices (with three different price levels) and combine them in the case study. The purpose of these case studies is to determine in which situations dynamic charging prices are advantageous for DSO and EV users.

It was verified that the use of dynamic pricing for EV charging is advantageous for the network operator in all of the considered cases due to reduced cost of operation in all the considered cases and user preference scenarios. These benefits are even more evident when considering high fixed charging prices (0.30€/kWh for slow charging and 0.40€/kWh for fast charging - 35.79% in the user price preference scenario, case L). The lowest cost reduction has been 0.24% in case H of the distance preference scenario. Moreover, when distance preference scenario and dynamic price were considered, it was verified that the PNS is zero, with the exception of case D, which presents an insignificant value (123.35€).

For the EV users, the dynamic pricing also presents considerable costs advantages, namely when the price preference is considered. In this scenario, the lowest advantage (4.03% better) was verified in case D compared with the lowest considered fixed charging prices (0.15€/kWh for slow charge and 0.25€/kWh for the fast charge). Also, for this scenario the advantages can reach 35.75% (case L), i.e., around 0.10€/kWh of savings if the fixed charging prices are 0.30€/kWh for slow charge and 0.40€/kWh for fast charge. If the distance preference is considered the dynamic EV charging price cases do not

TABLE 3.2: Case studies set.

	User Price Preference Scenario							User Distance Preference Scenario						
	DG	EV	ESS	Dynamic EV Charging Price	Fixed Price (€/kWh)			DG	EV	ESS	Dynamic EV Charging Price	Fixed Price (€/kWh)		
					SCh=0.15 FCh=0.25	SCh=0.2 FCh=0.3	SCh=0.3 FCh=0.4					SCh=0.15 FCh=0.25	SCh=0.2 FCh=0.3	SCh=0.3 FCh=0.4
Case A	No	No	No	Yes	No	No	No	No	No	No	Yes	No	No	No
Case B	Yes	No	No	Yes	No	No	No	Yes	No	No	Yes	No	No	No
Case C	Yes	No	Yes	Yes	No	No	No	Yes	No	Yes	Yes	No	No	No
Case D	No	Yes	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No
Case E	No	Yes	No	No	Yes	No	No	No	Yes	No	No	Yes	No	No
Case F	No	Yes	No	No	No	Yes	No	No	Yes	No	No	No	Yes	No
Case G	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Case H	Yes	Yes	No	Yes	No	No	No	Yes	Yes	No	Yes	No	No	No
Case I	Yes	Yes	No	No	Yes	No	No	Yes	Yes	No	No	Yes	No	No
Case J	Yes	Yes	No	No	No	Yes	No	Yes	Yes	No	No	No	Yes	No
Case K	Yes	Yes	No	No	No	No	Yes	Yes	Yes	No	No	No	No	Yes
Case L	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	No	No	No
Case M	Yes	Yes	Yes	No	Yes	No	No	Yes	Yes	Yes	No	Yes	No	No
Case N	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	No	No	Yes	No
Case O	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	No	No	No	Yes

present savings in comparison with the lowest fixed charging prices cases, namely when the fixed charging prices are 0.15€/kWh for slow charge and 0.25€/kWh for fast charge. Here, the user loses up to 15.66% for the dynamic EV charging price case D. Nevertheless, the dynamic price still presents considerable savings when fixed prices are higher, reaching up to 26.30%).

The results suggest that the dynamic energy pricing for EVs charge can be used as an efficient approach in smart cities that allows significant monetary savings for both the distribution system operator and EVs users.

Subsection Conclusions

The contribution of this publication to this Ph.D. work answers if the dynamic EV charging prices have a positive impact on the DN operation in a SG context and the EV user behavior. To this end, it was combined an EV behavior simulator with a proposed innovative smart DLMP-based distribution network operation and reconfiguration. In this module not only the classic objectives, such as power loss, minimization of power not supplied were met but also the problems related to the high DER integration, ESS, power congestion and power generation curtailment. The main contributions of the conducted study can be summarized as follows: a) an EV user behavior simulator has been adopted to generate a realistic population, considering the network size, and parking lot buildings; b) a distribution network operation and reconfiguration optimization model has been created in a SG context with high DER penetration concerning the behavior of the EV users and the dynamic EV charging price considering DLMPs using the Benders decomposition method; c) the positive impact of the dynamic EV charging prices on the DN operation and on the EVs users has been assessed. Thus, with all achievements obtained with the core publications *VI* and *VII*, all the answers to the research questions indicated in this section as well as the accomplishment on the fifth objective of this Ph.D. work are achieved.

3.5 Distribution Network Large-Scale Energy Resource Management Under Uncertainties in a Smart Grid Context

The core publication *III* answers the following main and sub-research questions and also fulfill the fourth objective of this Ph.D. work.

How can uncertainty from EVs, market price, solar, and wind power generation be handled by the ERM problems?

- *How can the problem be solved with several sources of uncertainty in an integrated model and with network validation?*
- *Can such large-scale problem be effectively and efficiently solved?*

Renewable energy sources present a high level of variability concerning energy generation. This unpredictability should be managed efficiently by the SG technologies to accommodate the high penetration of renewable energy. Transactive energy systems can contribute to providing the flexibility required by the SG, e.g., controllable loads, including EVs under interoperable architectures [183], [184]. This flexibility can be provided through energy aggregators, which are meant for small producers under market-oriented environments [185]. To allow efficient and cost-effective operation, energy aggregators require proper ERM tools to deal with the increasing number of resources. The day-ahead energy scheduling is an important part of an ERM system to obtain the expected operation cost (or profit) while providing adequate decisions one day in advance. However, energy scheduling is quite challenging due to the inherent uncertainties and the high number of resources. Adopting advanced energy management models that consider uncertainty factors is critical for successful implementation of SGs.

The day-ahead problem tackled in this core publication is a combinatorial problem of large-scale nature when many distributed energy resources are considered. Due to non-linearity features of the problem, it is usually classified as MINLP. MINLP techniques require significant computer resources.

In this core publication, a two-stage stochastic model for a large-scale energy resource scheduling problem of aggregators in a smart grid (using Benders' decomposition technique) is proposed. The idea is to address the challenges brought by the variability of demand, renewable energy, electric vehicles, and market price variations while minimizing the total operation cost. Benders' decomposition approach is implemented to improve the tractability of the original model and its computational burden. A realistic case study is presented using a real 180-bus distribution network in Portugal with high penetration of renewable energy and electric vehicles.

One step involving stochastic programming is typically the development of possible scenarios that represent the underlying uncertainty. This step is usually a cumbersome task where a lot of possible scenarios might be generated. Therefore, a second step is generally applied using scenario reduction techniques. The objective is to obtain a reduced set of likely scenarios that is feasible to be solved [186]. The third step involves developing a multi-scenario stochastic model to accommodate for the set of scenarios.

In stochastic problems, where a set of scenarios needs to be handled, the main issue is to construct a set of realizations for the random variable. These scenarios should adequately represent the probabilistic characteristics of the data [187]. In this stochastic model, the initial set of scenarios is a large data set generated by the MCS technique for representing the uncertainties which the aggregator faces while solving the problem.

Including all the generated scenarios in the optimization problem results in a large scale optimization problem [187]. Generally, there should be a trade-off between model accuracy and computation speed [188], [189]. To handle with the computational tractability of the problem, the standard scenario reduction techniques developed in [178] are used. These scenario reduction algorithms exclude the scenarios with low probabilities and combine those that are close to each other in terms of statistic metrics [178]. They determine a scenario subset of the prescribed cardinality and probability, which is closest to the initial distribution in terms of a probability metric [179]. The key purpose of scenario reduction is to decrease the dimensions of the problem.

The main decision variables are the optimal day-ahead market transactions and the generation scheduling of the controllable sources (first stage). They are made taking into account possible deviations in operation, like wind and solar power and EVs (second stage). The first-stage decisions do not change across the scenarios in the second stage. In other words, the decisions to be made one day in advance remain unchanged.

Four different case studies were considered in this core publication to show the impact of using storage and DR in the ERM, regarding the mitigation of uncertainty:

1. *Case A*: ESS and DR are considered;
2. *Case B*: ESS and DR are not considered;
3. *Case C*: ESS is considered and DR is not;
4. *Case D*: DR is considered ESS is not.

The case without both resources has higher costs for both stochastic (47,208 m.u.) and deterministic (48,668 m.u.) models. For cases C and D, the costs for the stochastic model are similar, but in the deterministic model, the costs are 8.85% higher when the ESS is not available. Results also suggest that ESS contributes to avoiding a higher cost when the deterministic model is used (case C). In case D, the DR resource is not as effective as ESS in case C. The comparison between cases C and D is a good proof of the previous statement, where the VSS is higher in case D (11.75%), which means that, without ESS, the stochastic model is more important to achieve lower expected costs mitigating the uncertainty.

The results showed that the lower cost is verified when ESS and DR are available. The two-stage stochastic model is more advantageous, compared to the deterministic counterpart, particularly in situations with higher risks for the aggregator's operation, such as limited flexibility, i.e., no DR and also when the ESS is not considered. The results also revealed that the increasing levels of uncertainty could be mitigated either with ESS or DR. In fact, the costs have been a higher reduction when ESS and DR have been both considered in the case study. It was verified that the ESS also reduced the impact of uncertainty more effectively than DR.

Subsection Conclusions

The contribution of this core publication to the Ph.D. work is a two-stage stochastic model using a decomposition technique, namely the Benders' decomposition to solve the challenging problem of considering several sources of uncertainty and with network validation. The uncertainty sources, include load demand variability, intermittency of wind and PV generation, EVs stochastic demand, and market price in the same model. The results reveal that the stochastic programming can be used as an efficient approach to deal with the uncertainty in ERM. Thus, the main and sub-research questions presented at the begin of this section have their answer in the core publication *III*. This core publication also fulfills the objective fourth.

3.6 Chapter Conclusions

The main contribution of this work is the response to the core research question of this Ph.D., namely: *How to deal with the unpredictability of renewable energy sources and electric vehicles adequately in the planning and operation of medium voltage distribution networks in smart grid context?*

The work developed in the scope of this Ph.D., in pursuit of the answers to the specific research questions, has ultimately resulted in the development of the *SupporGrid* DSS. This system provides the answer to the main research question by integrating a variety of different decision support solutions, directed to different purposes, which together contribute to the improvement of planning and operation of distribution networks in SG context. The soundness of the decision support methodologies developed in the scope of this Ph.D. work has been assessed through the test and validation of the proposed methods in elaborated and realistic case studies.

The encouraging results achieved from the realized studies support the thesis that the proper planning and operation of the distribution network under the SG paradigm can, in fact, improve its use and generate incomings to the DSO and clients.

The different decisions support modules that compose *SupporGrid* gives to the DSO a set of tools to face the issues of planning and operation of distribution networks under a SG context or not. The DSO can deal with the planning of radial distribution networks by using the *PlanTGrid* module. This module identifies the network components in which the DSO should invest at minimum cost, as well as the actions to be taken to improve the reliability of the network. If the distribution network is under a SG paradigm, the

DSO can use the *PlanSGrid* module which uses a two-stage stochastic model for a distribution network long-term planning in a SG context and solves the challenging problem of considering several sources of uncertainty associated with the renewable generation and demand. In this module, the possible scenarios that represent the underlying uncertainty are created. The DSO can chose the scenarios creation by using the Monte Carlo simulation and scenario reduction techniques (fast backward/forward method) or considering a set of sixteen scenarios corresponding to the combination of the four annual seasons (i.e., spring, summer, fall, and winter) and four daily periods (i.e., night, morning, peak and afternoon).

The DSO with *SupporGrid* also has a module to deal with the operation and reconfiguration of the distribution network with high DER and EVs penetration (*OperSGrid*). In this module, an innovative smart DLMP-based distribution network operation and reconfiguration with the objective to minimize the DSO operational costs is used to create the dynamic EV charging prices. The module was used together with an EV user behavior simulator which generates a realistic population, considering the size of the network and the parking lot buildings which was useful to carry out the studies in a more realistic environment (15 minutes periods).

SupporGrid also includes the *ERMGrid* module to offer to the DSO a tool for ERM. Indeed, not all DSOs do this, but *ERMGrid* module is a possibility in that kind of situations. However, it is worth to note that any aggregator / VPP can use this module.

The contributions of the work developed in the scope of this Ph.D. provide the answers to all the specific research questions, which together result in answer to the main research question. The research work leading to the achievement of such responses also allows fulfilling all the defined objectives for this Ph.D. work.

Next chapter, presents the main conclusions resulting from this work. The perspectives of future development are also presented.

Chapter 4

Conclusions and Future Work

This chapter finalizes the thesis manuscript by presenting the most relevant conclusions and contributions derived from this work and by giving directions for possible future work.

4.1 Main Conclusions

The efforts to minimize the carbon footprint using a large-scale integration of RES such as wind and solar energy have led to innovative developments in power distribution systems around the world. However, extensive penetration of RES greatly increases the risks of safe and economic operation of DN since this kind of DGs have inherently intermittent nature, which makes the planning and operation of distribution networks more challenging than ever before. Consequently, the entities involved in these fields must act quickly and rethink their business models, strategies, and behavior to take proper decisions. The vast increase of RES and the EVs mass penetration will change the current landscape of distribution electric power systems permanently, on the one hand bringing unique benefits, on the other hand giving place to challenges never experimented before. In this context, the SG plays an essential role by enabling to incorporate all of these new changes, in a sustainable, secure, efficient, and intelligent way.

The traditional distribution network planning aims to find feasible economic solutions, by the addition or expansion of substations and branches/ lines or replace/remove to reach an optimal DN configuration that supplies the load demands over the whole planning horizon. However, traditional distribution network planning is further complicated with the inclusion of DER units namely the RES and their related problems, i.e., with the optimal topology or reconfiguration, reliability concerns, load uncertainties, and RES variability. Thus, major power industry stakeholders recognize the need to address challenging issues and replan the DN structure according to the SG paradigm to overcome these issues and also to accommodate several DER types, ESS and EVs.

Moreover, it is known that one of the primary sources of CO_2 emissions is transportation. It is being analyzed in the scientific community the benefit of changing from traditional transportation (internal combustion engines) to EVs, in minimizing the transport sector's greenhouse gas emissions. But the increasing number of EVs make it necessary to develop new infrastructure for EV charging continually. So, growing energy demand will burden the DN (namely the EV fast charging stations). Furthermore, high penetration of DER challenging the conventional control and operation framework designed for passive distribution networks. Thus, DNR related to SG paradigm will be a fundamental and significant strategy for the DSO.

Additionally, due to the RES intermittency, load demand, EVs and market price uncertainty, an advanced energy resource management taking into account these factors is important for the DSO when works as a resource aggregator or for any other aggregator or VPP.

All these needs related to planning, operation, and ERM of the distribution network in a SG context have led to the definition of several research questions, which were the basis for the specification of this Ph.D. work objectives. This thesis presents *SupporGrid* a decision support system for traditional and distribution networks planning, operation and ERM in a SG context that enables the DSO surpassing the identified limitations in the fields and deal with the identified problems that compose the main topic addressed in this Ph.D. work. The *SupporGrid* is composed by four modules, namely the *PlanTGrid*, *PlanSGrid*, *OperSGrid*, and *ERMGrid*.

PlanTGrid executes the expansion planning model for traditional radial distribution networks without or with few DG units penetration, which identify the possibility of new investments to improve the repair time (r) and failure rate (λ) of the distribution networks components, while minimizing the costs of those reductions and the NSP costs, losses cost, and optimal capacitor location and size cost. Moreover, the improvement of reliability indexes is also ensured.

PlanSGrid deals with the long-term expansion planning of DN in a SG context with high penetration of distributed renewable energy sources. A two-stage stochastic model is created to overcome the issue related to the uncertainty of renewable generation and demand. This model can also use the seasonal and daily periods impact effect on the long-term distribution network planning. *PlanSGrid* proposes the optimal ESS size and location as well as the optimal type and location of new lines or the replacement of the existent ones as well as the reliability improvement minimizing at the same time the power losses, energy not supplied, load cut, and power generation curtailment costs.

The module *OperSGrid* is composed of a travel simulator to simulate real environments taking into account the behavior of real users. This simulator operates in conjunction with a smart distribution locational marginal pricing based on operation and reconfiguration. Additional, this module also permits understanding the impact of the dynamic energy pricing for EVs charging on both sides: the DN and the EV user.

The *SupporGrid* DSS also includes the *ERMGrid*, which is a module that uses a two-stage stochastic model for a large-scale energy resource scheduling. This module permits to deal with the variability of demand, renewable energy, electric vehicles, and market price as well as with the DR through direct load control and ESS. This module will be useful for the DSO if it also works as a resource aggregator.

Taking advantage on the developed case studies based on realistic data, it was possible to validate that the developed methodologies were fundamental to approve the proposed modules and their methods, guaranteeing the competence of the system in achieving its purpose in realistic scenarios.

The achieved results show that the *SupporGrid* modules present better results than the methods to which they were compared. From the achieved results:

- *PlanTGrid* presents considerable monetary benefits for the DSO by the proposed network investment actions with excellent values of internal rate of return (12.04%) and payback (8.1 years for 10 years of project lifetime). Moreover, high improvements in the reliability indexes are also verified;

- *PlanSGrid* leads to a robust overall cost reduction, economic indexes improvement when compared with a deterministic approach. Additionally, it contributes to mitigating the PGC costs by locating the ESS optimally and proposing new lines investment;

- *OperSGrid* proved that dynamic pricing for EV charging could be advantageous for the network operation (operation costs) and the EV users (charging prices) compared with fixed charging prices (mainly when the price preference scenario was considered);

- *ERMGrid* gives to the DSO (if it also works as an aggregator) a two-stage stochastic model which revealed to be an efficient approach to deal with the uncertainty sources in ERM problems. The results proved that the model is advantageous compared with the deterministic, mainly in situations where the flexibility is limited, i.e., no DR neither ESS.

The findings resulting from the development of *SupporGrid*, have enabled achieving the responses to the research questions, and the consequent accomplishment of all the defined objectives. Besides, *SupporGrid* has contributed to significant advances in the state of the art of power systems and electric mobility fields. The main contributions to the power systems field were focused into the planning, operation, and ERM domains; while in electric mobility field, they were explicitly related to the EV users behavior simulation and charging prices.

The results suggest that the *SupporGrid* can be used as an efficient DSS tool that allows important benefits for DSO and customers.

The eighteen scientific publications that have been published as result of this Ph.D. work and the contribution of this work towards the achievement of national and international projects' objectives are clear indications of the relevance of the achieved findings.

4.2 Main Contributions

The main contributions and originality of the present work can be summarized as follows:

Distribution Network Planning

- Multi-objective AC optimization based on MINLP considering the Pareto front technique to propose the optimal investment actions to reduce the repair time and failure rate of the DN components and improve the reliability;
- Two-stage stochastic model for a DN long-term planning in a SG context considering the uncertainties sources;
- The impact effect of the seasons (spring, summer, fall, and winter) and daily periods (night, morning, peak and afternoon) in the long-term DN planning under SG paradigm;

Distribution Network Operation

- Development of an EV user behavior simulator which deals with the stochastic EV user aspects, the importance of EV charging price, the importance of comfort, choosing slow or fast charge, and the user sensibility of the state of the battery;
- DN operation and reconfiguration optimization problem in an SG context with high DER penetration concerning the behavior aspects of the EV users and the dynamic EV charging price considering DLMPs using the Benders decomposition method;
- Understand how and to what extent dynamic EV charging prices can contribute to a positive impact on the distribution network operation and electric vehicles' charging price;
- Two-stage stochastic model considering technical network constraints and several sources of uncertainty in the same model to solve the ERM problem, using Benders' decomposition technique.

4.3 Perspectives of Future Work

The development of this thesis and the results achieved have opened some interesting lines of research that can be explored as future work. Among the possible developments that this work supports, a list of relevant ideas for each *SupporGrid* module to pursue or to be taken into account are given:

- *PlanTGrid*
  - Adapt the model to a decomposition methodology (e.g., Benders' decomposition) as well as to evolutionary algorithms to mitigate the possible computational burden resulted from the growth of the problem and consequently of its complexity;

  - Consider the power quality issues in the module;
  - Adapt the model to consider the possibility of EVs integration.

- *PlanSGrid*
  - Improve the proposed method to include the phased investment as well as incorporate the uncertainty in the scenarios data;
  - These two previous ideas can lead to a high computational burden, so meta-heuristics techniques may be considered to solve the problem;
  - Include other forms of remuneration for DG and ESS owners, whose role should be effectively separated from the operator duties;
  - Include in the developed models the power quality issues.

- *OperSGrid*:
  - For the EVs user behavior simulator, include more EVs user profiles;
  - An additional charging decision method which depends on the energy price to be also included in the EVs user behavior simulator;
  - An optimized ESS charge/discharge decision;
  - An optimization model for EV users costs minimization;
  - Solar-powered charging infrastructures in the parking lot buildings;
  - The possibility of vehicle-to-grid;
  - Flexibility charging strategies exploited by DR programs considering at the same time the congestion management issues;
  - Use other versions of decomposition approaches (e.g., Dantzig–Wolfe).

- *ERMGrid*
  - Tackle in the proposed stochastic model the non-linearities;
  - Use other versions of decomposition approaches (e.g., Dantzig–Wolfe);
  - Use evolutionary algorithms;
  - Adapt the stochastic model to real-time scheduling.

The majority of these future work suggestions has been considered, not only as the future development of this Ph.D. work but also as a relevant part of the core of some ongoing research projects, which guarantee the continuity of the research undertaken in the scope of this Ph.D., namely the following:

- **CENERGETIC** – Coordinated energy resource management under uncertainty considering electric vehicles and demand flexibility in distribution networks, reference PTDC/EEI-EEE/29893/2017;

- **BENEFICE** - Building resources management towards flexible contracted power, reference PTDC/EEI-EEE/29070/2017;
- **COLORS** - Contextual load flexibility remuneration strategies, reference PTDC/EEI-EEE/28967/2017;
- **MAS-Society** - Multi-Agent systems semantic interoperability for simulation and decision suppory in complex energy systems, reference PTDC/EEI-EEE/28954/2017;
- **DOMINOES** - Smart distribution grid: a market driven approach for the next generation of advanced operation models and services, reference No 771066.

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Appendix A

Core Publications

Core publication *I*

Bruno Canizes, João Soares, Zita Vale, Cristina Lobo, "Multi-criteria optimisation approach to increase the delivered power in radial distribution networks", IET Generation, Transmission & Distribution. 9 (2015) 2565–2574. doi:10.1049/iet-gtd.2014.1196 (**2015 Impact Factor is 1.576**).

Core publication *II*

Bruno Canizes, João Soares, Zita Vale, Cristina Lobo, "Optimal Approach for Reliability Assessment in Radial Distribution Networks", IEEE Systems Journal. 11 (2017) 1846–1856. doi:10.1109/JSYST.2015. 2427454 (**2017 Impact Factor is 4.337**).

Core publication *III*

João Soares, Bruno Canizes, Mohammad Ali Fotouhi Ghazvini, Zita Vale, Ganesh Kumar Venayagamoorthy, "Two-Stage Stochastic Model Using Benders' Decomposition for Large-Scale Energy Resource Management in Smart Grids", IEEE Transactions on Industry Applications. 53 (2017) 5905–5914. doi:10.1109/TIA.2017.2723339 (**2017 Impact Factor is 2.743**).

Core publication *IV*

Bruno Canizes, João Soares, Mohammad Ali Fotouhi Ghazvini, Cátia Silva, Zita Vale, Juan M. Corchado, "Long-term smart grid planning under uncertainty considering reliability indexes", in: Operation, Planning, and Analysis of Energy Storage Systems in Smart Energy Hubs, 2018. doi:10.1007/978-3-319-75097-2_13.

Core publication *V*

Bruno Canizes, João Soares, Fernando Lezama, Cátia Silva, Zita Vale, Juan M. Corchado, "Optimal expansion planning considering storage investment and seasonal effect of demand and renewable generation", Renewable Energy. 138 (2019) 937–954. doi:10.1016/j.renene.2019.02.006 (**2018 Impact Factor is 5.439**).

Core publication *VI*

Bruno Canizes, João Soares, Zita Vale, Juan M. Corchado, "Optimal Distribution Grid Operation Using DLMP-based Pricing for Electric Vehicle Charging Infrastructure in a Smart City", Energies. 686 (2019) 12(4). doi:10.3390/en12040686 (**2018 Impact Factor is 2.707**).

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Article

Optimal Distribution Grid Operation Using DLMP-Based Pricing for Electric Vehicle Charging Infrastructure in a Smart City

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Received: 22 January 2019; Accepted: 14 February 2019; Published: 20 February 2019

Abstract: The use of electric vehicles (EVs) is growing in popularity each year, and as a result, considerable demand increase is expected in the distribution network (DN). Additionally, the uncertainty of EV user behavior is high, making it urgent to understand its impact on the network. Thus, this paper proposes an EV user behavior simulator, which operates in conjunction with an innovative smart distribution locational marginal pricing based on operation/reconfiguration, for the purpose of understanding the impact of the dynamic energy pricing on both sides: the grid and the user. The main goal, besides the distribution system operator (DSO) expenditure minimization, is to understand how and to what extent dynamic pricing of energy for EV charging can positively affect the operation of the smart grid and the EV charging cost. A smart city with a 13-bus DN and a high penetration of distributed energy resources is used to demonstrate the application of the proposed models. The results demonstrate that dynamic energy pricing for EV charging is an efficient approach that increases monetary savings considerably for both the DSO and EV users.

Keywords: charging behaviors; distribution locational marginal pricing; distribution networks; electric mobility; electric vehicle; operation; reconfiguration; renewable energy sources; smart city; smart grid

1. Introduction

The efforts to minimize the carbon footprint using a large-scale integration of renewable energy sources (RES), such as wind and solar energy, have led to innovative developments in power distribution systems around the world. Moreover, a new agreement in the European Union (EU) aims to achieve 27% penetration of RES by 2030 [1], as one-third of EU countries have already achieved the 2020 target [2].

Currently, many people move to cities in search of a better quality of life, and this contributes to the continuous expansion of urban areas, which play a major role in modern economies. However, the urban population is responsible for most greenhouse gas emissions, and the United Nations estimates that the urban population will reach 70% of the world's total population by 2050 [3]. Consequently, it is necessary to make intelligent use of resources in urban environments, contributing to the development of smart cities [3]. The energy infrastructure of a smart city (SC), the so-called smart grid (SG), is one of the most important urban infrastructures that allows creating a sustainable city [4]. To this end, it is necessary to modernize grid functionalities through the implementation of innovative technologies, concretely, SG-enabling technologies for information and communication, sensing and measurement, automation, control, renewable generation integration, and storage [5,6].

One of the primary sources of CO_2 emissions is transportation [7,8]. Several authors have been analyzing the benefit of changing from traditional transportation (internal combustion engines) to EVs, in minimizing the transport sector's greenhouse gas emissions. It is widely acknowledged that the shift from internal combustion engines to EVs has many environmental and economic advantages. However, the increasing number of EVs makes it necessary to develop new infrastructure continually for EV charging, and this, in turn, leads to a growing energy demand [9,10]. These charging infrastructures are going to burden the distribution power grid [11–13], namely the high charging loads of fast EV charging stations. Furthermore, some distribution network operating parameters are going to degrade. Several published works describe the negative impacts of EV charging on the following distribution network parameters:

- Voltage profile [14–20];
- Peak load increase [21–24];
- Harmonic distortions [25–30].

Thus, a high EV penetration level may congest the distribution network. Congestion problems can be managed by the DSO, who reinforces the system through long-term planning or market-based congestion control methods [31]. The transmission systems concept of locational marginal pricing (LMP) can be extended to distribution systems [32]; it uses distributed generation (DG) units to handle congestion in distribution networks [33–37] and is usually referred to as distribution locational marginal pricing (DLMP). To deal with EV demand congestion in DN, the work in [38] proposed a step-wise congestion management whereby the DSO predicts congestion for the next day and publishes day-ahead tariff prior to the clearing of the day-ahead market, while [39] solved the social welfare optimization of the distribution system considering EV aggregators as price takers in the local DSO market and demand price elasticity. Liu et al. presented in [40] a market-based mechanism taken from the DLMP concept to alleviate possible distribution system congestion caused by the integration of EVs and heat pumps. Similarly, the authors in [41] proposed a DLMP based on quadratic programming to deal with the congestion in distribution networks with a high penetration of EVs and heat pumps.

As is known, the EVs are additional electric loads and represent mobile energy storage, usually with long resting times. Several mathematical models presented in [42–47] also studied the impact of EV charging in the distribution networks. The works in [48–53] assessed several possibilities for demand-side management, as well as better coordination of charging processes through price incentives that mitigate the impact of EV charging during peak-loads. The works in [54–58] proposed an increase in EV charging flexibility, contributing to increased utilization of the highly-variable renewable energy. Moreover, one of the main challenges in facilitating integrated EV charging in the distribution network is EV user behavior modeling and prediction [59]. Optimal control for allocating EV charging time and energy optimally has been proposed by Gan et al. [60]. However, the model requires that users frequently provide the charging schedule, requiring significant effort on the part of the customer. The algorithms developed in [61] used an EV random user behavior model with renewable generation for EV scheduling, while [62] provided a smart charging strategy according to time-of-use price from the day-ahead forecast. The authors in [63–66] examined EV users' charging behavior and measured psychological variables, an analysis that can help develop new charging strategies.

SCs feature an active power architecture with a high penetration of distributed energy resources (DER), challenging the conventional control and operation framework designed for passive distribution networks. In this context, the loads can be supplied not only by traditional generation units at the upstream power systems, but also by the DER [67]. Thus, a distribution network reconfiguration (DNR) will be a very important and significant strategy for the DSO. DNR is a process that changes the network topology using the remote switches such that all the network constraints are considered. Traditionally, the DNR is associated with system power loss minimization [68,69]; however, in the SG, context the DNR must not only meet the classic objectives, such as power loss, minimization of power not supplied, and improvement of the voltage profile, but also the problems related to the high DER integration and the intelligent reconfiguration related to the SG paradigm [70–72]. Several works considering mathematical [73–75], heuristics and metaheuristics [76,77], and hybrid models [78,79] were developed to deal with DNR and DER penetration.

The above-cited literature has not addressed distribution network operation and reconfiguration simultaneously in an SG context; neither have they considered the high penetration of DER and EV user behavior, nor dynamic EV charging price through DLMPs. Thus, to the best of the authors' knowledge, the answer to the question "Can dynamic EV charging price, have a positive impact on both the operation of the smart distribution network and on EV user behavior?" has not yet been answered. To answer this question, the authors combined an EV behavior simulator with a proposed innovative smart DLMP-based distribution network operation/reconfiguration. This kind of problem is classified as mixed-integer nonlinear programming (MINLP) due to its nonlinear features requiring significant computer resources. To deal with the issue of computational burden and at the same time improve the tractability of the model, the Benders decomposition method is used. This method uses duality theory [80,81] in linear and nonlinear mathematical programming, and it deals with complex problems by splitting them into subproblems. The main goal is to minimize all the DSO expenditures. To this end, the proposed methodology seeks the following:

- Minimize power loss;
- Minimize power not supplied;
- Minimize line congestion;
- Minimize the power generation curtailment;
- Minimize the power from external suppliers;
- Distribution network radial topology.

Considering the research gaps in previous works, this paper presents the following major contributions:

1. The use of an EV user behavior simulator. This simulator is used to simulate the EV user behavior aspects, such as: stochastic EV user aspects, importance of EV charging price, importance of comfort, choosing slow or fast charge, and the user sensibility of the the state of the battery;
2. Present a distribution network operation/reconfiguration optimization problem in an SG context with high DER penetration concerning the behavior aspects of the EV users and the dynamic EV charging price considering DLMPs using the Benders decomposition method;
3. Analyze how and to what extent dynamic EV charging prices contribute positively to smart distribution network operation;
4. Understand how and to what extent dynamic EV charging prices can contribute to a positive impact on the electric vehicles' charging cost.

To demonstrate the application of the proposed methodology, the BISITE (https://bisite.usal.es/en) laboratory's SC mockup model has been used with a 13-bus distribution network and high DER penetration. This paper is organized as follows: after this Introduction, Section 2 presents the proposed methodology and the details of the DLMP-based network operation, as well as the simulation of urban mobility. To verify the performance of the proposed methodology, a case study has been conducted and described in Section 3. The results and its discussion are presented in Section 4. Finally, Section 5 presents the most relevant conclusions.

2. Proposed Methodology

This section presents a detailed description of the adopted methodology (depicted in the Figure 1). Section 2.1 provides information about the EV user behavior simulator, while Section 2.2 describes the DLMP-based network operation model using the Benders decomposition method.

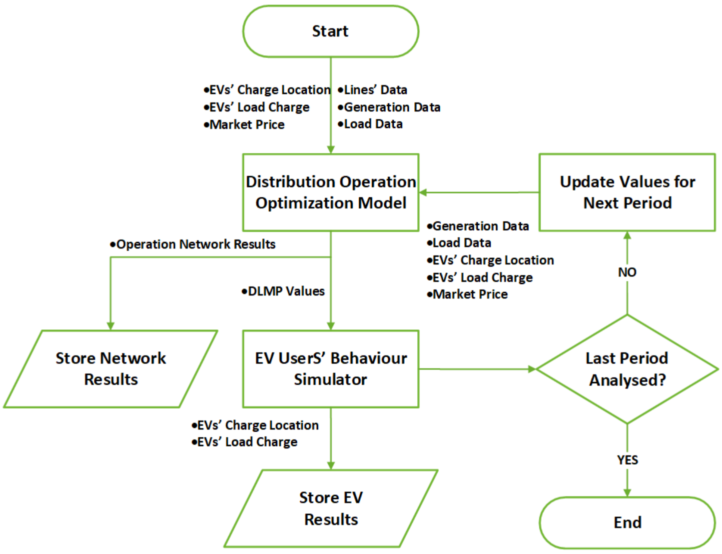

Figure 1. The proposed methodology's flowchart.

2.1. Simulator of Urban Mobility

The simulator module is able to generate a realistic population, considering the size of the network and the parking lots. It has several global and behavior-related parameters (user profiles) discussed later in this section. Figure 2 shows the flowchart of the simulator. After receiving the necessary information from the optimization model, i.e., the DLMP price in each bus of the network, the simulator loops for every individual car to perform the next period's decision (i.e., 15 min). There are only two possible types of decisions: the decision to travel to a destination or a charging decision. Indeed, some trips take more than 15 min, so the car can just keep traveling for a certain number of periods. According to each user preference and behavior, decisions will be affected by the price and distance to the parking lot. Since, in a realistic scenario, some prefer extra comfort even if they pay more, e.g., choosing a fast charge or closer parking lot, the simulator allows defining this range of preferences for each car. These preferences will affect the efficacy of the dynamic EV charging prices, since individual behaviors may neglect lower prices. Nevertheless, our case study provides a different range of behavioral aspects to provide an accurate research outcome in this work.

To determine the dynamic EV charging price, the simulator uses the following Equation (1):

$$DEP = (DLMP + TariffMV + ACNR) \cdot PLG \cdot VAT \tag{1}$$

where:
DEP: Dynamic EV charging price for each period (€/kWh)
DLMP: Distribution locational marginal pricing (€/kWh)

TariffMV: Energy tariff price for each period (in the Case Study Section, the reader can find the energy tariff price for each considered period) (€/kWh)
PLG: Additional profit margin of the parking owner
VAT: Value-added tax
ACNR: Additional cost related to the fixed term of network price rate to be charged to the customer (€/kWh) and given by (2):

$$ACNR = \frac{\left(\frac{0.397 \cdot CP}{720}\right)}{OPR} \quad (2)$$

The contracted power cost is 0.397 €/kW/month, to be paid to the DSO monthly (www.erse.pt); the *CP* is the charging power of the parking lot; 720 are the hours per month; and *OPR* is the parking occupation rate. With the *ACNR* term added to Equation (1), the contracted power cost is transferred to the final consumer. Moreover, it is important to note that *OPR* is introduced to approximate the real occupation rate of each parking lot and thus affects the *ACNR* cost, which decreases for each customer as the *OPR* rate increases.

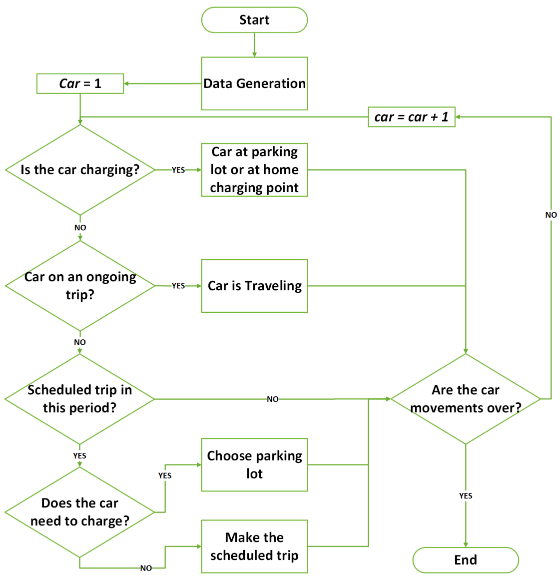

Figure 2. Flowchart for the EV users' behavior simulator.

The global parameters of the simulator are described in Table 1. These are permanent parameters in the simulation; however, their values can be modified according to the needs of each study. Since car travel is simulated using simplified mathematics for vehicle movement, parameter *cdist* represents the penalty on a given distance between two points, e.g., Origin A and Destination B, that the vehicle has to travel (trips). Ideally, the minimum distance to reach Destination B (e.g., work) would be the Euclidean distance; however, in a real-world scenario, the road network is not optimal in this sense. Parameter *sf* can be used to easily change the scale of the map and increase or decrease distances regarding a reference scenario. This allows easily studying the effects on the travel times and charging needs when the urban distance is varied. Parameter *hcpower* enables setting the amount of charge power available when users decide to charge at home. Parameter *chargineff* is the charging efficiency considered for the energy transactions with the electrical grid.

Table 1. Global simulator parameters.

Parameter	Description
ncars	Number of EVs
cdist	Distance increase between two Euclidean points
sf	Scale factor of the map
hcpower	Home charging power
chargineff	Charging mode efficiency

Table 2 describes the parameters related to the user profile, namely regarding the initial location of the car when the simulation begins and its location in subsequent steps. Each car in the simulation replicates the parameters depicted in this table. Among the defined parameters, the weights of *w1*, *w2*, and *ti* are significant. The weights correspond to the importance attributed to distance and price, respectively, while *ti* is used to prioritize trips, for instance going to work cannot be postponed. The weights allow the simulator to compute the behavioral score formula and in this way to decide where to charge the vehicle if needed. For users that give more preference to price while driving long distances in the quest for parking lots with lower charging prices, these prices are dynamic in time and space depending on the DLMP status of the grid. Users with $hc = 0$ cannot charge at home, but can charge at parking lots (street charging).

Table 2. User profile parameters.

Parameter	Description
Ilocation	Initial location of the car (usually home)
Clocation	Current location at period *j*
ISoC	Initial state of charge
CSoC	Current state of charge
ae	Car average economy
aeppkm	Car average economy percentage per kilometer
arp	Available range preference
times	Table with the times in which the scheduled trips will be made
as	Average speed
nd	Number of destinations each car has
dest1	Table with the coordinates of the places of the trips to be carried out
i	Boolean variable that determines whether the car will have more than one destination
w1, w2	Weights used in the calculation of the score to determine the best place for charging
ti	Table with the importance of each trip (1 being the least important and 3 the most)
hc	Boolean variable that determines whether the car has a home charger or not

2.2. DLMP-Based Network Operation

DLMP has been studied to provide electricity players with the effective economic signals for optimizing their assets. It is known that the resistance of the distribution network lines is higher than that of transmission lines. Thus, the distribution system losses can be considered one of the main factors that affect the DLMP.

bus voltage regulation is a critical issue, especially with DER proliferation, that is faced by the DSO. Therefore, the DLMP could reflect the voltage impact on the distribution system's economical operation.

In the proposed methodology, DLMP is defined through Lagrangian multipliers of the corresponding constraints (power balance) of the optimization problem, whose goal is to minimize the DSO expenditures.

The distribution network operation and reconfiguration problem in an SG context with high DER penetration concerning the behavior aspects of the EV users and dynamic EV charging price considering DLMPs is classified as MINLP due to the nonlinearity features. To solve complex problems like this, the Benders decomposition is an adequate technique [80,81]. This technique was presented in 1962 by Jacobus Franciscus Benders to solve mixed integer problems [82]. This method is based on the principle that the main problem can be decomposed into sub-problems. The Benders decomposition technique uses duality theory in linear and nonlinear mathematical programming to split a problem whose resolution is difficult into sub-problems [80]. These sub-problems consider specific variables that are solved iteratively until the optimal solution is reached [83].

The problem can be divided into subproblems (a master problem and one or more slave problems). The master subproblem is usually a linear or mixed integer problem including fewer technical constraints. On the other hand, slave subproblems are linear or nonlinear and attempt to validate if the solution of the master problem is technically feasible or not. At this level, the network's technical constraints are considered. A flowchart of the Benders decomposition technique used in this proposed research work is presented in Figure 3, and the diagram of the DLMP-based distribution network operation/reconfiguration model is presented in Figure 4. In Sections 2.2.1 and 2.2.2, the explanation of the Benders decomposition procedure is discussed.

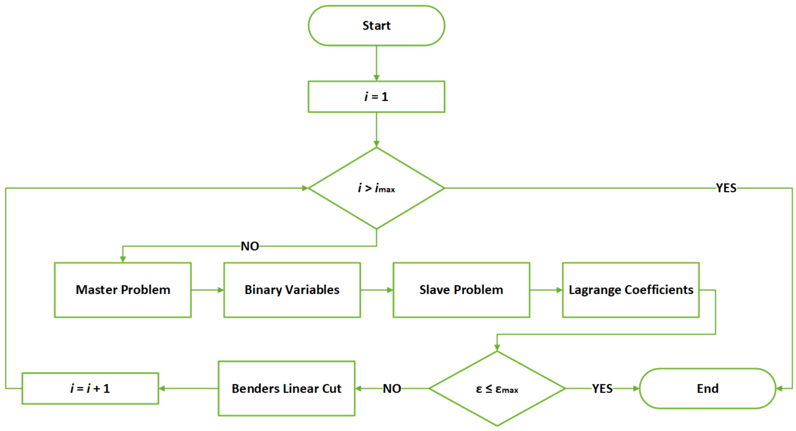

Figure 3. The Benders decomposition flowchart.

This work deals with a non-convex and non-linear slave subproblem (namely in the power flow equations) in which the zero-duality gap is not guaranteed. Thus, the Benders decomposition technique applied in this research work could not converge to the optimal solution. However, most of the science and engineering mathematical problems are non-convex with a very small duality gap in most of the cases [83]. Moreover, the convexity is a solid mathematical assumption, and the convexity is not necessarily restrictive from the practical viewpoint, as many science and engineering problems in the region where the solution of the interest is located are convex; in other words, where the solution is meaningful from the viewpoint of the science and engineering [83].

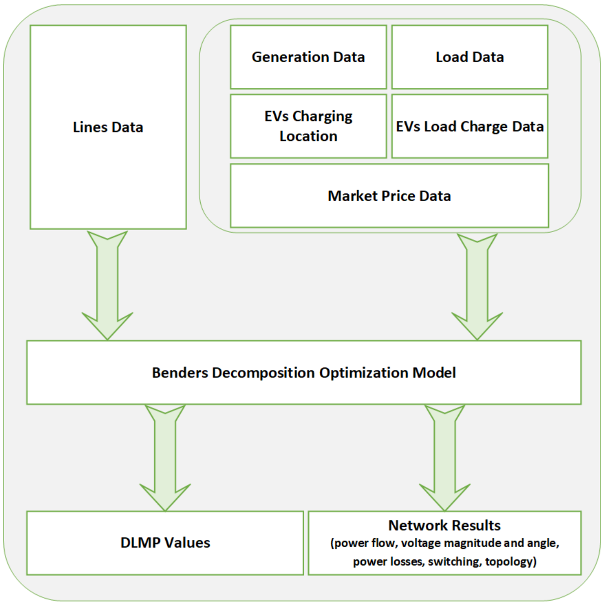

Figure 4. Diagram of the distribution operation optimization model.

2.2.1. Master Problem

The master subproblem goal consists of finding the network topology configuration for each considered period by opening/closing tie-switches (using binary variables {0,1}) to:

- Minimize the power losses' cost;
- Minimize the power not supplied cost;
- Minimize the lines' congestion cost;
- Minimize the power generation curtailment cost;
- Minimize the power from external suppliers' cost.

At this level, every binary variables must be included in the optimization problem. The master subproblem objective function minimizes the operation cost (MOC) and can be formulated as (3):

$$MOC = \begin{bmatrix} \sum\limits_{i \in \Omega_B} \sum\limits_{j \in \Omega_B} \left[\left(CongM_{(i,j)}^2 + CongM_{(i,j)} \right) \cdot Cost^{Cong} \right] + \\ \sum\limits_{i \in \Omega_{BS}^b} \left(ExtSup_{(i)} \cdot price^{Mk} \right) + \\ \sum\limits_{i \in \Omega_L^b} \left(PNSM_{(i)} \cdot Cost^{PNS} \right) + \\ \sum\limits_{i \in \Omega_B} \sum\limits_{j \in \Omega_B} \left(r_{(i,j)} \cdot FlowM_{(i,j)}^2 \cdot Cost^{Loss} \right) + \\ \sum\limits_{i \in \Omega_{DG}^{nd}} \left(P_{PGCM(i)} \cdot P_{PGC}^{Cost} \right) + \omega^* \end{bmatrix} \quad (3)$$

In the case of infeasibility, one variable is added to the master problem (ω^*), which is called linear Benders' cuts. In ideal circumstances, the value for this variable is zero, which means that the network topology along with its components fulfills every technical constraint. Otherwise, the value presented in this variable represents the minimal value cost change of the master solution.

The master subproblem (3) is subjected to constraints (4)–(25).

Network constraints

Power balance: First Kirchhoff law

Constraint (4) guarantees the power balance in each distribution network bus.

$$\begin{array}{l} \sum\limits_{i \in \Omega_{DG}^{nd}} \left(p_{DG(i)} - p_{PGCM(i)} \right) + \sum\limits_{i \in \Omega_{BS}^b} ExtSup_{(i)} - \\ \sum\limits_{i \in \Omega_L^b} \left(p_{Load(i)} - PNSM_{(i)} \right) - \sum\limits_{i \in \Omega_V^b} EVP_{(i)} + \\ \sum\limits_{i \in \Omega_E^b} \left(STdchM_{(i)} - STchM_{(i)} \right) + \\ \sum\limits_{i \in \Omega_B} \left(FlowM_{(i,j)} - FlowM_{(j,i)} \right) = 0 \quad \forall j \in \Omega_B \end{array} \quad (4)$$

Maximum admissible line flow

The maximum power flowing in each line of the network is guaranteed by (5).

$$0 \leq FlowM_{(i,j)} \leq Flow_{(i,j)}^{\max} \cdot X_{(i,j)}^{stat} \quad \forall X^{stat} \in \{0,1\}, \forall (i,j) \in \Omega_l \quad (5)$$

Unidirectionality of power flow

Constraint (6) guarantees unidirectionality between buses *i* and *j*.

$$X_{(i,j)}^{stat} + X_{(j,i)}^{stat} \leq 1 \quad \forall X^{stat} \in \{0,1\}, \forall (i,j) \in \Omega_l \quad (6)$$

Radial topology

To ensure the radial topology, Constraint (7) is applied. This constraint imposes that only one line can enter in each bus.

$$\sum_{j \in \Omega_j^b} X_{(i,j)}^{stat} = 1 \quad \forall X^{stat} \in \{0,1\}, \forall i \in \Omega_B \quad (7)$$

Avoid island creation

To avoid DG isolation from the substation, the constraints (8)–(11) are used. A fictitious flow ($d_{(i,j)}$) is created with a fictitious load of each DG ($D_{(g)}$) to be fed to the substation. If the island is permitted, the operator can omit these constraints.

$$\sum_{i\in\Omega_B}\sum_{j\in\Omega_B} d_{(i,j)} - \sum_{i\in\Omega_B}\sum_{j\in\Omega_B} d_{(j,i)} - D_{(g)} = 0 \quad \forall g \in \Omega_{DG} \tag{8}$$

$$D_{(g)} = 1 \quad \forall g \in \Omega_{DG} \tag{9}$$

$$D_{(g)} = 0 \quad \forall g \notin \Omega_{DG} \cup \Omega_{BS} \tag{10}$$

$$\left| d_{(i,j)} \right| \leq nDG \cdot X^{stat}_{(i,j)} \quad \forall (i,j) \in \Omega_l \tag{11}$$

Supplier constraint

Maximum and minimum limits for power supplier

The power is constrained by the maximum and minimum capacity that can be supplied (12).

$$ExtSup_{MinLimit(bs)} \leq ExtSup_{(bs)} \leq ExtSup_{MaxLimit(bs)} \quad \forall bs \in \Omega_{BS} \tag{12}$$

Curtailment constraints

Power generation curtailment

The power generation curtailment is verified when the excess generation of the generator g occurs. This variable is lower or equal to the power generation of the g generator (13).

$$0 \leq p_{PGCM(g)} \leq p_{DG(g)} \quad \forall g \in \Omega^{nd}_{DG} \tag{13}$$

Power not supplied

Constraint (14) guarantees that the power not supplied variable must be lower than or equal to the load demand.

$$0 \leq PNSM_{(lo)} \leq p_{Load(lo)} \quad \forall lo \in \Omega^b_L \tag{14}$$

Lines' congestion

Lines' power congestion

The power congestion in each line is constrained by Equation (15). In this work, we assume that the congestion occurs when the power flow $Flow_{(i,j)}$ is greater than or equal to a factor value ($CongMin$) multiplied by the maximum power line capacity ($Flow^{max}_{(i,j)}$). The factor value is a constant value between zero and one. In fact, this value represents the percentage of the line capacity that is being used. Equation $Cong_{(i,j)} \geq 0$ is used to ensure a positive or a zero value for $Cong_{(i,j)}$.

$$\begin{aligned} &CongM_{(i,j)} \geq FlowM_{(i,j)} - CongMin \cdot Flow^{max}_{(i,j)} \quad \forall (i,j) \in \Omega_l \\ &Cong_{(i,j)} \geq 0 \end{aligned} \tag{15}$$

Energy storage systems (ESS) constraints

Discharge limit for the energy storage systems

The maximum discharge limit of each ESS is represented by the constraint (16).

$$STdchM_{(e)} \leq STdchR_{(e)} \cdot STdM^{stat}_{(e)} \quad \forall e \in \Omega^b_E, STdM^{stat} \in \{0,1\}, STdchM \geq 0 \tag{16}$$

Charge limit for the energy storage systems

The maximum charge limit for each ESS is represented by the constraint (17).

$$STchM_{(e)} \leq STchR_{(e)} \cdot STcM_{(e)}^{stat} \quad \forall e \in \Omega_E^b, STcM^{stat} \in \{0,1\}, STchM \geq 0 \tag{17}$$

Discharge level limit considering the state of the energy storage system

The maximum discharge limit considering energy storage systems' capacity constraint for each ESS is given by (18). The Δt is represented in units of hours.

$$STdchM_{(e)} \cdot \frac{1}{def_{(e)}} \leq STdM_{(e)}^{stat} \cdot STstoM_{(e)} \cdot \frac{1}{\Delta t} \quad \forall e \in \Omega_E^b, STdM^{stat} \in \{0,1\}, STdchM \geq 0 \tag{18}$$

Charge level limit considering energy storage systems' capacity

The maximum charge limit considering energy storage systems' capacity constraint for each ESS is given by (19). The Δt is represented in units of hours.

$$\begin{gathered} STstoM_{(e)} + STchM_{(e)} \cdot cef_{(e)} \cdot \Delta t \leq STcM_{(e)}^{stat} \cdot STcap_{(e)} \\ \forall e \in \Omega_E^b, STcM^{stat} \in \{0,1\}, STchM \geq 0 \end{gathered} \tag{19}$$

State of charge of the energy storage systems

The state of charge of each ESS is given by (20). The Δt is represented in units of hours.

$$\begin{gathered} STstoM_{(e)} - \left(\Delta t \cdot STchM_{(e)} \cdot cef_{(e)}\right) + \left(\Delta t \cdot STdchM_{(e)} \cdot \tfrac{1}{def_{(e)}}\right) = STstoM_{(e)}^{t-1} \\ \forall e \in \Omega_E^b, STchM \geq 0, STdchM \geq 0 \end{gathered} \tag{20}$$

Maximum ESS capacity limit

The maximum capacity limit of each ESS is represented by (21).

$$STstoM_{(e)} \leq STcap_{(e)} \tag{21}$$

Minimum ESS capacity limit

The minimum capacity limit of each ESS is represented by (22).

$$STstoM_{(e)} \geq STstoM_{(e)}^{\min} \tag{22}$$

Charging and discharging status

The charging and discharging status of the ESSs are represented by $STcM_{(e)}^{stat}$ and $STdM_{(e)}^{stat}$, respectively. Charging and discharging cannot occur simultaneously (23).

$$STcM_{(e)}^{stat} + STdM_{(e)}^{stat} \leq 1 \tag{23}$$

where $STcM_{(e)}^{stat}$ is a binary variable. ESS are able to charge at any moment.

$STdM_{(e)}^{stat}$ is a variable that assumes zero or one according to the study period market price value and is given by (24).

$$\begin{gathered} STdM_{(e)}^{stat} = 1 \iff price^{Mk} \geq price_{\min}^{Mk} \\ STdM_{(e)}^{stat} = 0 \iff price^{Mk} \leq price_{\min}^{Mk} \end{gathered} \tag{24}$$

Linear Benders' cut

To support the decomposition technique, a linear cuts constraint (25) is used. This constraint represents feasibility cuts in the problem. These cuts are updated in each iteration applying new constraints to the problem. The linear cuts establish the link between the master subproblem and the slave subproblem. To better understand, let us imagine the existence of a cut. Thus, the master subproblem receives and considers the infeasibility data costs of the previous iteration ω^* and the sensitivities $\lambda_{(i,j)}^{m-1}$ and $\mu_{(i)}^{m-1}$. Those sensitivities are linked to the subproblem master decision in the previous iteration $\left(X_{(i,j)}^{stat}\right)^{m-1}$ and $\left(STcM_{(i)}^{stat}\right)^{m-1}$ already known. To make a new decision, the master subproblem is fed these new data.

$$\begin{aligned}
&\omega^* \geq Z_{up}^{m-1} + \\
&\sum_{i\in\Omega_B} \sum_{\substack{j\in\Omega_B \\ j\neq i}} \lambda_{(i,j)}^{m-1} \cdot \left[\left(X_{(i,j)}^{stat}\right)^{m} - \left(X_{(i,j)}^{stat}\right)^{m-1} \right] + \\
&\sum_{i\in\Omega_{BS}^{b}} \mu_{(i)}^{m-1} \cdot \left[\left(STcM_{(i)}^{stat}\right)^{m} - \left(STcM_{(i)}^{stat}\right)^{m-1} \right]
\end{aligned} \tag{25}$$

where index *m* represents the current iteration and *m-1* represents the previous iteration.

2.2.2. Slave problem

One of the goals of the slave subproblem is to verify the feasibility of the master problem. Moreover, through AC optimal power flow, the slave subproblem provides the optimal value for the operation variables. The slave subproblem objective function is represented by (26), where the operation costs and the slack variables ZA, ZQ, and ZF are minimized. Slack variables ZA and ZQ (for active and reactive power balance) and ZF (for thermal lines capacity) can take any positive value to make the optimization problem feasible. The value of these variables represents how much some constraints are being violated. The slave sub-problem cannot change the binary variables, but is free to explore the continuous variables in order to satisfy the several constraints, while minimizing the objective function and the value of the slack variables.

$$SOC = \left[\begin{array}{l}
\sum_{i\in\Omega_B} \sum_{j\in\Omega_B} \left[\left(CongS_{(i,j)}^2 + CongS_{(i,j)} \right) \cdot Cost^{Cong} \right] + \\
\sum_{i\in\Omega_{BS}^{b}} \left(P_{Supplier(i)} \cdot price^{Mk} \right) + \\
\sum_{i\in\Omega_{L}^{b}} \left(PNSs_{(i)} \cdot Cost^{PNS} \right) + \\
\sum_{i\in\Omega_{DG}^{nd}} \left(P_{PGCs(i)} \cdot P_{PGC}^{Cost} \right) + \\
\sum_{i\in\Omega_B} \sum_{j\in\Omega_B} \left(SLoss_{(i,j)} \cdot Cost^{Loss} \right) + \\
\sum_{i\in\Omega_B} \left(ZA_{(i)} + ZQ_{(i)} \right) \cdot Cost^{Inf} + \\
\sum_{i\in\Omega_B} \sum_{\substack{\in\Omega_B \\ \neq i}} \left(ZF_{(i,j)} \cdot Cost^{Inf} \right)
\end{array}\right] \tag{26}$$

The slave subproblem (26) is subjected to Constraints (27)–(52).

Network constraints

Voltage magnitude

The voltage magnitude of each bus is constrained by a maximum and minimum deviation (27).

$$V_{(i)}^{min} \leq V_{(i)} \leq V_{(i)}^{max} \qquad \forall i \in \Omega_B \tag{27}$$

Voltage angle

The maximum and minimum angle deviation is constrained by (28).

$$\theta_{(i)}^{min} \leq \theta_{(i)} \leq \theta_{(i)}^{max} \qquad \forall i \in \Omega_B \tag{28}$$

Active power balance

Constraint (29) guarantees the active power balance in each distribution network bus.

$$\begin{aligned}
&\sum_{i \in \Omega_{DG}^{nd}} \left(P_{DG(i)} - P_{PGCs(i)} \right) + \sum_{i \in \Omega_{BS}^{b}} P_{Supplier(i)} - \\
&\sum_{i \in \Omega_{L}^{b}} \left(P_{Load(i)} - PNSs_{(i)} \right) - \sum_{i \in \Omega_{V}^{b}} EVP_{(i)} + \\
&\sum_{i \in \Omega_{BS}^{b}} \left(STdchS_{(i)} - STchS_{(i)} \right) - \\
&\sum_{i \in \Omega_{B}} P_{Inj(i)} + ZA_{(i,j)} = 0
\end{aligned} \tag{29}$$

Reactive power balance

Constraint (30) guarantees the reactive power balance in each distribution network bus.

$$\begin{aligned}
&\sum_{i \in \Omega_{BS}^{b}} Q_{Supplier(i)} + \sum_{i \in \Omega_{CB}^{b}} Q_{Cbanks(i)} - \sum_{i \in \Omega_{L}^{b}} Q_{Load(i)} - \\
&\sum_{i \in \Omega_{B}} Q_{Inj(i)} + ZQ_{(i,j)} = 0
\end{aligned} \tag{30}$$

Injected active power

This Equation (31) represents the injected active power in each bus of the network.

$$P_{Inj(i)} = V_{(i)} \sum_{j \in \Omega_B} V_{(j)} \left(G_{(i,j)} \cdot \cos\theta_{(i,j)} + B_{(i,j)} \cdot \sin\theta_{(i,j)} \right) \qquad \forall i \in \Omega_B, \forall (i,j) \in \Omega_l \tag{31}$$

Injected reactive power

The injected reactive power in each bus is represented by the Equation (32).

$$Q_{Inj(i)} = V_{(i)} \sum_{j \in \Omega_B} V_{(j)} \left(G_{(i,j)} \cdot \sin\theta_{(i,j)} - B_{(i,j)} \cdot \cos\theta_{(i,j)} \right) \qquad \forall i \in \Omega_B, \forall (i,j) \in \Omega_l \tag{32}$$

Active power flow

The active power flow for each network line is given by the Equation (33).

$$\begin{aligned}
&P_{(i,j)} = (V_{(i)}^2 - V_{(i)} \cdot V_{(j)} \cdot \cos\theta_{(i,j)}) \cdot G_{(i,j)} - (V_{(i)} \cdot V_{(j)} \cdot \mathrm{sen}\theta_{(i,j)}) \cdot B_{(i,j)} \\
&\forall i \in \Omega_B, \forall j \in \Omega_B, \forall (i,j) \in \Omega_l
\end{aligned} \tag{33}$$

Reactive power flow

Equation (34) gives the reactive power flow for each line.

$$Q_{(i,j)} = -(V_{(i)}^2 - V_{(i)} \cdot V_{(j)} \cdot \cos\theta_{(i,j)}) \cdot B_{(i,j)} - (V_{(i)} \cdot V_{(j)} \cdot \text{sen}\theta_{(i,j)}) \cdot G_{(i,j)}$$
$$\forall i \in \Omega_B, \forall j \in \Omega_B, \forall (i,j) \in \Omega_l \tag{34}$$

Apparent power flow

The apparent power flow equation, as can be seen in Equation (35), is given by the square root of the active power flow and reactive power flow squares.

$$S_{(i,j)} = \sqrt{P_{(i,j)}{}^2 + Q_{(i,j)}{}^2} \qquad \forall (i,j) \in \Omega_l \tag{35}$$

Active power losses

The active power loss of each line is represented by Equation (36).

$$PLoss_{(i,j)} = \frac{P_{(i,j)}^2 + Q_{(i,j)}^2}{V_{(i)}^2} \cdot r_{(i,j)} \qquad \forall i \in \Omega_B,\ \forall (i,j) \in \Omega_l \tag{36}$$

Reactive power losses

To represent the reactive power loss, the following Equation (37) is used.

$$QLoss_{(i,j)} = \frac{P_{(i,j)}^2 + Q_{(i,j)}^2}{V_{(i)}^2} \cdot x_{(i,j)} \qquad \forall i \in \Omega_B,\ \forall (i,j) \in \Omega_l \tag{37}$$

Apparent power loss

To obtain the apparent power loss in each line, the following equation is used (38).

$$SLoss_{(i,j)} = \sqrt{PLoss_{(i,j)}^2 + QLoss_{(i,j)}^2} \qquad \forall (i,j) \in \Omega_l \tag{38}$$

Maximum admissible line flow

The maximum power flow in each line is constrained by (39).

$$0 \leq FlowS_{(i,j)} \leq Flow_{(i,j)}^{max} + ZF_{(i,j)} \qquad \forall (i,j) \in \Omega_l \tag{39}$$

Supplier constraints

Maximum and minimum limits for active power supplier

The active power is constrained by the maximum and minimum capacity that can be supplied (40).

$$P_{SMinLimit(bs)} \leq P_{Supplier(bs)} \leq P_{SMaxLimit(bs)} \qquad \forall bs \in \Omega_{BS} \tag{40}$$

Maximum and minimum limits for the reactive power supplier

The reactive power is constrained by the maximum and minimum capacity that can be supplied (41).

$$Q_{SMinLimit(bs)} \leq Q_{Supplier(bs)} \leq Q_{SMaxLimit(bs)} \qquad \forall bs \in \Omega_{BS} \tag{41}$$

Maximum and minimum limits for capacitor banks

The reactive power of a capacitor bank is considered a continuous variable in this model and is constrained by the maximum and minimum (zero) capacity that can be supplied (42).

$$0 \leq Q_{Cbanks(cb)} \leq Q^{\max}_{Cbanks(cb)} \qquad \forall cb \in \Omega_{CB} \tag{42}$$

Curtailment constraints

Power generation curtailment

Power generation curtailment occurs when the generator generates an excess of power g. This variable cannot be higher than the generation of the g generator (43).

$$0 \leq P_{PGCs(g)} \leq P_{DG(g)} \qquad \forall g \in \Omega^{nd}_{DG} \tag{43}$$

Power not supplied

Constraint (44) guarantees that the power not supplied variable must be lower or equal to the load demand.

$$0 \leq PNSs_{(lo)} \leq P_{Load(lo)} \qquad \forall lo \in \Omega^{b}_{L} \tag{44}$$

Lines' congestion

Lines' power congestion

The power congestion in each line is constrained by the Equation (45). The same considerations are taken into account in (15) and in (45).

$$\begin{aligned} &Cong_{(i,j)} \geq FlowS_{(i,j)} - CongMin \cdot Flow^{max}_{(i,j)} \qquad \forall (i,j) \in \Omega_{l} \\ &Cong_{(i,j)} \geq 0 \end{aligned} \tag{45}$$

Energy storage system constraints

Discharge limit of the energy storage systems

The maximum discharge limit determined by the constraint of each ESS (46).

$$STdchS_{(e)} \leq STdchR_{(e)} \qquad \forall e \in \Omega^{b}_{E}, STdchS \geq 0 \tag{46}$$

Charge level limit for the energy storage systems

The maximum charge level limit determined by the constraint of each ESS (47).

$$STchS_{(e)} \leq STchR_{(e)} \qquad \forall e \in \Omega^{b}_{E}, STchS \geq 0 \tag{47}$$

Discharge limit considering energy storage systems' state

The maximum discharge limit considering the capacity constraint of each energy storage system (48). Δt is represented in units of hours.

$$STdchS_{(e)} \cdot \frac{1}{def_{(e)}} \leq STstoS_{(e)} \cdot \frac{1}{\Delta t} \qquad \forall e \in \Omega^{b}_{E}, STdchS \geq 0 \tag{48}$$

Charge limit considering energy storage systems' capacity

The maximum charge level limit is determined considering the capacity constraint of each energy storage system (49). The Δt is represented in units of hours.

$$STstoS_{(e)} + STchS_{(e)} \cdot cef_{(e)} \cdot \frac{1}{\Delta t} \leq STcap_{(e)} \quad \forall e \in \Omega_E^b, STchS \geq 0 \tag{49}$$

State of charge of the energy storage systems

The state of charge of each ESS is given by (50). Δt is represented in units of hours.

$$\begin{aligned} &STstoS_{(e)} - \left(\Delta t \cdot STchS_{(e)} \cdot cef_{(e)}\right) + \left(\Delta t \cdot STdchS_{(e)} \cdot \frac{1}{def_{(e)}}\right) = STstoS_{(e)}^{t-1} \\ &\forall e \in \Omega_E^b, STchS \geq 0, STdchS \geq 0 \end{aligned} \tag{50}$$

Maximum energy storage systems' capacity limit

The maximum capacity limit for each ESS is represented by (51).

$$STstoS_e \leq STcap_{(e)} \quad \forall e \in \Omega_E^b \tag{51}$$

Minimum energy storage systems' capacity limit

The minimum capacity limit for each ESS is represented by (52).

$$STstoS_{(e)} \geq STstoS_{(e)}^{\min} \quad \forall e \in \Omega_E^b \tag{52}$$

3. Case Study

To show how the proposed methodology is applied, a medium voltage (MV) distribution network of an SC (mock-up) located at BISITE laboratory has been developed for this study (the schematic of the SC is presented in Figure 5, and the coordinates of each building can be seen in Table 3). In this case study, a high DER penetration is considered to represent a realistic scenario in the near future. The single-line diagram of the 13-bus 30-kV distribution network is presented in Figure 6.

Table 3. Building coordinates on the xy plane.

Building		L1	L2	L3	L4 to L18	L19	L20	L21	L22	L23	L24	L25	PL1 to PL2	PL3 to PL4	PL5 to PL6	PL7
Coordinates (km)	X Axis	10.50	0.50	9.00	3.75 to 8.25	0.50	0.50	2.50	3.00	4.50	6.00	8.00	1.00	7.00	6.00	11.00
	Y Axis	3.50	2.00	5.00	1.00 to 3.00	3.50	5.50	2.00	4.50	3.50	5.00	4.00	3.50	5.00	0.50	4.00

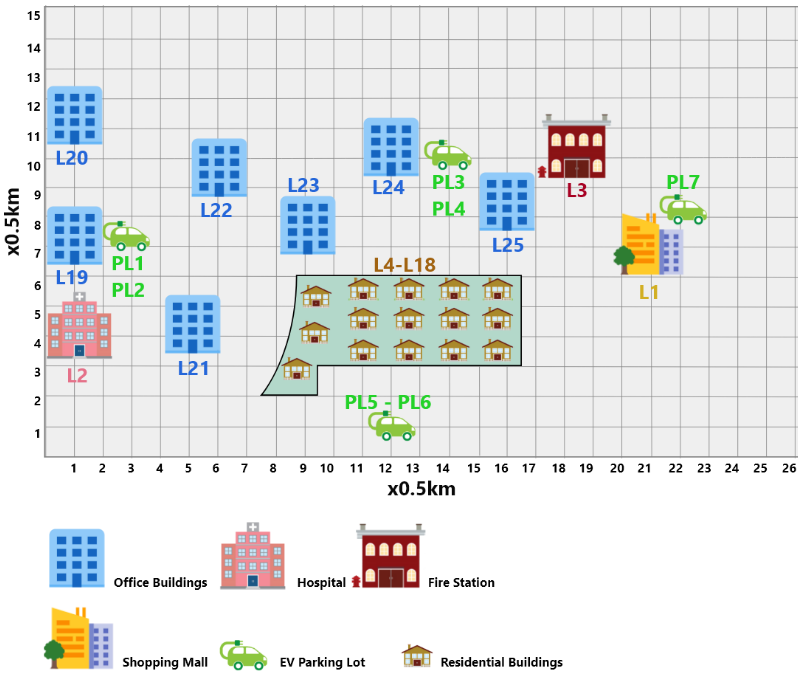

Figure 5. Smart city schematic.

This DN has one 30 MVA substation, 25 load points, and 3 ×35.88 km of underground cables. For the connections between the substation and the network (bus 1 to bus 2; bus 1 to bus 7), a cable of type LBHIOV 3 × 150 mm^2 (svrweb.cabelte.pt) has been used, while for the remaining connections, the cable type LBHIOV 3 × 70 mm^2 (svrweb.cabelte.pt) has been used. A total of 15 DG units (i.e., two wind farms and 13 PV parks) and four capacitor banks of 1 Mvar are included in the network, as can be seen in Figure 6.

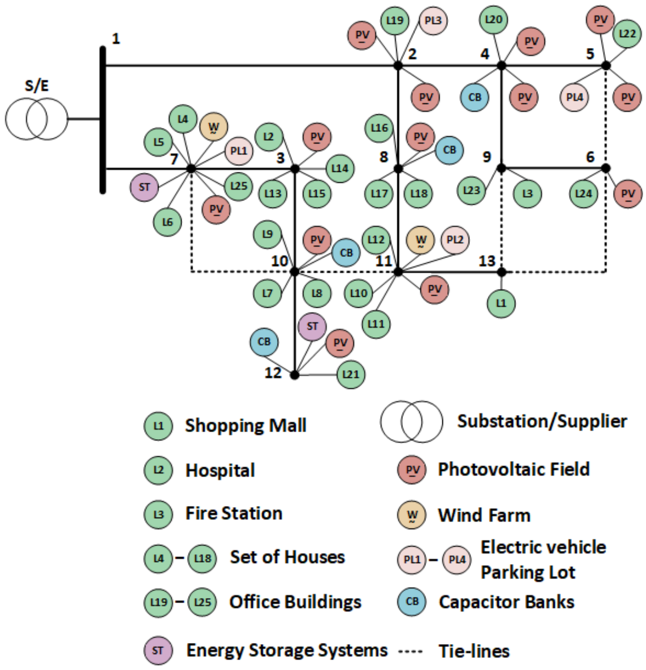

Figure 6. Single-line diagram of the 13-bus distribution network.

The DG penetration corresponds to 27% (10.925 MW) of the total installed power (24% corresponds to wind generation and 3% to PV). Each wind farm has six E48 800 kW ENERCON wind turbines (www.enercon.de). The characteristics of PV parking lots are presented in Table 4. The line congestion cost was 0.02 €/kW when power flow was above 50% of the thermal line rating capacity (*CongMin*).

The considered smart city presents five types of loads, namely:

- Residential buildings (1375 homes);
- Office buildings (seven buildings);
- Hospital;
- Fire Station;
- Shopping Mall.

Table 4. PV characteristics.

Nominal Power (W)	85.00
Short Circuit Current (A)	1.62
Nominal Operating Temperature of the Cell (°C)	45.00
Open Circuit Voltage (V)	56.70
Current at the Maximum Power Point (A)	1.41
Voltage at the Maximum Power Point (V)	45.50
Voltage High Temperature Coefficient (>25 °C) (V/°C)	−0.1531
Voltage Low Temperature Coefficient (−40 °C to 25 °C) (V/°C)	−0.1134
Current Temperature Coefficient (A/°C)	6.4800×10^{-4}
PV park at bus 12	
Number of Modules	104
Number of Panels	120
Total Number of Modules	12,480
PV parks at Buses 2–8, 10, and 11	
Number of Modules	104
Number of Panels	30
Total Number of Modules	3120

This study considered one week of input data for every 15-min period with the aim of showing the effectiveness of the proposed methodology (i.e., 672 periods were considered in the simulation process). The chosen week was 19 March 2017–25 March 2017. The total renewable generated power for each period is presented in Figure 7.

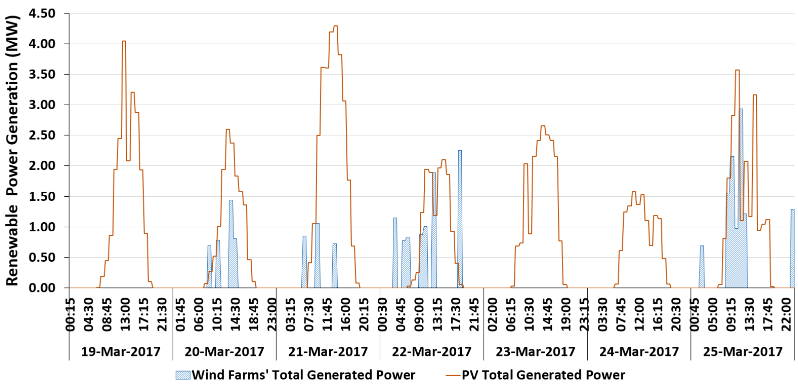

Figure 7. Renewable power generation.

Figures 8 and 9 present the power demand and the roof generation, respectively, of the office buildings, residential buildings, a shopping mall, a hospital, and a fire station. It is important to note that the power demand presented in these two figures corresponds to the subtraction of the initial demand for PV power generation, i.e., all the power generated by the PVs is consumed by the building. The generated power is therefore not sent to the grid in the present study.

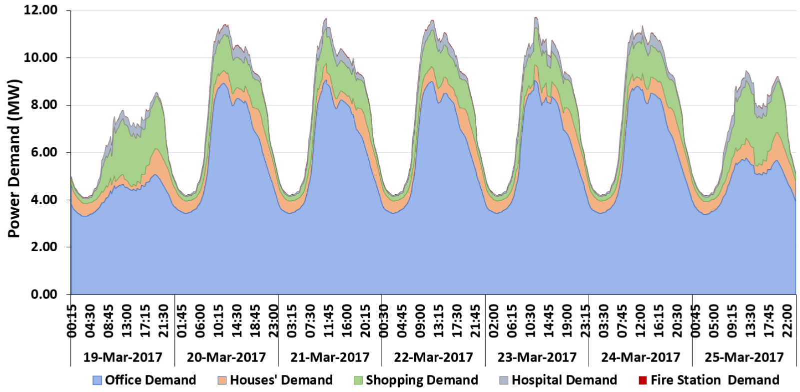

Figure 8. Power demand from office, residential, hospital, fire station, and shopping mall buildings.

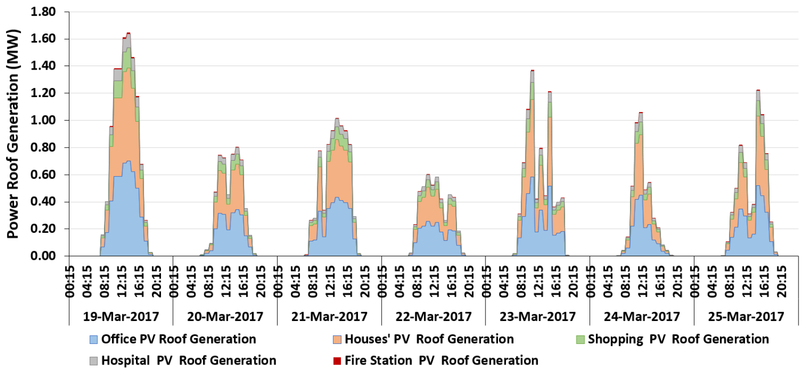

Figure 9. Roof PV generation from office, residential, hospital, fire station, and shopping mall buildings.

The market price for the chosen week was obtained from the Iberian electricity market operator (OMIE) (www.datosdelmercado.omie.es/pt-pt/datos-mercado) and can be seen in Figure 10.

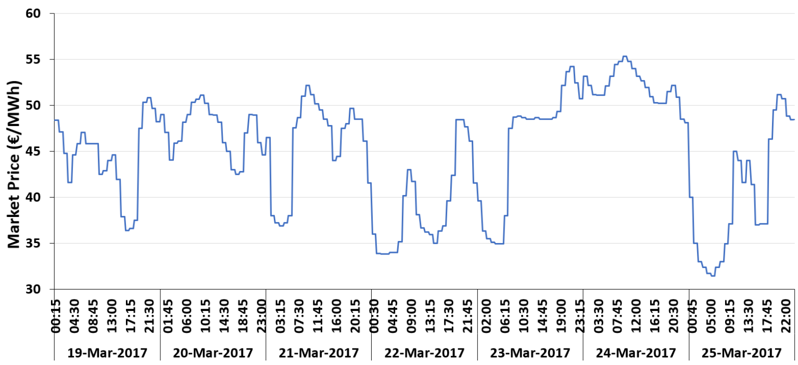

Figure 10. Market price.

Moreover, the SC has seven parking lot buildings for EV charging, four (two in bus 7 and two in bus 11) slow charging lots (7.2 kW for each connection point) and three (two in bus 2 and one in bus 5) fast charging lots (50 kW for each connection point). Each slow charging parking lot has 250 spaces for EVs, while each fast charging parking lot has 80 spaces. In this case study, we assumed that each parking lot had a 30% occupation rate (OPR). Thus, in the following equation (2), the additional cost related to the fixed term of network price rate to be charged to the customer (ACNR) for a slow charging parking space is 0.0132 €/kWh, while for a fast charging parking space, it is 0.0919 €/kWh. Furthermore, the parking owner charges an additional 5% fee and 23% of value-added tax (VAT). Moreover, consider that 50% of the EV users can charge their EV at home (3.7 kW charge point) with a fixed cost of 0.2094 €/kWh. A total of 5000 EVs were considered in this study, and the initial battery level was randomly generated between 40% and 65% of the battery capacity. The considered EV models and their characteristics are listed in Table 5. The weights ($w1$ and $w2$) attributed to the distance and price preference are presented in Tables 6 and 7, respectively. Two possible scenarios are considered: in one, the user's priority is to charge his/her EV at a charging station located as close as possible to them (Table 6); in the second scenario, the users prefer to find charging stations where they can charge their EV at a low price (Table 7).

Table 5. EV types.

Model	Battery (kWh)	Slow Charge Power (kW)	Fast Charge Power (kW)	Consumption (kWh/km)
Nissan Leaf	40.00	6.60	50.00	0.1553
Tesla Model S 70D	75.00	7.40	50.00	0.2100
BMW i3	33.20	7.40	50.00	0.1584
Renault Zoe	41.00	7.40	-	0.1460
Renault Kangoo	33.00	7.40	-	0.1926
VW e-Golf	24.20	7.20	40.00	0.1584
Ford Focus	33.50	6.60	50.00	0.1926
Hyundai IONIQ	30.50	6.60	50.00	0.1429

Table 6. Weights for the user distance preference scenario.

Preference	Weight (%)		Probability (%)
	w1	w2	
Price	40	60	30
Distance	**85**	**15**	**70**

Table 7. Weights for the user price preference scenario.

Preference	Weight (%)		Probability (%)
	w1	w2	
Price	**15**	**85**	**70**
Distance	60	40	30

Furthermore, two energy storage systems managed by the DSO were considered in the present case study, each one with 1 MWh of capacity and 0.5 MW of charge/discharge rate. Moreover, in this case, the ESS are able to charge at any moment and discharge when the energy market price is greater than or equal to 45 €/MWh. Is assumed that the ESS had a minimum of 5% of power stored, i.e., the power stored in the ESS cannot be less than 5%. The input data used in the case study can be found by the readers in [84].

In this research work, thirty different case studies were performed. Table 8 summarizes the characteristics of those studies. They have been divided into two types of EV user preference scenarios, namely the price preference scenario and distance preference scenario. For each of those scenarios, we considered DG, EV, ESS, dynamic EV charging price, and fixed prices (with three different price levels) and combined them in the case study. The purpose of these case studies was to determine in which situations dynamic charging prices were advantageous for DSO and EV users.

Table 8. Case study sets.

	User Price Preference Scenario							User Distance Preference Scenario						
	DG	EV	ESS	Dynamic EV Charging Price	Fixed Price (€/kWh)			DG	EV	ESS	Dynamic EV Charging Price	Fixed Price (€/kWh)		
					SCh= 0.15 FCh= 0.25	SCh = 0.2 FCh = 0.3	SCh = 0.3 FCh = 0.4					SCh = 0.15 FCh = 0.25	SCh = 0.2 FCh = 0.3	SCh = 0.3 FCh = 0.4
Case A	No	No	No	Yes	No	No	No	No	No	No	Yes	No	No	No
Case B	Yes	No	No	Yes	No	No	No	Yes	No	No	Yes	No	No	No
Case C	Yes	No	Yes	Yes	No	No	No	Yes	No	Yes	Yes	No	No	No
Case D	No	Yes	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No
Case E	No	Yes	No	No	Yes	No	No	No	Yes	No	No	Yes	No	No
Case F	No	Yes	No	No	No	Yes	No	No	Yes	No	No	No	Yes	No
Case G	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Yes
Case H	Yes	Yes	No	Yes	No	No	No	Yes	Yes	No	Yes	No	No	No
Case I	Yes	Yes	No	No	Yes	No	No	Yes	Yes	No	No	Yes	No	No
Case J	Yes	Yes	No	No	No	Yes	No	Yes	Yes	No	No	No	Yes	No
Case K	Yes	Yes	No	No	No	No	Yes	Yes	Yes	No	No	No	No	Yes
Case L	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	No	No	No
Case M	Yes	Yes	Yes	No	Yes	No	No	Yes	Yes	Yes	No	Yes	No	No
Case N	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes	No	No	Yes	No
Case O	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Yes	No	No	No	Yes

4. Results and Discussion

The proposed methodology has been applied to the case study presented in Section 3 to show its applicability. The proposed research work has been developed on a computer with one Intel Xeon E5-2620 v2 processor and 16 GB of RAM running Windows 10 Pro using the MATLAB R2016a and TOMLAB 8.1 64 bits with CPLEX and SNOPT solvers. As can be seen in Table 9, in each period, the optimization model dealt with the master problem, which had 566 constraints and 744 variables, where 171 were integer variables, and with the slave problem, which had 199 constraints (116 non-linear constraints) and 286 variables.

Table 9. Computational execution results.

Problem Level	Constraints			Number of Variables Per Period			Average Execution Time Per Period (s)	Peak Memory (kB)
	Linear	Non-Linear	Total	Continuous	Integer	Total		
Master problem	566	-	566	573	171	744	1.2	4656
Slave problem	83	116	199	286	-	286		

The average execution time was compatible with operation/reconfiguration time-frame, presenting an average value of 1.2 s (considering all case studies). The analysis of computer system resource impact was also evaluated with a memory test for which the MATLAB memory profiler tool was used. This tool shows the peak memory for each function in the code. The highest computer resource value is 4656 kB, which is perfectly compatible with today's computers.

This section looks at the results of the analysis from two perspectives: that of the operator (Section 4.1) and that of the EV user (Section 4.2).

4.1. The Operator's Perspective

In this subsection, the results are discussed from the perspective of the operator. Figure 11 presents the total operation and congestion cost (672 periods, one week) for all case studies. This figure makes evident the advantages in terms of cost when the DG and ESS systems are used in the network. (a) gives the total operation cost and the total congestion cost for the reference case, i.e., without EVs. Operation costs and congestion costs are reduced significantly when combined with distributed resources, namely with RES and ESS.

(b) (RES and ESS are not considered) verifies that with dynamic EV charging price, operation costs were reduced by 1.20%, 1.20%, and 2.10% when compared to the E, F, and G cases, respectively, for the user price preference scenario. In the user distance preference scenario, costs were reduced by 0.28%, 0.28%, and 3.20%. Moreover, congestion costs were reduced by 8.35%, 8.35%, and 15.20% thanks to dynamic EV charging prices in the user price preference scenario and by 2.29%, 2.29%, and 4.59% in the user distance preference scenario. From the analysis of (c) in Figure 11, compared to fixed prices (Cases I, J, and K), the dynamic EV charging prices presented a cost reduction in the user preference scenario by 1.43%, 1.43%, and 2.52% and in the user distance preference scenario by 0.24%, 0.24%, and 3.43%. Congestion costs were reduced by 13.87%, 13.87%, and 22.62% in the user price preference scenario and by 1.53%, 1.53%, and 4.60% in the user distance preference scenario. In (d), operation costs with fixed EV charging prices (Cases M, N, and O) were reduced by 1.47%, 1.47%, and 2.53% with dynamic EV charging prices. In the user distance preference scenario, cost was reduced by 0.29%, 0.29%, and 3.49%. Congestion costs were reduced by 5.25%, 15.25%, and 23.64% in the user price preference scenario and by 1.41%, 1.41%, and 4.48% in the user distance preference scenario. It is noted that there was no difference in operation costs between slow charging of 0.15 €/kWh or 0.20 €/kWh and fast charging of 0.25 €/kWh or 0.30 €/kWh. Thus, the operator was indifferent to the charging price for the EV user.

The use of dynamic prices for EV charging is beneficial in terms of reduced operation and congestion costs when compared to fixed price options. The reductions are more evident when the fixed prices are higher. Thanks to dynamic EV charging, different charging prices were offered to the users in the parking lots, and this helped alleviate certain power lines, contributing in this way to the operational cost reduction.

Total power loss, power generation curtailment, and power not supplied costs in each user preference scenario are presented in Figure 12a, i.e., with no electric vehicles. It has been verified that the costs associated with those three terms reduced once the distributed energy resources were included (RES and ESS). In fact, the power not supplied (PNS) cost was reduced to zero when the RES were considered alone or together with ESS. However, with RES and ESS, power generation curtailment (PGC) was present, but the costs were lower than with the PNS.

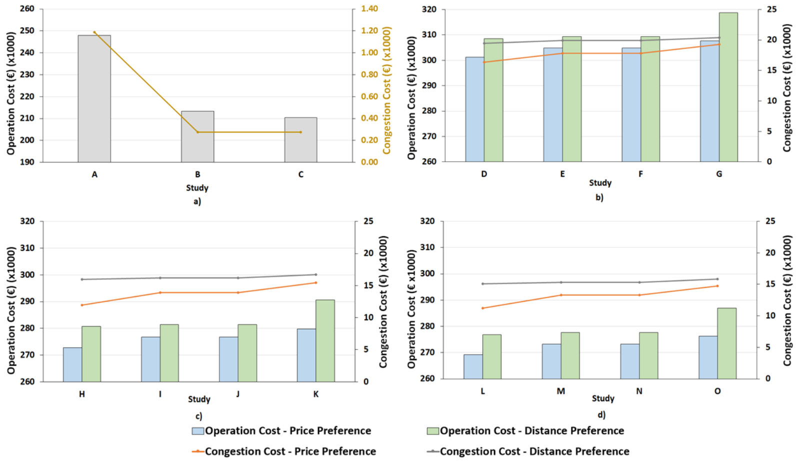

Figure 11. Total operation and congestion costs. (**a**) For cases without EVs. (**b**) For cases with EVs, but without DER. (**c**) For cases with RES, but without ESS. (**d**) For cases with DER (RES and ESS).

Through the analysis of (b) (RES and ESS were not considered) in Figure 12, it can be observed that the total power loss (PL) cost was equivalent to the three fixed-price cases with a cost of around 3662 € in the user price preference scenario. Through the use of the dynamic EV charging price method, the PL cost reduced by around 17%. Considering the user distance preference scenario, the dynamic EV charging prices presented a reduction of only 1.03% in Cases E and F and of 1.91% in Case G. The PNS occurred only in the user distance preference scenario. When the dynamic EV charging prices were included, the PNS cost was small compared to the fixed price (83.54% smaller than in Cases E and F and 98.67% smaller than in Case G). Considering the user price preference scenario in (c) of Figure 12, the observed PL cost reduction with dynamic energy pricing was of 16.75% in Cases I and J and 18.08% in Case K. Cost reductions were lower in the distance user preference scenario, reducing by 0.21% in Cases I and J and 1.52% in Case K. The PNS occurred only for the fixed price cases in the user distance preference scenario, being zero when the dynamic EV charging prices was used. The presence of RES will create the necessity of PGC in some periods. The dynamic EV charging prices can mitigate the costs associated with the PGC in the user price preference scenario, by 3.46% in Cases I and J and 4.32% in Case K. If the user distance preference scenario were considered, it would not be possible to benefit from dynamic EV charging prices. In (d), the presence of ESS was also considered, and its advantages in reducing PGC cost were evident. Through the use of dynamic EV charging prices, PL was reduced by 16.24% in Cases M and N and 18.03% in Case O in the user price preference scenario and by 2.19% in Cases M and N and 2.29% in Case O in the user distance preference scenario. With dynamic EV charging prices in the user price preference scenario, the PGC costs were reduced by 6.86% in Cases M and N and by 8.48% in Case O. In the user distance preference scenario, the cost of PGC did not reduce with dynamic EV charging prices. As can be seen, the use of dynamic EV charging prices is of great advantage in the PGC, leading to a zero value.

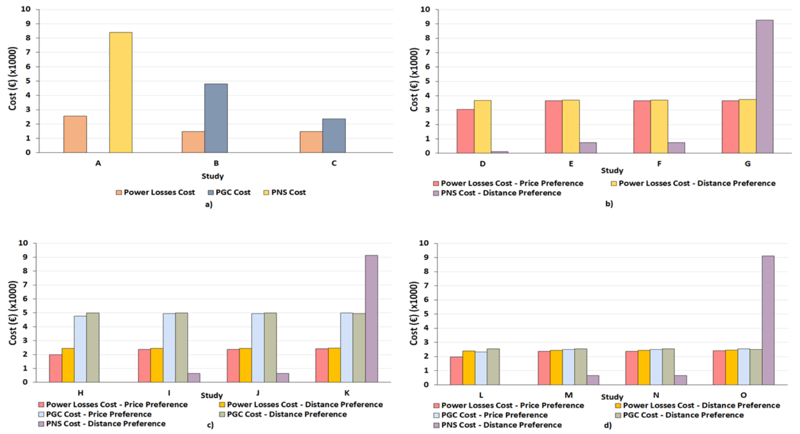

Figure 12. Total power loss, power generation curtailment, and power not supplied costs in each user preference scenario. (**a**) For cases with no EVs. (**b**) For cases with EVs, but without DER. (**c**) For cases with RES, but without ESS. (**d**) For cases with DER (RES and ESS).

Once again, the conclusion drawn from the above analysis is that using dynamic energy pricing for EVs' charging contributed greatly to a reduction in costs associated with power loss, power generation curtailment, and power not supplied. The reductions were more evident for PNS, where they reached 100% in Cases H and L.

Table 10 presents the maximum and the minimum voltage reached in each study. It also presents the buses where those values are verified. As can be seen in this table, the worst voltage values for the user price preference scenario and for the user distance preference scenario were verified in Case G at bus 6 and bus 5, respectively, mainly because these cases did not consider DG and ESS. When adopting dynamic pricing combined with the use of EVs (Cases D, H, and L in the user price preference scenario), it is possible to verify that this leads to better voltage levels (i.e., min. voltage), demonstrating the advantage of dynamic charging prices when EVs react to charging price.

Case L (which is a dynamic EV charging price case) and the case with 0.20 €/kWh for slow charge and 0.30 €/kWh for fast charge (fixed energy charging price) were chosen as an example to present the total energy charge consumption, the average charge power, and the preference percentages of the EV users for each bus that had parking lots. Figure 13 illustrates Case L, and Figure 14 presents the fixed price case.

The preference for a bus with an EV parking lot was counted from the moment the EV began to charge until the time it left the parking lot (one charging session).

In (a), it is possible to see that when the user price preference scenario was considered, the total energy consumed when charging an EV in bus 7 (slow charging parking lot) was 88,037 kWh, which in comparison to the other three buses was 69%, 88%, and 91% more, meaning that the energy price to charge at this bus was better than at the others. Thus, the average charging power followed the same trend as energy consumption. In the user distance preference scenario, energy consumption during charging was spread more evenly over the other parking lot buses. In this case, the highest consumption was the one in bus 2 (fast charging parking lot) with around 45,500 kWh. This bus consumed 19%, 35%, and 14% more energy than the remaining parking lot buses. Once again, the average charge power followed the energy charge consumption trend.

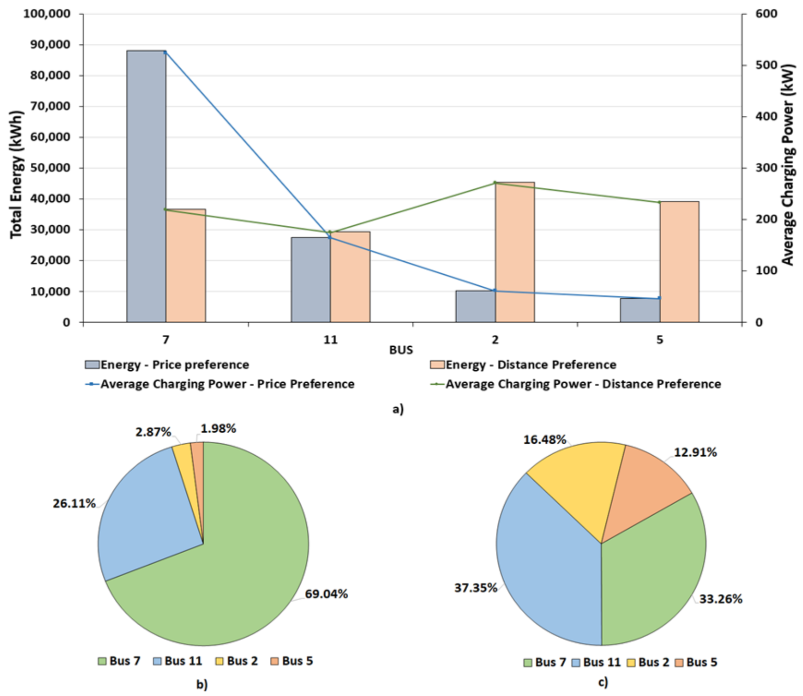

Figure 13. Energy and preference results in each bus that had parking lots for EV charging, considering the dynamic EV charging price in Case L. (**a**) Energy and average charge power at each EV parking lot bus. (**b**) Preference percentage for each parking lot bus considering the user price preference scenario. (**c**) Preference percentage for each parking lot bus considering the user distance preference scenario.

Figure 13b,c shows the preference percentages of the EV users for each bus with a parking lot, considering the user price and distance preferences scenarios, respectively. Figure 13b shows that the parking lot located at bus 7 was the one preferred by EV users, with 69.04% of charged EVs. The parking lot located in bus 11 was the second most chosen, while the fast charging parking lots were the ones least used, with a total of 4.85%. The slow charging parking lots were those that had the lowest energy charging price when compared to the fast charging parking lots. Then, since the user price preference scenario is being considered here, the choice of the less expensive parking lot was logical.

In Figure 13c, the user distance preference scenario is considered. In this scenario, the user preference was to find a parking lot that was as close as possible to the total route that the user would have to travel, i.e., the lowest summation distance between the current EV location and the parking lot and the distance between the parking lot and the next destination. In this user preference scenario, the fast charging parking lots obtained a higher preference when compared to the case where the user preference was defined by the price. This indicates that when the price was not the most important factor, fast charging parking lots could attract users who were located close to them. Nevertheless, we arrived at the conclusion that the location of those parking lots was not optimal, because even when considering the user distance preference scenario, the majority of the users chose the slow charging parking lots: the lease expensive ones.

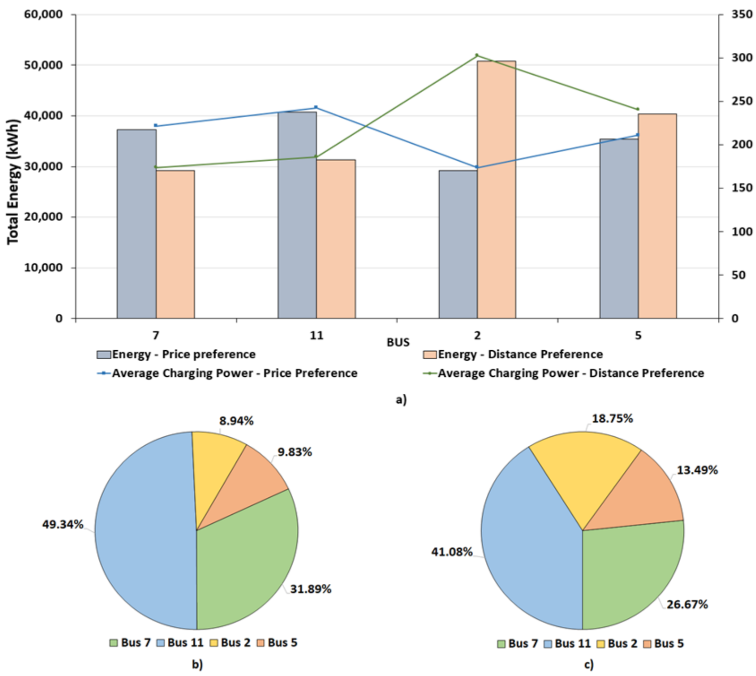

Figure 14. Energy and preference results at each bus that had parking lots at a fixed price for EV charging, with 0.20 €/kWh for slow charging and 0.30 €/kWh for fast charging. (**a**) Energy and average charging power in each EV parking lot bus. (**b**) Preference percentage for each parking lot bus considering the user price preference scenario. (**c**) Preference percentage for each parking lot bus considering the user distance preference scenario.

It is also important to note in the user distance preference scenario that even the parking lots located at bus 11 presented higher user charging preference when compared to the parking lots located at bus 7; the energy consumption and the average charging power at the parking lots of bus 11 were not higher than those at bus 7. This means that the energy price in bus 11 presented higher variations, and it was worse in general when compared to the energy price in bus 7 (it is possible to observe this in Section 4.2, second box plot figure), which contributed to higher energy charge consumption in bus 7 and a considerable charging preference (37.35%) even though there was only a 30% probability in the user price preference scenario (see Table 6). Moreover, due to the higher charge preference at bus 11, it is possible to conclude that the location of the parking lots at this bus was better (advantageous because EV users were at a shorter distance from them) when compared to the parking lots at bus 7.

The total energy charge consumption, the average charge power, and the preference percentages of the EV users for the fixed energy prices (0.20 €/kWh for slow charge and 0.30 €/kWh for fast charge) are presented in Figure 14.

In Figure 14a, it can be observed that in the user price preference scenario, the bus with the highest total energy consumption for EV charging was bus 11 with 40,733 kWh, that is 9%, 28%, and 13% more than buses 7, 2, and 5, respectively. Thus, the average charging power followed the same trend of the energy consumed during charging. In comparison, (a) in Figure 13 shows that the energy consumed by the charging EVs was spread more evenly among all the parking lot buses, while in the dynamic EV charging price case, energy consumption due to charging was more concentrated in bus 7 than the others. This means that bus 7 with respect to dynamic EV charging price presented a better charging price. In the user distance preference scenario, the energy charge consumption followed the same trend as in the dynamic EV charging price case, indicating energy consumption of 50,815 kWh at bus 2; the consumption was higher by 42%, 38%, and 21% in relation to the remaining buses. Regarding the average charging power, the trend was the same as for energy consumption.

Analyzing Figure 14b, which presents the preference percentages of the EV users for each bus with parking lots, considering the user price preference scenario, it can be seen that the parking lot in 11 was preferred among users with 49.34% of EV users choosing this lot. The parking lots located at bus 7 were in second place, while the fast charging parking lots had a total of around 19% preference among users, quite higher when compared with (b) of Figure 13. This means that in the dynamic EV charging price case, the most attractive prices were on the buses that had slow charging parking lots, leading to a great number of users choosing them over the fast charging parking lots. The majority of the users preferred slow charging due to the lower charging price (0.20 €/kWh).

Table 10. Maximum and minimum voltage magnitude for each case study.

Case	User Price Preference Scenario				User Distance Preference Scenario			
	Max Voltage		Min Voltage		Max Voltage		Min Voltage	
	bus	Value (p.u.)	bus	Value (p.u.)	bus	Value (p.u.)	bus	Value (p.u.)
A	2	0.9996	9	0.9819	2	0.9996	9	0.9819
B	7	0.9998	9	0.9844	7	0.9998	9	0.9844
C	7	0.9998	9	0.9844	7	0.9998	9	0.9844
D	2	0.9996	9	0.9814	2	0.9996	6	0.9690
E	2	0.9996	13	0.9761	2	0.9996	6	0.9688
F	2	0.9996	13	0.9761	2	0.9996	6	0.9688
G	2	0.9996	6	0.9685	2	0.9996	5	0.9623
H	7	0.9999	13	0.9826	7	0.9998	6	0.9692
I	7	0.9998	13	0.9763	7	0.9999	6	0.9690
J	7	0.9999	13	0.9763	7	0.9999	6	0.9690
K	7	0.9999	6	0.9687	7	0.9999	5	0.9624
L	7	0.9999	12	0.9832	7	0.9999	6	0.9710
M	7	0.9998	13	0.9763	7	0.9999	6	0.9690
N	7	0.9999	13	0.9763	7	0.9999	6	0.9690
O	7	0.9999	6	0.9687	7	0.9999	5	0.9624

Once again, in the user distance preference scenario, the fast charging parking lots were a more popular choice among users than in the user price preference scenario ((c) of Figure 14)). This also indicates that those parking lots could attract users who find themselves closer to the fast charging parking lots, if the price is not the most important factor. However, we arrived at the conclusion that those parking lost cannot be located optimally because the slow charging parking lots were highly preferred among users due to more attractive EV charging prices (even in the user distance preference scenario).

4.2. User Perspective

This subsection looks at the results of the case studies from the perspective of the EV users. Figures 15 and 16 present the box plots for the dynamic EV charging price cases considering the user price and distance preference scenarios, respectively. By comparing these two figures, it is possible to see that the differences between the same cases in each figure were small. The verified variations were mainly in Quartile 3 (Q3) and were higher in the user price preference scenario, in which the users gave priority to price.

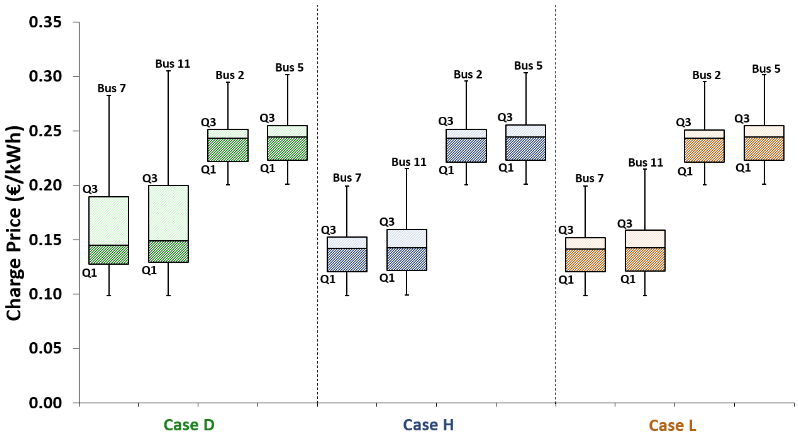

Figure 15. Electric vehicle charge price variation for the user price preference scenario.

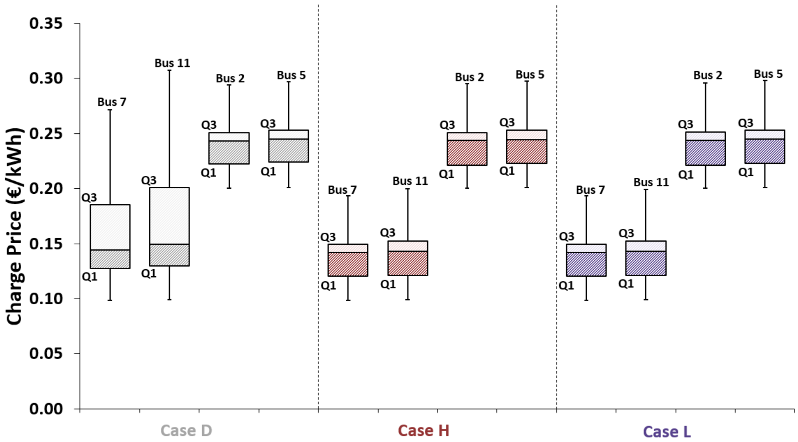

Figure 16. Electric vehicle charging price variation in the user distance preference scenario.

Let us take bus 11 in Case L as an example: it can be seen that the charge price variation in the user price preference scenario was between 0.0990 €/kWh and 0.2150 €/kWh, while in the user distance preference scenario, it was between 0.0990 €/kWh and 0.2000 €/kWh, corresponding to a 0.0150 €/kWh of difference. Fifty percent of the charge price values (interquartile range) were located between 0.1210 €/kWh and 0.1600 €/kWh for the user price preference scenario and between 0.1210 €/kWh and 0.1510 €/kWh for the user distance preference scenario (0.0090 €/kWh of difference). Twenty-five percent of the values varying between 0.0990 €/kWh and 0.1210 €/kWh for both user preference scenarios were located in the first quartile (Q1). Seventy five percent of the EV charging price values were represented by the third quartile (Q3) and varied between 0.0990 €/kWh and 0.1600 €/kWh in the user price preference scenario and between 0.0990 €/kWh and 0.1510 €/kWh in the user distance preference scenario. These two figures show that the highest variation in the charge prices among the dynamic EV charging price cases occurred specifically in slow charge buses in Case D. This is mainly due to the wind farms (one of them at bus 7 and the other one at bus 11, corresponding to 24% of the total installed power), which were not considered in Case D (it did not consider RES nor ESS).

Table 11 presents the results collected over a one-week period during which the case study was conducted; the average prices paid by EV users in the case of both dynamic EV charging prices and fixed charging prices. In these average prices values, the home charging price is included (0.2094 €/kWh). All dynamic EV charging price cases in the user price preference scenario show that the prices paid by EV users for EV charging were on average lower than what EV users normally would pay if the charging prices were fixed. However, this was not the case in the user distance preference scenario. To better understand the values presented in this table, let us analyze Tables 12–14, which stress the dynamic EV charging price cases with their homologous fixed price cases, presenting the gains in terms of the percentage of the EV users.

Table 11. Spent average charge price of the EV users for dynamic and fixed prices.

	Average Price (€/kWh)					
User Preference Scenario	**Cases**					
	D	**H**	**L**	**SCh = 0.15 €/kWh FCh = 0.25 €/kWh**	**SCh = 0.20 €/kWh FCh = 0.30 €/kWh**	**SCh = 0.30 €/kWh FCh = 0.40 €/kWh**
Price	0.1925	0.1877	0.1867	0.2005	0.2281	0.2907
Distance	0.2414	0.2180	0.2178	0.2087	0.2370	0.2955

In Table 12, it is possible to see that the dynamic EV charging price Case D for the user price preference scenario presented gains of 4.03%, 16.63%, and 33.79% over all the homologous fixed price cases (E, F, and G), respectively. Even comparing a dynamic EV charging price case that did not consider distributed resources with the lowest fixed prices case (0.15 €/kWh for slow charge and 0.25 €/kWh for fast charge) verified the charge prices' advantages. Regarding the user distance preference scenario, the dynamic EV charging price case did not present advantages in terms of charge price for the EV users when compared with fixed Cases E and F, which had 0.15 €/kWh for slow charge and 0.25 €/kWh for fast charge and 0.20 €/kWh for slow charge and 0.30 €/kWh for fast charge, respectively. Comparing with these two fixed prices cases, if the dynamic EV charging price were applied, the EV users would have had a loss of 15.66% and 1.88%, respectively, but obtained a gain of 18.30% when compared with the fixed charge price Case G.

Case H also presented charge price gains when compared with the homologous fixed charge prices, as can be seen in Table 13. In this case, the gains were 6.42%, 17.73%, and 35.45%, respectively, and when compared with Case D, it is possible to see a growth in those gains. For the user distance preference scenario, it can be seen that the dynamic EV charging prices were not also advantageous for the EV users when compared with the lowest considered fixed energy charge prices, but with a strong reduction when compared with the case that did not consider RES. Furthermore, a gain of 8%

can be seen with Case H (a growth of 9.88%) over the charge fixed energy price considered for Case J (0.20 €/kWh for slow charge and 0.30 €/kWh for fast charge), as well as a growth of 7.92% over the 0.30 €/kWh (slow charge) and 0.40 €/kWh (fast charge) fixed charge prices.

Table 12. Average charge price differences between dynamic Case D and the homologous fixed cases. The average prices paid by the EV users when Case D was used were 0.1925 €/kWh and 0.2414 €/kWh for the user price preference scenario and the user distance preference scenario, respectively. Blue color means that Case D is advantageous for the EV user, whereas the red color means that Case D is not advantageous for the EV user.

Dynamic Price	Fixed Prices		
	Case E	Case F	Case G
Case D	Price preference		
	4.03%	15.63%	33.79%
	Distance preference		
	−15.66%	−1.88%	18.30%

With the RES and ESS presented in the distribution network, the results' tendency was similar to Case H. Comparing the differences, it is possible to see through Table 14 that the gains of Case L were higher than the gains of Case H, namely due to the ESS consideration.

Table 13. Average charge price differences between dynamic Case H and the homologous fixed cases. The average prices paid by the EV users when Case H was used were 0.1877 €/kWh and 0.2180 €/kWh for the user price preference scenario and the user distance preference scenario, respectively. Blue color means that Case H was advantageous for the EV user, whereas the red color means that Case H was not advantageous for the EV user.

Dynamic Price	Fixed Prices		
	Case I	Case J	Case K
Case H	Price preference		
	6.42%	17.73%	35.45%
	Distance preference		
	−4.45%	8.00%	26.22%

Table 14. Average charge price differences between dynamic Case L and the homologous fixed cases. The average prices paid by the EV users when Case L was used were 0.1867 €/kWh and 0.2178 €/kWh for the user price preference scenario and the user distance preference scenario, respectively. Blue color means that Case L was advantageous for the EV user, whereas the red color means that Case L is not advantageous for the EV user.

Dynamic Price	Fixed Prices		
	Case M	Case N	Case O
Case L	Price preference		
	6.92%	18.17%	35.79%
	Distance preference		
	−4.33%	8.10%	26.30%

5. Conclusions

In this research work, the authors investigated if the dynamic EV charging prices have a positive impact on the smart distribution network operation and on the EV user behavior. To this end, the authors combined an EV behavior simulator with a proposed innovative smart DLMP-based distribution network operation/reconfiguration. The main contributions of the conducted study can be summarized as follows: (a) an EV user behavior simulator has been adopted to generate a realistic population, considering the network size and parking lots; (b) a distribution network operation/reconfiguration optimization model has been created in an SG context with high DER penetration concerning the behavior of the EV users and the dynamic EV charging price considering DLMPs using the Benders decomposition method; (c) the positive impact of the dynamic EV charging prices on the smart distribution network operation and on the electric vehicles users has been assessed.

The proposed methodology was tested in a case study, which has been conducted on a mock-up model of an SC located at the BISITE laboratory with a 13-bus distribution network. Furthermore, the distribution network operation/reconfiguration optimization model considering two user preference scenarios (price and distance preference) and using the dynamic EV charging prices were compared with the model using the EV fixed charging prices to demonstrate the advantage of the former.

It was verified that the use of dynamic pricing for EV charging is advantageous for the network operator in all of the considered cases due to reduced cost of operation and the user preference scenarios. These benefits are even more evident when considering high fixed charging prices (0.30 €/kWh for slow charging and 0.40 €/kWh for fast charging, −35.79% in the user price preference scenario, Case L). The lowest cost reduction was 0.24% in Case H of the distance preference scenario. Moreover, when the distance preference scenario and dynamic price were considered, it was verified that the PNS was zero, with exception of Case D, which presented an insignificant value (123.35 €).

For the EV users, the dynamic pricing also presented considerable cost advantages, namely when the price preference was considered. In this scenario, the lowest advantage (4.03% better) was verified in Case D compared with the lowest considered fixed charging prices (0.15 €/kWh for slow charge and 0.25 €/kWh for fast charge). Furthermore, for this scenario, the advantages can reach 35.75% (Case L), i.e., around 0.10 €/kWh of savings if the fixed charging prices are 0.30 €/kWh for slow charge and 0.40 €/kWh for fast charge. If the distance preference was considered, the dynamic EV charging price cases did not present savings in comparison with the lowest fixed charging price cases, namely when the fixed charging prices were 0.15 €/kWh for slow charge and 0.25 €/kWh for fast charge. Here, the user lost up to 15.66% for the dynamic EV charging price Case D. Nevertheless, the dynamic price still presented considerable savings when fixed prices were higher, reaching up to 26.30%.

The results suggest that the dynamic energy pricing for EVs' charge can be used as an efficient approach in smart cities that allows important monetary savings for both the distribution system operator and EV users.

The main drawbacks of the proposed work are: (a) the EV users' profiles were not adapted to the different weekdays; (b) the decision charge method was only based on the battery charge level; (c) vehicle-to-grid was not considered; (d) the ESS charge/discharge decision was limited and based on rules.

As future work, the authors suggest this research work include more EV user profiles, an additional charging decision method that depends on the energy price, an optimized ESS charge/discharge decision, an optimization model for EV users' costs minimization, solar-powered charging infrastructures in the parking lots, and also the possibility of vehicle-to-grid.

Author Contributions: Conceptualization, B.C. and J.S.; Data curation, B.C.; Formal analysis, B.C. and J.S.; Investigation, B.C.; Methodology, B.C. and J.S.; Project administration, Z.V.; Resources, Z.V. and J.M.C.; Software, B.C.; Supervision, Z.V. and J.M.C.; Validation, B.C.; Visualization, B.C. and J.S.; Writing—original draft, B.C.; Writing—review and editing, B.C., J.S., Z.V. and J.M.C.

Funding: This research has received funding from FEDER funds through the Operational Programme for Competitiveness and Internationalization (COMPETE 2020), under Project POCI-01-0145-FEDER-028983; and by National Funds through the FCT—Portuguese Foundation for Science and Technology, under Projects PTDC/EEI-EEE/28983/2017 (CENERGETIC), UID/EEA/00760/2019, and SFRH/BD/110678/2015 PhD scholarship.

Acknowledgments: This work has received funding from FEDER Funds through the COMPETE program, from National Funds through FCT under the project UID/EEA/00760/2019 and from the project PTDC/EEI-EEE/28983/2017-CENERGETIC. Bruno Canizes is supported by FCT Funds through the SFRH/BD/110678/2015 PhD scholarship.

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

Abbreviations

The following abbreviations are used in this manuscript:

DER	Distributed energy resources
DG	Distributed generators
DLMP	Locational marginal pricing
DN	Distribution network
DNR	Distribution network reconfiguration
DSO	Distribution system operator
ESS	Energy storage systems
EU	European Union
EV	Electric vehicle
FCh	Fast charge
LMP	Locational marginal pricing
MINLP	Mixed-integer nonlinear programming
MOC	Master subproblem objective function
MV	Medium voltage
OMIE	Iberian electricity market operator
PGC	Power generation curtailment
PL	Power losses
PNS	Power not supplied
PV	Photovoltaic
RES	Renewable energy sources
SC	Smart city
SCh	Slow charge
SG	Smart grid
VAT	Value-added tax
Indices	
c	Line options
i	Electrical buses
j	Electrical buses
lo	Loads
bs	External supplier
cb	Capacitor bank
g	Distributed generator unit
e	Energy storage systems
v	Electric vehicles parking lot
m	Bender's cuts iteration

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Parameters

P_{PGC}^{Cost}	Power generation curtailment cost [€/MW]
$price^{MK}$	Market price [€/MWh]
$Cost^{PNS}$	Power not supplied cost [€/MW]
$Cost^{Loss}$	Power losses cost [€/MW]
cef	Charge efficiency of energy storage systems
def	Discharge efficiency of energy storage systems
$Cost^{Cong}$	Lines congestion cost [€/MW]
$price^{Mk}$	Market price [€/MW]
$Cost^{PNS}$	Power not supplied cost [€/MW]
$r_{(i,j)}$	Resistance for *i,j* line[Ω]
$Cost^{Loss}$	Power losses cost [€/MW]
P_{PGC}^{Cost}	Power generation curtailment [€/MW]
$p_{DG(g)}$	Power generation for *g* DG unit [MW]
$EVP_{(i)}$	Power charge for EV parking lot in the bus *i* [MW]
$Flow^{max}{}_{(i,j)}$	Maximum admissible line flow between bus *i* and bus *j* [MW]
nDG	Number of DG units
$ExtSup_{MinLimit(bs)}$	Minimum limit of power supplied by substation/supplier *bs* [MW]
$ExtSup_{MaxLimit(bs)}$	Maximum limit of power supplied by substation/supplier *bs* [MW]
$p_{DG(g)}$	Generated power of distributed generation *g* [MW]
$p_{Load(lo)}$	Active power demand for load *lo* [MW]
$CongMin$	Power congestion factor
$STdchR_{(e)}$	ESS discharge rate [MW]
$STchR_{(e)}$	ESS charge rate [MW]
$STdM_{(e)}^{stat}$	Decision for ESS *e* discharge {0,1}
$STcap_{(e)}$	ESS *e* capacity [MWh]
$STdM_{(e)}^{stat}$	Decision for ESS *e* discharge {0,1}
Δt	Duration of the period [hours]
$STstoM_{(e)}^{t-1}$	Energy stored in *e* ESS in previous period for master subproblem [MWh]
$STstoS_{(e)}^{t-1}$	Energy stored in *e* ESS in previous period for slave subproblem [MWh]
$STsto_{(e)}^{\min}$	Minimum capacity limit of the ESS *e*
$price_{\min}^{Mk}$	Minimum market price value that will permit the ESS discharge
$\lambda_{(i,j)}^{m-1}$	Sensitivities associated to the radiality decision taken by the master problem in the previous iteration
$\mu_{(i)}^{m-1}$	Sensitivities associated to the ESS charge decision taken by the master problem in the previous iteration
$Cost^{Inf}$	Slave problem infeasibilities cost [€]
$V_{(i)}^{min}$	Minimum voltage magnitude limit in the bus *i* [V]
$V_{(i)}^{max}$	Maximum voltage magnitude limit in the bus *i* [V]
$\theta_{(i)}^{min}$	Minimum voltage angle limit in the bus *i* [rad]
$\theta_{(i)}^{max}$	Maximum voltage angle limit in the bus *i* [rad]
$Q_{Load(lo)}$	Reactive power demand for load *lo* [Mvar]
$Q_{Cbanks(cb)}^{\max}$	Maximum limit of the capacitor bank *cb* [Mvar]
$G_{(i,j)}$	Real term of the element *i,j* in the bus admittance matrix
$B_{(i,j)}$	Imaginary term of the element *i,j* in the bus admittance matrix
$x_{(i,j)}$	Reactance for *i,j* line [Ω]
$Ps_{MinLimit(bs)}$	Minimum limit of active power supplied by substation/supplier *bs* [MW]
$Ps_{MaxLimit(bs)}$	Maximum limit of active power supplied by substation/supplier *bs* [MW]
$Qs_{MinLimit(bs)}$	Minimum limit of reactive power supplied by substation/supplier *bs* [Mvar]
$Qs_{MaxLimit(bs)}$	Maximum limit of reactive power supplied by substation/supplier *bs* [Mvar]

Variables

$D_{(g)}$	Fictitious load for each distributed generator *g*
$ExtSup_{(bs)}$	Power supplied by substation *bs* [MW]
$PNSM_{(lo)}$	Power not supplied for load *lo* in the master subproblem [MW]
$FlowM_{(i,j)}$	Power flow in the line *i,j* for the master subproblem [MW]
$P_{PGCM(g)}$	Power generation curtailment for master subproblem in the *g* DG unit [MW]
ω^*	Linear Benders' cut variable
$STdchM_{(e)}$	Power discharge of ESS *e* for master subproblem [MW]
$STchM_{(e)}$	Power charge of ESS *e* for master subproblem[MW]
$X^{stat}_{(i,j)}$	Binary decision variable {0,1} for the line usage between bus *i* and bus *j*
$d_{(i,j)}$	Fictitious flow associated with branch *i,j*
$CongM_{(i,j)}$	Power congestion for line *i,j* in the master subproblem [MW]
$STcM^{stat}_{(e)}$	Binary decision variable {0,1} for ESS *e* charge
$STdM^{stat}_{(e)}$	Binary decision variable {0,1} for ESS *e* discharge
$STstoM_{(e)}$	Energy stored in *e* ESS for master subproblem [MWh]
Z^{m-1}_{up}	Sum of the infeasibilities of the slave problem
ZA	Slack variable for active power balance
ZQ	Slack variable for reactive power balance
ZF	Slack variable for thermal lines capacity
$CongS_{(i,j)}$	Power congestion for line *i,j* in the salve subproblem [MW]
$P_{Supplier(bs)}$	Active power supplied by substation bs[MW]
$Q_{Supplier(bs)}$	Reactive power supplied by substation bs[Mvar]
$P_{PGCs(g)}$	Power generation curtailment for slave subproblem in the *g* DG unit [MW]
$PNSs_{(lo)}$	Power not supplied for slave subproblem in the load *lo* [MW]
$SLoss_{(i,j)}$	Apparent power loss in the line *i,j* [MVA]
$V_{(i)}$	Voltage magnitude in the bus *i* [V]
$\theta_{(i)}$	Voltage angle in the bus *i* [rad]
$P_{Inj(i)}$	Active injected power in the bus *i* [MW]
$Q_{Inj(i)}$	Reactive injected power in the bus *i* [Mvar]
$Q_{Cbanks(cb)}$	Reactive power from capacitor bank *cb* [Mvar]
$P_{(i,j)}$	Active power flow in the *i,j* line [MW]
$Q_{(i,j)}$	Reactive power flow in the *i,j* line [Mvar]
$S_{(i,j)}$	Apparent power flow in the *i,j* line [MVA]
$PLoss_{(i,j)}$	Active power loss in the *i,j* line [MW]
$QLoss_{(i,j)}$	Reactive power loss in the *i,j* line [Mvar]
$FlowS_{(i,j)}$	Power flow in the *i,j* line for slave subproblem [MW]
$STdchS_{(e)}$	Power discharge of ESS *e* for slave subproblem [MW]
$STchS_{(e)}$	Power charge of ESS *e* for slave subproblem[MW]
$STstoS_{(e)}$	Energy stored in *e* ESS for slave subproblem [MWh]
DEP	Dynamic EV charging price for each period [€/kWh]
$TariffMV$	Energy tariff price for each period [€/kWh]
PLG	Additional profit margin of the parking owner
$ACNR$	Additional cost related to the fixed term of network price rate to be charged to the customer [€/kWh]

Sets

Ω_B	Set of buses
${\Omega^b}_{BS}$	Set of substation buses
${\Omega^b}_{CB}$	Set of capacitor banks buses
${\Omega^b}_{L}$	Set of load buses
${\Omega^b}_{E}$	Set of ESS buses
${\Omega^b}_{V}$	Set of EV parking lot buses
$\Omega_B S$	Set of substations
$\Omega_C B$	Set of capacitor banks
Ω_l	Set of lines
${\Omega^{nd}}_{DG}$	Set of non-dispatchable DG buses

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Core publication *VII*

Bruno Canizes, João Soares, Angelo Costa, Tiago Pinto, Fernando Lezama, Paulo Novais, Zita Vale, "Electric Vehicles User Charging Behaviour Simulator for a Smart City", Energies. 1470 (2019) 12(8). doi:10.3390/en12081470 (**2018 Impact Factor is 2.707**).

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Electric Vehicles' User Charging Behaviour Simulator for a Smart City

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Received: 18 February 2019; Accepted: 12 April 2019; Published: 18 April 2019

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Abstract: The increase of variable renewable energy generation has brought several new challenges to power and energy systems. Solutions based on storage systems and consumption flexibility are being proposed to balance the variability from generation sources that depend directly on environmental conditions. The widespread use of electric vehicles is seen as a resource that includes both distributed storage capabilities and the potential for consumption (charging) flexibility. However, to take advantage of the full potential of electric vehicles' flexibility, it is essential that proper incentives are provided and that the management is performed with the variation of generation. This paper presents a research study on the impact of the variation of the electricity prices on the behavior of electric vehicle's users. This study compared the benefits when using the variable and fixed charging prices. The variable prices are determined based on the calculation of distribution locational marginal pricing, which are recalculated and adapted continuously accordingly to the users' trips and behavior. A travel simulation tool was developed for simulating real environments taking into account the behavior of real users. Results show that variable-rate of electricity prices demonstrate to be more advantageous to the users, enabling them to reduce charging costs while contributing to the required flexibility for the system.

Keywords: electric charging behaviour; electric mobility; energy prices; EVs; travel simulator

1. Introduction

The need to reduce greenhouse gas emissions is ever increasing, and several nations have agreed on ambitious targets in the Paris Agreement Treaty [1]. This treaty has the aim to limit global temperature 2 °C above the pre-industrial levels. The transportation and its infrastructure represents 23% of greenhouse gas emissions and is only surpassed by fossil fuel emissions (e.g., energy production) [2]. This shows that the electrification of transport plays a significant role in making the planet a greener place, reducing dependence on fossil fuels.

The use of electric vehicles (EVs) not only has the potential to change individual mobility but also to reduce pollutant emissions, which is considered a major cause of air pollution and causes serious health problems in the global population. However, as an increasing number of charges will ideally be covered by renewable production to achieve decarbonization of the transportation sector, the introduction of dynamic electricity prices could increase the risk of substation overloads [3].

In Europe, growth in the use of EVs will result in extra energy demand, with consumption increasing from approximately 0.03% in 2014 to 9.5% in 2050 [4].

Generally, the population is accustomed to deal with fossil energies and with the convenience of easy to find service stations and fast refueling times. Thus, there are no concerns regarding waiting times or about the fuel needed to reach the intended destination. When using an electric vehicle it is essential to consider these factors as the current range of the vehicles is limited and changing stations are few. Also, there are other challenges such as increasing peak power demand if the charging events occur at the same instant as residential or industrial peak consumption [5]. The electrical network reacts according to the level of loads connected to it, and with growing usage of this mean of transportation in the future, it is necessary to study how the impact of the extra energy required can be mitigated. Understanding the behavior of electric vehicle users while at the same time recognize the changes in the network will be a crucial part.

Recent studies suggest that dynamic electricity prices can spur demand and help electric companies avoid costly investments in infrastructures [6]. However, the lack of variability in electricity prices does not allow the studies to be completely realistic or in line with the actual variability of renewable energy generation. In this context, it is crucial to address the following research question: can electric vehicle users change their charging patterns as a result of varying electricity prices?

Providing incentives to EV users in a way that behavior and charging patterns are changed and adapted accordingly to the variation of electricity prices is essential to ensure the EV's flexibility balances the variation of renewable energy sources. It is in this scope that this paper brings its main contributions, by presenting a study on the impact of electricity prices variation on EV users' charging habits.

This study compares the benefits when using a variable and fixed charging prices. The variable prices are determined based on the calculation of distribution locational marginal pricing (DLMP) using distribution network operation and reconfiguration optimization model, which enables achieving prices that are not only continuously recalculated and adaptable to the ongoing changes in the power network (variation of consumption and generation at each time) but also reflect the situation and needs in each different location of the network. These prices are used to incentive EV users to change their charging habits according to the variation of renewable generation in different places of the power network. A travel simulation tool specifically developed for this study is also presented. The simulator takes into account the behavior of real users to simulate their trips from the origin place (e.g., house or workplace) to multiple destinations, and back. The tool also considers different types of users and vehicles, thus allowing to create personalized profiles, destinations, and schedules. Moreover, the simulator enables defining the position of the vehicles in a power network continuously throughout time. In this way, the proposed tool simulates a real environment, with trips and charging stations (CS). Considering the defined scenarios, users make decisions regarding their charging process, i.e., if they charge their vehicles or not at each time, according to the behaviors previously analyzed. For this, intelligent charging is simulated considering variables such as distance and the price of electricity. In this way, it is possible to test the impact of different types of incentives on EV users' behavior. A physical laboratory model of a smart city (SC) located at BISITE laboratory with a 13 buses distribution network with high distributed energy resources (DER) penetration is used to demonstrate the application of the proposed methodology. Results show that variable charging prices prove to be more advantageous to the EV users, enabling them to reduce charging costs, while contributing to the required flexibility for the system. This allows mitigating the problems introduced with the large-scale penetration of distributed, variable renewable energy sources.

The rest of the paper is organized as follows: Section 2 presents a brief review of state of the art. The proposed simulator tool is described in Section 3, along with the methodology for the calculation of the variable electricity prices. The case studies are discussed in Section 4. Finally, the conclusions are shown in Section 6.

2. State of the Art

2.1. Electric Mobility

In 2017, the number of EVs on the road was about 3.1 million, an increase of 57% compared to 2016 (according to Figure 1). This increase was similar to that registered between 2015 and 2016, of 60% [7]. It is also possible to verify that purely electric vehicles (battery electric vehicle - BEV), had a more significant growth than the hybrid vehicles (plug-in hybrid electric vehicle - PHEV), representing two-thirds of the total. China is the country with the largest share, accounting for 40% of the total [7].

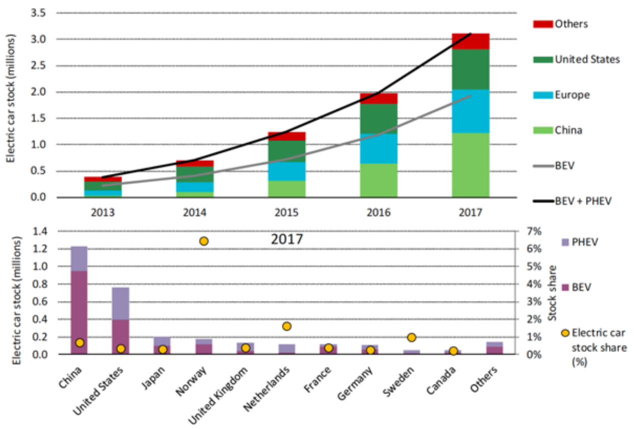

Figure 1. Number of EVs globally [7].

With the increasing popularity of EVs, there is the need to improve charging infrastructures and offer more affordable models. While governments offer incentives for adopting EVs and continue to invest in infrastructure, the motive that drives people to opt for this type of transportation is socially driven: it is the cleanest solution that will help sustain a habitable planet. This is reflected in the satisfaction of EVs' users, where 51% say that the most significant incentive to buy one is to contribute to a more sustainable future [8].

Overall, the results show that this adoption does not only depend on incentives but also fewer obstacles to a more comfortable driving. In this sense, it is essential that charging is accessible, both monetarily and geographically. It is important to have homes, shopping malls, workplaces, and parking lot buildings with charging stations.

Another aspect to consider is the type of charging since time spent stopped is perhaps the variable that the consumer values most. The high power capacity of fast chargers (with a power greater than 40 kW) makes them difficult to implement in residential homes due to possible hazards, which even being addressed, are still mostly underdeveloped. To this, the implementation of fast CS will facilitate the user by reducing waiting times.

2.2. Charging Behaviour

Between 2011 and 2013 data about driving and EV demand patterns were collected on a study conducted in Europe [9]. More than 230,000 charges have been registered. The average state of charge (SoC) of the battery was of 60% when users recharged it, which shows that users do not let the battery discharge completely and charge it whenever they have the opportunity and not when the battery is low. The average percentage of users who started a journey or a charge with a SoC level of less than 20% is less than 5%. Regarding the moment of the charging, it is verified that the majority are performed between 18:00 and 22:00, which corresponds to the peak hours of energy demand.

Franke and Krems [10] analyzed the charging behavior of users in Germany. They concluded that the true vehicle range affects charging decisions. They have also developed a conceptual model based on principles of self-regulation and control theory where it is possible to understand the use of energy resources. This model is based on the premise that whenever users interact with limited power sources, they continuously monitor and manage their mobility needs and their mobility resources. For instance, the mobility needs relate to the distance of a trip and the mobility resources relate to the remaining battery. Users often feel "range anxiety" that can be described as the experience of never having enough battery to reach a location and getting stranded. Thus, as the anxiety increases so does the likelihood of resorting to strategies to handle this situation, e.g., driving economically or charging the car more often.

Marmaras et al. [11] developed two behavioral profiles to be used in a simulation environment: unaware and aware. The unaware profile tries to find the best possible solution with limited access to information and minimal interaction with the environment and other EVs' users. In this case, the level of range anxiety is strong, and the user is always seeking to charge the vehicle even when it is not needed. The aware profile has more access to information and interacts with the environment and other EVs. This profile has a low anxiety level, charging the vehicle only when needed. The results of this research show that the unaware profile starts charging the vehicle as soon as it is parked, typically at home between 17:30 and 18:00, whereas the aware profile waits for the off-peak hours between 22:00 and 06:00 h.

Neubauer and Wood [12] applied a battery life analysis and simulation tool for vehicles (BLAST-V) of the National Renewable Energy Laboratory to study the sensitivity of EVs concerning range anxiety and different scenarios of different charging infrastructures. The results showed that the effects of range anxiety might be significant but reduced with access to additional charging infrastructures.

Nicholas et al. [13] studied the charging behavior when simulating trips and charging in public stations. The results show that more than 5% of trips would require recharging in a public charger for different charging autonomy and assumptions.

Xu et al. [14] used a mixed logic model to study which factors influence BEV users in the decision-making of the type of charging (normal or fast) and local. The results suggest that the battery capacity, the initial state of the battery and the number of fast charges carried out are the predictive factors for the choice of type and place of charging of the users. Also, the day range between the current and next trip positively affects normal charging at home/business.

2.3. Distribution Locational Marginal Pricing

The distribution network congestion may occur, with the high penetration level of EVs. However, the congestion problems can be handled by the distribution system operator (DSO) with the employment of market-based congestion control methods [15]. The way how locational marginal pricing (LMP) in transmission systems are obtained can be extended to the distribution systems [16], usually named as distribution locational marginal pricing (DLMP). It is known that the resistance of the distribution network lines is higher than that of transmission lines. Thus, the distribution system losses can be considered one of the main factors that affect the DLMP [17]. To deal with the EV demand congestion in distribution networks, Reference [18] proposes step-wise congestion management developed whereby the DSO predicts congestion for the next day and publishes day-ahead tariff before the clearing of the day-ahead market. Reference [19] solves the social welfare optimization of the distribution system considering EV aggregators as price takers in the local DSO market and demand price elasticity. Reference [20] presents a market-based mechanism using the DLMP concept to alleviate possible distribution system congestion due to EVs and heat pump integration. Additional, Reference [21] propose a DLMP-based algorithm with quadratic programming to deal with the congestion in distribution networks with high penetration of EVs and heat pumps.

2.4. Simulation Tools

SUMO (Simulation of Urban MObility) [22] is perhaps the best-known traffic simulator. It is an intermodal and multimodal traffic flow simulation platform, which includes vehicles, public transportation, and pedestrians. SUMO has several tools that allow it to perform tasks such as locating routes, importing networks and calculating emissions. It can be enhanced with custom templates and provides multiple application programming interfaces (API) to control the simulation remotely.

MatSim [23] is a framework for large-scale, agent-based simulations. Each agent has a transport demand represented by a chain of activities that must be done in a day at different times and locations. Decisions on how to travel between places are planned before the simulation. [24] presents a method for the synthesis and animation of realistic traffic flows in large-scale road networks. It uses a technique based on a model of continuous traffic flow. Other multi-agent models are often used to create drivers behavior models.

When incorporating EVs into the simulation aspects such as power consumption, charging stations available and the charging duration must be considered [25]. The problem of the shortest path and travel planning is studied in [26], where the authors designed an approximation scheme to calculate the most energy-efficient path. In [27] it is possible to do traffic simulations using only electric vehicles, where EVs are simulated on roads with online charging. A similar case is that of [28], in which a spatial and temporal model was constructed to charge EVs in highway public chargers. Soares et al. [29] presents a probabilistic simulator that generates driving and charging profiles of EVs that can be customized to adapt to different distribution networks. It simulates how vehicles move to estimate the impacts that charging may have on each configuration of the system, the energy consumed or emissions.

There are also other simulation tools related to EVs. FASTSim [30] is a simulation tool that compares vehicles powertrain and estimates the impact of technological improvements to vehicle efficiency, performance, cost, and battery life. V2G-Sim uses individual driving and charging models of EVs to generate spatial and temporal impact/opportunity provisions in the electric grid [31]. Alegre et al. [32] proposes a pure and hybrid EV model, using a Matlab/Simulink environment, focusing on different aspects of the vehicle such as engine power, battery, and observing how the distance traveled and performance can be affected by the changes of the vehicles' features.

Table 1 presents a summary of the main characteristics of the reviewed tools. It shows that the reviewed simulation tools share some limitations, such as the lack of charging decisions using learned to charge behaviors, and missing variable prices. Our proposed model overcomes both these limitations, by incorporating dynamic adaptation of charging behaviors from EV users, and the application of variable charging prices in the simulation model. Moreover, the proposed model includes several components also considered by other simulators, such as the simulation and analysis of trips, and the modeling and analysis of charging stations. The proposed model only partially considers the electrical network distribution impact of the EV user decisions. The effect of changes in demand and generation throughout the time of the electricity prices is considered using the DLMP-based distribution network operation and reconfiguration optimization model. The aim is to overcome several limitations in the current state-of-the-art developments.

Table 1. Analysed tools.

Tool	Charging Decisions Using Learned Charging Behaviours	Variable Prices	Simulation/ Trip Analysis	Model/Charging Stations Analysis	Electrical Network Impact
[24]	No	No	Yes	No	No
MATSim [23]	No	No	No	No	No
SUMO [22]	No	No	Yes	No	No
[26]	No	No	Yes	Yes	No
[25]	No	No	No	No	Yes
[28]	No	No	No	Yes	Yes
EVeSSi [29]	No	No	Yes	No	Yes
V2G-Sim [31]	No	No	No	No	Yes
Proposed tool	**Yes**	**Yes**	**Yes**	**Yes**	**Partially**

3. Proposed Simulation Tool

In this section, the simulation tool parameters and algorithm are described. The tool allows the simulation of electric vehicle trips in a simple way, and it was developed using *R* language using *RStudio* integrated development environment [33].

3.1. Parameters

The global parameters of the simulator are described in Table 2. These parameters mean that they are applied to all the generated profiles, i.e., for any moment of the simulation they are the same. These are default values but can be changed according to user preferences.

Table 2. Global tool parameters.

Parameter	Description	Example Value
ncars	Number of EVs	5000
cdist	Compensatory distance between two points	20%
sf	Map scale	1
hcpower	Home charging power	3.7 kW
chargingeff	Charge efficiency	85%

3.2. Simulator Algorithm

The simulator consists of two main parts: data generation and simulation of trips. Data is generated concerning the profile of each user, such as vehicle features (battery, consumption, etc.), trips to be performed (locations and departure times) and behavioral parameters.

3.3. Data Generation

Population generation is an iterative process in which each of the variables is generated randomly from a sample of values with individual probabilities. Initially, each profile is assigned an initial location, depending on the available positions in the city map. This location will be a residence or a point of exit/entry into the city, considering users that live the city. Values are generated for the initial SoC, the preferred charging level, and the travel profile. It also generated the value of the battery capacity that will determine the rest of the characteristics of the vehicle. In the same way, a weight is assigned for the distance in terms of the charging station choosing, being the remaining weights attributed according to this value. The last data sets to be generated are the trips and times as well as their importance. Algorithm 1 has the following structure:

Algorithm 1 Data generation algorithm.

```
for each of the cars do
    Add an x coordinate to variable x
    if x equal to some of the correspondent existent x available on the map then
        Add y coordinate to y variable
    end if
    Generate initial SoC, available range preference, battery capacity and trip importance
    Random generate w1
    if w1 equals to a specific value then
        w2 = 1-w1-w3
        w3 = 1-w1-w2
    end if
    if cars battery = value then
        Attribute all data to this car model in the cars data frame
    end if
    for i:=0 to 5 do
        Number of trips = 2, 3, 4 or 10-15
        Generate trips importance
        Generate locations for the number of trips
        Generate work day times, night times and/or leisure times
    end for
end for
```

3.4. Trip Simulation

The trips simulation runs in periods of 15 min, totalling to 96 (j = 96) for a full day. Its entire structure and mode of operation are described through a flow chart in Figure 2. Each vehicle has an initial location and a series of trips to be performed during the day. Each trip has a departure time, the period j in which the user will make that trip. When this happens, the Euclidean distance is calculated between the start location and the end location, with a margin of 20%, since the calculated distance is straight, and then it is multiplied by the scaling factor sf. Knowing the distance, the travel time is determined according to the average speed of the vehicle. For instance, if the calculated distance is 9000 m, and the average speed is 35 km/h, the travel time will be 15 min and 26 s, which is longer than one interval, and thus it will consume two periods. However, if the average speed is 40 km/h, the travel time will be 13 min and 30 s, which is equivalent to one period. The following equation determines the travel time:

$$T = \frac{\frac{d}{Vm \times \frac{1000}{3600}}}{60} \tag{1}$$

where:

T—Travel time (minutes)

d—Distance between destinations (meters)

Vm—Average vehicle speed (km/h)

3.5. Charging Stations

To simulate charging, four public charging stations (parking lot buildings) were created along with domestic chargers. Of the public stations, two are a slow charge (of 7.2 kW), and two are a fast charge (of 50 kW). The domestic chargers have a power of 3.7 kW.

The location of the stations was not chosen following a specific methodology. Their distribution covered all points of the city, with some randomness. In this sense, the objective is to understand what and how the various factors can influence the choice of charging sites and how energy prices influence EV users behavior.

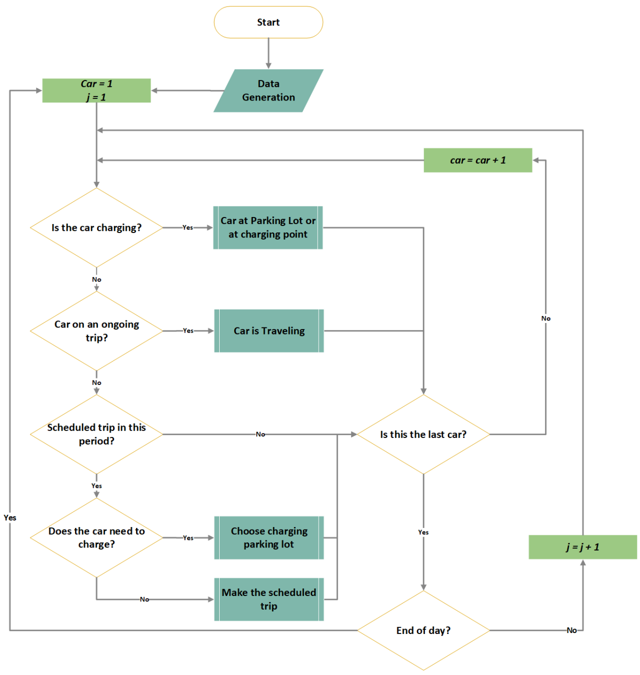

Figure 2. Flowchart of the travel simulation algorithm.

3.6. Charging Decisions

When the user decides to charge the EV, a location must be chosen (a charging station or house). For this simulation, three variables were considered: distance, energy price and charging time (slow or fast). After determining the scores of each of those variables and considering the preferences of each user, it is obtained the final score (Equation (2)). The charging station with the highest score is the one chosen to charge the vehicle.

$$FinalScore = Ds \times w_1 + Ps \times w_2 + Cts \times w_3 \tag{2}$$

where:

Ds—Distance score from 0 to 100
Ps—Price score from 0 to 100
Cts—Charge time score from 0 to 100
w—Weight for each of the variables (w_1 for distance preference; w_2 for price preference; w_3 for time preference)

The process of selecting the preferred place to charge follows the structure described in Figure 3. The distances to slow charging stations are calculated. These values, together with the energy price (€/kWh) and the charging time that the user has, allows a final score between 0 and 100 for each station. If the vehicle allows fast charging, this process is repeated for these types of charging stations. Finally, the scores of the charging stations are compared, and the highest is chosen.

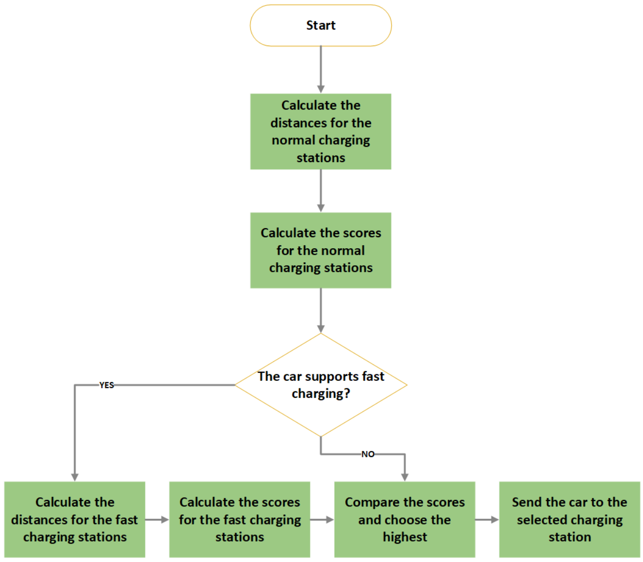

Figure 3. Flowchart for the charging station selection.

To determine how long each user can delay or not a trip to charge his vehicle a variable was introduced that defines its importance. Thus, three different levels were assigned:

1. *Low importance*: this trip is discarded, and the car is charged until the next trip;
2. *Medium importance*: the user delays the trip, and all subsequent ones, until a time limit that varies according to the user profile;
3. *High importance*: the user must carry out this trip, not being able to charge, unless the level of battery charge reaches critical values.

To ensure that each user always has sufficient charge to make the trips, it was considered a critical battery level. Following the results of [9] this value is set to 20%. Whenever a user reaches a level lower than this, regardless of the trip, the car must be charged. In this case, there are two options: either the user finds a place near the workplace (1st destination) and leaves the car there until the next trip, or looks for the nearest parking place and leave it there overnight until the next scheduled trip. It is assumed that the user leaves the car at this location and, hypothetically, does the rest of its travel using another mean of transportation.

3.7. Energy Prices

One of the variables that the users consider when deciding where to charge their vehicle is the energy price. This price differs between the type of station (slow or fast) and if they are public or domestic. Also, there are two domains where prices differ: fixed prices or variable prices.

In terms of simulation, in the case of fixed prices the user always pays the same regardless of the charging time. The only difference is whether it is a fast charging station or a domestic one, as a fast charging station is more costly. The variable prices vary by 15-min intervals. This is accomplished using the model described in Section 2.3. Firstly, an additional cost which is related to the fixed term of network price rate to be charged to the customer (Equation (3)) is calculated:

$$ACNR = \frac{\left(\frac{0.397 \cdot CP}{720}\right)}{OPR} \tag{3}$$

where:

$ACNR$—additional cost related to the fixed term of network price rate [€/kWh]. The contracted power cost is 0.397 €/kW/month paid to the DSO monthly (www.erse.pt)

CP—charging power of the charging station. 720 h per month

OPR—the park occupation rate.

Then the final energy price for the consumer is calculated (Equation (4)). This value is the sum of the DLMP received, with the energy tariff and the additional price previously calculated (Equation (3)). To Equation (4) a fee of 5% is added by the owner of the charging station and the VAT value.

$$Final\ Price = (DLMP + TariffMV + ACNR) \times PLG \times VAT \tag{4}$$

where:

$DLMP$—Distribution locational marginal pricing [€/kWh]

$TariffMV$—Energy tariff price for each period [€/kWh]

PLG—Additional profit margin of the parking owner

VAT—Value added tax

3.8. DLMP Optimisation Model Description

In this research work, the DLMPs (which will permit to determine the variable charging price (see Equation (4))) are defined through Lagrangian multipliers of the corresponding constraints (power balance) of the optimisation problem which has the goal to minimise the DSO expenditures [34]. Thus, the DSO seeks to:

- Minimize the power losses cost;
- Minimize the power not supplied cost;
- Minimize the power lines congestion cost;
- Minimize the power generation curtailment cost;
- Minimize the power from external suppliers cost.

The DLMPs optimization problem is classified as mixed-integer nonlinear programming (MINLP) due to the non-linearity features. To solve complex problems like this, Benders decomposition is an adequate technique [35,36]. The following constraints are considered:

- Network constraints:
  - Voltage;
  - Power balance;
  - Power flow equations;
  - Maximum admissible line flow.
- Supplier constraints:
  - Maximum and minimum limits for the power supplier;
  - Maximum and minimum limits for capacitor banks.
- Curtailment constraints:
  - Power generation curtailment;
  - Power not supplied.
- Lines congestion;

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- Energy storage systems constraints:
  - Charge and discharge limit;
  - Charge and discharge limit considering energy storage systems state;
  - State of charge;
  - Maximum and minimum energy storage systems capacity limit.

4. Case Studies

To carry out the case studies a physical model of SC by GECAD-BISITE [34] was used. The considered SC presents five types of loads, namely:

- Residential buildings (1375 homes);
- Office buildings (7 buildings);
- Hospital;
- Fire Station;
- Shopping Mall.

The schematic of the SC is presented in Figure 4 and the coordinates of each building can be seen in Table 3). The distribution network that feeds the entire city has one 30MVA substation and 25 load points. A total of 15 DG units (i.e., 2 wind farms and 13 PV parks), four capacitor banks of 1 Mvar, and are included in the network, as can be seen in Figure 5. Moreover, the SC has seven parking lot buildings (commonly referred as charging stations in this research work) for EV charging, four (two in bus 7 and two in bus 11) slow charging lots (7.2 kW for each connection point) and three (two in bus 2 and one in bus 5) fast charging lots (50 kW for each connection point). Each slow charging parking lot has 250 spaces for EVs and 80 spaces for each fast charging parking lot building. The considered value for OPR is 30% leading to an ACNR value of 0.0132 €/kWh for a slow charging parking space and a value of 0.0919 €/kWh for a fast charging parking space. Additionally, the parking owner charges an additional 5% fee and 23% of value-added tax (VAT). Furthermore, it is considered that 50% of the EV users can charge their EVs at home (3.7 kW charge point) with a fixed cost of 0.2094 €/kWh. The initial EV battery level is randomly generated between 40% and 65% of the battery capacity and the considered EV models, and their characteristics can be found in Table 4.

Table 3. Building coordinates on the xy plane.

Building		L1	L2	L3	L4 to L18	L19	L20	L21	L22	L23	L24	L25	PL1 to PL2	PL3 to PL4	PL5 to PL6	PL7
Coordinates (km)	X Axis	10.50	0.50	9.00	3.75 to 8.25	0.50	0.50	2.50	3.00	4.50	6.00	8.00	1.00	7.00	6.00	11.00
	Y Axis	3.50	2.00	5.00	1.00 to 3.00	3.50	5.50	2.00	4.50	3.50	5.00	4.00	3.50	5.00	0.50	4.00

Table 4. EVs types.

Model	Battery (kWh)	Slow Charge Power (kW)	Fast Charge Power (kW)	Consumption (kWh/km)
Nissan Leaf	40.00	6.60	50.00	0.1553
Tesla Model S 70D	75.00	7.40	50.00	0.2100
BMW i3	33.20	7.40	50.00	0.1584
Renault Zoe	41.00	7.40	-	0.1460
Renault Kangoo	33.00	7.40	-	0.1926
VW e-Golf	24.20	7.20	40.00	0.1584
Ford Focus	33.50	6.60	50.00	0.1926
Hyundai IONIQ	30.50	6.60	50.00	0.1429

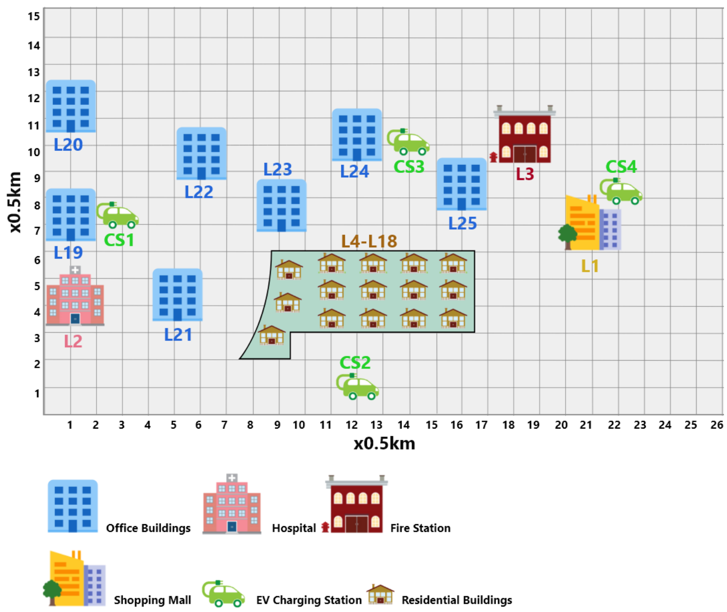

Figure 4. Smart city diagram [34].

Three user preference scenarios are considered, in one, the user's priority is to charge their EV at a charging station located as close as possible to them. In the second scenario, the users prefer to find charging stations where they can charge their EV at a low price. In the third scenario, the EV user gives its preference to the charging time.

The line congestion cost is 0.02 €/kW when power flow is above 50% of the thermal line rating capacity.

The study presented in this research paper considers one week of input data for every 15 min with the aim of showing the effectiveness of the proposed model (i.e., 672 periods are considered in the simulation process). The chosen week is the 19 March 2017 to 25 March 2017.

This work has been developed on a computer with one Intel Xeon E5-2620 v2 processor and 16 GB of RAM running Windows 10 Pro. In addition to *R* language (for EV user behavior simulator), the MATLAB R2016a and TOMLAB 8.1 64 bits with CPLEX and SNOPT solvers were used for the optimization problems.

Simulations were performed using fixed and variable energy charging prices for two different populations scenarios, i.e., considering 2500 EVs and 5000 EVs. For each simulation, the following user preferences were changed: distance, price and charging time. The following features are fixed for all simulations in each population scenario:

- The amount of vehicles and their models;
- The initial battery charge;
- The amount of trips;
- The trips schedule;
- The starting locations.

The fixed charging prices are equal for all periods of the day and are 0.15 €/kWh for slow charge and 0.25 €/kWh for fast charge.

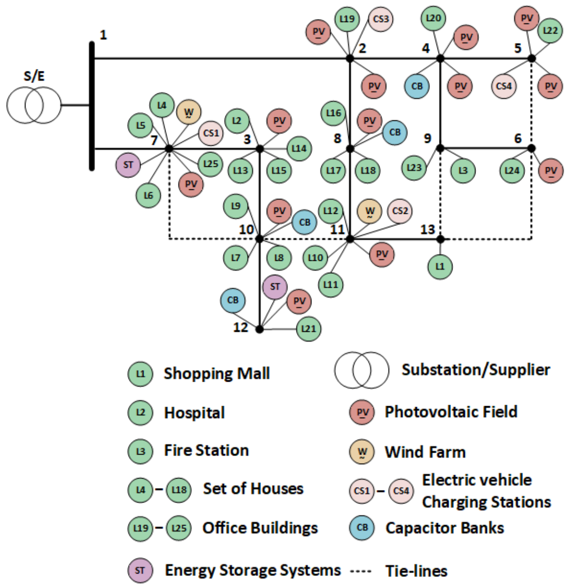

Figure 5. 13-bus distribution network diagram [34].

5. Results and Discussion

This section presents the results for the carried out simulations. Section 5.1 presents the results for a scenario with 2500 EVs, while Section 5.2 provides the results for a 5000 EVs population scenario.

5.1. Population Scenario with 2500 EVs

Considering a 2500 EVs scenario and using the fixed charging price, it is possible to see in Figure 6 the correspondent charging sessions percentages for each user scenario preference (distance Figure 6a, price Figure 6b, and time Figure 6c). It is worthy to note, that one charging session is counted from the moment the EV beings to charge until the time of it leaves the charging station. Analysing Figure 6a (where the preference is the charging stations proximity to the total path that the user will have to do, i.e., the lowest sum value of the distance between the current location and the CS and the distance between the CS and the next EV user destination), it can be seen that the charging station 2 was preferred by users, with 37% of charging sessions. Since for this user preference scenario, the only differentiation between normal charging stations is the distance, and it can be concluded that CS 2 will be nearest to the users' destinations when compared to the remaining CSs. Figure 6b) (EV users' gives priority to the price over the distance and charging time at the moment to chose a CS) shows that the CS 2 presents the higher charging sessions around 47% while the CS 1 was the second chosen one. The CS 3 and CS 4 (fast charging stations) presents together only a percentage around 21% of the total charging sessions. This is as expected result once the slow charging stations present lower charging prices compared to the fast charging stations. When the user time preference scenario is considered the majority of the users prefer the fast charging stations. As can be seen in Figure 6c fast charging stations present 55.2% of the total charging sessions. However, this value also shows that the influence of the distance (CS 2 lower distance) and charging price (slow charging stations—lower price) have a strong influence on the users'.

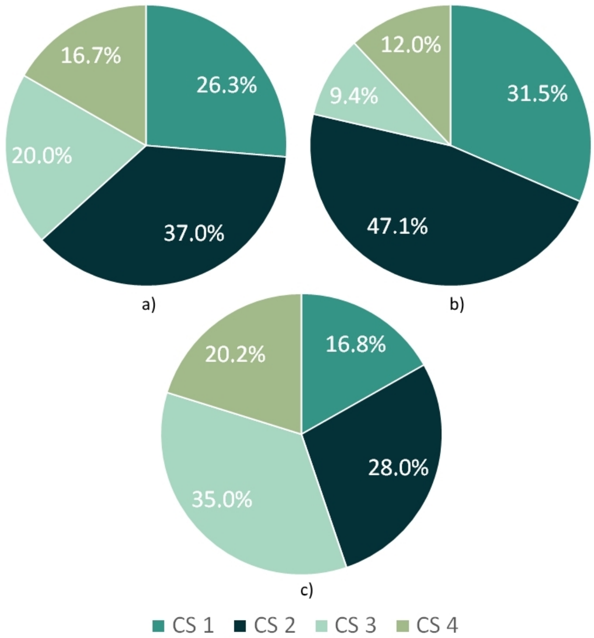

Figure 6. Charging sessions using fixed charging prices considering the 2500 EVs scenario. (**a**) User distance preference scenario charging sessions. (**b**) User price preference scenario charging sessions. (**c**) User time preference scenario charging sessions.

Figure 7 depicts the charging sessions when the variable charging prices model is used. Like the fixed prices method when user distance preference is considered the variable model charging price also gives more sessions to CS 2 (Figure 7a), leading to the same conclusion—this is the CS nearest to the users' destinations. Checking Figure 7b it is possible to conclude that CS 1 is the cheapest one due to the high percentage of charging sessions (71.7%). Regarding to the user time preference scenario (Figure 7c), the results are very similar to the case where the fixed prices are considered, i.e., the majority of the users preferring the fast charging stations.

For the user distance and time preference scenarios, the fast charging station obtained a higher preference when compared to the case where the user preference is defined by the price. This indicates that when the price is not the most important factor, fast charging stations can attract users who are located close to them. Nevertheless, we concluded that the location of those charging stations is not optimal, because even when considering the user distance preference scenario, the majority of the users choose the slow charging stations—the cheapest ones. Moreover, to highlight this conclusion, when charging time is the most important factor the slow charging stations also present high preference, being the CS 2 the second most preferred.

A comparison between the fixed charging prices and the proposed variable charging prices model are shown in Figure 8. As can be seen, the proposed model presents advantages in all scenarios for the EVs users in terms of charging prices. When the user distance preference scenario is considered, the proposed model presents 4% of gains for users' (0.0083 €/kWh), for price and time user preference scenario the benefits are 10% (0.0210 €/kWh), and 2% (0.0046 €/kWh), respectively.

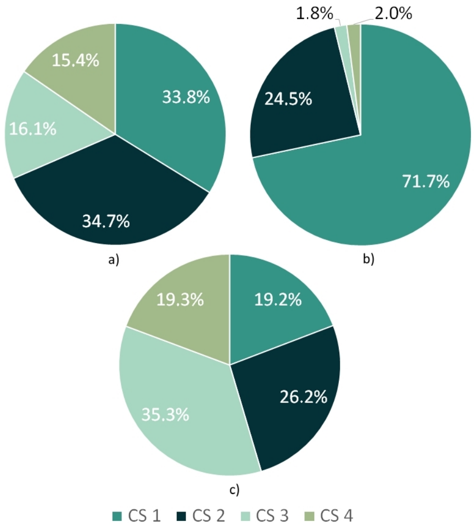

Figure 7. Charging sessions using variable charging prices considering the 2500 EVs scenario. (**a**) User distance preference scenario charging sessions. (**b**) User price preference scenario charging sessions. (**c**) User time preference scenario charging sessions.

5.2. Population Scenario with 5000 EVs

In this subsection, it is presented the simulation results for a scenario with 5000 EVs. Figure 9 presents the charging session results for each Charging station in the three EV user scenarios preference considering fixed charging prices. The achieved conclusions are the same when the scenario with 2500 EVs is considered. Seeing Figure 9a it is also checked through the presented values that CS 2 is near one to the users' destinations. Also, when the price preference is considered, the slow charging stations are proffered (Figure 9b), since they present the lower charging prices. When the charging time is crucial for the EVs users, the set of charging stations presents a percentage of charging sessions around 51% (Figure 9c). Nevertheless, it is also verified that slow charging stations have a strong influence on the users' choice.

The charging sessions result considering the variable charging price model is depicted in Figure 10. Once again, the results are very similar to the scenario with 2500 EVs, with more charging sessions in CS 2 when it is considered the user distance preference scenario (Figure 10a)—CS 2 is the near one to the users' destinations. For the user price preference scenario, the CS 1 presents the higher percentage of charging sessions (Figure 10b). Thus, it can be concluded that CS presents more competitive charging prices compared to the remaining CSs. Considering the user time preference scenario, the higher percentage of EVs users' (Figure 10c) prefer the fast charging stations (51%).

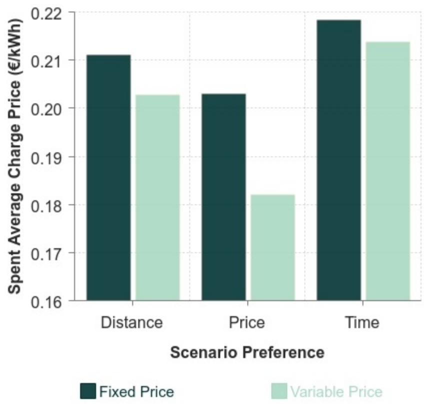

Figure 8. Average charging price comparison considering the 2500 EVs scenario.

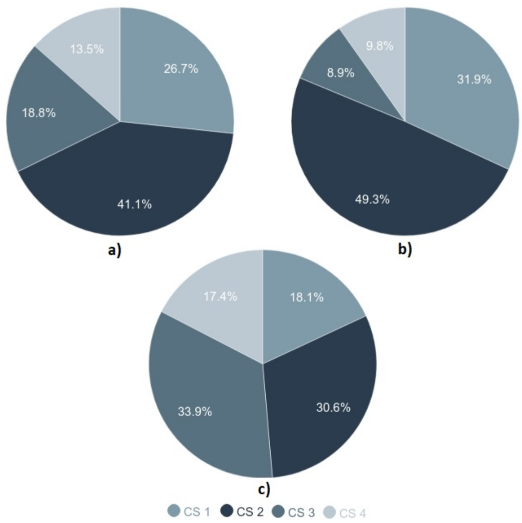

Figure 9. Charging sessions using fixed charging prices considering the 5000 EVs scenario. (**a**) User distance preference scenario charging sessions. (**b**) User price preference scenario charging sessions. (**c**) User time preference scenario charging sessions.

The conclusions are the same when the scenario with 2500 EVs is considered, i.e., if time is not the most important factor, the users can be attracted by the fast charging station which can be closer to them. However, once again, it can be seen that the location of fast charging stations is not optimal (the majority of the users choose the slow charging stations even when the user distance preference scenario is considered). Also, as in the 2500 EVs scenario, when the most important factor for the users is the charging time, the slow charging stations also present a considerable preference, with the CS 2 as the second most preferred.

Figure 11 presents a comparison between the fixed charging prices and the proposed variable charging prices model. The proposed variable charging price model presents considerable advantages for the EVs users' when distance and price preference scenarios are considered, with gains of 5% (0.0120 €) and 18% (0.0418 €), respectively. Regarding user charging time preference scenario the variable charging price model does not present advantages in terms of charge price for the EVs users when compared with fixed charging price (3% higher—0.0073 €).

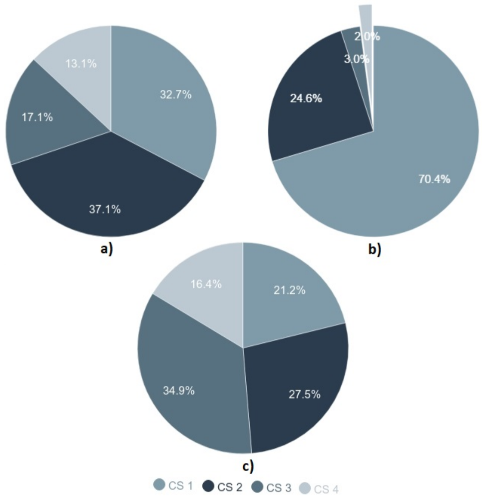

Figure 10. Charging sessions using variable charging prices considering the 5000 EVs scenario. (**a**) User distance preference scenario charging sessions. (**b**) User price preference scenario charging sessions. (**c**) User time preference scenario charging sessions.

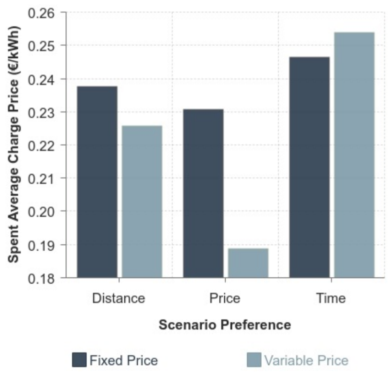

Figure 11. Average charging price comparison considering the 5000 EVs scenario.

6. Conclusions

This research paper presents a study of the impact of the variation of the energy charging prices on the behavior of electrical vehicle users. It also compared its benefits when using the variable and fixed charging prices. To this end, the authors developed an EV behavior simulator and combined it with an DLMP-based distribution network operation and reconfiguration optimization model. The main contributions of the conducted study can be summarized as follows: (1) EV user behavior simulator has been developed to generate a realistic population, considering the city size, and charging stations; (2) the positive impact of the variable EV charging prices on the electric vehicles users has been assessed.

The proposed methodology was tested in a case study which has been conducted on a mock-up model of a SC located at the BISITE laboratory with a 13 buses distribution network. Moreover, three users scenarios preferences (distance, price and time) were considered and were used to compare the results of the variable EV charging prices and EV fixed charging prices to demonstrate the advantage of the former.

It was verified that the use of variable pricing for EV charging is advantageous for the EV users in all scenarios when it is considered 2500 EVs. The gains are 4%, 10%, and 2%, respectively for distance, price, and time preferences. With 5000 EVs, the variable pricing does not present savings in comparison with the fixed charging prices when time scenario preference is considered. However, the proposed variable charging price model still presents considerable savings when the distance and price preference scenarios are considered. These two scenarios present for EV users 5% and 18% of gains, respectively.

The results suggest that the use of variable prices is promising, and can be used as an efficient approach in smart cities by offering to EVs' users more options (in terms of price) when deciding where to charge their EVs.

The main disadvantages of the proposed model are: (a) the EV users profiles are not adapted to the different weekdays; (b) the decision charge method is only based on the battery charge level; (c) vehicle-to-grid is not considered.

In terms of future work, the authors will address more user profiles and additional charging decisions that depend on the energy price (increasing the flexibility), and also the possibility of vehicle-to-grid.

Author Contributions: The authors contributions were: Conceptualization, B.C., J.S., A.C., T.P., F.L., P.N., Z.V.; Methodology, B.C., J.S., A.C., T.P., F.L., P.N., Z.V.; Software, B.C., J.S., A.C., T.P., F.L., P.N., Z.V.; Validation, B.C., J.S., A.C., T.P., F.L., P.N., Z.V.; Formal analysis, B.C., J.S., A.C., T.P., F.L., P.N., Z.V.; Investigation, B.C., J.S., A.C., T.P., F.L., P.N., Z.V.; Writing—original draft preparation, B.C., J.S., A.C., T.P., F.L., P.N., Z.V.; Writing—review and editing, B.C., J.S., A.C., T.P., F.L., P.N., Z.V.; Visualization, B.C., J.S., A.C., T.P., F.L., P.N., Z.V.

Funding: This work has received funding from FEDER Funds through COMPETE program, from National Funds through FCT projects UID/EEA/00760/2019 and UID/CEC/00319/2019 and PTDC/EEI-EEE/28983/2017-CENERGETIC. Bruno Canizes is supported by FCT Funds through SFRH/BD/110678/2015 PhD scholarship. Angelo Costa is supported by the FCT Post-Doc Grant SFRH/BPD/102696/2014.

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

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