Seyed Mahoor Ebrahimi

Future Electricity Network Management

Effects and Possibilities of Local Markets and Electric Vehicles

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TIIVISTELMÄ

Väitöskirjassa kehitetään uusia mahdollisia ratkaisuja tulevaisuuden sähkönjakeluverkkojen hallintaan keskittyen erityisesti laajamittaisen sähköautojen integroinnin, virtuaalivoimalaitosten ja paikallisten markkinaratkaisuiden hyödyntämismahdollisuuksiin. Työssä tarkastellaan jakeluverkon toimijoiden välisiä vuorovaikutuksia ja ehdotetaan kaksitasoisen Stackelbergin peliteoriaan perustuvan optimointistrategian hyödyntämistä jakeluverkkojen hallinnassa. Kyseisessä strategiassa jakeluverkonhaltijan on mahdollista epäsuorasti säädella virtuaalivoimalaitosten toimintaa pätö- ja loistehon hinnoittelun avulla. Lisäksi väitöskirjassa ehdotetaan kompleksisuutta vähentävää ns. virtuaaliakkua sekä kustannustehokasta laturien jakamismenetelmää sähköautojen pysäköintialueille.

Sähköautojen laajamittainen yleistyminen ja lataaminen saattaa aiheuttaa ns. pullonkaulatilanteita jakeluverkoissa kasvavissa määrin tulevaisuudessa. Tämä tarkoittaa sitä että tietyillä ajanhetkillä sähköjohtojen ja muuntajien olemassa oleva siirtokapasiteetti ei välttämättä riitä ilman joustoja. Työssä tarkasteltujen paikallisten pätö- ja loistehopohjaisten joustomarkkinoiden avulla onkin mahdollista parantaa sähköjärjestelmän ja jakeluverkkojen kokonaistehokkuutta sekä jakeluverkkojen kykyä integroida enemmän vaihtelevaa uusiutuvaa energiantuotantoa sekä sähköautoja esimerkiksi erilaisten hallinta- ja ohjausstrategioiden avulla. Väitöskirjassa ehdotetun virtuaaliakkumallin todettiin kuvaavan onnistuneesti sähköautojen pysäköintialueen kokonaislatausprofiilia samalla yksinkertaistaen ja nopeuttaen laskentaa. Lisäksi ehdotetun sähköautojen pysäköintialueiden latausasemien jakamismenetelmän avulla on mahdollista tehokkaammin palvella useampia sähköajoneuvoja pienmmällä latausasemien määrällä mikä taasen pienentää kokonaisinvestointikustannuksia

Avainsanat: Jakelujärjestelmän hallinta, Sähköajoneuvot, Virtuaalivoimalaitokset, Paikallinen energiamarkkina, Kaksitasoinen optimointi, Laturien jakamislataus

ABSTRACT

This dissertation develops new potential solutions for the management of future electricity distribution networks, focusing in particular on the possibilities of large-scale electric vehicle integration, virtual power plants and local market. The work examines the interactions between distribution network agents and proposes the use of a Stackelberg game-based bilevel optimization framework for distribution system management. In this approach, the distribution system operator can indirectly regulate the operation of virtual power plants through active and reactive power pricing. In addition, the dissertation proposes a so-called virtual battery model for electric vehicle (EV) parking lot that reduces computational complexity of EV-related simulations and a cost-effective charger allocation method for electric vehicle parking areas.

The widespread use of EVs and its consequent charging demand may increasingly cause congestion in distribution networks in the future. This means that, at certain times, the existing transmission capacity of power lines and transformers may not be sufficient. The local active and reactive markets examined in this work can improve the overall efficiency of the electricity system and distribution networks. These markets enhance the ability of distribution networks to integrate more variable renewable energy resources and electric vehicles through efficient management and control strategies. Moreover, the proposed virtual battery model successfully represents the charging profile of EV parking lots, providing accurate results with reduced computational complexity. The charger-sharing approach optimizes the utilization of EV chargers, allowing parking lots to serve more vehicles with fewer charging stations, thereby reducing investment costs and promoting the expansion of EV infrastructure.

Keywords: Distribution System Management, Electric Vehicles, Virtual Power Plants, Local Energy Market, Bilevel Optimization, Charger-Sharing Charging

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ABBREVIATIONS

ADN	Active Distribution Network
DER	Distributed Energy Resource
EV	Electric Vehicle
VPP	Virtual Power Plant
DSO	Distribution System Operator
DG	Distributed Generation
TSO	Transmission System Operator
P2P	Peer-to-Peer
PV	Photovoltaic
EVPL	Electric Vehicle Parking Lot
G2V	Grid-to-Vehicle
V2G	Vehicle-to-Grid
SOC	State of Charge
DA	Day-Ahead
RT	Real-Time
RES	Renewable Energy Source
DR	Demand Response
ESS	Energy Storage System
PDF	Probability Distribution Function
CDF	Cumulative Distribution Function
DS	Distribution System
UDEVCH	Unidirectional Electric Vehicle Charger
BDEVCH	Bidirectional Electric Vehicle Charger
RTEM	Real-Time Electricity Market
OFE	Objective Function of End-users
OFDSO	Objective Function of Distribution System Operator
OFA	Objective Function of Aggregators
MILP	Mixed-Integer Linear Programming
AC	Alternating Current
DC	Direct Current
IoT	Internet of Things
FSP	Flexibility Service Providers
AI	Artificial Intelligence
ML	Machine Learning
V2X	Vehicle-to-Everything
CNN	Convolutional Neural Network
FERs	Flexible Energy Resources

LIST OF PUBLICATIONS

The dissertation is based on the following refereed articles:

Publication I : **Mahoor Ebrahimi**, Mahan Ebrahimi, Miadreza Shafie-khah, Hannu Laaksonen, ”EV-Observing Distribution System Management Considering Strategic VPPs and Active & Reactive Power Markets”, Applied Energy, Volume 364, 2024, 123152, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2024.123152.© 2024 The Authors. Published by Elsevier. CC BY.

Publication II : **Mahoor Ebrahimi**, Miadreza Shafie-khah, Hannu Laaksonen, ”Uncertainty-Observed Virtual Battery Model for An Electric Vehicle Parking Lot Enabling Charger-Sharing Modelling”, Journal of Energy Storage, Volume 89, 2024, 111578, ISSN 2352-152X, https://doi.org/10.1016/j.est.2024.111578. © 2024 The Author(s). Published by Elsevier. CC BY.

Publication III : **Mahoor Ebrahimi**, Amin Shokri Gazafroudi, Hannu Laaksonen and Miadreza Shafie-Khah, ”Two-Layer Game-Based Framework for Local Energy Flexibility Trading”, IEEE Access, vol. 10, pp. 68768-68777, 2022, 10.1109/ACCESS.2022.3186027. © 2022, IEEE. Reprinted with permission.

Publication IV : **Mahoor Ebrahimi**, Amin Shokri Gazafroudi, Mahan Ebrahimi, Hannu Laaksonen, Miadreza Shafie-Khah and J. P. S. Catalão, ”Iterative Game Approach for Modeling the Behavior of Agents in a Competitive Flexibility Trading”, IEEE Access, vol. 9, pp. 165227-165238, 2021, 10.1109/ACCESS.2021.3134937. © 2021, IEEE. Reprinted with permission.

Publication V : **Mahoor Ebrahimi**, Mahan Ebrahimi, Miadreza Shafie-khah, Hannu Laaksonen, ”The Role of EV Parking Lots for Supporting the Distribution System Operation Considering EV Uncertainties”, Transportation Research Procedia, Volume 70, 2023, Pages 263-270, ISSN 2352-1465, https://doi.org/10.1016/j.trpro.2023.11.028. © 2023 The Authors. Published by Elsevier. CC BY-NC-ND.

Publication VI : **Mahoor Ebrahimi**, Mahan Ebrahimi, Hannu Laaksonen, Miadreza Shafie-khah, ”Impact of Voltage Violation Penalty Cost on Distribution System Operation Considering Electric Vehicle”, 2023 International Conference on Future Energy Solutions (FES), Vaasa, Finland, 2023, pp. 1-6, 10.1109/FES57669.2023.10182657. © 2023, IEEE. Reprinted with permission.

Publication VII : **Mahoor Ebrahimi**, Sara Haghifam, Hannu Laaksonen, Miadreza Shafie-khah, Yue Xiang, ”Optimal planning of a virtual power plant hosting an EV parking lot”, CIRED Porto Workshop 2022: E-mobility and power distribution systems, Hybrid Conference, Porto, Portugal, 2022, pp. 631-635, 10.1049/icp.2022.0785. © 2022, IEEE. Reprinted with permission.

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AUTHOR’S CONTRIBUTION

Publication I: “EV-Observing Distribution System Management Considering Strategic VPPs and Active & Reactive Power Markets”

Mahoor Ebrahimi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Mahan Ebrahimi: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis

Miadreza Shafie-khah: Investigation, Conceptualization, Supervision, Writing – review & editing.

Hannu Laaksonen: Conceptualization, Supervision, Writing – review & editing.

Publication II: “Uncertainty-Observed Virtual Battery Model for An Electric Vehicle Parking Lot Enabling Charger-Sharing Modelling”

Mahoor Ebrahimi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Miadreza Shafie-khah: Writing – review & editing, Supervision, Investigation, Conceptualization.

Hannu Laaksonen: Conceptualization, Supervision, Writing – review & editing.

Publication III: “Two-Layer Game-Based Framework for Local Energy Flexibility Trading”

Mahoor Ebrahimi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Amin Shokri Gazafroudi: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Hannu Laaksonen: Investigation, Conceptualization, Supervision, Writing – review & editing

Miadreza Shafie-khah: Investigation, Conceptualization, Supervision, Writing – review & editing

Publication IV: “Iterative Game Approach for Modeling the Behavior of Agents in a Competitive Flexibility Trading”

Mahoor Ebrahimi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Amin Shokri Gazafroudi: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Mahan Ebrahimi: Writing – review & editing, Writing – original draft, Investigation.

Hannu Laaksonen: Investigation, Conceptualization, Supervision, Writing – review & editing.

Miadreza Shafie-khah: Investigation, Conceptualization, Supervision, Writing – review & editing.

João PS Catalão: Writing – review & editing, Writing – original draft, Investigation.

Publication V: “The Role of EV Parking Lots for Supporting the Distribution System Operation Considering EV Uncertainties”

Mahoor Ebrahimi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Mahan Ebrahimi: Writing – review & editing, Writing – original draft, Investigation.

Miadreza Shafie-khah: Investigation, Conceptualization, Supervision, Writing – review & editing.

Hannu Laaksonen: Investigation, Conceptualization, Supervision, Writing – review & editing.

Publication VI: “Impact of Voltage Violation Penalty Cost on Distribution System Operation Considering Electric Vehicle”

Mahoor Ebrahimi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Mahan Ebrahimi: Writing – review & editing, Writing – original draft, Investigation.

Miadreza Shafie-khah: Investigation, Conceptualization, Supervision, Writing – review & editing.

Hannu Laaksonen: Investigation, Conceptualization, Supervision, Writing – review & editing.

Publication VII: “Optimal planning of a virtual power plant hosting an EV parking lot”

Mahoor Ebrahimi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Sara Haghifam: Investigation, Writing – review & editing.

Hannu Laaksonen: Investigation, Conceptualization, Supervision, Writing – review & editing.

Miadreza Shafie-khah: Investigation, Conceptualization, Supervision, Writing – review & editing.

Yue Xiang: Investigation, Writing – review & editing.

1 INTRODUCTION

1.1 Background and motivation

The increasing penetration of renewable energy resources into the power system has introduced new challenges, necessitating enhanced support from the demand side and distribution-level assets to ensure stable and cost-effective system operation. Consequently, traditional passive distribution networks are being transformed into active distribution systems. Thus, the optimal operation of distribution-level assets is becoming increasingly critical. In this regard, active distribution networks (ADNs) have emerged as an important concept in modern power systems. Unlike traditional passive distribution networks, which facilitate one-way power flow from the transmission grid to end-users, ADNs enable two-way power flow and the active integration of distributed energy resources (DERs), such as renewable energy sources, energy storage systems, and electric vehicles.

The advantages of ADNs include enhanced system reliability, improved energy efficiency, and reduced carbon emissions. By leveraging DERs, ADNs can address key power system challenges, such as voltage fluctuation and distribution network congestion. However, implementing ADNs involves several challenges. A primary challenge is the need for sophisticated control and communication systems to ensure the network's reliable and efficient operation, as well as the establishment of communication networks to support data exchange between various network components. Another significant challenge is the need for accurate modeling and forecasting of DERs, which can be complex due to the uncertain nature of renewable energy sources and EV charging behaviors. Additionally, regulatory frameworks and local market structures are essential to incentivize DER deployment and support the network's efficient operation.

In distribution systems, direct and indirect (price-based) incentives are two primary approaches for controlling and managing the integration of DERs, energy storage, and electric vehicles. These control mechanisms are essential in modern distribution systems, where dynamic demand, fluctuating renewable generation, and system reliability require sophisticated strategies for balancing supply and demand. Direct control involves the distribution system operator (DSO) or a third party directly managing and adjusting DERs or other devices connected to the network. This method relies on communication networks, sensors, and controllers to remotely control specific assets. For instance, the DSO can curtail solar generation, manage battery storage discharge, or adjust the charging schedules of electric vehicles to maintain grid stability.

Direct control offers a reliable and predictable way of managing the system, as the DSO has precise control over DERs and can respond quickly to changes in demand or generation. However, this approach requires extensive communication infrastructure, strong cybersecurity measures, and clear agreements with DER owners regarding operational control. Additionally, direct control may raise concerns over user autonomy and privacy, as it involves external management of privately owned assets. Indirect control, also known as price-based incentives or market-based control, relies on financial signals to influence the behavior of DER owners and other consumers. In this approach, the DSO uses time-based pricing, demand charges, or dynamic tariffs to encourage users to adjust their energy usage patterns in ways that benefit grid stability. For example, during peak demand periods, the DSO might raise electricity prices, prompting consumers to reduce their load or discharge energy from storage systems. Indirect control is advantageous because it respects consumer autonomy, allowing users to respond to price signals according to their preferences. This approach can also promote energy efficiency, as consumers are incentivized to shift their consumption to times when electricity is cheaper and grid demand is lower.

To enable effective indirect control within a distribution system, a well-defined local market framework is essential. Such a framework should allow the DSO to effectively manage and coordinate the activities of local market participants, including DERs like renewable energy resources, energy storage systems, electric vehicle charging stations, and other demand response assets. Through this local market structure, the DSO can influence participants' operational behaviors by issuing targeted price signals, thereby guiding market players' actions in alignment with overall grid stability objectives. The development of this local market framework requires careful consideration of pricing mechanisms, as the effectiveness of indirect control relies heavily on the design of price signals that accurately reflect the grid's needs at different times.

In addition, the widespread adoption of EVs has the potential to significantly influence the management of distribution systems. On the positive side, EVs can serve as a source of distributed energy storage, helping to mitigate the variability of renewable energy sources. Managed EV charging can be synchronized with periods of excess renewable generation, thereby reducing curtailment and enhancing the utilization of renewable energy. Moreover, EVs can contribute to voltage support and reactive power compensation through smart charging strategies designed to respond dynamically to system requirements. However, uncoordinated and high levels of EV charging pose considerable challenges, including distribution network congestion and voltage instability. To address these challenges, effective strategies must be developed for managing EV charging and discharging.

In this context, it is crucial to evaluate the impact of EV operations on power system management and their potential benefits and challenges by accurately modeling their characteristics. EV modeling presents a significant challenge due to the uncertain behavior of EVs, which complicates their integration into power system models, particularly when modeling the aggregation of a large number of EVs. Additionally, the high investment costs associated with EV chargers pose a barrier to the widespread deployment of EVs. Therefore, it is imperative to identify strategies to reduce the required investment in charging infrastructure by deploying chargers in the most efficient and cost-effective manner.

1.2 Scope and objective of the thesis

This thesis seeks to address several key research questions related to the management of distribution systems, the role of local markets, and the integration of EVs. In this topic, there is a need for further research across different fields, some of which are practical-oriented and some are theoretical-oriented. In this thesis, a more theoretical and future-oriented approach has been chosen to address the topic, rather than focusing on practical device-level testing and piloting. This approach aims to provide a comprehensive understanding of the potential advancements and challenges in the integration of DERs and EVs within ADNs. By emphasizing theoretical models and simulations for future power systems, the study seeks to offer insights into the long-term implications and strategic planning required for the effective management and operation of modern power systems. The questions guiding this research are as follows:

- How can the concept of a Virtual Power Plant (VPP) be employed to coordinate the operations of assets such as wind power plants, PV systems, Distributed Generators (DGs), battery energy storage systems, and EV parking lots within the distribution system?
- How do different agents such as DSOs, aggregators, and end-users, interact within the local markets, and in what ways do their operational decisions influence the functioning of others?
- What local market framework can be developed to accommodate network and asset constraints while integrating market interactions and system operational constraints with low simulation time?
- How can local markets be utilized to effectively manage the operation of distribution systems?
- How does the reactive power market influence the proposed management framework?

In addition to these questions concerning distribution system management and local markets, the research addresses the following:

- What are the potential challenges and opportunities that EVs introduce to distribution systems?
- How can EVs support the distribution system through scheduled charging?
- How can EVs contribute to the system by providing reactive power, leveraging the power electronic facilities in charging stations?
- Given the uncertainty in EV owner behavior, how can EV aggregations be modeled to enable seamless integration into distribution system management frameworks without imposing high computational burdens?
- Is it possible to optimize the utilization of EV chargers to minimize their investment costs, thereby promoting further development of EV infrastructure?

Based on the above research questions, the objectives of the thesis can be listed as below:

- To investigate the cooperation of wind power plants, PV systems, DGs, battery energy storage systems, and EV parking lots as a VPP, and to analyze how such cooperation can reduce overall costs. Additionally, to conduct VPP planning to evaluate the synergy between different generation assets and EV charging stations.
- To understand local market interactions by deploying iterative game-based approaches, allowing all agents to react to the decisions of others with equal decision-making power. Furthermore, to evaluate the performance of these interactions under different market regulation scenarios.
- To develop a bilevel optimization framework based on the Stackelberg game to model market interactions. The bilevel optimization will be simplified into a single-level equivalent problem and linearized using the duality theorem and other applicable methods. The framework will enable the DSO at the upper level to send price-based control signals while considering VPP behaviors at the lower level.
- To design a local market framework for both active and reactive power, enabling the distribution system operator to send price-based signals for reactive power in addition to active power.
- To study the operation of the distribution system considering both active and reactive power flows. This includes analyzing system operations under various scenarios for Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) charging, as well as evaluating the capability of EV chargers to provide reactive power and their impacts on the distribution system.

- To develop an uncertainty-observed EV parking lot model suitable for system-level applications, and to validate its performance through a robust validation framework to demonstrate its reliability and accuracy.
- To propose and evaluate a novel charger-sharing approach, in which a single charger is used to serve multiple EVs in a parking lot. The effectiveness of this approach will be assessed by calculating the profit generated from its implementation.

1.3 Summary of publications

In this section, a brief summary of publications included in the dissertation is presented. Figure 1 depicts how different publications cover the topics in the dissertation.

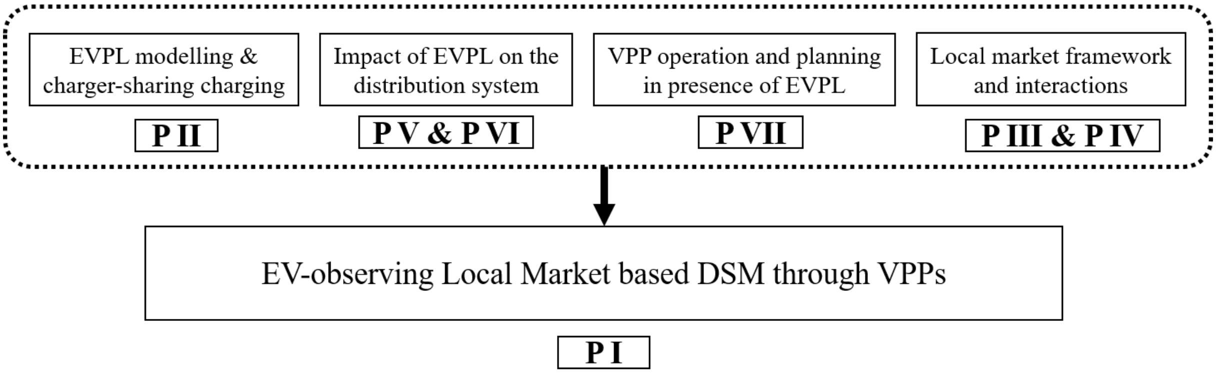


Figure 1. Coverage of dissertation topics across various publications.

Publication I:

This paper introduces a management framework for distribution systems leveraging the concept of VPPs as aggregators of multiple agents and local power markets. VPPs enable the strategic interaction between the DSO and distributed resources. The framework utilizes a bilevel optimization approach to model this interaction, where the DSO's objective in the upper level is to minimize operational costs by managing its assets and setting hourly active and reactive power prices for VPPs, taking into account the power flow within the network. At the lower level, VPPs aim to minimize their costs by optimally scheduling their assets in response to the prices defined by the DSO.

The study demonstrates the benefits of nodal pricing in local markets, highlighting its potential to enhance the operational efficiency of distribution systems. Furthermore, it reveals the role of reactive power support from VPP-owned Electric Vehicle Parking lots (EVPLs) in reducing VPP costs. By participating in the reactive power market, VPPs not only gain profits but also improve their active power market participation, thereby contributing to overall system efficiency. It fills a gap in existing literature by modeling the interaction between DSOs and VPPs, considering the high penetration of EVs and their potential as flexible loads, reactive power providers, and their operation in V2G mode.

Publication II:

This paper proposes charger-sharing approach to enable multiple EVs to charge using a single EV charger. Moreover, existing models fail to address uncertain EVPL modeling with charger-sharing effectively. Furthermore, most methods for modeling EVPL uncertainty are unsuitable for planning and large-scale system-level studies due to their complexity and high computational requirements.

To address these challenges, a virtual battery model is introduced, allowing for charger-sharing while incorporating uncertainty in EV arrival and departure patterns. The model treats the EVPL as a battery with time-variant parameters derived from these patterns. Validation of the proposed model against the scenario-based approach in Day-ahead (DA) and Real-time (RT) power market participation of a 24-bus distribution system with 12 EVPLs shows comparable performance, while the computational burden is reduced to approximately 2.24% of the scenario-based model.

The findings highlight that the charger-sharing approach significantly increases EVPL profitability by accommodating more EVs. A sufficiently high charging tariff incentivizes EVPL owners to host a substantial number of EVs. For example, with 200 chargers, the EVPL can host about 3200 EVs, compared to only 200 EVs under the exclusive charger approach. This demonstrates the efficiency and scalability of the proposed method in managing EVPL operations.

Publication III:

In this paper, we introduce a two-layer game-based framework that models the behavior and interactions of DSO, aggregators, and customers. This paper fills a gap in the literature by proposing a novel two-layer game-based model for local flexibility trading, enabling independent decision-making by the DSO, aggregators, and customers, and analyzing their competitive behavior and interactions. Initially, in the inner layer, customers and aggregators determine their decision variables by considering each other's decisions through an iterative game process. Upon the conclusion of the inner layer game, the distribution system operator sets its decision variable based on the decisions made by the aggregators and customers in the outer layer. If the convergence condition is met, the outer layer game concludes; otherwise, another inner game followed by an outer game is initiated until convergence is achieved. Consequently, customers, aggregators, and the DSO possess comparable decision-making authority, as each can make and adjust their decisions in response to the others. To analyze our model, we examine three scenarios with varying degrees of decision-making freedom for customers, influenced by different levels of constraints to prevent arbitrage. Our findings demonstrate that our iterative approach converges after a few iterations in both the inner and outer layers. Additionally, customers under contract with the same aggregator exhibit similar behavior. While aggregators benefit from the increased freedom of customers, this freedom proves detrimental to the DSO, leading to an increase in its objective function.

Publication IV:

To facilitate the increased participation of small-scale end-users in flexibility service provision, a novel model for flexibility trading is essential to account for the behavior and interactions of various agents within energy communities. The innovation of our work lies in the introduction of an iterative game-based approach, wherein all agents, including the DSO, aggregators, and customers, can determine their decision variables to optimize their respective objective functions and interact to adjust their decisions based on the decisions of others. Additionally, three scenarios are examined to assess the effects of agents' decision-making freedom by removing one of their constraints in their respective decision-making problems. Furthermore, this paper investigates the impact of interruptible loads compared to shiftable loads. Simulation results indicate that each agent can improve its performance in a scenario in which it has higher decision-making freedom. However, the improvement level is not the same for all agents. Moreover, in scenarios where end-users face fewer constraints, interruptible loads allow end-users to achieve greater income compared to the cases without interruptible loads.

Publication V:

This paper aims to address a gap in the literature by investigating the role of EV parking lots in supporting the distribution system, with a particular focus on reactive power support, considering the uncertain arrival and departure times of EVs. The optimal operation of distribution system components, including EVPLs, renewable energy resources, distributed generation units, and energy storage, is managed based on hourly active and reactive power prices, network topology, line capacity, and fixed active and reactive loads, utilizing a linearized Alternating Current (AC) power flow formulation. Our findings indicate that EVPLs can adjust their charging schedules and provide positive or negative reactive power support, thereby improving system conditions in terms of congestion and voltage, which allows for the deployment of more cost-effective generation sources, ultimately reducing the total system cost. Furthermore, the location of EVPLs significantly impacts the optimal operation of the system and the extent of benefits derived from their active and reactive power support.

Publication VI:

This paper examines the impact of EVPLs on the optimal operation of the distribution network, with a particular emphasis on their potential for providing reactive power support in scenarios where the DSO incurs penalty costs for voltage limit violations. This paper seeks to address the gap in the literature by exploring how EVPLs can lower distribution system costs and enhance voltage conditions while proposing a method to quantify the voltage violation penalty costs for unsatisfied power quality. Our findings indicate that the flexible charging of EVs and the reactive power support from EVPLs significantly reduce system costs, especially when penalty costs for voltage violations are considered. Additionally, this approach facilitates the increased deployment of DG and Renewable Energy Sources (RES), while also mitigating the costs associated with voltage violations.

Publication VII:

In this paper, we investigate the optimal operation and planning of a VPP situated in a specific part of the network, comprising wind turbines, Photovoltaic (PV) units, and both unidirectional and bidirectional EV charging stations. Our proposed approach determines the optimal planning assuming that the system will be dispatched optimally. Simulation results indicate that the behavior of EV owners can significantly influence the optimal planning decisions of the VPP. Furthermore, the optimal number of unidirectional and bidirectional EV charging stations is contingent upon the proportion of PV and wind generation, as well as the capacity of the line connecting the VPP to the upstream grid.

1.4 Outline of the thesis

Chapter 2 introduces the topics explored in this dissertation. It includes a literature review that examines recent developments and proposed methods, highlighting existing research gaps to be addressed.

Chapter 3 which is linked with Publication V, Publication VI, and Publication VII addresses the topic of distribution system management, detailing the optimization of distribution system operations with consideration of power flow and voltage limitations. It further explores how EVPL charging management and reactive power support can enhance system operations and mitigate voltage-related challenges. Additionally, this chapter discusses the optimization of VPP operations and planning.

Chapter 4 which is linked with Publication II explores the topic of electric vehicle modeling, focusing on the proposed virtual battery model for EVPLs to be utilized in system-level studies. The chapter also explains the validation framework employed to evaluate the performance of the proposed virtual battery model. Furthermore, it discusses the proposed charger-sharing mechanism and demonstrates its benefits.

Chapter 5 which is linked with Publication III and Publication IV examines the local market framework and interactions, focusing on the one-level and two-level iterative game approaches. This chapter demonstrates how various agents influence each other's market decisions under different regulatory scenarios.

Chapter 6 which is linked with Publication I presents the final stage of the dissertation, introducing a bilevel local market-based optimization framework for distribution system management in the presence of EVs, considering the private ownership of VPPs. The optimal operation of assets owned by the DSO and VPPs is analyzed. Additionally, the impact of nodal pricing for active and reactive power is investigated. Furthermore, the role of EVPLs within this bilevel management framework is examined.

Chapter 7 concludes the summary part of the dissertation and outlines the outcomes of the dissertation and potential future research developments in the field.

2 LITERATURE REVIEW AND STATE OF THE ART

2.1 Flexibility needs in the future power systems

2.1.1 Existing and future flexibility markets

The European Union has initiated research projects across various countries aimed at enhancing the integration and management of flexibility in power systems. These projects focus on flexible energy production, demand, and storage-based virtual power plants for electricity markets and resilient DSO operation. The primary function of any flexibility platform is to offer market participants efficient access to and visibility over flexibility needs and availability. This ensures that all relevant stakeholders can identify and respond to the market's flexibility requirements (Cired Working Group, 2021).

A wide range of local flexibility projects is being led by Transmission System Operators (TSOs), DSOs, and third parties. Each entity is experimenting with and implementing its approach to flexibility management, extending beyond traditional TSO market platforms. This variety underscores the evolving nature of flexibility markets. High competition in the ancillary services market poses challenges for new entrants, creating barriers for smaller or newer participants who may find it difficult to compete with established entities (Cired Working Group, 2021).

Economic obstacles such as price volatility, low profitability for large generators, and the lack of clear price signals for DSO flexibility products are significant challenges that need to be addressed to create a more stable and attractive market for flexibility services. Technical challenges, including delays in the implementation of advanced metering infrastructure and complex market structures, can hinder the effective deployment and utilization of flexibility resources (Cired Working Group, 2021).

Flexibility markets aim to incentivize participation by providing a competitive and equitable platform for all types of Flexible Energy Resources (FERs) to sell their flexibility to system operators. While these markets are predominantly designed for TSOs, participation is generally limited to large flexibility owners and aggregators. Local-level flexibility markets are infrequently observed in practice. Dynamic tariffs in distribution networks can also provide incentives and leverage the available flexibility of the network. Both ”implicit flexibility” (where customers respond to price signals) and ”explicit flexibility” (where third parties control customers' assets) are needed to address flexibility challenges in distribution networks. Dynamic tariffs would be more effective if combined with local flexibility markets (Khajeh, 2024).

2.1.2 Regulatory developments related to the flexibility utilization in distribution networks

Currently, there is no universal regulation for the integration of flexibility, which should be based on tariffs, rules, connection agreements, or market structures. Different regulations can result in segmented markets with varying rules, ultimately hindering the optimal use of resources. Harmonizing regulations across regions and countries is essential to ensure efficient and effective utilization of flexibility. EU member states are required to develop regulatory frameworks that encourage DSOs to use flexible services if profitable, as outlined in Article 32 of the Directive (EU) 2019/944 on “Incentives for the use of flexibility in distribution networks.” This directive highlights the need for regulatory support to promote the use of flexibility in distribution networks (Cired Working Group, 2021).

Standardized regulations can accelerate the integration of renewable energy and facilitate the utilization of available flexibilities in the distribution system. Consistent regulations can streamline processes and reduce barriers to the integration of renewable energy sources and flexibility resources. The rapid development of electric vehicles as a part of the clean energy transition has placed significant stress on traditional distribution grids. Integrating EVs requires careful planning and regulatory support to ensure they contribute positively to grid flexibility (Cired Working Group, 2021). While most countries widely use TSO-level flexibility markets, only Great Britain, the Netherlands, and France have established commercial markets to offer flexibility to DSOs. Norway and Sweden have introduced advanced trial offerings (Cired Working Group, 2021).

The European electricity market is characterized by a variety of approaches to promote flexibility and consumer engagement, with each country facing unique challenges. Common issues include regulatory barriers for aggregators, economic difficulties, and delays in the deployment of smart meters. In the Nordic countries, financial incentives and smart meters empower consumers, with Finland and Norway implementing 15-minute measurement intervals to improve tariff structures. Spain has recently integrated demand-side and storage installations into the balancing market, although regulatory openness for aggregators remains limited. Italy is advancing its market for distributed resources through pilot projects, while the UK has developed local flexibility markets despite challenges such as price volatility and market complexity. Belgium permits consumer participation but imposes significant barriers for aggregators. Greece prioritizes system stability through interruptible loads, whereas Cyprus lacks support for flexibility services. Germany allows participation in wholesale and balancing markets but faces administrative hurdles and regulatory resistance to flexible network charges. (Cired Working Group, 2021).

Despite some countries making strides in developing flexibility platforms, many remain behind due to the lack of EU-level regulation for integrating flexibility into electricity markets. The existing regulatory frameworks are insufficient to establish flexibility markets across all European nations, leading to several challenges (Cired Working Group, 2021). These challenges include limited access for aggregators, intense competition in ancillary services, economic obstacles like price volatility and low profitability for large generators, and technical difficulties such as delayed implementation of advanced metering infrastructure and complex market rules (Cired Working Group, 2021).

2.2 Active distribution system

Active distribution networks have emerged as a key concept in modern power systems, offering a transition from the conventional passive distribution networks that were designed for one-way power flow from the transmission grid to consumers. Unlike these traditional systems, ADNs enable bidirectional power flow and incorporate active participation from distributed energy resources, such as renewable energy sources, energy storage systems, and electric vehicles (Rawat, Niazi, Gupta, and Sharma, 2022). The integration of DERs within ADNs provides several benefits, including enhanced system reliability, greater energy efficiency, and reduction in carbon emissions (Lei, Yu, Shao, and Jian, 2023). ADNs can also address power system issues like voltage instability, power quality concerns, and the risk of overloading the distribution network by leveraging the flexibility of DERs (Zhao et al., 2019).

Despite these advantages, the implementation of ADNs presents significant challenges. A primary obstacle is the requirement for advanced control and communication systems that are necessary to manage the network efficiently and reliably. Adequate communication infrastructure is also needed to facilitate real-time information exchange between network components (Y. Lu et al., 2023). Another challenge is accurately modeling and forecasting DERs, which is complex due to the variability and unpredictability of renewable energy generation and EV charging behaviors (Rangu, Lolla, Dhenuvakonda, and Singh, 2020). Additionally, the development of regulatory frameworks and local market mechanisms is essential to incentivize DER deployment and ensure the network's cost-effective operation (Ebrahimi and Sheikhi, 2023).

2.3 Virtual power plant

The growing integration of renewable energy sources, along with their unpredictable nature, has introduced several technical, economic, and regulatory challenges. These challenges can be addressed by coordinating the operation of non-dispatchable renewable units with various dispatchable resources, such as thermal power plants, flexible loads, and energy storage systems. To enable this coordination, the concept of a virtual power plant has emerged (Khaledi and Saifoddin, 2023). A VPP brings together a diverse range of distributed energy resources and manages them in a coordinated manner. This approach not only helps balance the variability of renewable energy generation but also enables these DERs to participate in energy markets and provide grid support services (Rouzbahani, Karimipour, and Lei, 2021). VPPs aim to maximize their profits. Therefore, an optimal operation and planning strategy is essential to achieve the highest possible revenue.

There exist multiple interpretations of the VPP concept. In this thesis, the VPP is defined as an aggregation of DERs that can be utilized to participate in the market and to offer different services to the power system operator, similar to VPP definition in the majority of the literature such as (Pudjianto, Ramsay, and Strbac, 2007), (Yi, Xu, Zhou, Wu, and Sun, 2020a), (T. Zhang et al., 2023), and (Q. Li et al., 2023). In such a definition, VPP components can connect to different points of the distribution network. This allows for the optimization of the operation of the DERs in response to the needs of the grid, and the provision of various grid services such as peak shaving, frequency regulation, and voltage support (Jayachandran et al., 2022). One of the key advantages of VPPs is their ability to provide a cost-effective solution for managing the integration of DERs into ADNs (Panda, Mohanty, Rout, and Sahu, 2022). By aggregating the output of multiple DERs, VPPs can provide a more reliable and predictable source of energy compared to individual DERs, which can be variable and intermittent (Bhuiyan et al., 2021). This can help reduce the need for costly upgrades to the power system. Additionally, VPPs can provide valuable grid services such as demand response, which can help to manage the load during times of peak demand (Jeon, Cho, and Lee, 2020).

The integration of VPPs into ADN systems presents unique challenges due to the diverse parties involved, including price-sensitive demand response, distributed generators, and flexible load aggregators (Kerscher and Arboleya, 2022). To ensure effective collaboration, VPP agents need to provide their aggregated external characteristics to the distribution system operator, who then computes optimal operational decisions and issues dispatching decisions to VPP agents (Venegas-Zarama, Muñoz-Hernandez, Baringo, Diaz-Cachinero, and De Domingo-Mondejar, 2022). However, conflicts of interest can arise when VPP agents and DSOs belong to different owners. To address this, bilevel programming models are often used to separately consider the economic objectives and operational constraints of both VPPs and ADN (Yi et al., 2020a). By encouraging the participation of VPPs through reasonable pricing strategies, DSOs can improve the overall economy of the system, leading to more efficient and sustainable grid operations.

2.3.1 VPP operation

Several studies have been conducted to design frameworks that facilitate the participation of VPPs in the distribution-level markets. For instance, the authors in (Zangeneh, Shayegan-Rad, and Nazari, 2018) utilized the multi-leader–follower concept from game theory to model the bilevel interaction between VPPs and ADNs. Their research focused on determining the optimal pricing for annual bilateral contracts between VPPs to foster competition within the ADN. In a related study, (Rider, López-Lezama, Contreras, and Padilha-Feltrin, 2013) proposed an approach to optimize the location and contract pricing of VPP-owned DG within the distribution network.

Additionally, (Asl, Bagherzadeh, Pirouzi, Norouzi, and Lehtonen, 2021) developed a two-layer energy management model for smart distribution networks that include VPPs operating in day-ahead energy and reserve markets. The first layer focuses on maximizing the profits of VPPs while accounting for constraints related to renewable energy sources, flexible energy resources, and coordination with the VPP operator. The second layer focuses on minimizing distribution system energy losses and voltage deviations, incorporating uncertainties such as load, market price, and the maximum output of renewable energy sources.

Similarly, (Hamedi, Talavat, Tofighi, and Ghanizadeh, 2021) introduced a bilevel approach in which a distribution company and a retailer compete at the upper level, while consumers, at the lower level, aim to minimize their energy expenses. In addition, (Z. Li, Liu, Xie, and Zhu, 2022) proposed a robust optimization model to aggregate an Autonomous Distribution System as a VPP and determine its feasible range of active power and ramp rates over time. Their robust optimization approach accounts for uncertainties such as dispatch orders from the transmission system operator and the variability of renewable distributed generators.

2.3.2 VPP planning

Several studies have focused on optimal planning strategies for VPPs, considering their operational constraints. For example, a bilevel programming framework proposed in (J. Li, Lu, Wang, and Zhu, 2021) determines the optimal location and capacity of energy storage systems within a VPP. The upper level focuses on the planning problem aimed at maximizing the VPP's net profit, while the lower level addresses its operational strategy. In (Baringo, Baringo, and Arroyo, 2021), a risk-based stochastic method is used to study investment planning for VPP trading in the electricity market. This model seeks to maximize the profit of a VPP that includes conventional and renewable generation, storage systems, and flexible demands.

In (Geng, Tan, Niu, and Guo, 2021), a multi-objective optimization approach is employed for optimal capacity allocation within a VPP that incorporates EVs, aiming to boost net revenue while reducing pollution and addressing environmental concerns. Similarly, (Nishimwe H and Yoon, 2021) presents an optimization framework for the operational planning of an integrated system that combines renewable resources, energy storage, and EV charging stations to provide services to the upstream grid. This study seeks to optimize system configuration and maximize profit, while factoring in operational constraints.

A mixed-integer linear programming model is used in (Mohamed, Sabillon, Golriz, and Venkatesh, 2021) to optimize the planning of an aggregator integrating a wide range of DERs at the distribution level, with the goal of maximizing net present value from services provided to the upstream network. Finally, a bilevel stochastic model proposed in (Liu et al., 2019) addresses the capacity allocation of energy storage within a VPP, with the upper level focused on minimizing investment and maintenance costs, and the lower level aimed at reducing power fluctuations from renewable energy sources.

2.4 Local electricity and flexibility markets

Due to the increasing integration of renewable energy sources, which are often variable and non-dispatchable, the power system is encountering new challenges in balancing demand and generation (H. Li, Lu, Qiao, Zhang, and Lin, 2021). This situation necessitates the development of new resources to manage balance and other flexibility services (Nizami, Hossain, and Mahmud, 2021). End-users play a key role in providing energy flexibility by adjusting their consumption patterns (Correa-Florez, Michiorri, and Kariniotakis, 2020). For example, they can offer flexibility through load adjustments, the use of energy storage systems, or leveraging the thermal inertia of buildings (S. Lu et al., 2020). As a result, end-users are becoming more involved in the distribution system management processes (Schick, Klempp, and Hufendiek, 2020). However, traditional centralized approaches are insufficient to effectively model the active participation of end-users in this evolving energy landscape (Gazafroudi, Corchado, Shafie-khah, Lotfi, and Catalão, 2019). Hence, new approaches are required to model the new type of energy transactions and interactions among agents in the distribution system.

2.4.1 Newly emerging local market frameworks

In the literature, several papers have proposed new frameworks for energy and flexibility trading in distribution systems. For instance, (Gazafroudi, Khorasany, Razzaghi, Laaksonen, and Shafie-khah, 2021) presents a two-stage approach that allows end-users to trade flexibility and energy on a peer-to-peer platform, which is overseen by the local market operator and the DSO. In (Bagheri, Doostizadeh, and Aminifar, 2021), a chance-constrained method is introduced to handle uncertainties in flexibility transactions between microgrids and the DSO. A pricing and bidding mechanism is proposed in (Annala et al., 2021) to enhance the local flexibility market's integration with retail, ancillary service, and wholesale markets. A stochastic model for aggregated prosumers is also developed in (Iria, Soares, and Matos, 2019), considering uncertainties related to PV generation, loads, outdoor temperature, and user behavior. Another study, (Esmat, Usaola, and Moreno, 2018), proposes a distributed local flexibility market aimed at helping DSOs manage demand uncertainty and network congestion more efficiently.

Managing a power system composed of numerous prosumers, who are responsible for providing system flexibility, presents significant difficulties. Hence, an intermediary, such as an aggregator, VPP, microgrid, or energy community is essential to pool the energy and flexibility provided by prosumers. For example, (Olivella-Rosell et al., 2018) introduces a local flexibility market model where aggregators control multiple devices to offer services within the distribution system. Similarly, (Morstyn, Teytelboym, and McCulloch, 2018) proposes a decentralized market design where aggregators encourage prosumers to offer energy flexibility to the DSO. In (Iria, Soares, and Matos, 2018), a two-stage stochastic optimization is proposed to enhance aggregators' involvement in energy and ancillary services markets. The performance of aggregators in delivering flexibility to the DSO under high uncertainty is examined in (Heinrich, Ziras, Syrri, and Bindner, 2020). Moreover, a decentralized bottom-up control strategy to exploit the flexibility potential of virtual power plants is proposed in (Zhou et al., 2021). The cooperative market mechanism presented in (Bahmani, Karimi, and Jadid, 2020) determines energy transactions and prices for microgrids under both isolated and connected modes, taking into account renewable energy and demand uncertainties.

Customers, with their demand response capabilities and use of distributed generation units, hold significant potential to participate in energy and flexibility trading within distribution systems. Therefore, it is essential to design a trading framework that encourages customer participation and enhances their flexibility contributions. A game-based model that equips customers with decision-making capabilities could effectively facilitate their involvement in the flexibility market. Furthermore, customers should have the right to trade flexibility directly with the DSO, as flexibility is primarily derived from the demand side. This direct trading empowers customers to take on a more prominent role, making the market more competitive and helping the DSO leverage customer flexibility to manage intermittent renewable energy resources (C. Zhang et al., 2016).

2.4.2 Game-based approach

The active participation of customers and prosumers in energy and flexibility trading not only transforms the energy market but also introduces new dynamics that require effective frameworks to manage. This brings attention to the role of aggregators and the importance of direct interactions between prosumers and the DSO, which enhance competition and improve flexibility utilization. Aggregators provide substantial value in flexibility trading by optimizing the combined flexibility of end-users. They achieve this by pooling resources, using market expertise, and employing advanced technologies. To accomplish this, aggregators need accurate real-time data, advanced analytical tools, reliable communication systems, supportive regulations, and strong relationships with end-users. By integrating these components, aggregators can improve the efficiency and profitability of flexibility trading. Since different agents in a competitive market seek to maximize their profits, it becomes essential to adopt a method that addresses both competition among agents and their interactions. Game-based approaches have been widely explored for this purpose, as they enable agents in the distribution system to make independent decisions in a competitive market while also modeling their strategic behavior and interactions. These approaches provide a mathematical framework that helps in optimizing the participation of various agents in energy and flexibility markets.

In this evolving landscape, game theory-based models offer insights into how agents can effectively engage in these markets. For instance, (Coninx, Deconinck, and Holvoet, 2018) uses game theory to analyze the strategies of flexibility providers and their optimal partner selection to maximize profits. Similarly, (Maharjan, Zhu, Zhang, Gjessing, and Basar, 2013) applies a Stackelberg game to manage demand response between utility companies and end-users, focusing on optimizing utility income and user payments. A comparative study in (Gazafroudi, Shafie-Khah, Prieto-Castrillo, Corchado, and Catalão, 2020) examines monopolistic and game-based approaches to flexibility trading, where DSOs and aggregators act as strategic agents in two distinct scenarios. A decentralized, game-based framework for energy transactions between microgrids is proposed in (Lee, Guo, Choi, and Zukerman, 2015), while (Reihani, Eshraghi, and Motalleb, 2018) models competition among aggregators, who aim to maximize their profits by selling demand response services to DSOs.

In addition, in (Chai, Chen, Yang, and Zhang, 2014), the authors proposed a demand response management system using a two-level game. At the lower level, residential users determine their consumption needs, while at the higher level, utility companies set the price and power supply based on the consumption defined by users. In (Pinto, Wooldridge, and Vale, 2021), a game theory model was introduced to help flexible consumers identify the most profitable coalition for flexibility trading. Similarly, (Aguiar, Dubey, and Gupta, 2021) employed a network-constrained Stackelberg game to determine the price of flexibility traded by consumers. (Tsaousoglou, Pinson, and Paterakis, 2021) applied algorithmic game theory for managing energy in flexible prosumer communities, taking into account resource constraints. Furthermore, (Coninx et al., 2018) used game theory to analyze the flexibility providers' strategies to select optimal business partners to maximize profits.

2.4.3 Iterative game-Based approach

To simulate the real behavior of agents, it is beneficial to employ iterative approaches that reflect the dynamic interactions among players in a competitive trading environment. Most non-iterative methods tend to fail to capture the independent decision-making behaviors of all agents, as they typically account for only a limited number of decision-makers. Additionally, these decision-makers often do not possess equal decision-making power in non-iterative models. In contrast, iterative approaches may allow for a fairer trading framework where all agents have similar authority, enabling the observation of how agents might react to each other's actions. Furthermore, it could be crucial to model the trading structure accurately to reflect the behaviors of existing market participants; otherwise, this may result in misanalysis of trading actions and potential failures for some agents.

In Publication IV, we proposed a single-layer triangular iterative method for trading flexibility within the distribution system. However, this approach may often require numerous iterations to converge, indicating that the single-layer framework might struggle to efficiently model agents' interconnections. To achieve a more realistic representation of flexibility trading, we propose a two-layer structure in Publication III that could accommodate the independent decision-making capabilities of the DSO, aggregators, and customers. This structure enables agents to adjust their decisions based on others' actions while maintaining equal autonomy in the decision-making process. Our approach can also examine flexibility transactions from the regulatory body's perspective, potentially assisting regulators in assessing the impacts of new policies and regulations. By implementing this two-layer model, which highlights the close interconnections between customers and aggregators in the inner layer and their interactions with the DSO in the outer layer, we can achieve quicker convergence with fewer iterations, thus reducing the time required to solve the problem.

2.4.4 Bilevel approach

Among non-iterative game-based approaches, the bilevel model serves as a powerful tool for both theoretical exploration and practical application, contributing to the development of more resilient, efficient, and sustainable local electricity markets as deployed in (Mendicino et al., 2021), (Angizeh and Parvania, 2019), (Asimakopoulou, Vlachos, and Hatziargyriou, 2015), (Zangeneh et al., 2018), and (Rider et al., 2013). A bilevel model for local energy markets offers a sophisticated framework to analyze the interactions and decision-making processes between various market participants, particularly in the context of DERs and demand response. This approach is structured to reflect the hierarchical relationships that exist within the electricity markets, allowing a clearer understanding of how different agents, such as consumers, aggregators and DSOs interact in a decentralized energy landscape. In the upper level of the bilevel model, the decision-making entity, often the DSO or market operator, focuses on optimizing grid operations, ensuring reliability, and managing the integration of renewable energy sources. This level addresses the high level goals of the electricity system, such as minimizing costs, maximizing efficiency, and maintaining service quality. Conversely, the lower level involves individual agents, such as prosumers and consumers, who make decisions based on their own preferences, constraints, and objectives, which may include maximizing profits, minimizing costs, or enhancing their sustainability practices. This dual structure enables the exploration of complex scenarios, such as the impact of price signals on consumer behavior or the effect of regulatory policies on aggregator strategies. Furthermore, the bilevel model can incorporate various uncertainties, such as fluctuating demand, variable renewable generation, and market dynamics, thereby enhancing the robustness of the analysis.

2.4.5 Energy and flexibility trading for system support

Some studies have explored the potential of flexibility trading to support the system operator in managing the power grid. In these studies, the system operator makes decisions regarding flexibility transactions among various market participants, while other agents lack decision-making capabilities. For example, in (Gazafroudi et al., 2021), the local market operator, in collaboration with the DSO, determines flexibility transactions between customers on a peer-to-peer (P2P) trading platform. Similarly, (Oikonomou, Parvania, and Khatami, 2020) discusses how the DSO manages flexibility scheduling to maximize profits from offering flexibility in the day-ahead market. (Gazafroudi, Corchado, Keane, and Soroudi, 2019) presents three strategies for managing the flexibility of electric vehicles within the distribution system. The third strategy introduces a local coordinator responsible for managing the charging of electric vehicles and end-users' flexibility. Furthermore, (Liao and Milanović, 2019) proposes a methodology to optimize flexibility exchange for voltage profile improvement and preventing line congestion. In line with this, (Evangelopoulos, Avramidis, and Georgilakis, 2020) introduces a two-stage stochastic programming model to help the DSO manage flexibility at the distribution level, minimizing voltage violations and line congestion. The approach in (Ge, Li, He, and Liu, 2021) integrates local electricity, heat, and gas systems to utilize demand flexibility in a coordinated energy system, where the electricity, heat, and gas market operators collaborate. (Tsaousoglou, Giraldo, Pinson, and Paterakis, 2021) presents an incentive-compatible mechanism designed to help the DSO acquire flexibility from aggregators while motivating them to declare their costs truthfully.

Some other studies focus on how flexibility and energy transactions can assist different agents in the distribution system in finding optimal strategies. For instance, (Mendicino et al., 2021) introduces a model where energy communities, consisting of nanogrids, offer flexibility to the system through their excess demand-side generation. In (Angizeh and Parvania, 2019), a two-stage stochastic approach is presented for managing the flexibility of large customers, accounting for uncertainties in solar generation and market prices. Some researchers have employed bilevel optimization approaches, which provide solutions for the leader in the problem using a Stackelberg game framework. In such a setup, the leader determines the optimal strategy while considering the actions of followers, even though the problem is primarily studied from the leader's perspective. The leader, in this case, has more autonomy, as they can anticipate the followers' responses, while followers do not possess similar foresight. In this context, (Asimakopoulou et al., 2015) presents a bilevel approach to address the interdependence of decision-making between distributed resources and aggregators, helping aggregators choose the best strategy. (S. Wang, Tan, Liu, and Tsang, 2021) also applies bilevel optimization to minimize aggregators' costs at the upper level, taking into account the market clearing process at the lower level, where the independent system operator's generation costs are minimized.

In addition, (Attar, 2025) presents a comprehensive approach to understanding market-based congestion management, focusing on the interactions between DSOs, local flexibility markets, and Flexibility Service Providers (FSPs). Its innovative approach involves a system-of-systems perspective, supported by detailed modeling and a co-simulation platform, which provides a comprehensive view of multiple stakeholders' roles and interactions. This method helps develop practical solutions. The research examines the smart grid architecture model, especially the information and functional layers, and addresses the challenges of data exchange among stakeholders, such as protecting FSPs' business interests and ensuring cybersecurity. The thesis also analyzes different local flexibility market designs, looking at both market-based and non-market-based CM solutions, and provides a qualitative assessment of various market setups.

To further illustrate the practical implementation of local electricity and flexibility markets, recent projects such as OneNet and HEDGE-IoT serve as appropriate examples. These projects aim to enhance the European electricity system by integrating advanced grid services and Internet of Things (IoT) solutions, respectively. Both projects contribute to the development of local electricity and flexibility markets by addressing the increased electricity demand and the increasing need for flexibility, thereby supporting the system operator in managing the power system and facilitating energy and flexibility trading among various market participants.

OneNet aims to create a European electricity system that connects all participants across countries in near real-time, improving energy management and establishing an open and fair market. The project focuses on increasing consumer involvement and aligning market and network operations. Its main goal is to develop advanced grid services that make full use of demand response, storage, and distributed generation, ensuring fair and transparent conditions for consumers. This is achieved by creating new markets, products, services, and a unique IT architecture that supports platform federation (Seitsamo et al., 2022).

OneNet introduces the role of the FSP, which connects customers offering flexibility resources to the flexibility market. Customers provide flexibility primarily for economic reasons, and the FSP defines reward mechanisms and control logic that minimally impacts living comfort. OneNet identifies two types of flexibility contracts: those combining electricity sales with flexibility and those solely for flexibility. It highlights flexibility resources such as hot water boilers, electric vehicle chargers, solar power, and batteries. Private flexibility resources need aggregation, while commercial resources can achieve relevant volumes independently. The project identifies the potential and increasing flexibility to be utilized particularly from electric vehicles (Seitsamo et al., 2022).

HEDGE-IoT, an EU-funded project under Horizon Europe, aims to transform the energy sector with IoT solutions. It deploys IoT assets at various levels and enhances edge and cloud intelligence using Artificial Intelligence (AI) and Machine Learning (ML) tools. The project introduces a digital framework to connect cloud and edge, improving grid resilience, flexibility, and market opportunities, ensuring seamless communication and standardized data exchange. The project aims to implement its framework in six large-scale field demonstrators (Wehrmeister, Hoegen, Rharrab, Sianidou, and Briguglio, 2024).

The HEDGE-IoT project has developed a comprehensive framework for managing flexibility in the energy market, aiming to improve grid operation and address congestion issues. This framework includes defining flexibility requests and offers, market clearing processes, and creating a local flexibility market, involving key players such as DSO and FSPs in requesting, offering, and trading flexibility. A specific use case within this framework focuses on enabling the trading of residential DERs flexibility in a cloud-based local flexibility market, using near real-time measurements from IoT devices for flexibility settlements and transaction management. The main objectives are to create an independent marketplace to solve grid issues, act as a central hub for market processes like registration and trading, and facilitate coordinated data exchange among participants, with system operators requesting and buying flexibility and flexibility service providers registering and selling clients' flexibility to effectively address grid problems (Wehrmeister et al., 2024).

2.5 Electric vehicle support opportunities for power system

The charging and discharging of electric vehicles can have significant effects on the management of distribution systems. On the positive side, EVs offer a form of distributed energy storage and flexible load that helps to balance the variability of renewable energy sources (Hasan, 2020). By coordinating EV charging with periods of surplus renewable generation, curtailment can be reduced, and the utilization of renewable energy resources can be increased (Dixon, Bukhsh, Edmunds, and Bell, 2020). Additionally, EVs can provide voltage support and reactive power compensation through smart charging strategies that adapt to the needs of the system (Hu, Ye, Ding, Tang, and Liu, 2021).

However, on the downside, uncoordinated and high levels of EV charging can overload the distribution network and other system components, potentially causing voltage instability and damage to equipment (Ahmed et al., 2021). To address these challenges, distribution system operators must develop strategies for managing EV charging and discharging. This includes the use of smart charging algorithms, advanced monitoring and control systems, and the implementation of suitable policies and regulations (Lipu et al., 2021).

The impact of EV charging and discharging patterns on the distribution system has been a key focus of several studies (Eltoumi, Becherif, Djerdir, and Ramadan, 2021). For instance, in (Alinejad, Rezaei, Kazemi, and Bagheri, 2021), the authors proposed an optimized charging and discharging pattern aimed at enhancing distribution system efficiency. EV integration also offers potential benefits in terms of energy security and independence, as explored in (Butt, Zulqarnain, and Butt, 2021). Research in (Sadati, Moshtagh, Shafie-khah, Rastgou, and Catalão, 2019) introduced a bilevel method for incorporating EV parking lots into energy and reserve markets, aiming to reduce costs and address distribution grid constraints. Similarly, in (ur Rehman, 2022), a scheduling plan for small-scale parking lots was suggested to maintain frequency stability within the distribution system, while (Dalvi and Thale, 2020) explored a comparable plan using operating envelopes.

A model for scheduling EV charging that leverages optimal AC power flow to minimize energy costs and efficiently meet EV demand was presented in (Hua, Wang, and Zhou, 2014). To achieve similar objectives, (Kabir, Assi, Tushar, and Yan, 2020) proposed a decentralized model for EV charging strategies based on game theory. Various strategies for allocating EV charging lots and their impacts on distribution systems were analyzed in (Firouzjah, 2022). Finally, in (Guo, Nojavan, Lei, and Liang, 2021), a charging and discharging approach for EV parking lots was developed, which considered both demand response and energy consumption costs within its objective function.

Meanwhile, the number of EVs has significantly increased in recent years, impacting power systems. Given the widespread deployment of EVs at the distribution level, VPPs can take advantage of this by selling electricity to EVs and using their batteries as energy storage to stabilize fluctuations caused by the intermittent nature of renewable energy sources (Abo-Khalil et al., 2022). As a result, by incorporating EV charging stations and accommodating EVs, VPPs can enhance the efficient use of renewable energy (Yang and Zhang, 2021). However, over-investing in charging infrastructure may not yield a satisfactory return on investment. Therefore, it is crucial to develop an optimal operation and planning strategy for VPPs that integrate EV charging stations.

To illustrate the practical applications and advancements in the field of electric vehicle support for power systems, several projects have been undertaken to address various aspects of EV integration, smart charging, and energy management. These projects provide valuable insights and solutions that can be leveraged to enhance the efficiency and stability of distribution systems.

The DRIVE2X project aims to expedite the transition to widespread electromobility by implementing innovative smart charging techniques and advancing bidirectional charging technologies. By testing and validating cost-effective bidirectional charger units across eight demonstrators, the project supports the broad adoption of vehicle-to-everything (V2X) technology. The objectives of DRIVE2X include increasing public awareness of V2X concepts, developing affordable and user-friendly V2X solutions for mass electric vehicle deployment, creating a user-centric local V2X marketplace that utilizes flexible energy from smart charging, addressing user experience and behavioral challenges with innovative bidirectional charging strategies, profiling mobile citizens for the years 2035 and 2050 to understand the expectations of V2X users, policymakers, and businesses, and advancing V2X research and market expansion through the development of Open Access tools, models, and data sets (Homaee et al., 2024).

EEBUS is an initiative dedicated to developing a universal language for energy within the IoT. Its main objectives are to establish a common language for devices to communicate about energy across various industries and continents, provide a standard-based language that is freely accessible to all devices and platforms regardless of manufacturer or technology, ensure the proper functionality of devices during energy shortages, and enable companies to offer plug-and-play solutions for both residential and commercial applications. EEBUS emphasizes the standardization of data models required for the technical implementation of use cases, promoting interoperability and flexibility within the ecosystem.

The project has contributed to the field of EV charging processes with several notable findings. It has optimized energy consumption and costs, allowing customers to evaluate their cost and energy efficiency goals. This includes a summary of total costs, the amount of charged energy, the cost and quantity of self-produced photovoltaic

PV energy, and energy consumed from the grid. The project also addresses grid stability, emphasizing the importance of balancing consumption and production through energy management systems to maintain stable grid conditions as EVs become more common. It suggests that EV batteries could be used to stabilize the grid in the future. Additionally, the project has developed new use cases to improve EV charging processes. These include visualizing the EV battery's charging status, enabling bi-directional charging, and fleet management ("E-mobility Use Cases", 2019).

2.6 Electric vehicle modelling

The optimal operation and planning of EV charging facilities and infrastructures, such as EV Parking Lots and charging stations, are becoming very important (Hussain, Sulaiman, Hussain, and Jabir, 2021). This importance comes from the need to analyze the performance of EV charging stations from various perspectives, including those of EV owners, parking lot or charging station proprietors, power system operators, potential investors, and policymakers (Ray, Kasturi, Patnaik, and Nayak, 2023).

Studies focusing on EV owners typically model single EV charging, as individual owners generally possess a single EV (Nabi, Ray, Rashid, Al Hussam, and Muyeen, 2023). However, to address EV-related issues from the viewpoints of other stakeholders, it is essential to develop models for the aggregation of EVs, such as EVPLs. Several papers have proposed models to simulate the operation of EV aggregations. For instance, (Pertl et al., 2018) presented a storage model for EVPL charging, utilizing historical data from an existing parking lot to derive the parameters of the equivalent storage model.

In modeling electric vehicles, uncertain parameters such as arrival and departure times are significant. However, some studies have neglected these uncertainties for simplicity, enabling the use of straightforward and low-computational burden approaches. For example, authors in (Cao et al., 2020) proposed an optimal scheduling approach for an EV aggregator to determine charge and discharge strategies, similar to (Pertl et al., 2018), but without considering uncertainty. (Onishi, Antunes, and Trovão, 2020) proposed an approach for the optimal participation of an EVPL-owned microgrid in the energy and reserve market, also without considering EV uncertainties. (Singh and Verma, 2022) proposed a load scheduling approach for EVs to reduce charging costs by optimally providing ancillary services for the grid, neglecting the uncertainty of EV arrival and departure times due to the deterministic formulation of the problem. However, neglecting uncertainty can result in unreliable analysis and inaccurate outputs.

A part of the literature has attempted to consider EV uncertainties in EV-related studies. Some studies address uncertainty by generating values for uncertain parameters of each EV within the aggregation based on the Probability Distribution Function (PDF) of the parameters. In (Sadati, Moshtagh, Shafie-khah, and Catalão, 2018), an approach is proposed to assist the distribution system operator with optimal operation in the presence of an EVPL and demand response program, generating random values for uncertain parameters based on truncated normal distribution. Another approach in the literature involves generating a single scenario by random value generation based on the PDF or random value selection from historical data. (Zeng et al., 2020) studies the role of EV aggregation in enhancing the sustainability of the power system, generating random values for EV arrival and departure times based on historical data. In (Turan, Ates, Erdinc, Gokalp, and Catalão, 2019), the impact of a PV-equipped EVPL on the distribution network is investigated, modeling EVPLs based on the expected loading profile generated by randomly selected EVs' parking durations.

Another part of the literature generates multiple scenarios for uncertain EV parameters and employ scenario-based approaches. (Ahrabi et al., 2021), similar to (Pertl et al., 2018), proposed a storage-equivalent model for EV parking, addressing EV uncertainties via a scenario-based stochastic formulation. Authors in (Mohammad, Zamora, and Lie, 2020) presented transactive energy management for EVPLs, generating multiple scenarios for arrival and departure times based on normal distribution. The uncertainty of EVs in (Moradijoz, Heidari, Moghaddam, and Haghifam, 2020), which intends to integrate EVPLs in the distribution system, is handled by introducing 24 groups of EVs classified based on arrival and departure times, generated from truncated normal distribution. In (Zheng, Yu, Shao, and Jian, 2020), authors proposed an optimal bidding strategy for EV aggregators, studying the problem in several scenarios based on EV types. Similarly, in (Şengör, Erdinç, Yener, Taşcıkaraoğlu, and Catalao, 2018), energy management of an EVPL is conducted under a load reduction-based demand response program, generating eight scenarios for the reference power profile based on EV driving cycles. Authors in (Abapour, Zare, et al., 2019), for conducting optimal planning of EVPLs, generate several scenarios for EV uncertain parameters using Monte Carlo simulation, reducing the number of scenarios with the Kantorovich distance technique. (Nazari-Heris et al., 2021) proposed a stochastic approach for optimal charge and discharge scheduling of a parking lot, generating scenarios based on truncated normal distribution, with a fixed total number of arrived EVs. (Khalafian et al., 2024) utilized a scenario-based approach to evaluate the profitability of compressed air energy storage in uncertain smart EV charging. Authors in (Norouzi, Aghaei, Pirouzi, Niknam, and Fotuhi-Firuzabad, 2022) investigated the flexibility potential of EV parking lots in both V2G and G2V modes within microgrids, using a stochastic programming methodology to address EV uncertainty via multiple scenarios.

In addition to scenario-based approaches, parameter prediction based on historical data is another method for considering EV uncertainties. In this regard, (Guner and Ozdemir, 2020) tries to deploy the potential of EVPLs to increase distribution system reliability. It models an existing EVPL as available storage capacity, using sequential Monte Carlo simulations to determine the equivalent model based on historical data. (Madahi, Kamrani, and Nafisi, 2022) presented a data-driven approach to predict EV owners' behavior in an EVPL, subsequently modeling the EVPL as an aggregation of single EVs. Authors in (Barhagh, Mohammadi-Ivatloo, Anvari-Moghaddam, and Asadi, 2019) deployed an energy storage model for EV aggregators to present a robust optimization approach for their participation in energy markets, based on forecasted demand for different types of EVs under the aggregator contract. (Osório et al., 2021) presented an approach for defining the optimal operational strategy for an EVPL equipped with local photovoltaic generation, utilizing historical data from a real-case parking lot to forecast charging characteristics. EVs' arrival and departure uncertainty in (Srilakshmi and Singh, 2022), which studies the optimal operation of an EVPL in a microgrid, is addressed by deploying a Markov chain model to predict EV availability using historical data.

In this context, the thesis (Simolin, 2022) makes significant contributions to the modeling of EV charging characteristics. It recognizes the phenomenon of ”non-ideal charging characteristics,” where the realized charging current deviates from the maximum current limit, particularly in three-phase charging. A simulation model that accounts for these non-ideal characteristics is developed, based on comprehensive measurements of commercial EVs, and validated by comparing simulation results to laboratory measurements. The thesis also investigates the influence of temporal resolution in EV charging load modeling. Furthermore, it compares different charging profile modeling methods, demonstrating that linear models may oversimplify simulations and lead to inaccuracies, whereas bilinear models can be quite accurate, suggesting that more complex models may not be necessary in most cases.

Furthermore, the thesis (Tikka, 2024) aims to enhance the modeling of EV charging impacts on the power grid by identifying key factors influencing peak power accumulation, energy demand, and load curve shape. Key factors include kilometers driven, charging preferences, ambient temperature, battery capacity limits, and charging locations. The thesis identifies the significant impact of distribution of arrival times and the duration of charging events on peak power. The thesis also presents modeling methods to analyze EV smart charging flexibility, which impacts various energy sector players such as DSOs, retailers, and aggregators. Additionally, it demonstrates the potential of convolutional neural networks (CNN)-based spatial modeling to estimate temporal and spatial features of EV smart charging, aiding network planning despite dataset limitations. Lastly, the thesis identifies potential business cases for V2X technologies, reviewing six bidirectional charging strategies to understand their value propositions and support services.

3 DISTRIBUTION SYSTEM MANAGEMENT

3.1 Distribution system management today and in the future

The future role of DSOs is evolving significantly due to the increased integration of DERs such as distributed generation, energy storage, and controllable loads like EVs. Traditionally, DSOs have been responsible for planning, maintaining, and managing networks, as well as handling supply outages and energy billing. However, with the emergence of DERs, DSOs are now expected to take on additional roles, including peak load management, network congestion management, reactive power support, procurement of voltage support, and technical validation for power market. The deployment of new roles for DSOs is supported by four key factors: the implementation of smart meters, the enhancement of real-time monitoring, ensuring fair competition for aggregators, prosumers, and other providers of flexibility services, and the establishment of local marketplaces ("Future Role of Distribution System Operators", 2019).

Several initiatives and projects are already underway to support this transition. For example, UK Power Networks, a DSO operating in the UK, is shifting from its conventional role as an electricity delivery agent to implementing a virtual power plant framework. A technology trial resulted in a 60% reduction in peak demand from the grid (Hill, 2018). The European Union's draft electricity regulation mandates DSOs to support the integration of DERs. Both the US and EU countries are leading the expansion of DSO responsibilities ("Future Role of Distribution System Operators", 2019).

The transformation of DSOs will have significant benefits, including increased flexibility in distribution networks, reduced network investments, and enhanced renewable energy penetration. DSOs will need to leverage data to better forecast demand and optimize system operation, while regulatory frameworks must evolve to support these new roles and responsibilities ("Future Role of Distribution System Operators", 2019).

3.2 Virtual power plant

As mentioned in Chapter 2, VPP aggregates various DERs, loads, energy storage systems, and EVs. The VPP manager, by managing the operation of its assets, tries to address the challenges raised by renewable energy intermittency and uncertainty while enabling market participation and grid support. In this regard, effective operation and planning are key for VPPs to maximize profits. VPP assets typically include distributed energy resources like solar panels, wind turbines, battery storage systems, electric vehicles, and controllable loads. EVs with bidirectional charging capability can act as mobile storage units, providing power back to the grid when parked and connected. Known as V2G technology, this enhances grid flexibility. Demand response assets include industrial and commercial loads that can adjust their electricity consumption in real-time to match supply conditions, helping to balance the grid.

VPPs are clearly motivated to enhance their profitability, and an optimal planning strategy plays a critical role in maximizing their potential income. Meanwhile, the number of EVs has grown significantly in recent years, with increasing impacts on power systems. The widespread deployment of EVs at the distribution level offers VPPs opportunities to meet their energy demands more effectively. By selling electricity to EVs and using their batteries as storage systems, VPPs can mitigate fluctuations caused by the variable generation of renewable resources. This allows for improved utilization of renewable resources through EV charging infrastructure. However, excessive investment in charging stations might not yield a sufficient return on investment. Therefore, it is essential to establish an optimal plan for VPPs with EV charging stations.

Given the importance of planning decisions for VPPs and the growing integration of EVs, Publication VII aims to identify the optimal installed capacity of unidirectional and bidirectional EV charging stations and renewable energy units within a VPP while considering the operational constraints of each component. Additionally, it explores how investment in charging stations varies for VPPs with differing levels of renewable generation. This analysis is intended to support the broader adoption of renewable energy and EVs, promoting a sustainable and environmentally friendly energy sector for the future.

To model the optimal operation of a VPP, the related optimization problem must be formulated. In this problem, the objective function is formulated based on the operational goal of the VPP manager which is minimizing the cost or maximizing the revenue. The other important part of the optimization problem is constraints. In this regard, some constraints are operational constraints of all VPP assets, and others are constraints associated with the VPP's participation in the local market. The constraints are presented in as presented in equations (1)-(21) of the Publication VI. Similarly, for VPP planning problems, to find the optimal capacity expansion, an optimization framework is required in which the objective function minimizes the total VPP cost over the planning horizon, which equals the summation of the investment cost and the net present value of the total operational cost of the VPP over its lifecycle, taking into account the operational constraints of the VPP. The first component of the operational cost is the revenue earned from electric vehicle owners for charging their vehicles (with negative sign) and the second component accounts for the total expense incurred by the VPP for purchasing power from the power system as presented in equation (1) of the Publication VII.

The optimal operation and planning of the case study VPP is explained below. The operation optimization is conducted using Python, with the Gurobi solver employed to achieve optimal solutions. For planning, we calculated the objective function of each scenario, selecting the scenario with the lowest objective function value as the optimal planning decision.

3.3 Optimal operation of VPP

In this section, we analyze the operational performance of the VPP considering one unidirectional and one bidirectional charging station. Figure 2 illustrates the charge and discharge power of the bidirectional station, the charge power of the unidirectional station, and the day-ahead electricity prices. As expected, for both chargers, charging happens during hours when electricity prices are lower. Conversely, discharging at the bidirectional station aligns with hours of higher electricity prices. Thus, the bidirectional EV charging station functions as an energy storage system, generating income through optimized charging and discharging strategies. Additionally, simulations were conducted for different scenarios to assess the impact of EV entry and exit times on the VPP's total operational cost over the lifecycle. The results show that when EVs arrive earlier and depart later, the overall operational cost decreases, as there is more flexibility in scheduling charging and discharging. Notably, an earlier arrival has a greater impact on reducing costs than a later departure. For example, when EVs enter at 7 a.m. and leave at 3 p.m., the operational cost is €258,478, which is lower than when EVs enter at 8 a.m. and leave at 4 p.m., despite similar durations in both scenarios. Consequently, an earlier entry time is preferable for the VPP operator. Future studies should further investigate the behavior of EV owners regarding arrival and departure times, as well as explore uncertainties and risks, ideally through probabilistic modeling.

3.4 Optimal planning of VPP

3.4.1 Optimal planning - optimization only on EV chargers

In this section, we aim to determine the optimal number of unidirectional and bidirectional charging stations to be installed at the EV parking lot owned by the VPP. The VPP is assumed to have one wind turbine and one PV system. Initially,

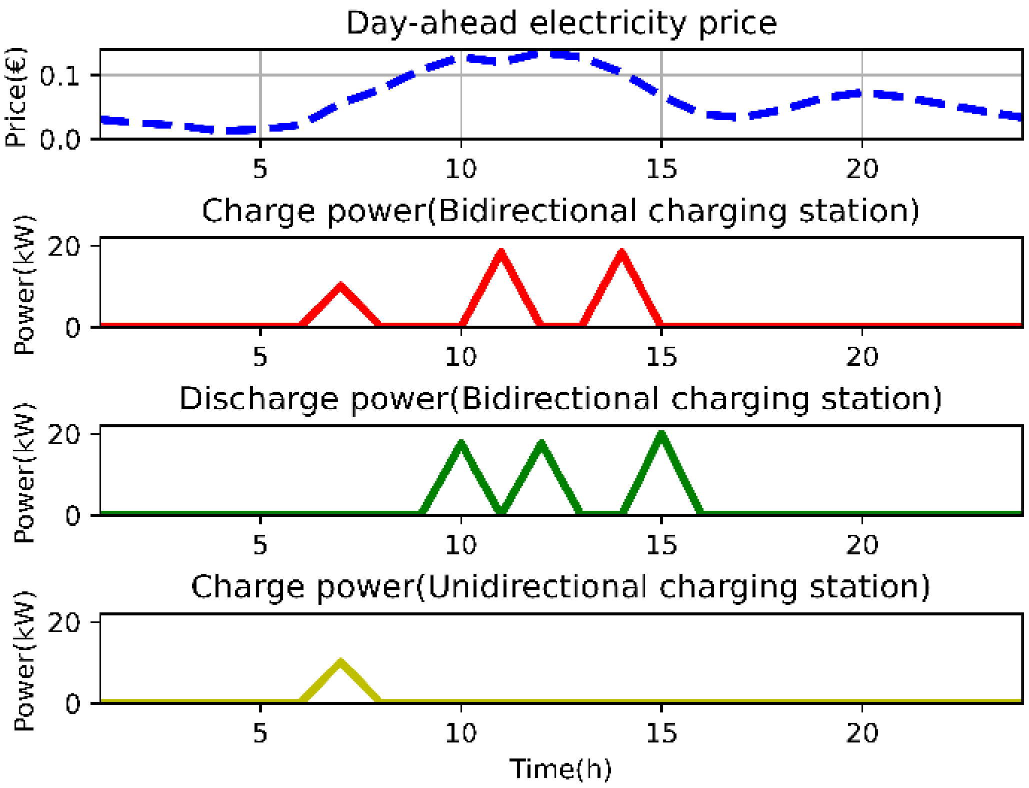


Figure 2. Charge and discharge power as well as day-ahead electricity price (Publication VII).

we analyze five different VPPs with different capacities of the line connecting the VPP to the upstream grid, while keeping all other characteristics constant. Figure 3 illustrates that VPPs with higher line capacities between the VPP and the grid require a greater number of bidirectional charging stations. This is because increased grid-connecting line capacity allows the VPP to trade larger amounts of power each hour, enhancing the potential to purchase power during low-price periods and sell during high-price periods through bidirectional EV charging stations. Consequently, bidirectional charging stations become more profitable in such setups. Additionally, seven scenarios were evaluated for the initial State of Charge (SOC) of EVs entering the VPP. As the initial SOC increases, the optimal number of bidirectional stations decreases. This trend occurs because a lower initial SOC creates more opportunity for revenue from charging EVs, as EVs require more energy. Conversely, a higher initial SOC reduces this revenue potential, diminishing the return on investment for charging stations as initial SOC levels rise.

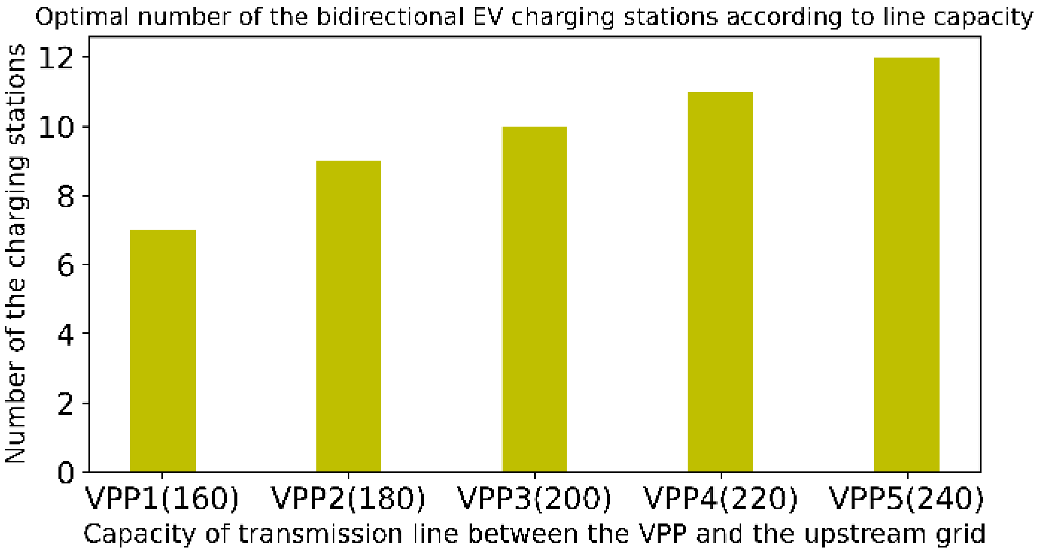


Figure 3. Optimal number of the bidirectional EV charging stations for different line capacities (Publication VII).

3.4.2 Optimal planning - optimization on PV and wind turbines as well as EV chargers

In this section, we explore the optimal planning of the VPP, considering the number of PV units, wind turbines, and EV charging stations as decision variables. To achieve this, we examined five distinct VPPs with varying grid-connecting line capacities, while keeping all other attributes consistent. Optimal sets of decisions for each VPP are shown in Figure 4. These results suggest that the higher line capacity of VPP2 compared to VPP1 makes bidirectional EV charging stations more economically favorable than unidirectional ones, as the larger capacity allows for greater use of bidirectional stations as energy storage systems, gaining profit from price fluctuations by charging during low-price hours and discharging during high-price hours. This operational benefit outweighs the higher investment costs.

With VPP3, which has a 220 kW line capacity, the optimal configuration expands to include one additional PV unit, while the number of unidirectional charging stations increases to 10. This result indicates that higher PV generation can justify a greater number of unidirectional charging stations. When comparing VPP4 with VPP3, we observe that the optimal numbers of PV units and wind turbines are similar, yet unidirectional EV charging stations are more profitable for VPP4 than for VPP3, consistent with the observed trend in VPP1 and VPP2.

An important finding is that the 260 kW capacity line in VPP5 shifts profitability toward wind turbines, reducing the relative benefit of PV units compared to VPP4. In VPP5, a higher proportion of wind generation increases the profitability of bidirectional EV charging stations over unidirectional ones. Overall, these results indicate that when wind generation constitutes a larger share of capacity mix, bidirectional EV charging stations become more attractive for VPP owners.

It is also noteworthy that there is a significant drop in wind speed at hour 4, which may result in a substantial decrease in overall power generation if the wind generation capacity is high. Although this phenomenon may not occur frequently, it remains a possibility. In scenarios where the system is connected to the upstream grid, this drop does not pose a major challenge. However, in island operations, the system must manage such a significant change in renewable generation either through curtailment, which may not be efficient, compensation by DGs, or by utilizing the BESS to store the excess generation or discharge. Consequently, for island systems with high renewable penetration, it is essential to ensure sufficient BESS and DG capacity to effectively handle such occurrences.

To conclude, our case study results indicate that an increased share of PV generation can enhance the profitability of unidirectional EV charging stations. Conversely, a higher proportion of wind generation favors the use of bidirectional EV charging stations. Another key finding is that the behavior of EV owners, specifically, their entry and exit times and the initial SOC of EVs upon entering the parking lot significantly influence outcomes. Consequently, to support more reliable planning decisions, future studies should address the uncertainties associated with these factors. It is crucial to acknowledge that these conclusions are specific to the case study with the particular load and renewable profiles analyzed and cannot be generalized to all scenarios.

3.5 Impact of EV parking lots on the distribution system

The charging and discharging of electric vehicles can substantially impact the management of distribution systems. On the positive side, EVs function as distributed energy storage units and flexible loads, which can be leveraged to help balance the variability of renewable energy sources. When EV charging is aligned with periods of excess renewable energy generation, it can reduce curtailment and enhance the utilization of these energy sources. Additionally, smart charging strategies enable EVs to provide voltage support and reactive power compensation in response to the system's needs. Conversely, high levels of uncoordinated EV charging can strain distribution system components, potentially leading to voltage instability and network congestion. To mitigate these negative effects, distribution system operators must develop robust EV charging management strategies, incorporating smart charging algorithms, advanced monitoring and control systems, and appropriate policies and

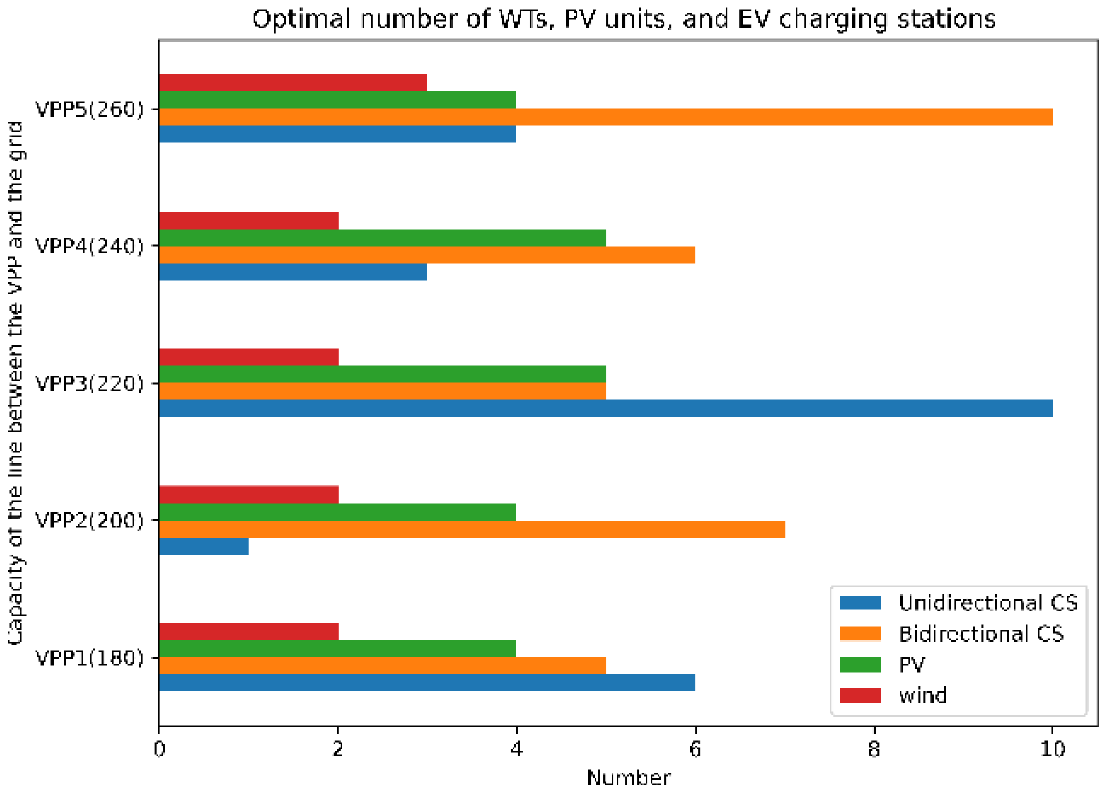


Figure 4. Optimal number of WTs, PV units, and EV charging stations (Publication VII).

regulations.

While several studies have examined the role of EV charging stations and parking lots, their potential to provide reactive support to the power system remains underexplored. Furthermore, in the literature, quantifying the penalty costs the DSO should pay as compensation to consumers for failing to meet power quality standards related to voltage violations is not addressed. Publication V and Publication VI aim to address these gaps by exploring how EV parking lots can help reduce distribution system costs and improve voltage conditions. By functioning as flexible active loads and supplying reactive power support, EVPLs contribute to voltage stability, particularly when the penalty costs for voltage violations are factored into overall system costs along with other operational expenses.

While there are regulations in some countries requiring system operators to compensate consumers for power quality issues, to the best of the author's knowledge, a systematic regulation that mandates DSOs to compensate consumers specifically for voltage violations has not yet been implemented at the time of writing this paper. In this regard, our proposed approach can be adopted to facilitate a systematic method for calculating voltage-related penalties, which consequently results in fewer voltage issues and better protection of consumers' rights.

3.5.1 Problem definition

The DSO problem is structured as an optimization task, aiming to minimize operational costs across the distribution system while adhering to the operational constraints of the system, including the grid, EVPL, distributed generation, renewable energy sources, and consumer loads. The constraints are presented in equations (4)-(30) of Publication VI. It is worth noting that the formulation for active and reactive power flow (equations (4)-(9)) incorporates all grid and distribution line characteristics, including reactance and resistance. Consequently, these factors are taken into account when calculating reactive power injections and assessing their impact on system voltage. To obtain the available renewable generation addressing the uncertainty in RES forecast, a chance-constrained formulation is applied (represented in equation (15) of Publication VI). The generation output of various renewable units may differ due to their distinct geographical locations and unique generation profiles.

The objective function of the DSO is to minimize total operational costs of the system, encompassing DG and RES generation costs, the cost of trading active and reactive power with the upstream grid, and the costs associated with voltage violations that the DSO is obligated to pay as compensation to consumers. The objective function is presented in equation (1) of Publication VI. It is important to note that DGs and RESs within the distribution system are not necessarily owned by the DSO. Nevertheless, they are included in the distribution system's objective function because the DSO seeks to minimize system costs, considering social welfare maximization across the distribution system. Additionally, the distribution system losses and their associated costs could be considered in the objective function. However, these factors are not included in this study because they are not the primary focus and they introduce complexity due to their nonlinear characteristics.

The DSO is required to maintain voltage levels within an acceptable range for consumers. Compensation mechanisms apply when voltage levels deviate from this range. In this regard, there are two levels of voltage violation explained in equations (2) and (3) in Publication VI.

-Proper Voltage Violation Range: This is a minor deviation where the DSO is not required to compensate consumers. Voltage violations below 0.05 fall into this category.

-Critical Voltage Violation Range: For more significant deviations, where the DSO must compensate consumers, a linear relationship exists between the compensation amount and the degree of voltage violation. In this study, violations between 0.05 and 0.1 are considered critical. Violations exceeding 0.1 are not permissible under any circumstances. This framework allows the DSO to balance costs effectively while maintaining voltage quality within regulated limits. However, such compensation formula creates a nonlinear objective function. In this regard, using variables, the nonlinear optimization problem is converted to a mixed-integer linear problem explained in detail in the section III of Publication VI.

3.5.2 Results and discussion

To analyze the effects of voltage violation costs and the provision of reactive power support from EVPLs, we considered two cases and two scenarios in our simulation:

-Case (a): Assumes there is no voltage violation penalty cost for the DSO. -Case (b): Includes the voltage violation penalty cost within the DSO's objective function. In addition to these cases, we define two scenarios regarding EVPL reactive power support capabilities:

-Scenario 1: EVPL chargers are unable to provide reactive power support. -Scenario 2: EVPL chargers can provide reactive power support.

Figure 5 shows the charging power schedule of EVPLs in Scenario 1, where they are unable to provide reactive power support. The charging schedules vary across different EVPLs in both cases due to their different locations within the power system, which are subject to different network constraints impacting scheduling. Each EVPL's charging schedule is determined by hourly power prices and DG and RES generation, ensuring that voltage levels across the system remain within allowable limits. Additionally, the charging schedules differ between cases (a) and (b) for each EVPL. In Case (b), where a voltage violation cost is included, reducing voltage violation levels becomes a higher priority than in Case (a).

The charging schedule is optimized to help the DSO achieve a lower voltage violation level, as shown in Figure 6, because adjustments to the schedule lead to changes in hourly generation and the traded power. By operating as a flexible load, the EVPL supports the DSO in reducing voltage violations across the power system. Additionally, it is evident that if the DSO incurs a voltage violation penalty, there will be a significant increase in its costs, even with the optimized EVPL charging schedule that effectively reduces overall system voltage violations.

In Scenario 2, EVPLs are equipped to provide reactive power support for the DSO. It is observed that the total system cost in this scenario for Case (a) is 1.37 % lower than the corresponding system cost in Scenario 1. This reduction is expected, as

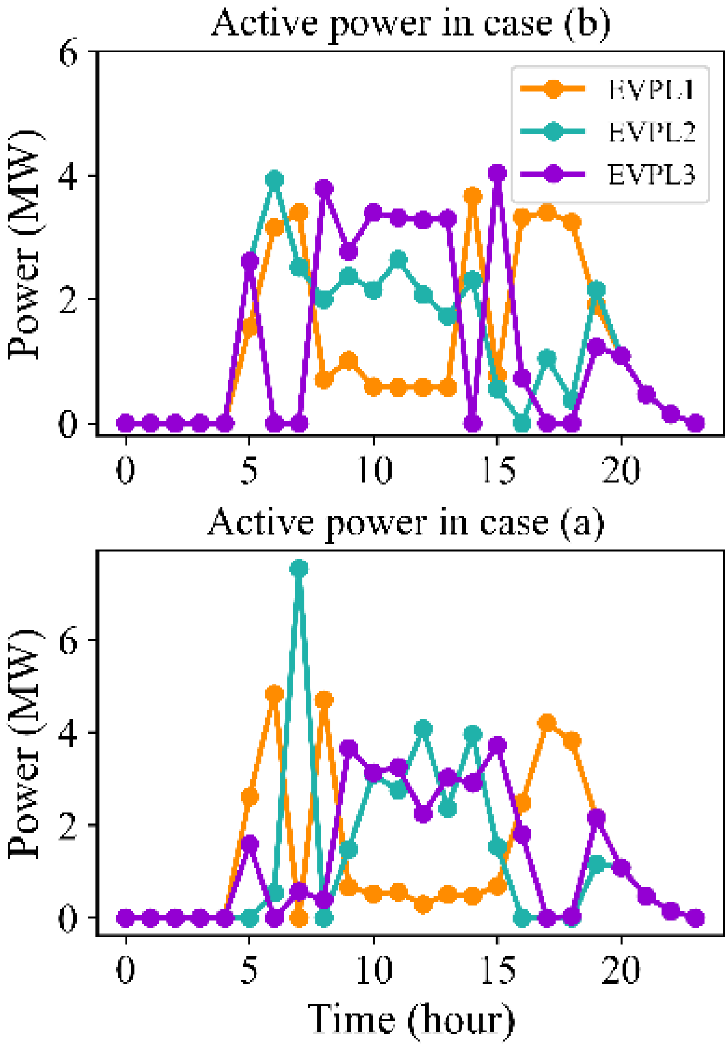


Figure 5. The active power of EVPLs for case (a) and case (b) in scenario 1 (Publication VI).

reactive power support from EVPLs can improve system voltage conditions, allowing DGs to increase generation and leading to a more cost-effective power supply mix. Consequently, the total system cost decreases. Reactive power support in Scenario 2 has an even greater impact in Case (b), where the total system cost is 11.23 % lower than in Scenario 1. This emphasizes the value of EVPLs' reactive power support, particularly when voltage violation penalties are included in the DSO's costs.

It may be conceivable that injecting reactive power into a bus to fix an undervoltage issue may raise the voltage of nearby buses, potentially causing overvoltage in other buses. However, it is important to note that reactive power support can be provided at other buses to correct this situation.

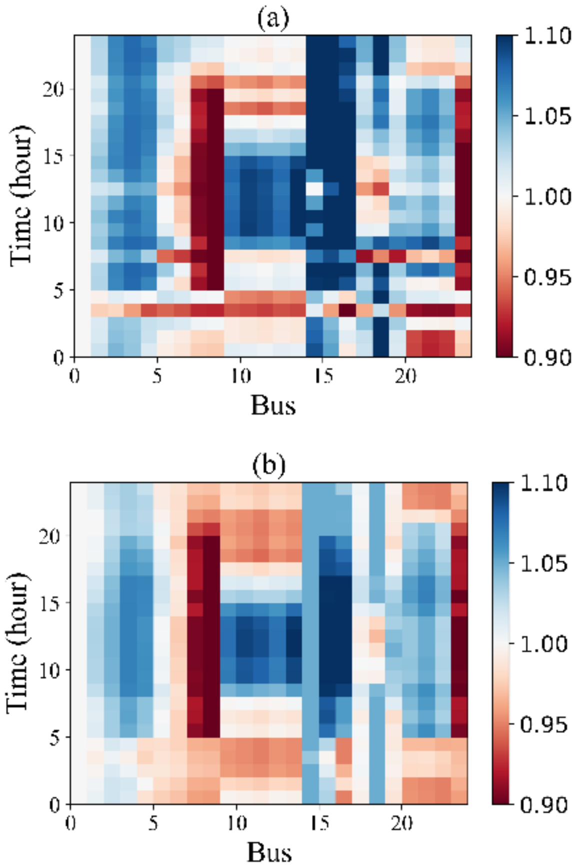


Figure 6. System voltage for case (a) and case (b) in scenario 1 (Publication VI).

Table 1. Total system cost and voltage violation.

Scenario, case	total voltage violation	total system cost
Scenario 1, case (a)	27.3365	18597.12
Scenario 1, case (b)	23.3558	21623.89
Scenario 2, case (a)	28.19	18352.35
Scenario 2, case (b)	18.63	19194.94

Figure 7 illustrates the active and reactive power outputs of EVPLs for Case (a) and Case (b) in Scenario 2. In this scenario, EVPLs adjust their charging schedules (relative to Scenario 1 in Figure 5) to provide reactive power support, significantly improving system voltage stability, as shown in Figure 8. This adjustment leads to reduced voltage violations and, consequently, lower overall system costs. Table 1 further demonstrates that when the DSO incurs penalties for voltage violations exceeding 0.05, total system voltage violations decrease by approximately 34 %. This substantial reduction in voltage violations underscores the effectiveness of EVPLs in enhancing voltage stability throughout the system.

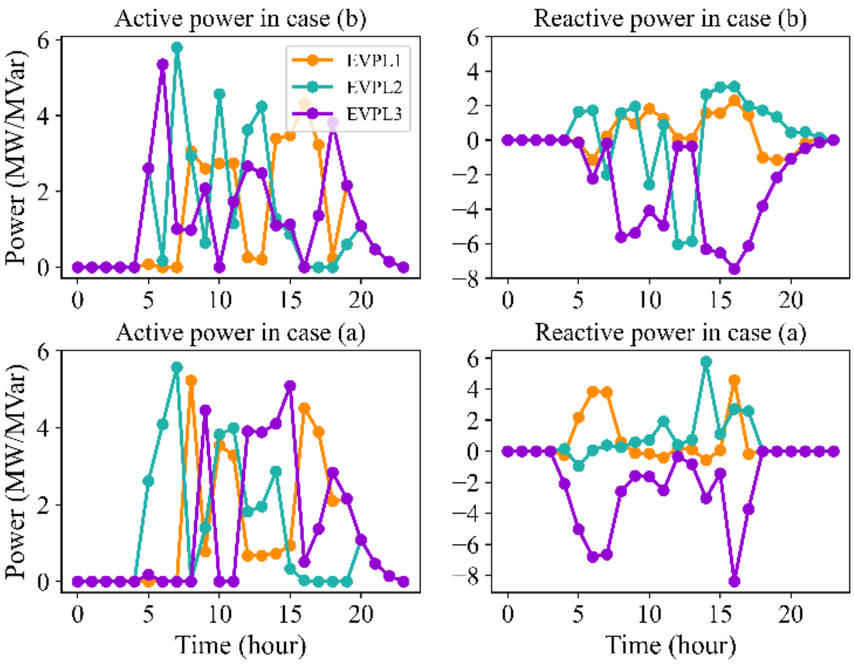


Figure 7. The active and reactive power of EVPLs for case (a) and case (b) in scenario 2 (Publication VI).

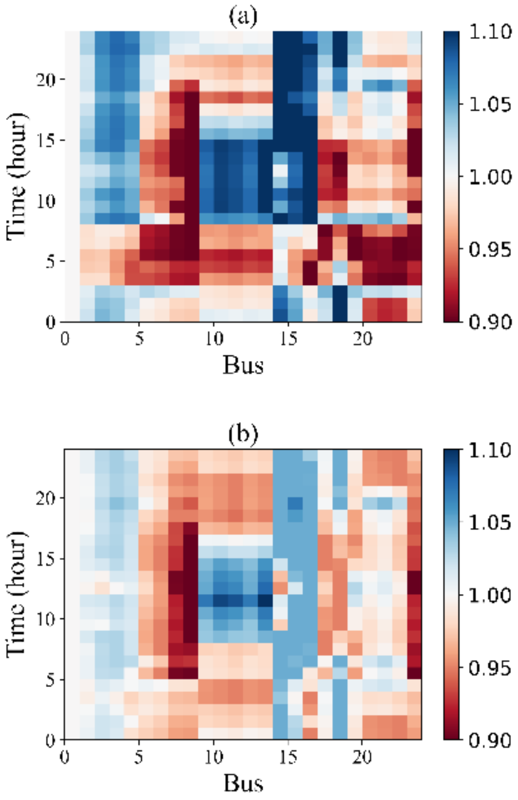


Figure 8. System voltage for case (a) and case (b) in scenario 2 (Publication VI).

4 ELECTRIC VEHICLES MODELLING

4.1 Electric vehicles deployment today and future scenarios

In 2024, global electric car sales exceeded 17 million units, accounting for more than 20% of total car sales. The additional 3.5 million electric cars sold in 2024 compared to the previous year surpasses the total number of electric cars sold worldwide in 2020 (“IEA Global EV Outlook”, 2025). The global market for electric vehicles is expected to achieve another record-breaking year in 2025 as the costs of lithium-ion batteries decrease and the production of more affordable models increases. Plug-in electric vehicles are estimated to represent one in four passenger vehicles sold globally, with more than half of the market share in China. This marks a significant increase from just a few years ago when electric vehicles constituted less than 5% of global new vehicle sales.

The future of EV looks very promising, with many scenarios showing continued growth and widespread use. Predictions for EVs suggest strong growth, driven by supportive policies, technological improvements, and favorable market conditions. These forecasts indicate that EVs will be important in moving towards sustainable transportation, helping to meet climate goals and reduce air pollution (“IEA Global EV Outlook”, 2025). The International Energy Agency’s (IEA) Global EV Outlook 2025 expects the global EV fleet to grow four times larger by 2030 under the Stated Policies Scenario (STEPS). This scenario includes the current policy environment, covering existing and new policies, regulations, and investments. By 2030, the EV fleet across all types, except two- and three-wheelers, is expected to reach 250 million units, with electric cars making up more than 90% of this total (“BNEF Electric Vehicle Outlook”, 2025).

BloombergNEF’s Electric Vehicle Outlook 2025 supports this positive outlook, predicting that EVs will make up 56% of global passenger vehicle sales by 2035 and 70% by 2040 in BNEF’s Economic Transition Scenario. (“BNEF Electric Vehicle Outlook”, 2025) highlights key factors that will drive this growth, including improvements in battery technology, lower manufacturing costs, and more charging stations. Both IEA and BloombergNEF reports stress the need for ongoing investment and innovation in the EV sector to achieve these future scenarios.

4.2 Electric vehicles charging solutions today

Recent improvements in EV chargers have greatly enhanced their capabilities in terms of charging power, design, and functionality. Modern EV chargers now provide higher charging power, allowing for faster recharging times similar to refueling with gasoline or diesel. Ultra-fast chargers can deliver power levels exceeding 350 kW, significantly reducing the time needed to charge an EV. Additionally, the design of chargers has become more compact and user-friendly, making installation and use easier in various settings (Saraswathi and Ramachandran, 2024).

There are primarily two methods for charging an EV: using a charging station or a socket outlet. Charging stations can be categorized into regular AC charging and fast direct current (DC) charging. AC charging involves an on-board charger (OBC) within the EV that converts AC to DC to charge the battery. In contrast, DC charging utilizes an off-board charger at the charging station to directly supply DC to the EV's battery (Simolin, 2022).

Bidirectional charging, known as V2G, enables EVs to draw power from the grid and also feed electricity back into it, acting as mobile energy storage units. This helps stabilize the grid and supports the integration of renewable energy. Advanced chargers also offer reactive power support, which improves the efficiency of the electrical grid. Despite these advancements, challenges remain. Public EV charging costs have risen sharply since 2022 in many markets, including Europe and the US, making the cost per kilometer higher than gasoline. It is crucial to manage the cost of public fast charging and ensure it remains competitive with traditional fuels to encourage continued EV adoption (Saraswathi and Ramachandran, 2024).

EV chargers are classified according to their power levels ranging from 3.7 kW to 350 kW, determining how quickly they can charge an EV. These power levels address different charging needs, from overnight residential charging to rapid public charging stations, significantly reducing charging times and making EVs more convenient for long-distance travel and daily use (Saraswathi and Ramachandran, 2024). Key vendors such as ChargePoint, Tesla, Kempower, Siemens, and ABB are leading the development and deployment of advanced charging solutions to support this growth.

4.3 EV modelling research gaps

The growing penetration of EVs in recent years has made them a central factor in operational and planning decisions across the energy and transportation industries. EVs connected to the power system, including the distribution network, can provide flexibility. These EVs are categorized into EVs plugged into grid-connected homes, EVs plugged into grid-connected commercial buildings, and EVs connected to public charging stations. The flexibility services that can be provided by EVs include reducing electricity costs, reducing CO2 footprint, and grid stabilization (Homaee et al., 2024). Therefore, optimizing the operation and planning of EV charging infrastructures—such as EV Parking Lots and charging stations—has become critically important.

For studies involving existing parking lots, modeling EVPL uncertainties through predictive analysis based on historical data is applicable. However, this approach is ineffective for planning studies because it relies on forecasting uncertain parameters using historical data from current EV charging stations, which is unavailable for parking lots that are not yet constructed.

Additionally, the use of single or multi-scenario generation for uncertainty modeling presents challenges. First, a limited set of generated scenarios may fail to capture the full characteristics of the probability density function. Scenario-based approaches also introduce complexity due to stochastic elements that add difficulty to the formulation and modeling process. When several uncertain parameters are involved, computational burdens increase significantly, especially when a large number of scenarios must be generated to capture a wide range of possible outcomes.

Moreover, another limitation of scenario-based uncertainty modeling is that, in this approach, random values are generated for each EV's arrival and departure times based on a selected PDF, defining the number of EVs arriving at the parking lot each hour. As a result, the total number of EVs arriving or departing each day is treated as a parameter and remains fixed. Thus, scenarios are generated with a predefined number of EVs and incorporated into the stochastic method. However, this approach is unsuitable for studies in which the number of EVs is unknown or variable, a common case in planning problems where future EV numbers cannot be pre-assumed.

The literature review reveals that almost all studies on EVPLs within power systems assume that EV charging in parking lots or charging stations follows an exclusive charger model. This approach means each EV in the parking lot is assigned a dedicated charger, connected to the EV for the entire duration of its stay. Such studies typically assume that every parking space is equipped with a separate EV charger. However, since EVs are often parked for extended periods while their actual charging time is only a few hours, it is unnecessary to provide each parking space with an individual charger.

To address this, Publication II introduces a charger-sharing model that allows EVPL operators to assign a single charger to multiple parking spaces. This approach enables EVPL owners to make more efficient operational and planning decisions, increasing operational profit and reducing investment costs for planning. Notably, the structure of our proposed virtual battery model supports this charger-sharing strategy, whereas existing EVPL models cannot adequately incorporate it due to inherent limitations.

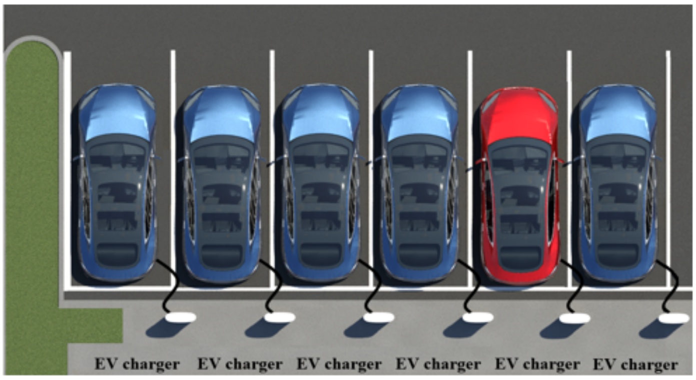
Despite numerous studies on aggregated EV charging models, there is still a need for a straightforward, compact model that minimizes computational demands while accounting for EV arrival and departure uncertainties and enabling charger-sharing capabilities. Our proposed virtual battery model for EVPL (incorporating both unidirectional and bidirectional chargers) addresses these gaps. It enables a comprehensive analysis of aggregated EV charging interactions with other energy system components from the perspective of charging station operators, power system operators, and other stakeholders involved in EVPL-related operational or planning analyses. Using this virtual battery model, EV aggregation can be modeled similarly to a battery system, which is based on the estimation of the number of arriving, departing, and parked EVs in each hour. This estimation is based on the cumulative distribution function of the truncated normal distribution, with values adjusted to the maximum daily capacity of EVs hosted in the parking facility.

This modeling approach is suitable for large-scale operational or planning studies that incorporate arrival and departure uncertainties without adding significant computational burden. The virtual battery model's effectiveness has been validated by comparing its performance in simultaneous day-ahead and real-time markets participation with that of scenario-based methods. As previously highlighted, an additional contribution of our work is the charger-sharing approach, which enables EVPL operators to maximize the number of EVs accommodated without requiring an individual charger at each parking space. For a specified number of EVs, the EVPL can use a single charger to serve multiple vehicles, as shown in Figure 9. Both the exclusive charger setup and the charger-sharing setup depicted feature chargers of equivalent type and capacity. This approach takes advantage of the fact that while EVs may remain parked for hours, the actual charging time is considerably shorter, eliminating the need for a dedicated charger per space. Instead, a single charger can sequentially charge multiple EVs parked in different spaces, thus supporting optimal planning by reducing the required number of chargers.

4.4 Virtual battery model

In our proposed approach, the EVPL is modeled as a time-variant storage system, with the characteristics of energy storage determined by the arrival and departure times of EVs, as illustrated in Figure 10. Unlike a conventional battery, which has constant maximum charging and discharging power and fixed minimum and maximum states of charge, the proposed virtual battery has time-variant parameters. Specifically, for each hour, these parameters are calculated based on the number of arriving, departing, and parked EVs during that hour.

(a) Exclusive charger charging approach



(b) Charger sharing charging approach

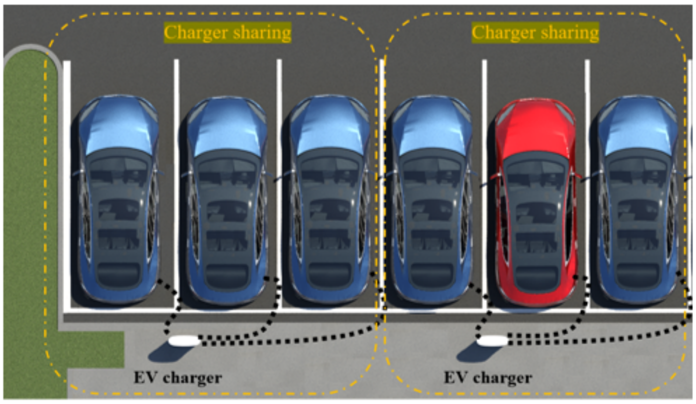


Figure 9. (a) exclusive charger and (b) charger-sharing charging (Publication II).

Our model incorporates the uncertainties of EV arrival and departure times to define the parameters of the equivalent storage model. Once the equivalent storage model is established, energy management strategies can be applied to optimize both the operation and planning of the parking lot. In this work, we assume that the parking lot will accommodate various classes of EVs, each with different battery capacities, charging and discharging powers, as well as distinct initial and final SOCs. The energy stored in the parking lot at any given hour is calculated based on the energy stored during the previous hour, in addition to the energy associated with the incoming and outgoing EVs during that hour.

To determine the energy contained in the arriving and departing EVs, it is essential to calculate the number of EVs arriving and departing each hour. As per existing literature, the uncertainty in the arrival and departure times of EVs is modeled using a truncated normal distribution function, which has been widely recognized as a reliable probability distribution function for capturing such uncertainties. Numerous

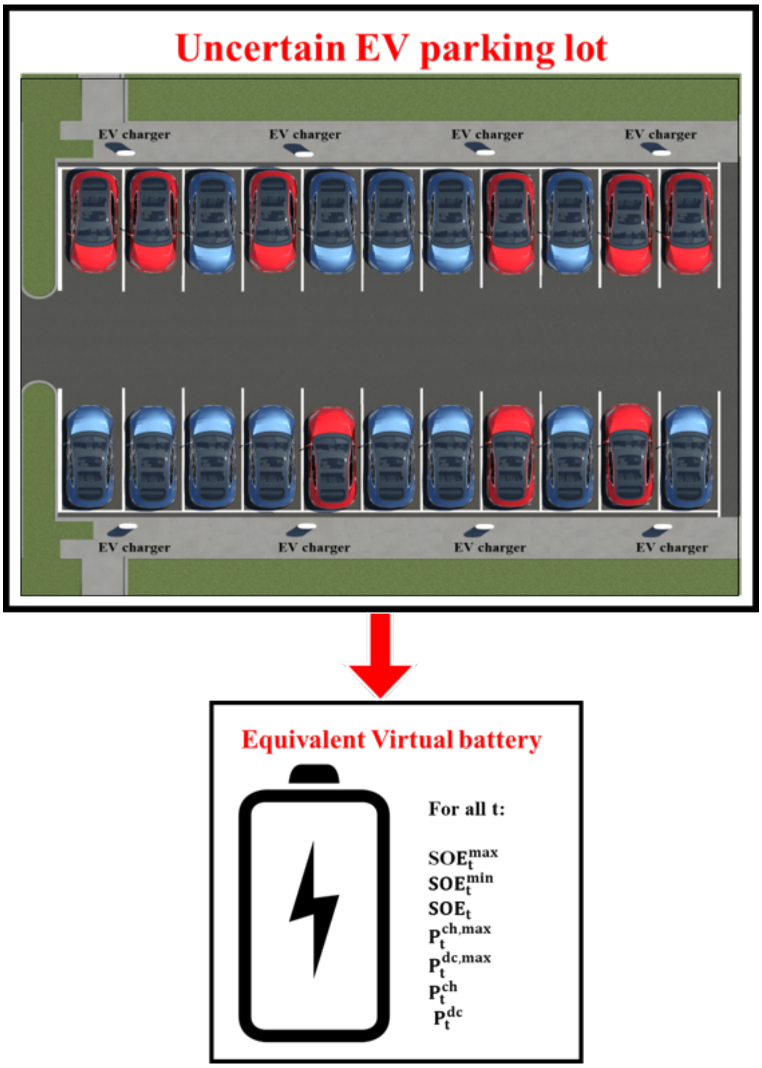


Figure 10. Virtual battery model for an uncertain EVPL (Publication II).

studies in the literature have employed this distribution function. Some of these studies include (Tang, Chau, and Liu, 2023), (Anselmo and Mahmood, 2021), (Mudgal and Tiwari, 2022), (Limmer and Rodemann, 2024), (Karimi-Arpanahi, Jooshaki, Fotuhi-Firuzabad, and Lehtonen, 2020), (Shafie-Khah, Siano, Fitiwi, Mahmoudi, and Catalao, 2017), (Vagropoulos and Bakirtzis, 2013), (Chang, Xie, Qiu, and Ge, 2022), (Islam, Mithulananthan, and Hung, 2017), and (Y. Wang, Jia, Li, Zhang, and Zhang, 2021). Using the cumulative distribution function of the truncated normal distribution and the total number of EVs expected to arrive at the parking lot throughout the whole day, we can calculate the number of EVs arriving and departing each hour.

It is important to note that, in our proposed method, the energy management process also considers the maximum number of EVs that can be parked at the parking lot, which is optimized to ensure the most efficient use of charging stations. This maximum number is determined based on the optimal operation of the system. Additionally, the total number of EVs that arrive in the parking lot daily must be less than or equal to the number of EVs available in the surrounding area that are expected to arrive.

As mentioned above, to establish the EVPL's equivalent storage model, it is essential to define the hourly maximum and minimum limits for both charging and discharging power, as well as the amount of energy stored in the EVPL. First, the charging power of the parking lot for each hour should not exceed the total charging capacity of the parking lot, which is determined by the combined maximum charging power of all charging stations present. Notably, with the charger-sharing approach, the number of EV chargers may be fewer than the number of parked EVs, as a single charger can serve multiple EVs over time.

Additionally, the charging and discharging power should not exceed the total maximum charging power of the EVs parked in the lot at any given hour. The number of parked EVs in each hour is calculated based on the count of parked EVs in the previous hour, adjusted by the number of EVs arriving and departing during that hour. This approach ensures that both the power limits and the energy storage capacity of the EVPL are dynamically aligned with real-time changes in EV occupancy. The stored energy in the parking lot at any given hour must remain below the combined energy capacity of the EVs parked at that time, as defined by their maximum allowable SOC. Additionally, using the minimum permissible SOC of the parked EVs in each hour, we establish a lower bound for the stored energy in the parking lot for that hour. This approach ensures that the storage model for the parking lot accurately reflects the SOC constraints of the EVs present, maintaining operational efficiency within safe energy limits. The detailed explanation about the proposed virtual battery model is explained in section 2 of Publication II (equations (1)-(18)).

4.5 Market-based validation framework

To assess the effectiveness of our proposed virtual battery model, we evaluated its performance within a representative problem and compared it to other established approaches. Specifically, we selected the optimal operation of a distribution system with a high penetration of EVPLs in the DA market. This evaluation context allows us to analyze the performance of our model in uncertainty modeling, particularly against the widely-used scenario-based approach for EV uncertainty. The operational market participation problem provides a precise validation setting for our approach, highlighting its effectiveness in capturing uncertainty and optimizing performance.

For a fair evaluation, we designed the pricing of the DA and RT markets such that inaccuracies in uncertainty modeling would directly impact the EVPL's cost. Here, the RT market's selling price is lower than that of the DA market, while the purchasing price in RT is higher than in DA. Therefore, if the parking lot fails to accurately model EV uncertainties and predict its load profile, it will be forced to trade in the RT market, incurring higher costs. This pricing mechanism ensures the importance of accurate uncertainty modeling and allows us to effectively demonstrate our approach's performance.

In addition, we utilized a day-ahead price profile that follows the typical day-ahead price pattern characterized by two daily peaks. Furthermore, the maximum price significantly exceeds the minimum price, and there are notable price fluctuations. Consequently, varying scheduling strategies for electric vehicle parking lots result in different energy costs. Therefore, this validation framework is robust and reliable for evaluating the performance of the virtual battery model in large-scale system-level applications involving electric vehicles. Our virtual battery model, which is computationally light, is not recommended for use in small-scale trading applications, as there is no computational burden issue when employing detailed scenario-based models. However, for employing the virtual battery model for pure trading applications of EVPLs on specific days where the price profile deviates from the common pattern, it is suggested to conduct further validations using these specific price profiles, especially for higher resolution markets such as 5-minute intervals.

Since other EV uncertainty modeling techniques do not support charger-sharing, we compared our virtual battery model to scenario-based modeling under the assumption of exclusive charger usage. This setup ensures that the total number of arriving EVs matches the total number of chargers available. For simplicity, we assumed all chargers in the parking lot are unidirectional, without EV discharge capability. In the subsequent sections, we describe the market participation problems for each approach and outline their cost calculations in realization scenarios. The overall validation process is illustrated in Figure 11.

4.5.1 Market participation with proposed virtual battery model

Using the proposed virtual battery model, the Distribution System (DS) manages its market participation to minimize costs in the DA market. Importantly, our virtual battery model does not rely on any stochastic process to predict RT arrival and departure statuses of EVs. Instead, DA decisions are based on the characteristics of the virtual battery model, which are derived from the PDF of the uncertain parameters related to EV arrival and departure. Further explanation about the validation framework can be found in the section 3 of Publication II.

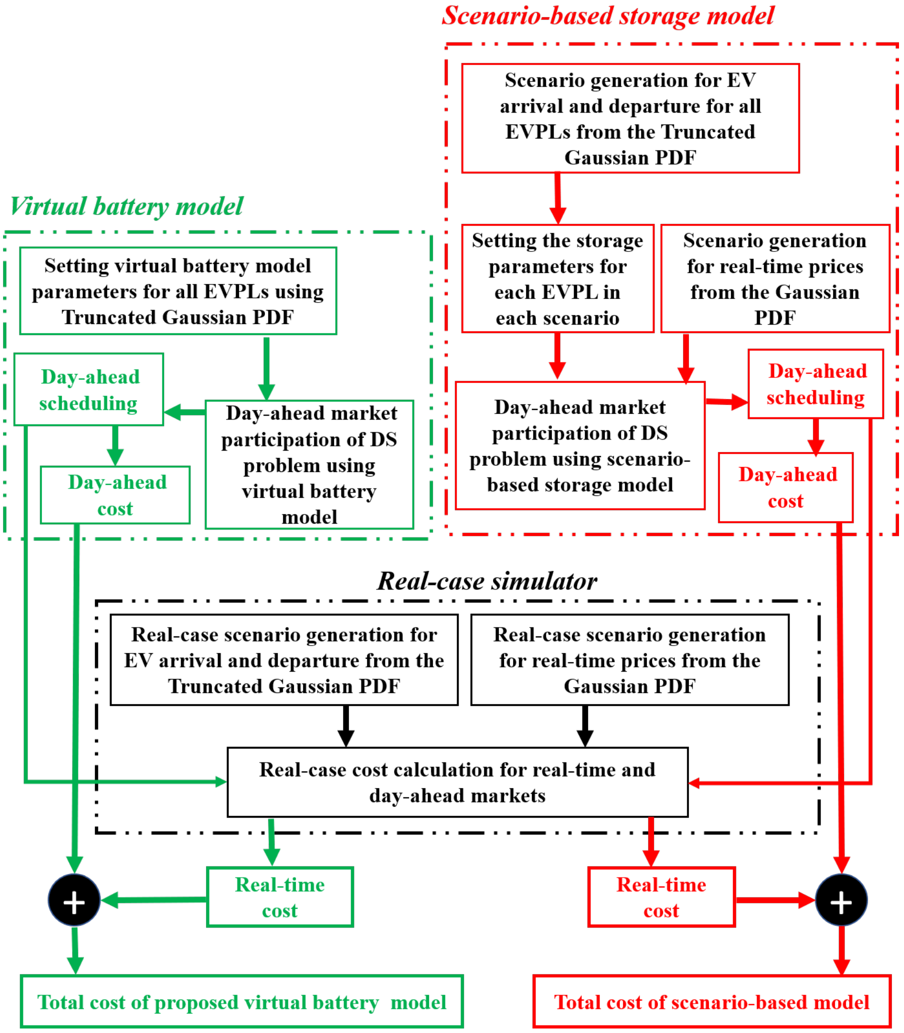


Figure 11. Validation process flowchart (Publication II).

4.5.2 Market participation with scenario-based storage model

In the scenario-based approach, to model EV uncertainty, the RT status of EVs is generated using a truncated normal distribution function. Optimal DA market decisions for the DS are then determined via two-stage stochastic programming. Each scenario generates parameters for the EVPLs' storage model in this process based on the number of EVs arriving and departing per hour. These parameters are then used to calculate the optimal DA decisions for DS market participation, ensuring compliance with operational constraints.

The objective function in this approach is minimization of total DS costs, including both DA costs and the expected RT costs, weighted by scenario probabilities presented in equation (19) of Publication II. Thus, DA decisions are optimized based on anticipated RT scenarios and their associated costs. Notably, the RT price is treated as another uncertain factor, with its hourly values following a normal PDF centered around the DA price for that hour, with a standard deviation set at 30% of the mean. The DA price and generated scenarios for the RT price (purchasing and selling) are shown in Figure 12

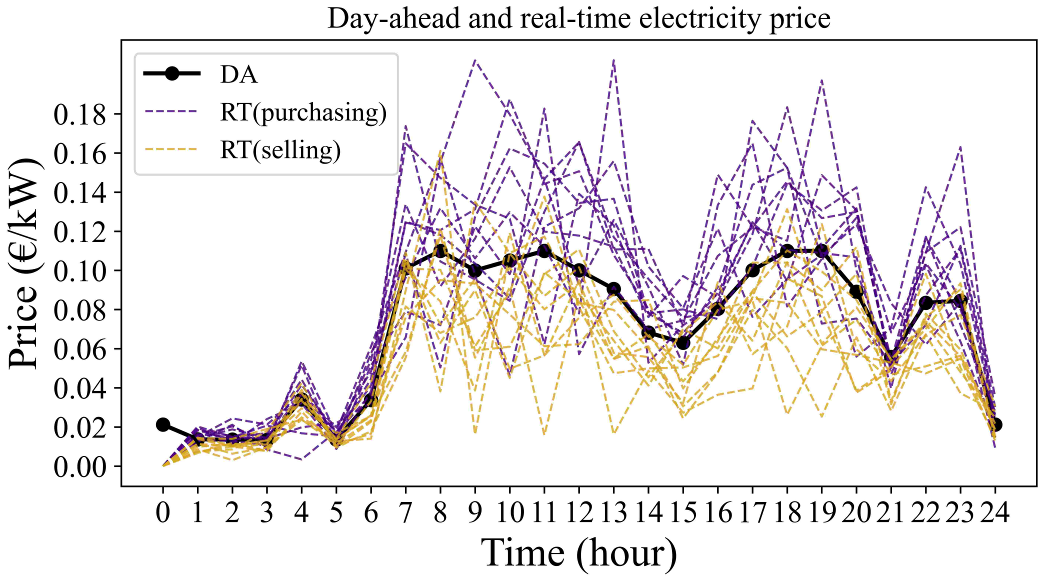


Figure 12. PDF of RT purchasing and selling price for hour t (Publication II).

4.5.3 Cost calculation in the realization scenarios

In this section, new realization scenarios are generated for EV arrival and departure. Based on the DA power trade determined in the previous section and these new realization scenarios, the RT power trade is calculated for each approach. Subsequently, the total cost of the DS in the RT market is assessed using these generated realization scenarios. More specifically, realization scenarios are created from the truncated normal PDF to represent real-time conditions. For each approach, the traded power in RT is derived based on its scheduled DA power, allowing us to determine the DS cost in the RT stage across these realization scenarios. This cost is then combined with the DA stage cost, providing a comparative overview of total costs across both DA and RT stages for each approach. To enhance the reliability of the output, multiple realization scenarios are used instead of a single scenario. This multi-scenario approach yields a more robust comparison of performance across the two methods. The related formulation is presented in equations (25)-(30) of Publication II.

4.6 Validation results

To evaluate the performance of our proposed virtual battery model in handling arrival and departure uncertainties, we compared the operational cost of an EVPL-owned DS under virtual battery and scenario-based approaches. The results demonstrate that our virtual battery model performs comparably to the scenario-based approach with 21 scenarios, but imposes significantly less computational burden.

As shown in Figure 13 (a), the DA power purchased from the upstream grid is very similar between the two approaches, though not identical. Figure 13 (b) highlights this difference in DA power purchases, leading to varied real-time trades across different realization scenarios as illustrated in Figure 14. Despite these differences in day-ahead decisions, both approaches ultimately adopt similar market strategies, resulting in comparable total DS costs. Specifically, the daily operational cost of the DS in the DA and RT markets is 1692.06 € with the scenario-based method, while it is 1689.78 € with our virtual battery model. A key distinction is the simulation time; our proposed approach completes in 4.92 seconds, whereas the scenario-based approach takes 219.53 seconds, meaning our method requires only 2.242 % of the computational effort of the scenario-based approach. This reduction in computational demand becomes even more valuable in large-scale problems where multiple EVPLs and additional uncertainty sources, like renewable generation, are involved. In such cases, a scenario-based method requires a larger number of scenarios to maintain accuracy, which increases its computational burden. In contrast, our virtual battery model achieves consistent performance without additional computational burden, even for complex, large-scale applications. Thus, our proposed model is an efficient tool for both operational studies and planning applications from a system-level perspective, especially in high-EVPL-penetration scenarios. Its simplicity and compact formulation make it well-suited for large-scale energy management and planning problems.

4.7 Charger-sharing approach profitability

This section demonstrates the profitability of the charger-sharing approach by assessing its impact on reducing operational costs compared to the traditional exclusive charger setup. Specifically, we evaluate the optimal operation of an existing EVPL under both the exclusive charger and charger-sharing approaches, assuming ample parking spaces are available to accommodate additional EVs. This analysis highlights the potential operational savings offered by the charger-sharing model.

Figure 15 illustrates the charging and discharging power of the EVPL in exclusive charger charging, alongside the maximum capacity of EV chargers and the maximum

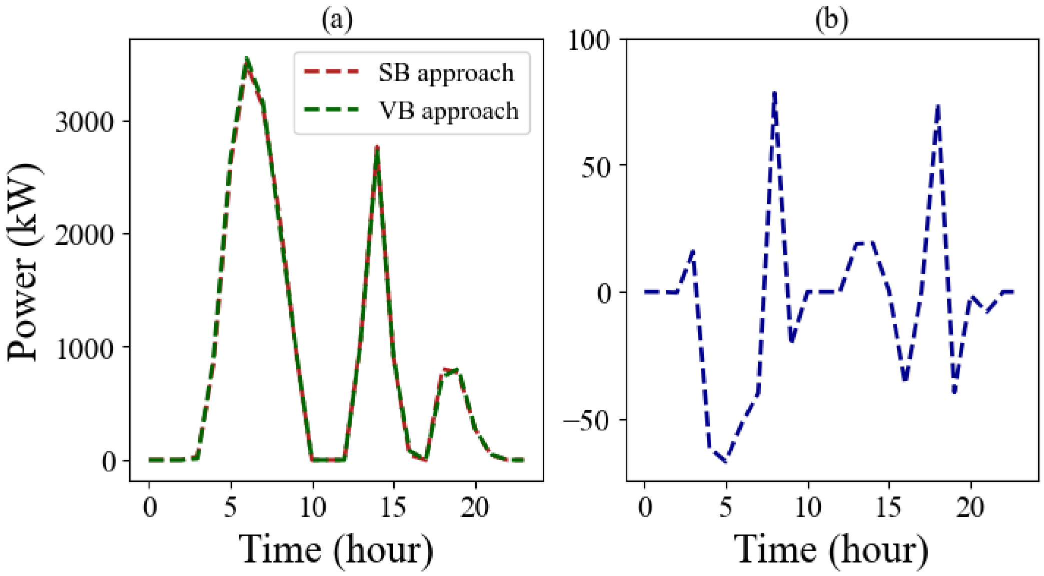


Figure 13. (a) DA purchased power of DS for the proposed virtual battery and scenario-based approaches (b) difference of the DA purchased power for two approaches (Publication II).

possible charging and discharging power, determined by the number of parked EVs each hour, based on their arrival and departure times. The EVPL's charging and discharging operations are optimized to minimize costs, achieving the desired final SOC for all EVs by their departure times. This is accomplished by charging during low-price hours and discharging during high-price hours, while taking EV arrival and departure patterns into account.

In the exclusive charger setup, the available charging and discharging capacity remains largely underutilized. For instance, while the total charging capacity of the parking lot is 2000 kW, the peak charging power, observed around hour 14, only reaches about 1100 kW, significantly below the total capacity. The unused capacity is visually represented by the purple arrows, which highlight the disparity between potential and actual usage. This inefficiency highlights the rationale for adopting the charger-sharing approach, allowing EVPLs to more effectively utilize the capacity of existing chargers.

The dotted curves represent the maximum charging and discharging potential of the parked EVs, reflecting the number of EVs present in each hour and their nominal charging and discharging capabilities. When no EVs are parked, the maximum potential is zero, rising as more EVs are parked and decreasing as they depart, notably after hour 12, when departures outnumber arrivals. This dynamic demonstrates the potential benefits of a charger-sharing approach for enhancing the efficiency and cost-effectiveness of EVPL operations.

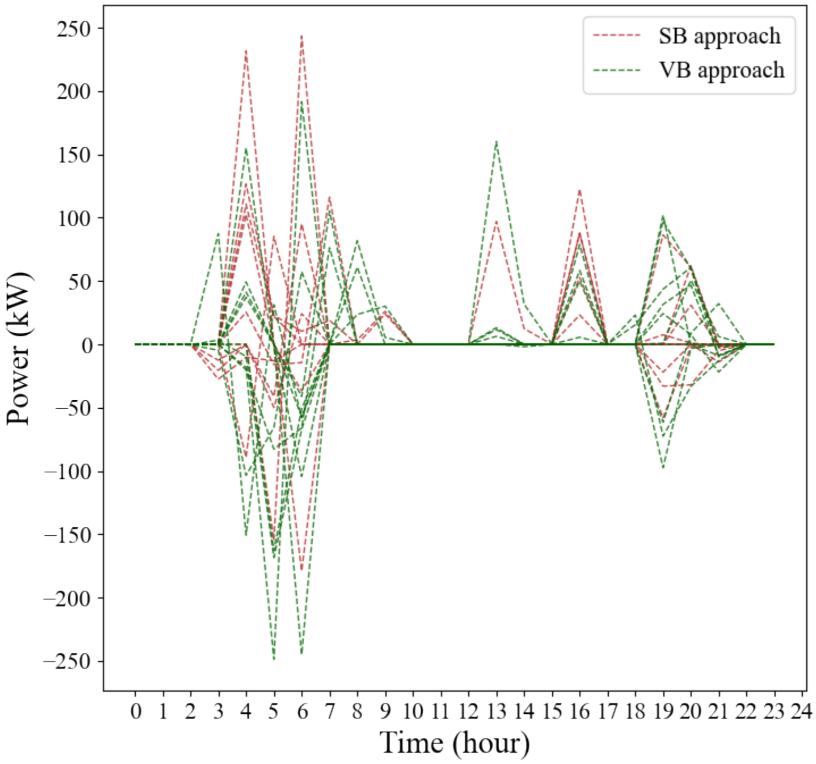


Figure 14. RT traded power of EVPL in (a) scenario-based approach and (b) the proposed virtual battery model (Publication II).

Figure 16 illustrates how the EVPL's state of energy changes hourly, accounting for the previous hour's state, energy gained through charging, energy used in discharging, and the net energy from arriving and departing EVs. When EVs arrive, they contribute stored energy to the EVPL's total energy, equivalent to their initial SOC, and upon departure, they reduce the EVPL's total energy by an amount equivalent to their final SOC. Additionally, the energy added or removed by EV charging or discharging adjusts the EVPL's total energy. This dynamic management ensures the EVPL meets all EV energy needs optimally, so each EV departs on time with its target SOC.

The results demonstrate how the charger-sharing approach enhances EVPL profitability by improving the deployment of EV charger capacity compared to the exclusive charger model. Figure 17 shows that under charger-sharing, the total charger capacity is fully utilized in hours 13, 14, and 15, a contrast to exclusive charging where charger capacity often remains underused. This optimized utilization results from hosting more EVs while meeting each EV's final SOC requirement upon departure,

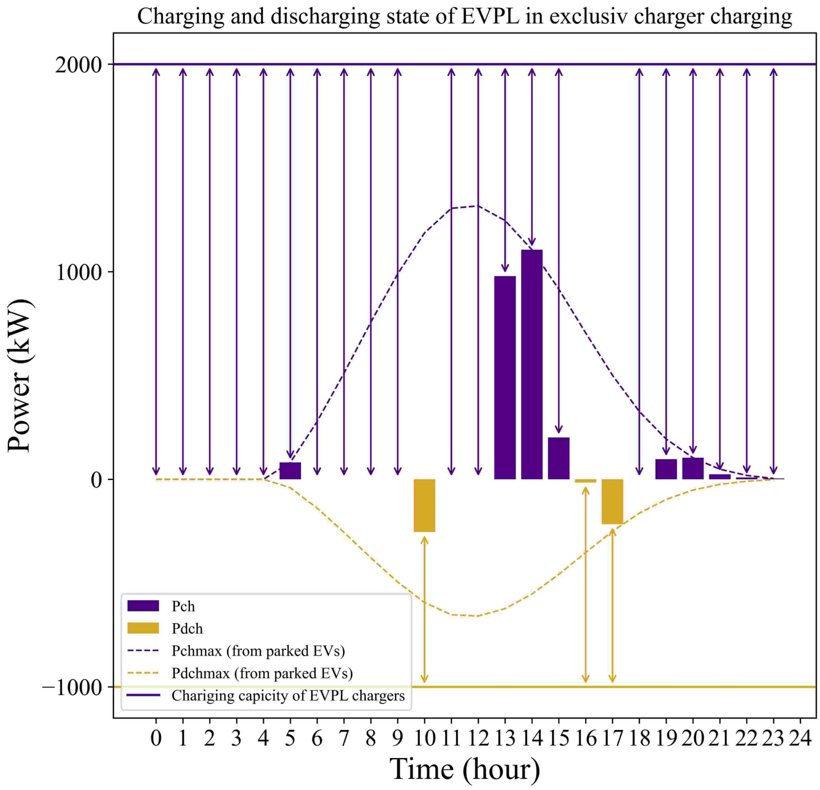


Figure 15. Charging and discharging state of EVPL in exclusive charger charging (Publication II).

thereby increasing revenue.

Table 2. Number of accepted EVs for connecting to unidirectional and bidirectional EV chargers for different charging tariffs.

Tariff	Accepted EVs for UDCH	Accepted EVs for BDCH
0.07	0	160
0.08	220	181
0.09	343	221
0.1	514	514
0.11	1143	1143
0.12	1601	1601
0.13	1601	1601

Seven scenarios with varying charging tariffs were analyzed, each assuming an

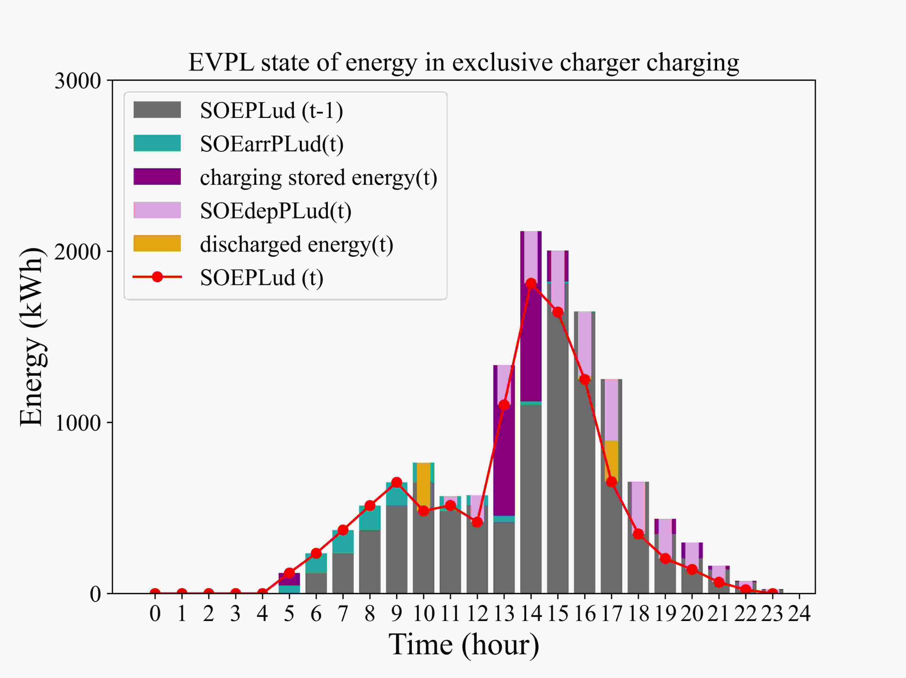


Figure 16. EVPL state of energy in exclusive charger charging (Publication II).

acceptable fee for both the EVPL and EV owners. Results indicate that, with a tariff of 0.09 €/kWh, the EVPL could optimally host 343 EVs for Unidirectional EV Charger (UDEVCH) users and 221 for Bidirectional EV Charger (BDEVCH) users, assuming no parking space limitations. Higher tariffs further incentivize the EVPL to accommodate more EVs, provided charger capacity is sufficient. Table 2 shows the optimal EV hosting numbers for different tariffs, indicating that as tariffs rise, hosting more EVs becomes more profitable. However, when the tariff reaches 0.13 €/kWh, charger capacity limits the number of EVs that can be accepted, as EVPLs must adhere to the required final SOC for each EV.

The charger-sharing approach's efficiency is particularly notable in high-tariff scenarios, where the EVPL could host approximately 3,200 EVs using only 200 chargers (based on the specific EV and charger characteristics defined in the case study). By comparison, an exclusive charger model would limit entry to just 200 EVs. This efficiency gain suggests that the charger-sharing approach can maximize installed charger utility and reduce future investment in EV chargers. Figure 18 further illustrates the EVPL's hourly energy state resulting from optimized scheduling.

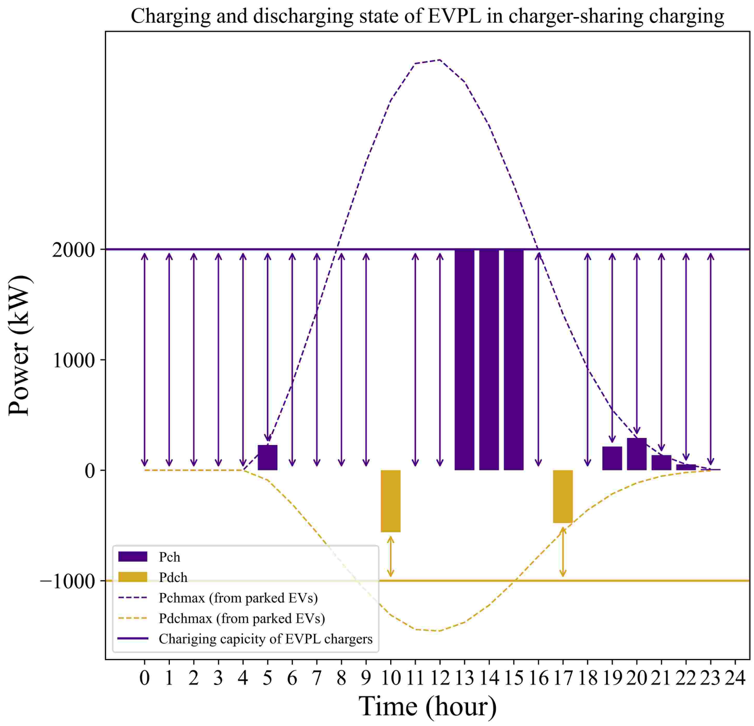


Figure 17. Charging and discharging state of EVPL in charger-sharing charging (Publication II).

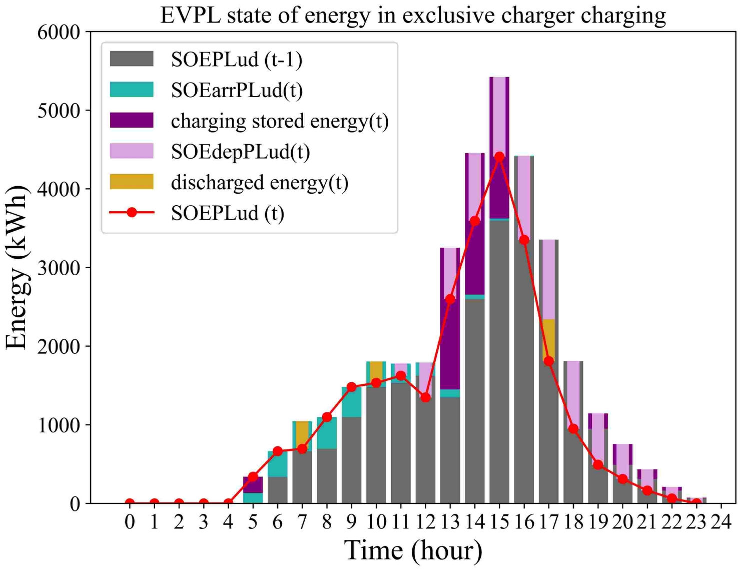


Figure 18. EVPL state of energy in charger-sharing charging (Publication II).

5 LOCAL MARKET INTERACTIONS

The ability of end-users to generate power and adjust their consumption patterns positions them as a valuable resource for delivering energy and flexibility in the distribution system. To take advantage of this potential effectively, active end-users must be provided with adequate incentives alongside automated trading and management systems. Flexibility sellers and buyers at the local flexibility market participate with the primary objectives of fulfilling their flexibility requirements and maximizing their profit. Regulatory frameworks play a crucial role in shaping the operation of these markets and ensuring fair competition (Homaee et al., 2024).

Enabling greater participation of small-scale end-users in flexibility service provision necessitates the development of innovative flexibility trading frameworks that address their specific needs and operational scales. Consequently, traditional models are insufficient to address the active engagement of market participants. Therefore, innovative approaches are essential to effectively capture the behavior and interactions of active agents within the distribution system. In this chapter, agents' behavior and interactions are modeled and studied in single-layer and two-layer iterative game-based frameworks.

5.1 One-layer iterative game

Publication IV proposes an iterative game to model the rational behavior of end-users, aggregators, and the DSO in a competitive flexibility trading framework. There are various agents interacting with consumers in the distribution system, including aggregators, retailers, and VPPs. However, incorporating all of them into a single model can significantly increase the complexity and simulation time, making it impractical for detailed analysis. Therefore, we are focusing on aggregators in this study to maintain a manageable and efficient modeling framework. The game enables agents to actively participate, adapt their decisions, and respond dynamically to the decisions of other agents. In addition, the influence of shiftable and interruptible loads is analyzed. Moreover, three scenarios are explored, each relaxing a specific constraint in the agents' decision-making process, to evaluate the impact of agent freedom on their decisions and validate simulation outcomes.

Our iterative game approach enables all agents to make independent decisions and iteratively adjust them in response to others' decisions, effectively simulating real-world agent behavior in flexibility trading where each agent pursues its optimal strategy. This capability allows energy sector policymakers to analyze trading behaviors and agent interactions comprehensively. Consequently, policymakers can assess the potential impacts of new regulations and rules on agent behavior and the trading platform, facilitating more informed decision-making.

5.1.1 Problem statement

As depicted in Figure 19, the model employs a hierarchical structure where the total flexibility exchanged between end-users and aggregators is ultimately transacted through aggregators and the DSO. Additionally, end-users have the capability to trade flexibility directly with both their corresponding aggregator and the DSO. This dual trading opportunity mitigates monopoly risks and enhances agents' freedom to participate in flexibility trading, fostering a more competitive trading environment. By allowing end-users to transact flexibility with both aggregators and the DSO, the model incentivizes higher engagement in flexibility provision. These elements collectively contribute to establishing a dynamic and competitive trading framework. Furthermore, the model assumes that each aggregator maintains a bilateral contract with its associated end-users, enabling bidirectional flexibility transactions. End-users can adjust their load profiles to provide either positive or negative energy flexibility, aligning with the needs of the trading framework. In this framework, aggregators and end-users try to minimize their trade costs (and maximize their trade revenue) with other agents, while the main aim of the DSO is to minimize the trade with the real-time electricity market to increase the self-sufficiency of the distribution system.

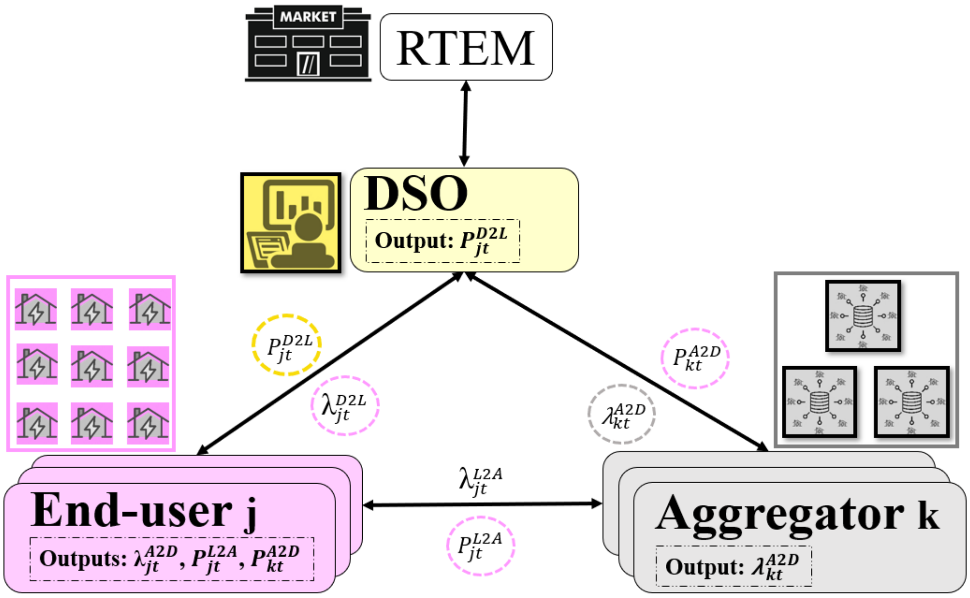


Figure 19. Interaction among agents in our proposed local flexibility trading model (Publication IV).

End-users' loads are classified into three categories: non-flexible, shiftable, and interruptible. While non-flexible loads are not adjustable for flexibility provision, shiftable and interruptible loads offer significant potential as flexibility resources. For shiftable loads, a key constraint ensures that their total real-time energy consumption over 24 hours, after providing flexibility, equals their total scheduled energy consumption.

5.1.2 Proposed flexibility trading

In our proposed framework, there are three types of trade. First is traded flexibility between end-users and aggregators. In this trade, the price is based on the fixed rates based on the contract between each end-user and its corresponding aggregator. Additionally, end-users decide on the sale or purchase amount. The second one is the trade between end-users and the DSO in which end-users decide on the price and the DSO decides on the amount. The third one is the trade between aggregators and the DSO where aggregators determine the price. It is worth mentioning that the amount of this trade is equal to the total trades between an aggregator and its end-users.

The interdependence among agents in the flexibility trading framework means that one agent's decision variables can affect others' optimal decisions. This interaction is handled through an iterative game-based approach, where agents optimize their objective functions and update their decisions based on the latest actions of others. The decision-making process begins with end-users solving their optimization problem, referred to as Problem E (equation (11) of Publication IV), and determining their decision variables using initialized inputs and system parameters. Once the end-users have made their decisions, aggregators proceed to solve their optimization problem, known as Problem A (equation (12) of Publication IV) and decide on their decision variable. Finally, the DSO addresses its own optimization problem, referred to as Problem D (equation (13) of Publication IV). The DSO's decisions are influenced by the flexibility transactions between end-users and aggregators, as well as its direct interactions with end-users. In each iteration, the decisions made by the DSO impact the optimal amount of flexibility traded among all parties, thereby influencing the subsequent decisions of end-users and aggregators.

The iterative process continues until a convergence condition is satisfied. The convergence criterion is based on the difference in the objective functions of the agents between two consecutive iterations. Specifically, the sum of the variations in the agents' objective functions must fall below a sufficiently small threshold, indicating that an optimal and stable solution has been reached (equation (14) of Publication IV). The flowchart of the proposed trading framework is depicted in Figure 20.

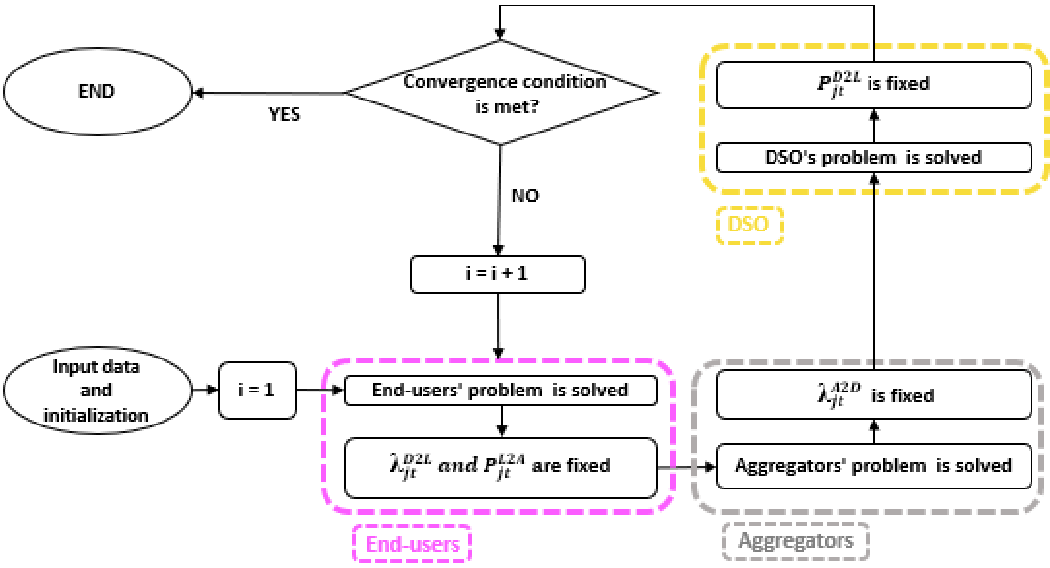


Figure 20. Flowchart of the proposed iterative game-based algorithm (Publication IV).

5.1.3 Scenario definition

In this section, three distinct scenarios are defined to explore how varying levels of freedom for the DSO and end-users in determining their decision variables influence flexibility trading. These variations arise from the inclusion or exclusion of constraints designed to prevent arbitrage in the traded flexibility between end-users and the DSO, as well as constraints on flexibility traded between end-users and their respective aggregators.

Notably, the level of freedom for aggregators remains constant across all scenarios. The freedom for end-users and the DSO, however, increases when one of their respective constraints is removed from their decision-making problem. The scenarios represent varying degrees of arbitrage prevention, enabling a comparative analysis of agent behaviors under different regulatory conditions.

Scenario 1: In this scenario, the end-users' problem includes a restriction to prevent arbitrage in flexibility transactions between end-users and their respective aggregators. Additionally, the DSO's problem incorporates a constraint to prevent arbitrage in flexibility transactions between the DSO and end-users. Both these constraints are enforced, creating a highly regulated environment for flexibility trading.

Scenario 2: Here, the structure of the aggregators' and the DSO's problems remains identical to Scenario 1. However, the restriction preventing arbitrage in flexibility transactions between end-users and aggregators is removed from the end-users' problem. The DSO's problem, however, still retains the arbitrage prevention constraint, ensuring that arbitrage in flexibility trading between the DSO and end-users is avoided.

Scenario 3: In this scenario, the end-users' and aggregators' problems are the same as in Scenario 1. The distinction lies in the DSO's problem, where the arbitrage prevention constraint on flexibility trading between the DSO and end-users is removed. Despite this, the constraint to prevent arbitrage in flexibility trading between aggregators and end-users remains intact.

These scenarios offer a framework to evaluate the effects of arbitrage prevention constraints on the behavior and interactions of agents in the flexibility trading market. Further explanation can be found in section III of Publication IV.

5.1.4 Results and discussion

In this paper, the proposed flexibility trading algorithm was evaluated using a 33-bus test system, as depicted in Figure 21.

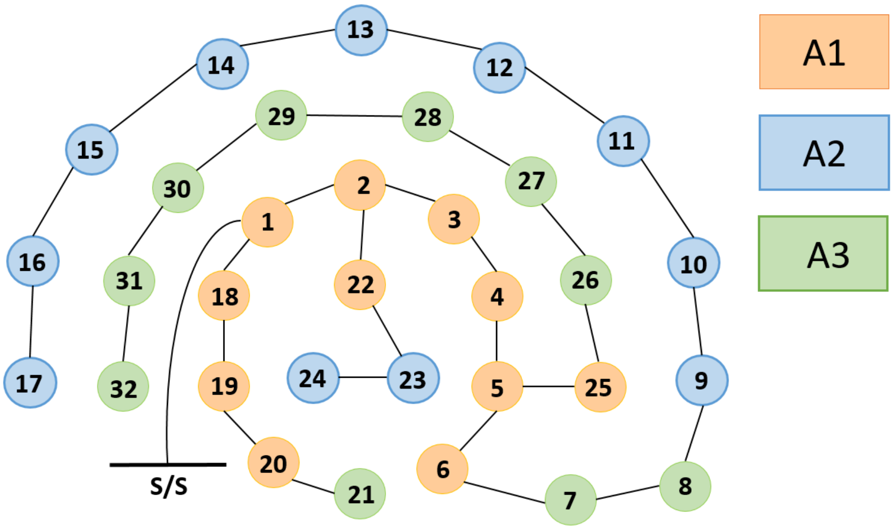


Figure 21. 33-bus test system (Publication IV).

Scenario 1 Analysis:

The convergence condition was met after 59 iterations. Figure 22 illustrates the progression of the objective functions for end-users, aggregators, and the DSO across iterations. Notably, the aggregators achieved a negative value for their objective function, indicating that flexibility trading was profitable for them. Conversely, end-users initially recorded a negative objective function value, signifying income generation, but subsequent iterations influenced by the decisions of other agents led to a positive objective function value. This reflects a shift in the cost-benefit dynamics of end-users throughout the trading process. Furthermore, the fluctuations in the end-users' and aggregators' objective functions were minimal across iterations, demonstrating stability in their decision-making.

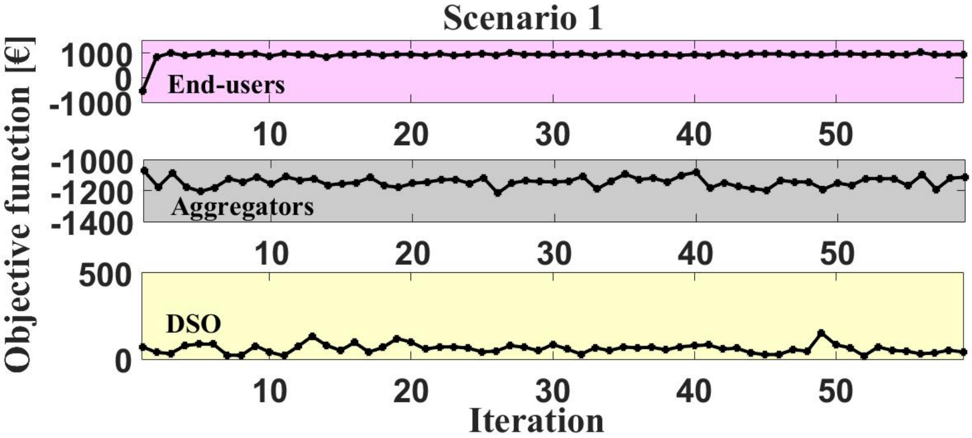


Figure 22. Objective function of end-users, aggregators, and the DSO in different iterations, Scenario 1 (Publication IV).

Figure 23 and Figure 24 illustrate the amount of flexibility traded between aggregators and the DSO and the corresponding price variations, respectively. Additionally, Figure 25 depicts the energy flexibility transacted between the DSO and the real-time electricity market. The results reveal that in most hours, the volume of transactions with Real-Time Electricity Market (RTEM) was close to zero, underscoring a limited reliance on external market trades. Consequently, the DSO's objective function value was relatively low. Table 3 presents the objective function outcomes for end-users, aggregators, and the DSO across all three scenarios. In Scenario 1, the objective function values for end-users, aggregators, and the DSO were €943.62, €-1110.42, and €41.65, respectively. This highlights the profitability for aggregators and the limited cost impact on the DSO within this scenario.

Table 3. Agents' objective function in different scenarios.

Scenario	End-users' OF	Aggregators' OF	DSO's OF
1	943.627	-1110.42	41.65
2	525.46	-2426.83	3253.48
3	1228.74	-1145.49	16.21

Scenario 2 Analysis:

In Scenario 2, the convergence condition was reached after 11 iterations, significantly fewer than in Scenario 1. Figure 26 displays the changes in the objective functions

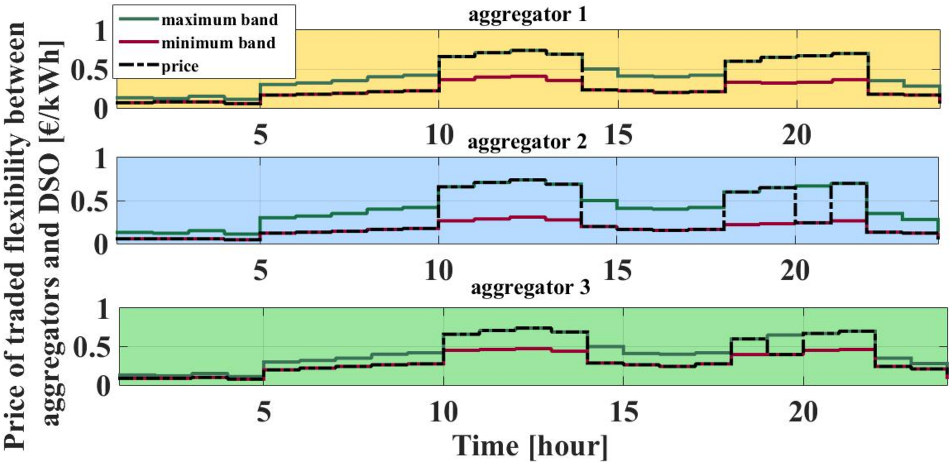


Figure 23. Price of flexibility transacted between aggregators and the DSO, Scenario 1 (Publication IV).

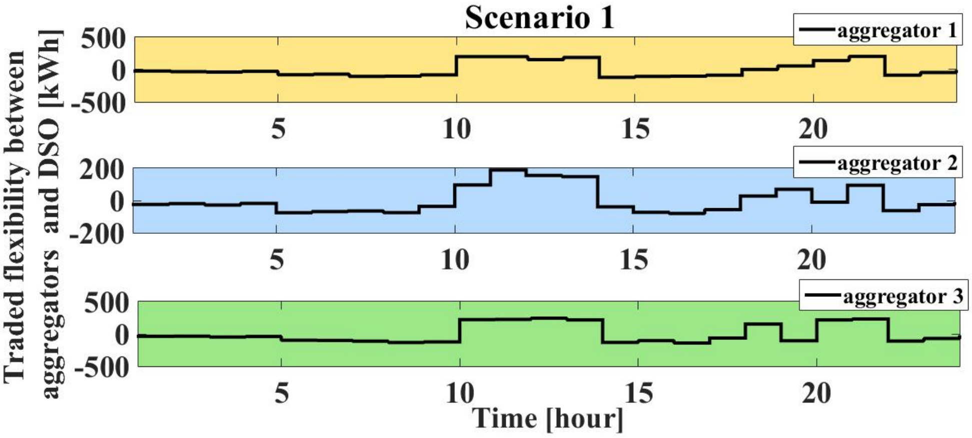


Figure 24. Flexibility traded between aggregators and the DSO, Scenario 1 (Publication IV).

of end-users, aggregators, and the DSO throughout the iterations. Aggregators demonstrated improved profitability in Scenario 2 compared to Scenario 1, as their objective function decreased from -€1,110.42 in Scenario 1 to -€2,294.28. This increase in profitability is attributed to a higher volume of flexibility traded between aggregators and the DSO, as illustrated in Figure 28, and the corresponding price trends shown in Figure 27. The increased trading volume enabled aggregators to achieve greater income.

End-users, while experiencing positive objective functions in all iterations except the first, ended with a value of €522.46, lower than their result in Scenario 1 (€943.62). This reduction reflects their financial benefit due to fewer constraints on decision-making. For the DSO, the results were different. The DSO's objective function in Scenario 2 rose to €3,253.48, a substantial increase compared to its value of €41.65

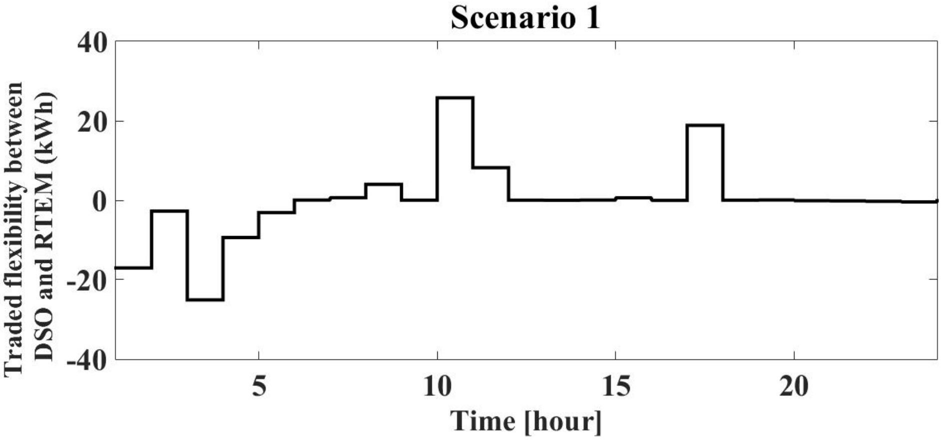


Figure 25. Real-time energy exchanged between the DSO and the RTEM, Scenario 1 (Publication IV).

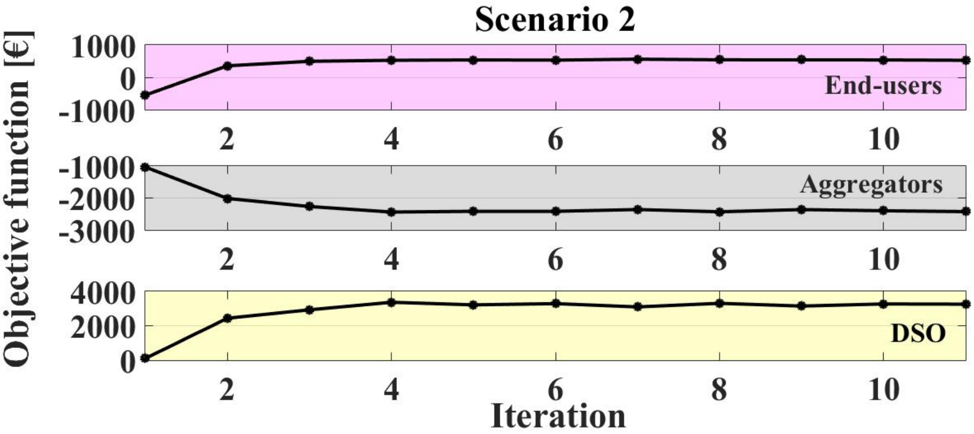


Figure 26. Objective function for end-users, aggregators, and the DSO in different iterations, Scenario 2 (Publication IV).

in Scenario 1. This dramatic rise in the DSO's costs is attributed to the significantly increased energy flexibility traded with the RTEM, as depicted in Figure 29. The higher volume of transactions with the RTEM imposed a considerable financial burden on the DSO. Therefore, while aggregators and end-users may achieve higher profitability and lower costs, the DSO's objective of attaining greater self-sufficiency is not adequately met in this scenario.

Scenario 3 Analysis:

In Scenario 3, the problem converged after 13 iterations, with Figure 30 illustrating the changes in the objective functions of end-users, aggregators, and the DSO across iterations. The DSO showed a marked improvement in its performance in Scenario 3, reducing its objective function from €41.65 in Scenario 1 to €16.21, reflecting a 60 % improvement. This reduction is primarily due to a lower volume of energy

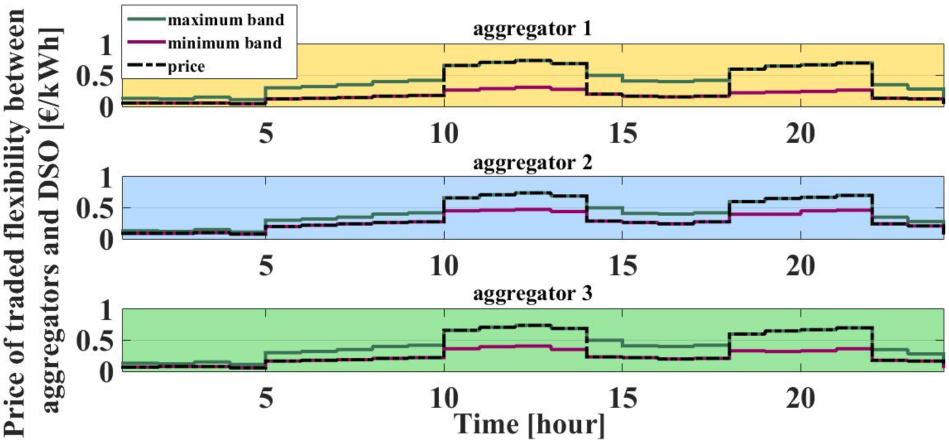


Figure 27. Price of flexibility transacted between aggregators and the DSO, Scenario 2 (Publication IV).

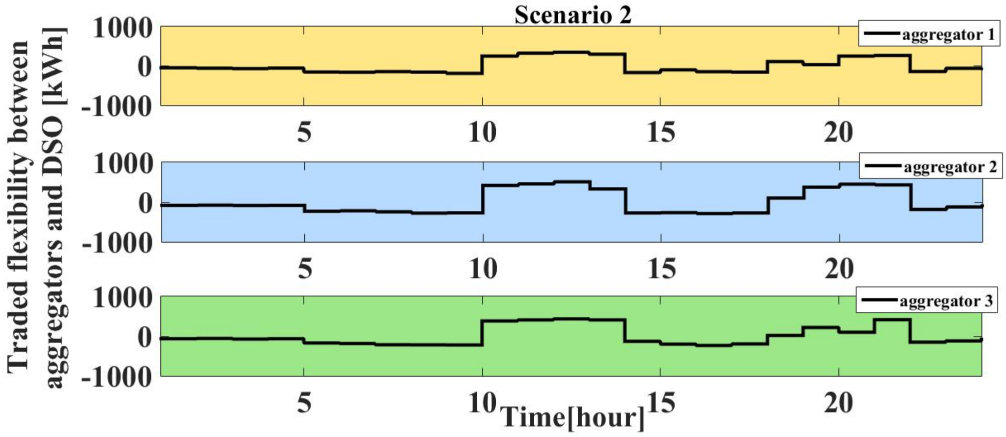


Figure 28. Flexibility traded between aggregators and the DSO, Scenario 2 (Publication IV).

flexibility traded between the DSO and the RTEM, as seen in Figure 33, compared to Scenario 1.

End-users, however, experienced diminished performance in Scenario 3. Their objective function rose to €1,228.74, a significant increase compared to €943.62 in Scenario 1 and €525.46 in Scenario 2, indicating higher costs or reduced profitability. Aggregators, on the other hand, saw minimal change in their objective function. Their value in Scenario 3, at €-1,145.49, was nearly identical to that in Scenario 1 (€-1,110.42). This suggests that changes in the constraints had a negligible impact on their overall performance. Figure 32 and Figure 31 depict the flexibility traded between aggregators and the DSO and its price trends in Scenario 3. The results suggest that the adverse impact of greater freedom for end-users on the DSO's performance (Scenario 2) is far greater than the adverse impact of the DSO's increased freedom on the end-users' performance (Scenario 3).

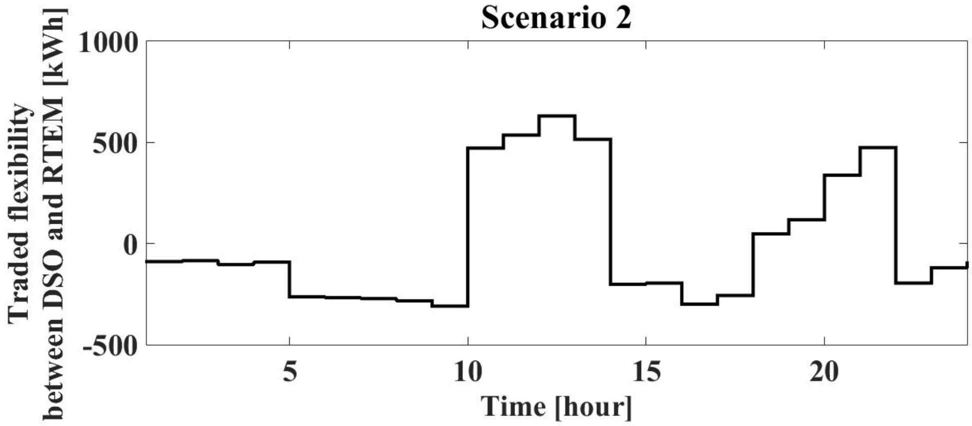


Figure 29. Real-time energy exchanged between the DSO and the RTEM (Scenario 2, (Publication IV).

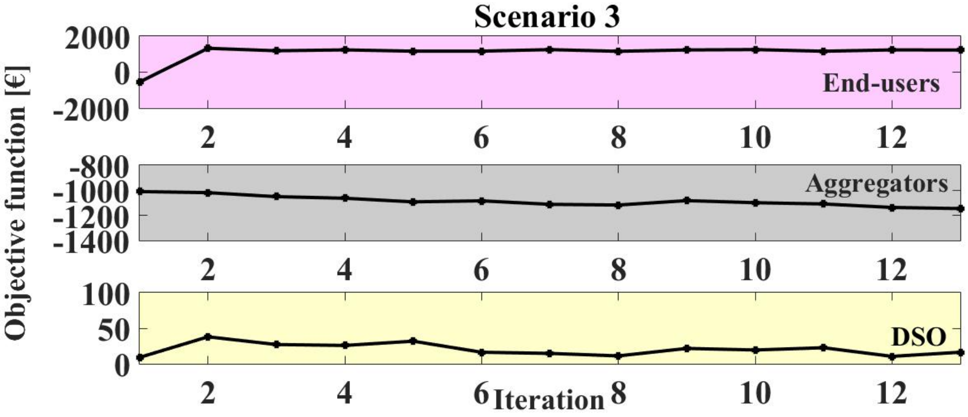


Figure 30. Objective function for end-users, aggregators, and the DSO in different iterations, Scenario 3 (Publication IV).

5.2 Impact of interruptible loads

In the previous sections, it was assumed that the end-users' loads consisted only of shiftable loads. This section evaluates the behavior of agents when interruptible loads are also present, represented by the parameter α, which indicates the share of interruptible loads relative to shiftable loads. The results for $\alpha = 0.1$ and $\alpha = 0.15$ are summarized in Tables 4 and Tables 5, with a radar plot in Figure 34 illustrating the changes in the objective functions of end-users and aggregators across scenarios for $\alpha = 0$, $\alpha = 0.1$, and $\alpha = 0.15$.

End-Users' Objective Function: - In Scenario 1, the end-users' objective function initially increases as α rises from 0 to 0.1. However, as α increases further to 0.15,

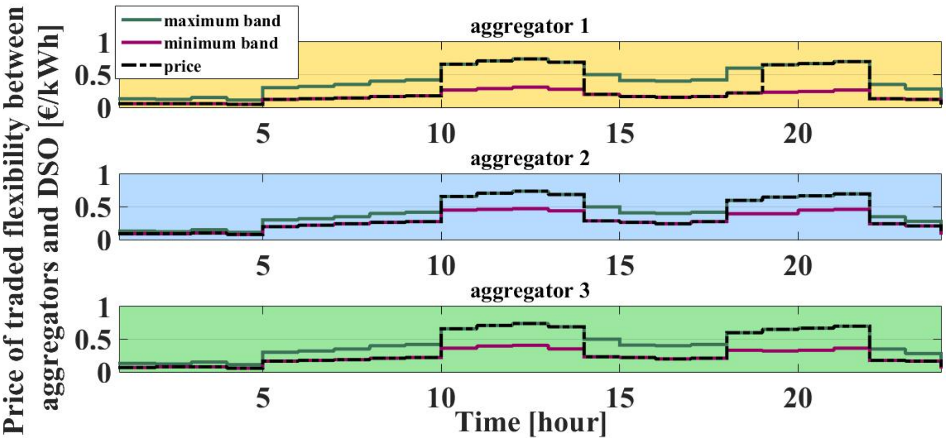


Figure 31. Price of flexibility transacted among aggregators and the DSO, Scenario 3 (Publication IV).

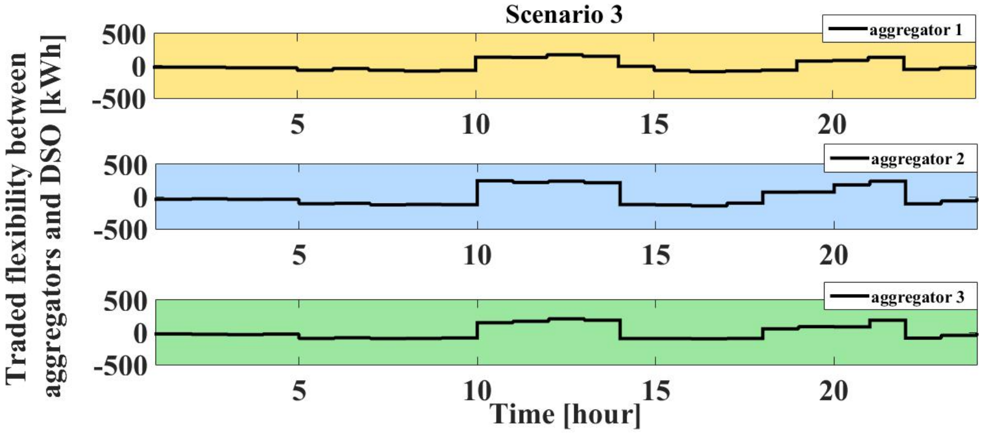


Figure 32. Flexibility traded between aggregators and the DSO, Scenario 3 (Publication IV).

the objective function decreases. - In Scenario 2, the end-users' objective function decreases consistently with an increase in α. - In Scenario 3, the opposite trend is observed; the end-users' objective function increases with higher values of α.

Aggregators' Objective Function: - In Scenarios 1 and 2, the aggregators' objective function decreases steadily as α increases. - In Scenario 3, a non-linear pattern is observed: the aggregators' objective function decreases with an increase in α from 0 to 0.1 but increases when α rises further from 0.1 to 0.15.

- DSO's Objective Function: - Unlike end-users and aggregators, the DSO's objective function exhibits a consistent trend across all scenarios. As α increases, the DSO's objective function rises, reflecting higher costs or reduced efficiency in managing flexibility transactions.

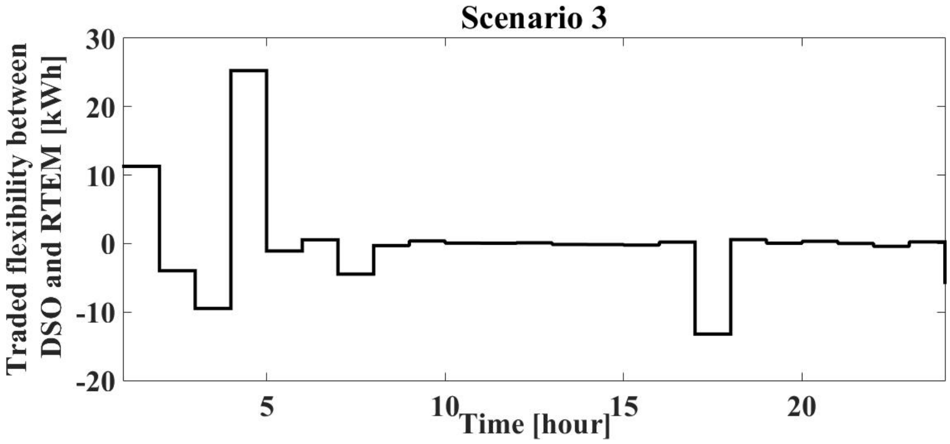


Figure 33. Real-time energy exchanged between the DSO and the RTEM, Scenario 3 (Publication IV).

Table 4. Agents' OF in different scenarios for $\alpha = 0.1$.

Scenario	End-users' OF	Aggregators' OF	DSO's OF
1	1286.67	-2294.28	222.91
2	-387.97	-4666.51	4224.48
3	1559.55	-2333.99	18.02

5.3 Two-layer iterative game

In the previous section, we introduced a single-layer triangular iterative approach for flexibility trading in the distribution system. While this method can successfully model the interactions among agents, it often requires a large number of iterations to converge, especially in complex scenarios. This limitation highlights that a single-layer framework struggles to efficiently capture the intricate interconnections among agents within a short time frame. To address this issue, in Publication III, a two-layer structure is proposed as shown in Figure 35. In the two-layer structure, the close interconnections between customers and aggregators are modeled within an inner layer, while their interactions with the DSO are handled in an outer layer. This separation allows for a more efficient modeling approach by focusing on the hierarchical nature of interactions. As a result, the two-layer structure significantly reduces the number of iterations required to reach convergence, thereby decreasing the computational time needed to solve the problem effectively. In this approach, agents' objectives and constraints are similar to the previous section. In addition, the trading relations are also similar to the one-layer approach where customers can both trade flexibility with aggregators and the DSO. The DSO also trades flexibility with RTEM in addition to aggregators and customers. Aggregators trade flexibility with their corresponding customers and the DSO. In our proposed model, two iterative

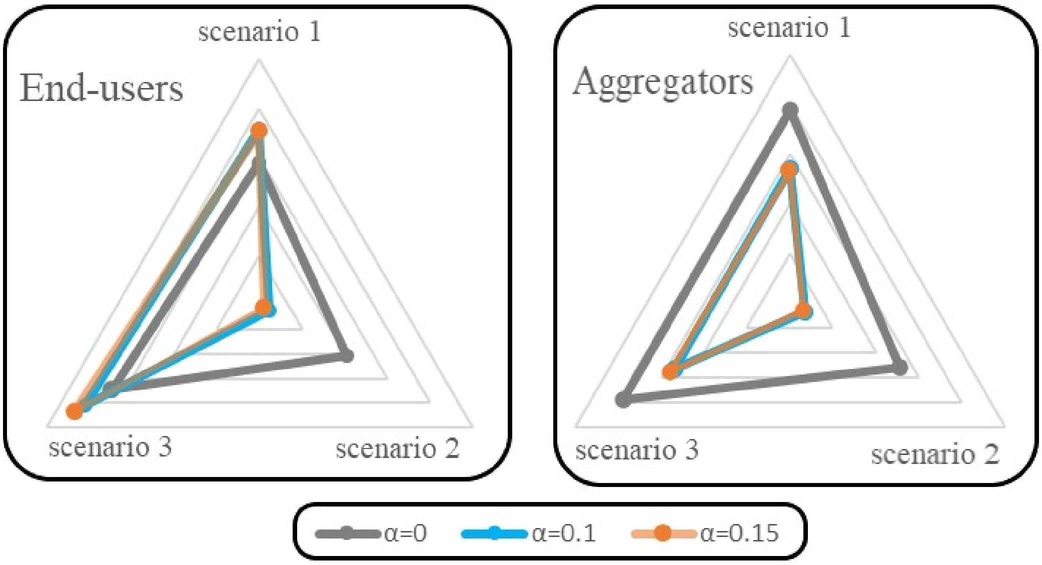


Figure 34. Objective functions for end-users and aggregators in different scenarios for $\alpha = 0$, $\alpha = 0.1$, and $\alpha = 0.15$ (Publication IV).

Table 5. Agents' OF in different scenarios for $\alpha = 0.15$.

Scenario	End-users' OF	Aggregators' OF	DSO' OF
1	1260.54	-2333.75	227.75
2	-442.09	-4698.113	4321.04
3	1669.54	-2220.78	32.46

games are utilized to facilitate decision-making: the inner game and the outer game. The inner game focuses on the interactions between customers and aggregators. Initially, customers make decisions regarding their variables based on initialized data. Subsequently, aggregators determine their decisions based on the input received from customers. Following this, both customers and aggregators iteratively update their decision variables, taking into account the decisions of the other party. This process continues until the inner game convergence condition is satisfied, indicating that customers and aggregators have reached an agreement on their decision variables.

Once the inner game converges, the DSO steps in to determine its decision variables based on the outcomes of the inner game. At this stage, the outer game convergence condition is evaluated. If this condition is not met, the process loops back to the inner game, where customers and aggregators refine their decisions further. The DSO then updates its decision variables based on the revised output of the inner game. This iterative interaction between the inner and outer games continues until the outer game convergence condition is fulfilled. Once achieved, all agents—customers, aggregators, and the DSO—reach a consensus, and the decision-making process

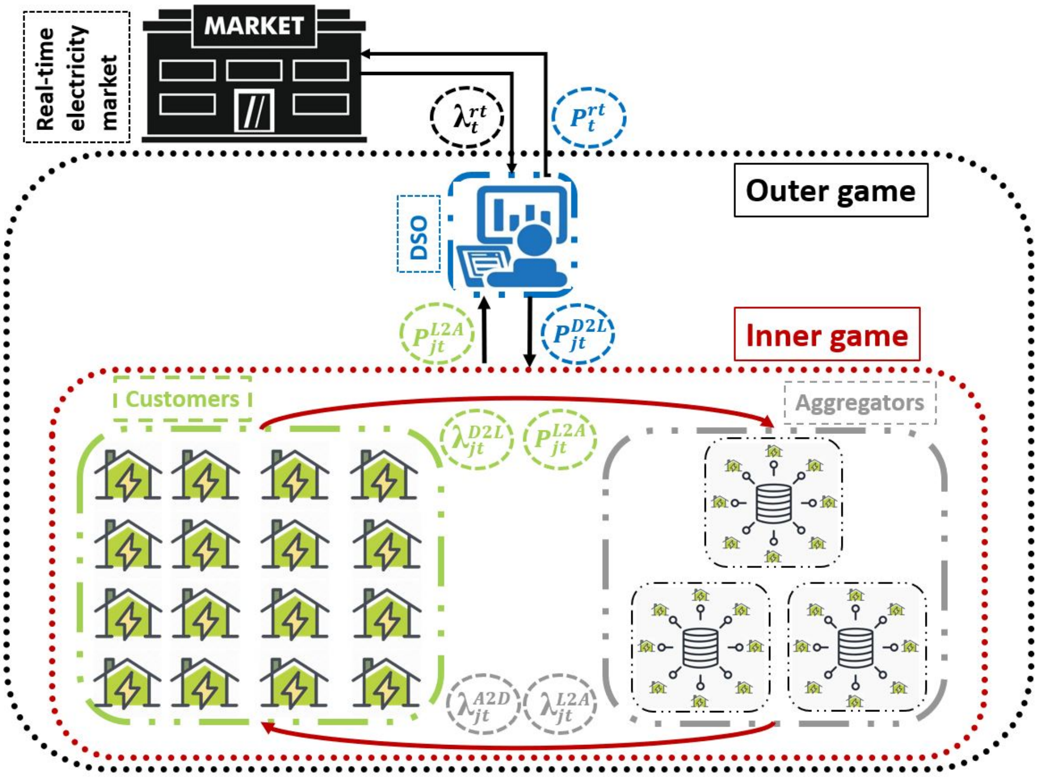


Figure 35. Our proposed two-layer iterative game structure (Publication III).

concludes. This hierarchical structure ensures efficient collaboration among all agents, as illustrated in the flowchart presented in Figure 36. It allows for streamlined interactions, balancing the computational complexity while accurately modeling the agents' interdependencies. To study and validate the proposed models, the same three scenarios introduced in the previous section are applied in this section as well. These scenarios provide a consistent framework for analyzing and comparing the outcomes of the proposed iterative games and evaluating the performance of agents under varying conditions.

5.3.1 Game interactions

The findings reveal that in scenarios 1 and 2, the convergence condition is achieved within a few iterations for both the inner and outer layers, while in scenario 3, the inner layer converges quickly but the outer layer requires 18 iterations to reach convergence. Table 6 and Table 7 provide details on the number of outer-layer iterations and their corresponding inner-layer iterations. In scenario 1, the outer layer converges after five iterations. During the first iteration of the outer layer, five inner games occur between customers and aggregators, where decisions are refined until convergence is reached by the fifth inner game. In subsequent outer-layer

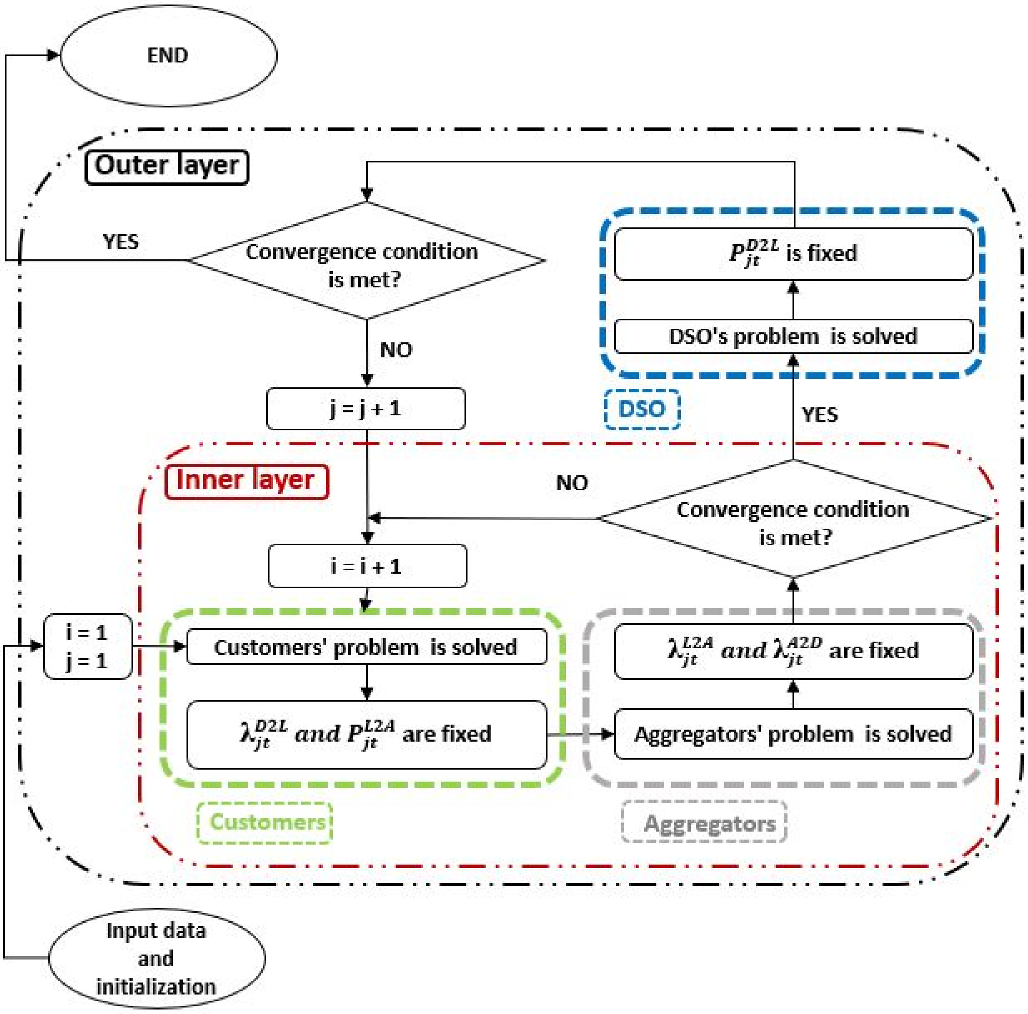


Figure 36. Two-layer iterative game structure (Publication III).

iterations (2nd to 5th), customers and aggregators only require two inner games to agree, indicating that agreements are reached more quickly as the process progresses. The decision-making concludes after the outer layer converges in the fifth iteration. The final objective functions in scenario 1 are €1752 for customers, €-2608 for aggregators, and €18.89 for the DSO. This indicates that aggregators benefit from flexibility trading by strategically adjusting their variables, while customers incur losses due to their positive objective function.

In scenario 2, the process concludes after four outer-layer iterations. During the first outer-layer iteration, customers and aggregators achieve convergence after three inner games. For the remaining outer-layer iterations (2nd to 4th), only two inner games are needed per iteration to reach agreement. Compared to scenario 1, the reduced constraints in scenario 2 grant customers more freedom to make decisions. In the

Table 6. Number of iterations of game in outer layer for different scenarios.

Scenario	Number of outer iterations
1	5
2	4
3	18

Table 7. Number of iterations of inner games in different iterations of game in outer layer for different scenarios.

Scenario	1	2	3
Iteration of outer layer	scenario 1	scenario 2	scenario 3
Iteration 1	5	3	2
Iteration 2 to last iteration	2	2	2

first outer-layer iteration, customers' objective function is €-2245 due to decisions based on initialized data. In the second outer iteration, the DSO's decisions raise the customers' objective function to €-537, then to €-434 in the third iteration, and finally stabilize it at €-444 in the fourth iteration. Meanwhile, aggregators experience significant increases in profitability, with their objective function improving from €-2583 in the first outer-layer iteration to €-5179 in the third, before leveling off with only minor changes in the final iteration. This indicates that while the DSO's decisions impose restrictions on customers' profitability, they create opportunities for aggregators to maximize their gains.

In scenario 3, the outer layer requires 18 iterations to converge, the highest among the scenarios. Despite this, the inner layer converges efficiently, with three inner games during the first outer-layer iteration and only two for each subsequent iteration. This highlights the efficiency of the two-layer framework, especially in scenarios 1 and 2, where both layers require relatively few iterations. Even in scenario 3, despite extended negotiations in the outer layer, the inner layer stabilizes quickly, facilitating agreements between customers and aggregators. In scenario 1, both customers and the DSO are more limited in defining their decision variables, while in scenario 2, reduced constraints provide customers with greater flexibility. This difference is reflected in the variations in objective functions for customers, aggregators, and the DSO across these scenarios. While customers initially gain income due to negative objective functions in the first outer game, subsequent decisions by the DSO push customers to achieve positive objective functions in later outer iterations, particularly in scenarios 1 and 2. The initialized values of traded flexibility with the DSO often explain customers' negative objective functions in early iterations, but as the DSO resolves its own problem, customers face increased limitations that diminish their potential gains.

5.3.2 Behaviour analysis of agents

In our game model, customers compete with aggregators in the inner game. The results indicate that the traded flexibility between customers and their respective aggregators follows a similar pattern. This is logical since there is no constraint linking customers directly to one another, so customers contracted with the same aggregator exhibit comparable behavior. Figure 37 displays the traded flexibility over 24 hours for six customers under contract with aggregator 2. It demonstrates that customers 11 and 14, as well as customers 23 and 24, trade flexibility at the same level because their real-time loads are identical. Additionally, all six customers share a similar 24-hour profile, indicating that their traded flexibility ratios remain nearly constant throughout the day. Consequently, their behavior is entirely aligned, as anticipated. As discussed previously, our model allows each aggregator to set

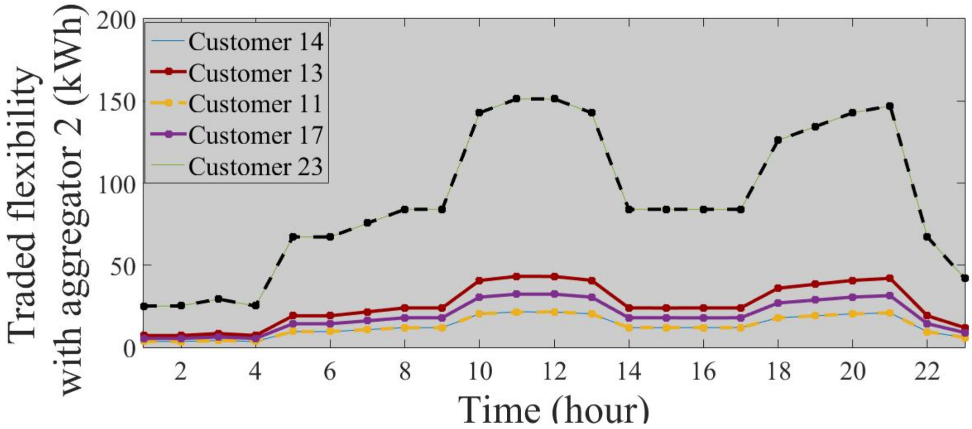


Figure 37. Traded flexibility between aggregator 2 and customers (Publication III).

distinct prices for trading flexibility with its customers. However, the results reveal that aggregators establish uniform prices for all customers they serve, as illustrated in Figure 38. Specifically, the flexibility prices for customers contracted with the same aggregator at hours 5, 9, 14, and 22 are consistent. This uniform pricing can be attributed to customer behavior: customers with the same aggregator demonstrate similar patterns, prompting the aggregator to treat all its customers equally and apply the same pricing strategy across all hours.

To analyze the DSO's behavior, its flexibility exchanges with the RTEM across three scenarios, as depicted in Figure 39, were examined. In scenario 3, where the DSO has greater freedom to set its decision variables, the traded flexibility remains close to zero throughout the day. Similarly, in scenario 1, where both customers and the DSO have restricted freedom, flexibility trading with the RTEM is near zero during most hours, though slightly higher compared to scenario 3. Conversely, in scenario 2, where customers have greater freedom while the DSO operates under more constraints, the traded flexibility with the RTEM is significantly higher at

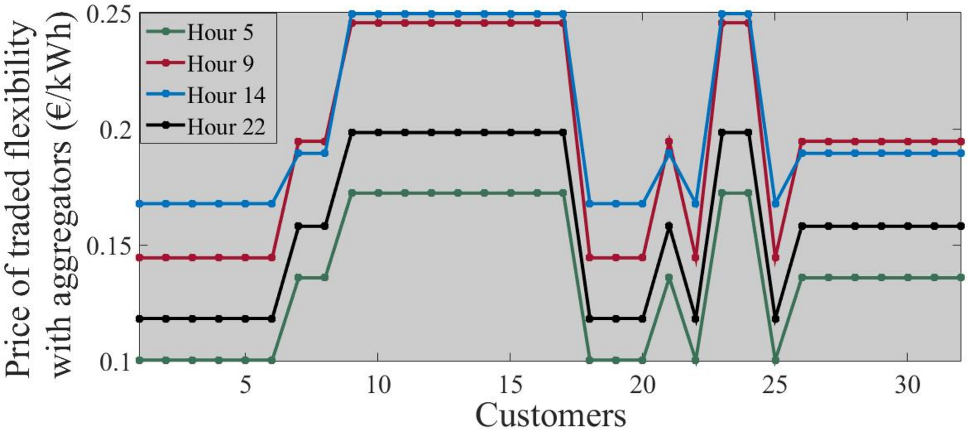


Figure 38. Price of traded flexibility between customers and their corresponding aggregator (Publication III).

all hours. This trend correlates with the DSO's objective function in different scenarios, demonstrating that increased customer freedom substantially raises the DSO's objective function, underscoring the adverse impact of customer freedom on the DSO's performance.

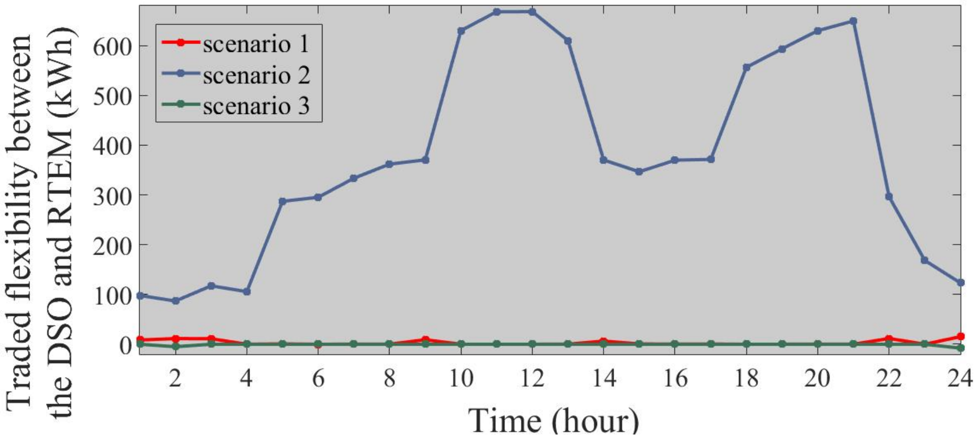


Figure 39. Real-time energy traded among the DSO and the RTEM (Publication III).

5.3.3 Scenario discussion

This section examines the performance of the DSO, aggregators, and customers across different scenarios and discusses the impact of their respective levels of freedom. As previously noted, the three scenarios differ based on the presence or absence of arbitrage prevention constraints in the flexibility transactions between customers, aggregators, and the DSO. Consequently, it is anticipated that customers' objective function will be lowest in scenario 2, while the DSO's objective function will be minimized in scenario 3.

As expected, Objective Function of End-users (OFE) in scenario 2 is significantly lower compared to scenarios 1 and 3, and Objective Function of Distribution System Operator (OFDSO) achieves its lowest value in scenario 3. With greater decision-making freedom, customers are able to reduce their objective function from €1752.33 in scenario 1 to €-444.24 in scenario 2, representing approximately a 125 % decrease. Similarly, the DSO benefits from removing one of its constraints in scenario 3, reducing its objective function by about 90.5 % (from €18.89 in scenario 1 to €1.78). Aggregators also benefit from increased customer freedom, as their objective function in scenario 2 decreases to €-5230.7 from €-2608.33 in scenario 1, a reduction of approximately 100.5 %. However, granting increased freedom to customers has a significant adverse impact on the DSO, causing its objective function to surge dramatically in scenario 2 to €4851.8. In contrast, the DSO's freedom has a much less effect on customers; their objective function in scenario 3 (€1799.99) is only about 2.7 % higher than in scenario 1. While aggregators benefit from customer freedom, the DSO's increased freedom does not negatively impact aggregator performance. Aggregators' objective function in scenario 3 remains comparable to that in scenario 1.

Comparing the results of the two iterative game-based approaches discussed in this chapter, it is evident that the performance of the same agents in identical scenarios varies between the two approaches. This variation occurs because the one-layer and two-layer game-based approaches create different local market frameworks, leading to different agent performances. Many aspects can be considered when deciding which of the proposed frameworks is more suitable for a specific distribution system. In this regard, although the implementation of the one-layer approach appears simpler due to its one-layer market structure, it results in more iterations before convergence compared to the two-layer approach. Conversely, the implementation of the two-layer approach may be more challenging due to its dual-layer structure, although it achieves a fewer iterations before convergence compared to the one-layer approach. Moreover, depending on the primary objectives and priorities for designing the local market, such as achieving DSO self-sufficiency or minimizing consumer costs to enhance their motivation to engage in flexibility provision, one approach may be more suitable than the other with the same structure. Furthermore, it is possible to define different objective function for the DSO other than self-sufficiency. This way, the performance and iterations before convergence of the one-layer and two-layer approaches can be different from the studied case.

Both approaches are innovative and different from the current existing local market frameworks. Furthermore, both proposed approaches can be utilized to design the local electricity and flexibility market structure, as well as to analyze the behavior of distribution system agents.

6 LOCAL MARKET-BASED DISTRIBUTION SYSTEM MANAGEMENT

To ensure comprehensive management of distribution systems, it is essential to model all key elements, including energy resources and loads such as DG, RES, EVs, Energy Storage System (ESS), flexible and static loads, and demand response programs. Additionally, the DSO must ensure stable network operation by managing voltage and power flow, as modeled in this study.

The generation and storage assets may be privately owned or, in some cases, owned by the DSO. Similar to Yi, Xu, Zhou, Wu, and Sun (2020b), our proposed model in Publication I accommodates both ownership scenarios, although it can be adjusted for cases where the DSO cannot own assets. In the results section, the performance of EVPLs owned by DSOs and those owned by VPPs are analyzed separately. If the DSO does not own any generation or storage assets, it will need to rely more heavily on the power and flexibility resources provided by VPPs to ensure stable and reliable system operation. Therefore, implementing an efficient local market framework becomes even more important in this scenario.

Local active and reactive power markets play a critical role in motivating flexible resources to act as active agents within the distribution system. These markets can employ nodal pricing schemes to efficiently respond to system needs for active and reactive power in different parts of the distribution system. Such pricing structures encourage agents to respond in line with the DSO's operational requirements. Single-level optimization frameworks, however, cannot adequately address conflicts between the DSO and VPPs. A bilevel optimization model is therefore employed, where the DSO at the upper level minimizes costs while maintaining network stability, and VPPs at the lower level optimize their operational costs based on local market prices. Given the key role of EVs in future systems, their use as flexible loads, energy storage systems in vehicle-to-grid mode, and sources of active/reactive power support is explored. This approach seeks to address their operational challenges while enhancing system reliability and market efficiency.

The DSO's determination of active and reactive power prices is critical for efficient operation at the distribution level. Accurate pricing must consider multiple factors, including the behavior of VPPs, which act as price-makers in local markets. The local market clearing process is formulated as a bilevel optimization problem. At the upper level, the DSO sets hourly prices for active and reactive power, while VPPs at the lower level provide feedback on trades. The management framework allows the DSO to make optimal decisions on pricing, bidding strategies in wholesale markets, and dispatching its resources, including EV chargers, ESS, DG, PV, and wind turbines. These decisions consider network constraints, power flow, voltage levels, and cost minimization, using data from VPP assets, wholesale price forecasts, and weather predictions.

VPP managers dispatch power based on the prices set by the DSO. VPPs include resources such as EV parking lots, DG, PV, wind power, price-sensitive demand response aggregators, flexible loads, and inelastic loads. A part of these assets such as RES and EV should be modeled considering their related uncertainties. For example, EV parking lots are modeled as uncertain storage systems, with characteristics derived from probability distributions of arrival and departure patterns.

The bilevel optimization model ensures that the DSO's upper-level decisions incorporate the constraints of VPP operations at the lower level. The DSO is assumed to participate in the wholesale market as a price-taker, with wholesale prices forecasted and their uncertainties neglected. However, uncertainties in renewable output are addressed using a chance-constrained formulation. The total demand within the system is met through a combination of DSO-owned resources, VPP-owned assets, and the upstream grid. Optimization determines resource allocation for load supply, minimizing costs and ensuring no loss of load. VPPs submit aggregated profiles of their assets to the DSO, which sets local market prices and allows VPPs to disaggregate dispatch plans for their individual assets. Unlike microgrids, joining a VPP is voluntary, offering increased profitability through aggregation. Assets are remunerated based on their contribution to VPP profits, incentivizing participation. Our distribution system management framework is presented in Figure 40.

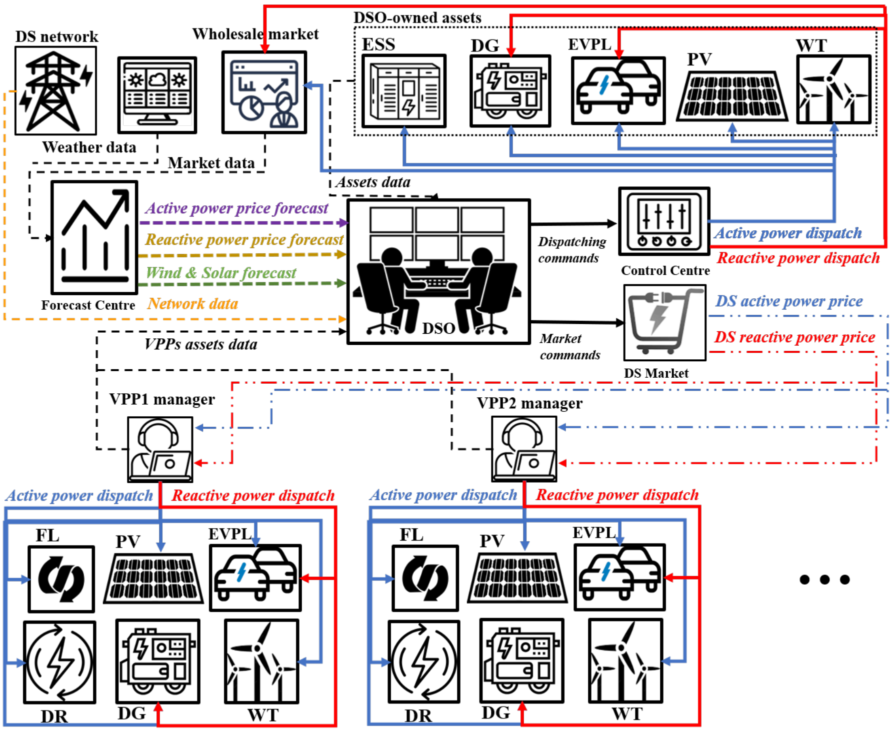


Figure 40. Overall distribution system management framework (Publication I).

6.1 Bilevel framework

6.1.1 Upper-level problem

As outlined earlier, the DSO's primary objective in this study is to minimize the overall distribution system cost including generation cost of DSO-owned DGs and RES as well as cost of active and reactive power trade with the upstream grid and VPPs. Detailed objective function formulation is explained in section 3.1 of Publication I (equation (1)). The DSO schedules its assets, manages power transactions with the upstream grid, and sets active and reactive prices in the local market. By determining these prices, the DSO indirectly controls VPP operations. The DSO's objective function accounts for the costs associated with active and reactive power transactions with the upstream grid, the generation costs of DSO-owned RES and DG, and the income generated from selling active and reactive power to VPPs. The DSO oversees the active and reactive power flow within the distribution network to ensure current and voltage levels remain within permissible limits. To achieve this, a linearized formulation of AC power flow is employed, which incorporates the network losses (equations (4)-(9) in Publication I). In addition, EVPLs are modeled based on the virtual battery model explained previously. Additionally, to address the uncertainty in RES generation, a chance-constrained formulation is applied (equation (33) in Publication I). This approach is particularly effective for large-scale systems with a significant share of RES, as it offers low computational complexity while efficiently modeling such uncertainties.

6.1.2 Lower-level problem

As previously mentioned, VPPs in this study oversee the operation of their assets in response to the active and reactive prices set by the DSO in the lower level of the proposed bilevel optimization framework. It is important to note that a VPP here represents the aggregation of various DERs, directly connected to the same substation within the distribution system. Consequently, there is no internal network within the VPPs in this model. VPPs optimize the operation of their assets, including EVPLs with unidirectional chargers, DG, PV, WP, price-sensitive Demand Response (DR) aggregators, flexible loads, and inelastic loads, to minimize costs. Their objective function encompasses the utility function of DR aggregators, modeled using a piecewise linear function, the operational costs of DG and RES, and the expenses associated with trading with the DSO. This minimization is performed under the operational constraints of all VPP assets, as detailed in the related publication. VPPs' objective functions and constraints are presented in equations (38)-(60) of publication I.

6.2 Simplification

The quadratic constraints in the lower-level problem introduce non-linearity, potentially causing non-convexity when transforming the bilevel model into an equivalent single-level model. To address this, a piecewise linearization approach is applied (equations (61)-(63) of Publication I). Additionally, solving the bilevel optimization problem requires converting it into a single-level format. Since the lower-level problem is a linear and convex optimization, this transformation is achieved by applying the KKT optimality conditions (equations (64)-(68) of Publication I). To handle the non-linearity of bilinear terms in the constraints, the Fortuny-Amat transformation is employed. Furthermore, the objective function of the equivalent single-level problem includes bilinear terms involving the product of two variables. To eliminate this non-linearity, the strong duality theorem is used, replacing the bilinear terms with the dual objective function of the lower-level problem (equation (69) of Publication I).

6.3 Operation results of the DSO

As stated earlier, the DSO manages the operation schedule of its assets to ensure optimal system performance. Figure 41 illustrates the active and reactive power outputs of DSO-owned DGs, along with the power output and state of energy of the ESS. The charging and discharging of the ESS are strategically scheduled based on power prices, with charging occurring during low-price hours and discharging during high-price hours. Additionally, DG operation is aligned with system needs to supply active and reactive power at their respective buses, adhering to rated capacity limits that create a link between active and reactive power outputs.

Figure 42 (a) and (b) display the available and scheduled power of DSO-owned RES, showing that available RES generation is fully utilized in all hours. The output power and energy storage levels of DSO-owned EVPLs are depicted in Figure 44 (a) and (c). Due to bidirectional EV chargers, EVPLs can operate EVs in V2G mode when needed. For instance, EVPL 3 frequently utilizes V2G mode because of system requirements and the lack of critical grid limitations at bus 3. The charging and discharging profiles ensure EVs meet their desired SOC upon departure, satisfying their arrival and departure patterns.

In addition to resource management, the DSO sets active and reactive power prices within the distribution system, as depicted in Figure 43 (a) and (b). Using a nodal pricing scheme, the DSO establishes varying prices for VPPs based on their location in the system. This price difference reflects the varying active and reactive power requirements across the system, influenced by generation and consumption profiles

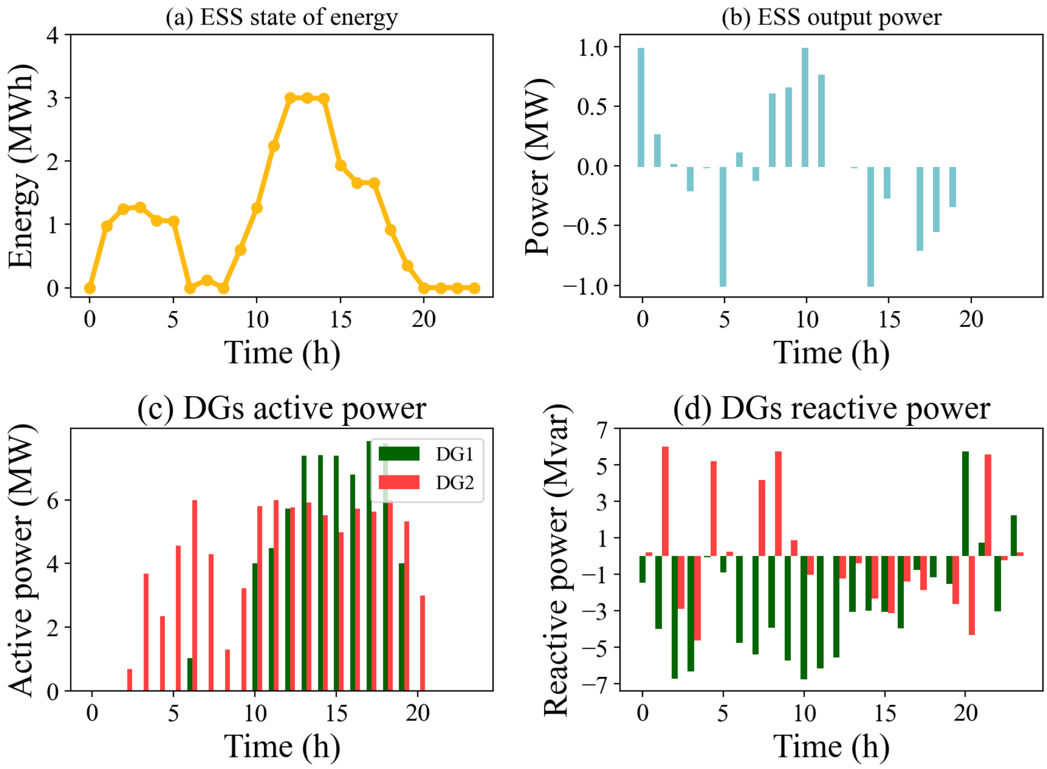


Figure 41. Operation of DSO-owned assets (Publication I).

as well as grid constraints. By setting active and reactive power prices, the DSO incentivizes VPPs to align their operations with the system's needs, indirectly controlling VPPs' behavior. Finally, the system's stability and reliability are maintained, as demonstrated in Figure 45, where all voltage levels and power flows remain within permissible limits throughout the grid.

6.4 Operation results of VPPs

Besides active power, VPPs also interact with reactive power by either consuming it or, leveraging their DGs and EVPLs, providing positive (consumption) or negative (injection) reactive power to the system. This capability enables them to participate in the reactive power market, benefiting from their flexible assets. By simultaneously managing the active and reactive power of their resources and loads, VPPs optimize their participation in both markets to achieve the minimum overall cost, as shown in Figure 43(c) and (d).

The management of active and reactive power is inherently linked through the nominal capacity limits of VPP assets, ensuring that their consumption and generation

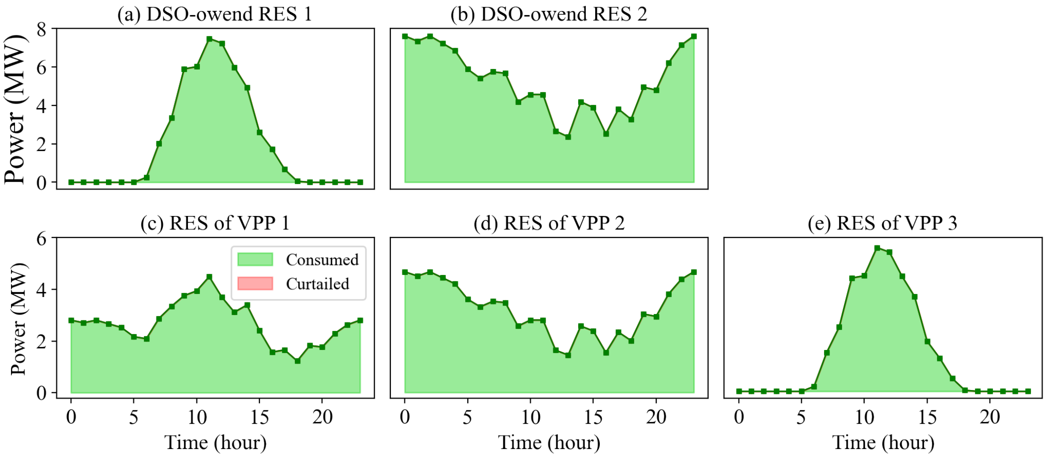


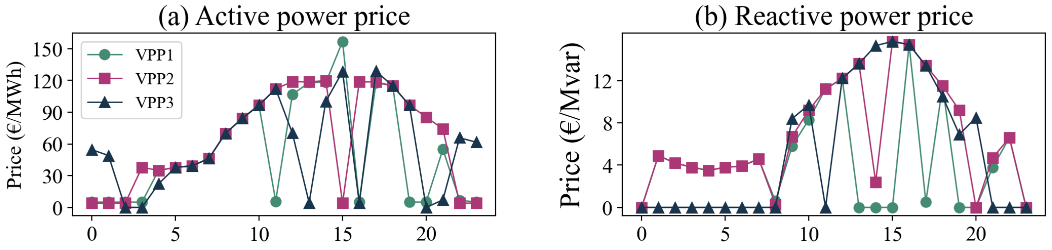
Figure 42. RES curtailment (Publication I).

schedules align with the hourly active and reactive prices defined by the DSO. As shown in Figure 42(c), (d), and (e), all VPPs utilize the full available power of their RES without any curtailment.

Additionally, Figure 44(b) and (d) depict the charging power and stored energy levels of VPP-owned EVPLs. Unlike DSO-owned EVPLs, which can operate in both charging and V2G modes, VPP-owned EVPLs are equipped with unidirectional chargers and thus operate solely in G2V charging mode. The results demonstrate that the charging profiles of VPP EVPLs vary among VPPs due to differences in active and reactive power prices and operational constraints specific to each VPP.

6.5 Impact of the nodal pricing

The DSO has the flexibility to either set a uniform price for VPPs across the distribution system or adopt a nodal pricing approach, where active and reactive power prices vary for VPPs at different buses. The results demonstrate that the DSO achieves the lowest cost when both active and reactive power prices are determined using nodal pricing. By implementing this nodal pricing scheme, the DSO's costs decrease by 462 €, corresponding to an approximate 4.6 % profit increase compared to scenarios without nodal pricing.



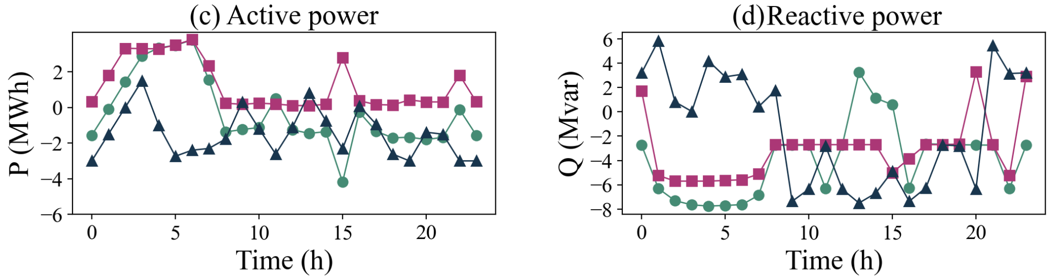


Figure 43. Reactive and active power price for different VPPs and their consumption (Publication I).

6.6 Impact of V2G charging and reactive power support from DSO-owned EVPLs

In most distribution system management problems, both voltage and line power constraints impact the optimal operation of the system. However, their effect on the optimal operating point depends on the strategies implemented. Deploying reactive power support and V2G capability helps mitigate the restrictive impact of these constraints on achieving the optimal operational state. This is reflected in the reduced overall distribution system costs. The simulation results in Table 8 highlight the advantages of V2G charging from EVPLs for the DSO. When DSO-owned EVPLs operate in V2G mode, the DSO's cost decreases by approximately 2.34 % compared to when EVPLs only support G2V charging. Additionally, RPS capabilities in EVPLs yield a cost reduction of around 4.64 % for the DSO. By deploying both V2G charging and RPS capabilities simultaneously, the DSO can achieve a cost savings of 598 €, equating to a 6.14 % profit increase relative to the baseline case.

Beyond cost reductions, RPS from EVPLs enhances network operational conditions, improving voltage profiles and branch flow constraints. This is evident in the voltage and branch flow comparisons in Figures 45 and 46, with significant improvements in system performance when RPS is utilized. Figure 47(a) demonstrates the voltage improvement at bus 17, a critical location in scenarios lacking RPS. The RPS capability reduces deviations from the reference voltage (1 pu), thereby stabilizing network operation.

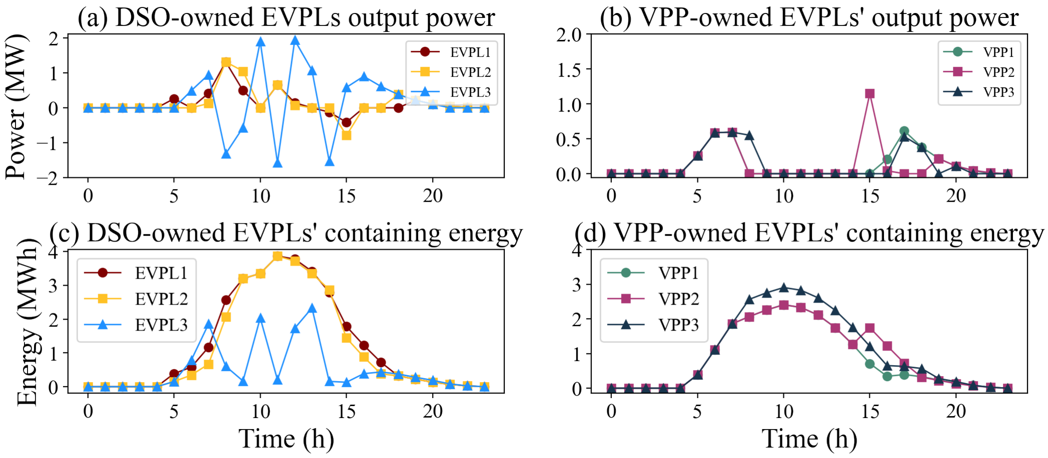


Figure 44. The power output and containing energy of VPP-owned EVPLs (Publication I).

Table 8. Cost of the DSO in cases 1, 2, 3, and 4 (€).

Case	Reactive power	V2G charging	DSO cost
Case 1	✗	✗	9741
Case 2	✗	✓	9513
Case 3	✓	✗	9289
Case 4	✓	✓	9143

When the voltage of a bus is close to its upper or lower limit, it imposes operational constraints on the assets within that bus and its neighboring buses. In other words, the assets in the surrounding area cannot operate at their optimal levels due to the voltage issue. Mathematically, in such cases, the constraint that keeps voltage within the lower and upper limits acts as a limiting constraint in the optimization problem, preventing the achievement of minimum system cost and optimal asset scheduling. Therefore, resolving voltage issues would lead to more optimal scheduling of the system and lower overall system costs.

Furthermore, the improved voltage conditions enhance the line's capacity for bidirectional trade with the upstream grid, lowering overall costs by facilitating increased active power trade. Congestion issues within the distribution system can lead to reduced utilization of the line connecting the DSO to the upstream grid. This limitation would result in decreased trade between the DSO and the wholesale market in both directions, restricting the DSO's ability to freely buy and sell power based on wholesale market tariffs. Consequently, this would lead to lower revenue for the distribution system. Therefore, addressing congestion issues to enable higher trade between the DSO and the upstream grid can lead to reduced overall distribution system costs. This synergy between voltage improvement and enhanced trade capacity underscores the critical role of RPS and V2G in optimizing distribution system operations.

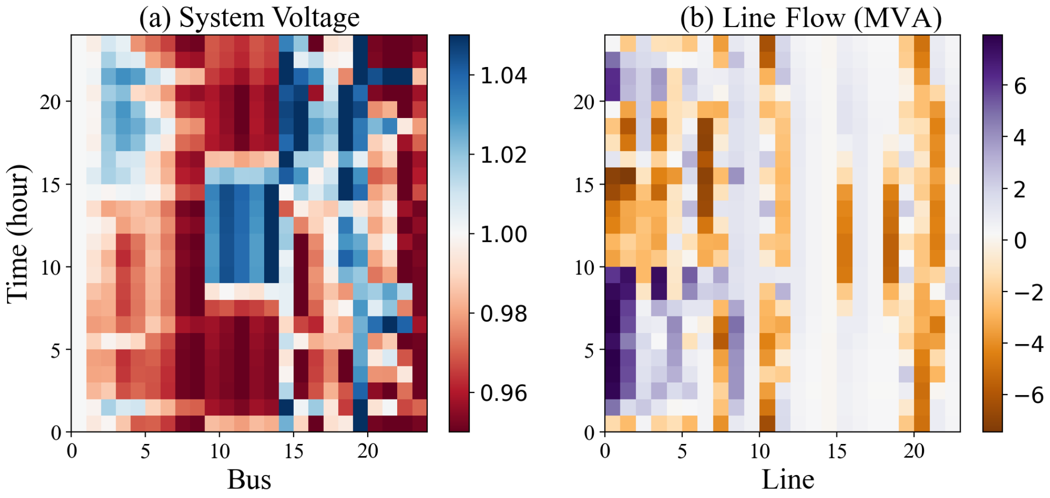


Figure 45. Voltage and line power of the system (Publication I).

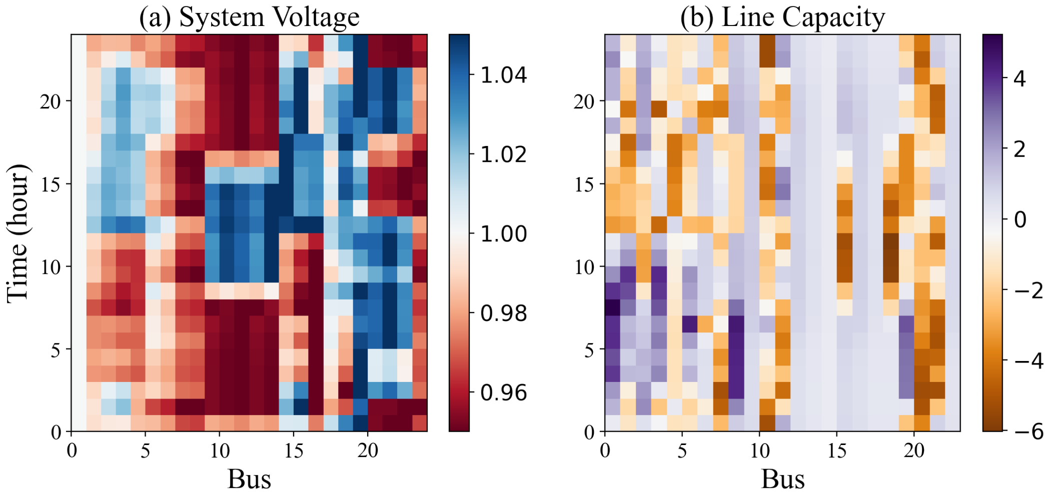


Figure 46. Voltage and line power of the system without RPS from EVPLs (Publication I).

Table 9. Cost of VPPs in cases α, β, and γ (€).

Case	VPP1 cost	VPP2 cost	VPP3 cost
Case α	-3331	-4852	-31981
Case β	-2358	-5392	-3382
Case γ	-2842	-4562	-4128

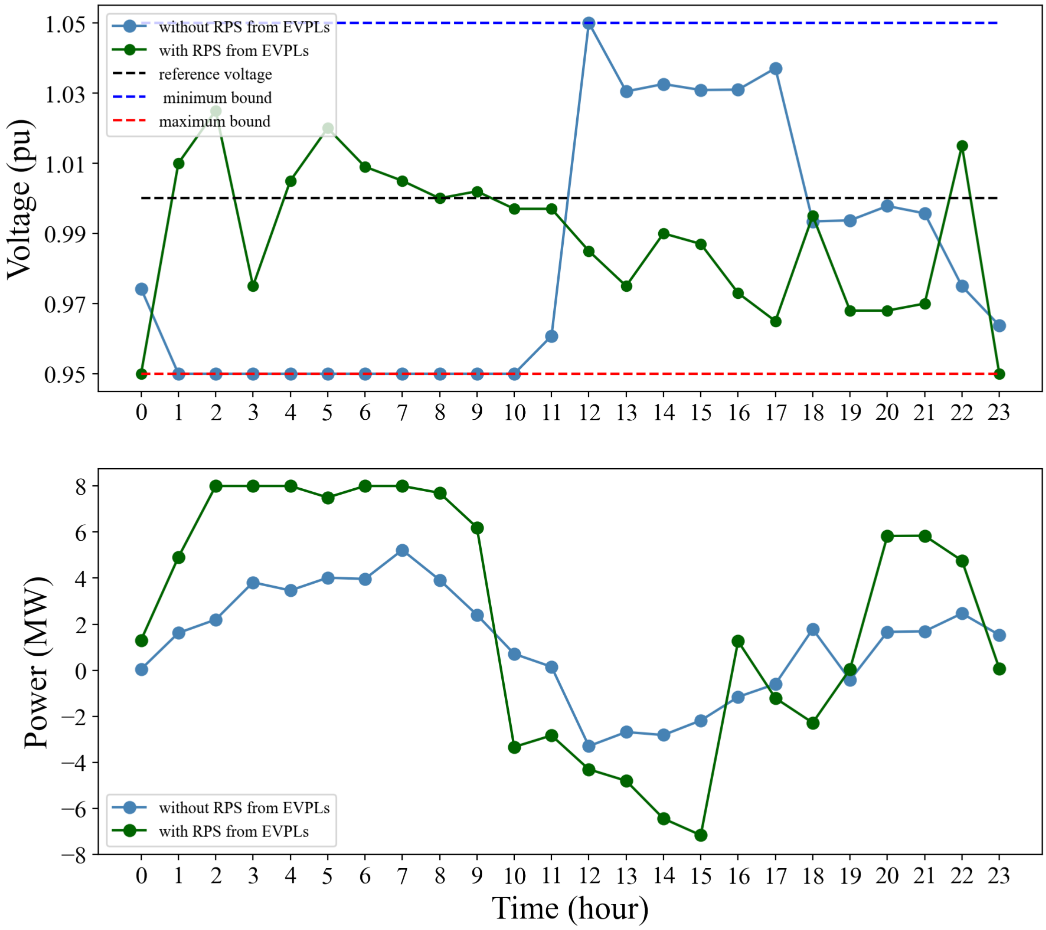


Figure 47. (a) Voltage of bus 17 and (b) power flow between DS and upstream grid with and without RPS from EVPLs (Publication I).

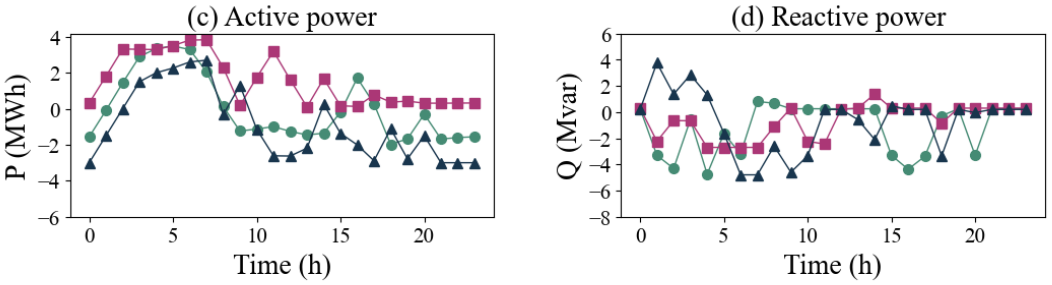


Figure 48. Reactive and active power for different VPPs without RPS from EVPLs (Publication I).

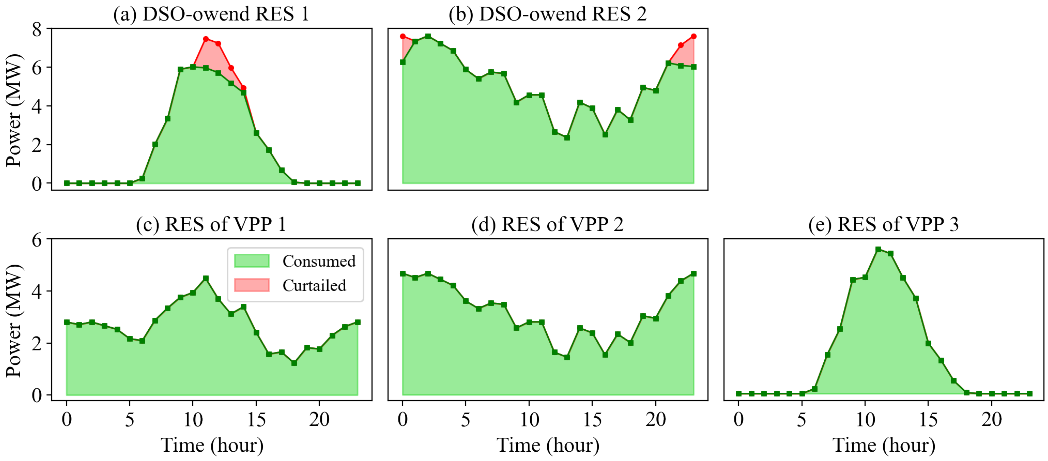


Figure 49. RES curtailment without RPS from EVPLs (Publication I).

6.7 Impact of reactive power support from VPP-owned EVPLs

When EVPLs lack the ability to provide positive or negative reactive power, the DSO must adapt its pricing strategy, which in turn affects the scheduled active and reactive power of VPPs. This dynamic is illustrated in Figure 48, where the operational response of VPPs under different scenarios is presented. By comparing Figures 49 and 42, the role of reactive power provision from EVPLs in enhancing system performance and RES utilization becomes evident. Without reactive power support from EVPLs, RES curtailment occurs, whereas its availability ensures full utilization of RES. This demonstrates how EVs, typically seen as potential challenges for DSOs, can positively contribute to system operation by delivering RPS. To evaluate the benefits of reactive power capabilities, three cases α, β, and γ are examined, focusing on VPP costs in each scenario as summarized in Table 9:

- Case α: Only the EVPL of VPP1 provides reactive power. - Case β: Reactive power is supplied solely by the EVPL of VPP2. - Case γ: Reactive power provision is limited to the EVPL of VPP3.

The results reveal that each VPP incurs lower costs when its respective EVPL has reactive power capability. However, the degree of benefit varies across VPPs, influenced by their locations within the distribution system and the system's specific reactive power requirements at each bus.

7 CONCLUSIONS

7.1 Research outcomes

1. How can the concept of a VPP be employed to coordinate the operations of various assets within the distribution system? VPPs act as aggregators of distributed energy resources, enabling the coordination of diverse assets like RES, distributed generators, energy storage systems, and EV parking lots. By integrating these resources under a unified control strategy, VPPs optimize their operation to minimize costs and improve system reliability. This coordination extends to participation in active and reactive power markets, ensuring that local system constraints and economic goals are met.

2. How do agents in local markets interact, and what is the impact of one agent's decisions on other agents? Agents in local markets interact through price signals and trading mechanisms, creating a complex web of interdependencies. A novel iterative game-based framework was proposed to effectively capture these interactions and their cascading effects. The analysis revealed that the decisions of individual agents can significantly influence the strategies and outcomes of others. Such interdependencies highlight the need for a holistic design of local markets that considers agent-specific goals and system-level constraints.

3. What local market framework can be developed to accommodate network and asset constraints while integrating market interactions and system operational constraints with low simulation time? The iterative approach, while effective in accurately modeling interactions, imposes a significant computational burden. This highlights the need for an alternative local market framework that can capture market dynamics while efficiently handling the operational constraints of the distribution system. A bilevel optimization framework, based on Stackelberg game theory, has been identified as a suitable solution. This framework allows the DSO to consider the decisions made by VPPs before determining its own strategies, fostering a hierarchical yet interconnected decision-making process.

4. How can local markets for active and reactive power be utilized to effectively manage the operation of distribution systems? Local markets facilitate efficient management of distribution systems by establishing appropriate pricing mechanisms. Specifically, the determination of nodal prices for active and reactive power incentivizes participants to align their operations with the system's requirements. The results demonstrated that incorporating local active and reactive power markets reduces system costs, alleviates grid constraints, and ensures stable operation under high penetration of EVs and RES.

5. What are the potential challenges and opportunities that EVs introduce to

distribution systems? The widespread adoption of EVs poses significant challenges, including increased load demand, potential grid congestion, and risks of voltage violations. However, EVs also offer substantial opportunities to enhance system stability and reduce operational costs. Scheduled charging enables EVs to act as controllable loads, aligning their energy consumption with low-price periods. By leveraging smart charging strategies, EVs can function as flexible loads, and when equipped with bidirectional chargers, they can operate as energy storage systems. Furthermore, EVs can contribute to reactive power support through the power electronic facilities embedded in their charging infrastructure leading to improved system voltage. By managed participation in local active and reactive power markets, EV parking lots generate additional revenue while alleviating grid constraints, thus turning potential challenges into valuable system contributions.

6. Given the uncertainty in EV owner behavior, how can EV aggregations be modeled to enable seamless integration into distribution system management frameworks without imposing high computational burdens? A virtual battery model was proposed to represent the aggregated behavior of EVs in EVPLs, considering the probability distribution function of the uncertain arrival and departure pattern. This model provides accurate results with significantly reduced computational complexity compared to scenario-based methods, making it suitable for large-scale and real-time applications.

7. Is it possible to optimize the operation of EV chargers to minimize their investment costs, thereby promoting further development of EV infrastructure? The proposed charger-sharing approach in this thesis optimizes the utilization of EV chargers, allowing EVPLs to serve more vehicles with fewer charging stations. In this approach, instead of charging a single EV with a single charger, multiple EVs can be connected to a single charger. This reduces investment costs and encourages the expansion of EV infrastructure while ensuring that EVs meet their desired state of charge upon departure.

By addressing these research questions, this thesis presents a comprehensive framework for enhancing distribution system management through VPPs, local markets, and the effective integration of EVs. The proposed methodologies and models offer significant contributions to achieving a flexible, cost-effective, and sustainable energy system.

7.2 Summary of the main contributions

In this section, we summarize the main contributions of the thesis, highlighting the innovative approaches, models, and frameworks developed to enhance the management and operation of distribution systems with high penetration of electric vehicles.

- Proposing an innovative charger-sharing strategy for EVPLs, enabling a specified number of charging stations to serve a maximum number of EVs while ensuring that each EV reaches its desired final SOC upon departure.
- Developing a compact virtual battery model to represent aggregated EV charging, capturing the uncertainty in EV arrival and departure. This model facilitates the study and integration of EVPL operations with charger-sharing and exclusive charger modes into large-scale power system, with minimal computational burden.
- Designing a two-stage validation framework to assess the effectiveness of the proposed virtual battery model in the market participation of a 24-bus distribution system with a high penetration of EVs.
- Investigating the role of EVPLs in reducing distribution system costs and improving voltage conditions by functioning as flexible active loads and providing reactive power support and assessing the impact of voltage violation penalty costs alongside other operational costs, demonstrating how EVPLs can mitigate such penalties and enhance overall system performance.
- Proposing a framework to model the strategic behavior of agents, including the DSO, aggregator, and customers, in the distribution system through a novel one-layer and two-layer game-based models. These models empower agents to make independent trading decisions while updating these decisions based on interactions with other agents, reflecting the interconnected nature of customers and aggregators.
- Proposing a comprehensive market-based framework for distribution system management that accounts for private VPP ownership, encompassing the DSO's pricing strategy, VPPs' bidding strategy, dispatch strategies of both the DSO and VPPs, market mechanisms for active and reactive power, uncertainties, system topology, network constraints, and various DSO- and VPP-owned resources, including RES, DG, EVPLs, flexible loads, DR, and ESS.
- Modeling and analyzing the potential of EVPLs as flexible loads, reactive power providers, and V2G participants within the competitive active and reactive power market framework. This approach addresses challenges from high EV penetration and leverages their capacity to enhance system operations.

7.3 Thesis limitation and future research

It is crucial to understand the limitations of the proposed distribution system management framework and the potential challenges in implementing it in real systems. These challenges include the unpredictable behavior of VPP participants, ensuring secure access to their data, and the need to make optimal decisions quickly, especially for real-time applications. The primary objective of this thesis is to design a local active and reactive power market that encourages VPPs to provide services aimed at improving the operation and economic efficiency of ADN, with a focus on the pricing mechanism in the day-ahead stage.

It is important to note that the power market is a complex research area that involves different time scales, various commodities, and communication considerations. Our proposed methodology addresses the complexity of a bilevel optimization problem with uncertain variables by converting it into a deterministic Mixed-Integer Linear Programming (MILP) formulation. This conversion is achieved using effective uncertainty modeling techniques for EVs and RES, along with various simplification methods. Although this framework is designed for the day-ahead stage, where real-time responsiveness is not critical, it still provides fast responses, making it suitable for large-scale systems and real-time applications.

In the future, this framework can be extended to integrate the real-time market with the day-ahead market, including services such as active and reactive power for reserve. However, implementing such a framework requires a communication infrastructure that ensures the secure and efficient transmission of transaction signals during the real-time stage. For future studies on EVs, it is necessary to investigate the role of residential EVPLs in supporting the distribution system. Additionally, the effect of EVPLs' size (capacity) and location should be studied to support decision-makers in defining the proper locations for both residential and commercial EVPLs. Furthermore, in the future, the establishment of EV charging stations, where EVs park temporarily to receive a full charge, will become increasingly prevalent. It is imperative to develop an effective model for these charging stations in future research.

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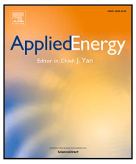

EV-observing distribution system management considering strategic VPPs and active & reactive power markets

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ABSTRACT

The growing deployment of new flexible resources, renewable energy resources (RES), and Electric Vehicles (EV) in the distribution system necessitates new methods to manage the distribution system operation optimally. In this regard, our paper, by deploying the concept of Virtual Power Plants (VPPs) as the aggregation of multiple agents and local power markets that are known as important tools for future power systems presents a management framework for the distribution systems with high penetration of EVs. To this end, the interaction of the DSO and VPPs is studied based on their strategic behaviour through the local active and reactive power markets. This way, a bilevel optimization approach is proposed where the DSO aims to minimize its operational cost by setting the operation point of its own facilities and determining the hourly active and reactive power prices for VPPs considering the distribution system congestion in the upper level. At the lower level, VPPs try to minimize their cost by scheduling their assets based on the local active and reactive power prices set by the DSO. The results show how nodal pricing in local markets could improve the distribution system operation. In addition, it is indicated that Reactive Power Support (RPS) from VPP-owned EVPLs can decrease the VPPs' cost by gaining profit in the reactive power market and facilitating their participation in the active power market.

1. Introduction

1.1. Background

Active distribution networks (ADNs) have become an increasingly popular concept in the field of power systems. Unlike traditional passive distribution networks, which are designed for one-way power flow from the transmission system to consumers, ADNs allow for two-way power flow and active participation of distributed energy resources (DERs) such as renewable energy sources, energy storage systems, and electric vehicles [1]. ADNs offer several advantages, including improved system reliability, increased energy efficiency, and reduced carbon emissions [2]. By utilizing DERs, ADNs can help to mitigate power system problems such as voltage fluctuations, power quality issues, and overloading of the distribution network [3]. However, there are several challenges associated with the implementation of ADNs. One of the main challenges is the need for advanced control and communication systems to ensure the efficient and reliable operation of the network, and communication networks must be in place to facilitate the exchange of information between different components of the network [4]. Another challenge is the need for accurate modelling and forecasting of DERs, which can be difficult due to the variability and uncertainty of renewable energy sources and EV charging patterns [5]. In addition, regulatory frameworks and local market mechanisms must be developed to incentivize the deployment of DERs and ensure the cost-effective operation of the network [6].

VPPs have emerged as a promising technology to address the challenges associated with the integration of DERs in ADNs [7]. There exist some interpretations of the VPP concept. In our paper, the VPP is an aggregation of DERs that could be utilized to make contracts in the market and to offer different services to the power system operator, the explanation presented in the majority of the literature such as [8–10], and [11]. In such a definition, VPP components can connect to different points of the distribution network. This allows for the optimization of the operation of the DERs in response to the needs of the grid, and the provision of various grid services such as peak shaving, frequency regulation, and voltage support [12]. One of the key advantages of VPPs is their ability to provide a cost-effective solution for managing the integration of DERs into ADNs [13]. By aggregating the output of multiple DERs, VPPs can provide a more reliable and predictable source of energy compared to individual DERs, which can

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Nomenclature

Indices

i/j	DSo-owned assets located in bus i/j
k	VPP and assets owned by that VPP
t	Time

Parameters

$\Delta_i^{DG,max}$	DG ramp rate
η_{ch}/η_{dc}	Charge/discharge efficiency of EV
η_{in}/η_{out}	Charging/discharging efficiency of ESS
ρ	Power factor
$c^{RES}/c_n/d_{k,n}$	Cost of RES/DG/marginal utility of DR
$C_{ins}^{PL,ch}$	Total charging capacity of the installed EV chargers
Cap_{cl}^{EV}	Battery capacity of the EV class cl
E_k^{AGG}	Total demand of aggregator
$e_{m,1-2}^X/f_m^X$	Coefficients in the linearized model
E_t^{arr}	Added energy to EVPL due to EVs arrival
E_t^{dep}	Depleted energy from EVPL due to EVs departure
k_t^P/k_t^Q	Wholesale active/reactive energy price
$N^{EV,ent}$	Number of total arrived EVs in a day
$N_t^{EV,arr}/N_t^{EV,dep}$	Number of arrived/departed EVs at time t
$P_{L,i,t}^{Fix}/Q_{L,i,t}^{Fix}$	Inelastic active/reactive load
S^{DG}/S_k^{VPP}	DG/VPP feeder capacity
S_{ij}	Line capacity
Sh_{cl}	Share of EVs class cl from all available EVs
SOC_{cl}^{arr}	Arriving SOC of the EVs class cl
SOC_{cl}^{dep}	Departing SOC of the EVs class cl
$T_{k,start}^{AGG}/T_{k,end}^{AGG}$	Start/end time of aggregator

Variables

$\delta_{i,t}^{ESS}$	ESS charging/discharging status
$\pi_{k,t}^P/\pi_{k,t}^P$	Local active/reactive energy price
$E_{i,t}^{ESS}$	ESS residual energy
E_t^{PL}	EVPL stored energy
$P_{i,t}^{ESS,in}$	ESS Charging power
$P_{i,t}^{ESS,out}$	ESS Discharging power
$P_i/Q_i/V_i/\theta_i$	Active/reactive power injection/voltage amplitude/angle of bus i
$P_{k,t}^{AGG}/Q_{k,t}^{AGG}$	Active/reactive power the aggregator
$P_{k,t}^{DR}/Q_{k,t}^{DR}$	Active/reactive power of DR
$P_{k,t}^{DR}$	Active power of the nth segment of DR
$P_{k,t}^{VPP}/Q_{k,t}^{VPP}$	Transacted active/reactive power between VPP and the DSO
$P_{n,t}^{DG}$	Active power production of the nth segment of DG
P_t^{DG}/Q_t^{DG}	Active/reactive generated power of DGs
P_t^{DN}/Q_t^{DN}	Transacted active/reactive power between DSO and wholesale market
$P_t^{PL,ch}/P_t^{PL,dc}$	Charge/discharge power of EVPL
P_t^{RES}	RES power output

be variable and intermittent [14]. This can help to reduce the need for costly upgrades to the distribution network and the installation of additional grid infrastructure. Additionally, VPPs can provide valuable grid services such as demand response, which can help to manage the load on the grid during times of peak demand [15].

The integration of VPPs into ADN systems presents unique challenges due to the diverse parties involved, including load-serving entities, price-sensitive demand response, distributed generators, and flexible load aggregators [16]. To ensure effective collaboration, VPP agents need to provide their aggregated external characteristics to the Distribution System Operator (DSO), who then computes optimal operational decisions and issues dispatching trajectories to VPP agents [17]. However, conflicts of interest can arise when VPP agents and DSOs belong to different owners. To address this, bi-level programming models are often used to separately consider the economic objectives and operational constraints of both VPPs and ADN [9]. By encouraging the participation of VPPs through reasonable pricing strategies, DSOs can improve the overall economy of the system, leading to more efficient and sustainable grid operations.

In this regard, some studies have been conducted to design a framework that models the local market consisting of VPP and distribution system. Authors in [18] used the multi-leader–follower concept of game theory to model its bilevel interaction among VPP and ADN. The research aims to determine the annual bilateral contract's optimal prices of VPPs to form a competition inside the ADN. Ref. [19] proposed an approach for determining the optimal location and contract pricing of distributed generation (DG). The authors of [20] developed a two-layer energy management model for the smart distribution network that incorporates VPPs participating in day-ahead energy and reserve markets. The first layer focuses on maximizing profits for VPPs, while also considering constraints such as renewable and flexible energy sources and coordination with the VPP operator. The second layer aims to optimize the distribution system operator's management of the distribution network by minimizing network energy loss and voltage deviation, taking into account uncertain parameters such as load, market price, and maximum power of renewable energy sources.

Ref. [21] did the same with this difference that the distribution company and a retailer compete at the upper level. At the lower level, consumers buy energy with the aim of minimizing their own expenses. The authors in [22] proposed a robust optimization approach to aggregate an Autonomous Distribution System as a VPP and determine its time-varying feasible range of active power and ramp rates. The robust optimization model considers uncertainties such as dispatch orders from the transmission system operator (TSO) and renewable distributed generators.

1.2. Contributions

Characteristics of the previous studies about distribution system management are presented in Table 1. The classification includes local active and reactive power markets, power flow, DR, RES, EV, as well as strategic VPP, Microgrid, or aggregator. In this regard, the private ownership of the VPPs and the conflict between the objective of such private agents and the DSO has been considered in some studies. A part of reviewed papers in the literature investigated the possible role of the active power market in distribution system management neglecting the potential impact of the reactive power market framework. This has been investigated in [9] where a framework for both the local active and reactive power market has been considered in the interaction between VPPs and the DSO. However, the impact of EVs as one of the most important elements in the future energy system has not been taken into account. This paper by filling the mentioned gap proposes bilevel programming modelling the local active and reactive power market framework at the distribution level to find the optimal management strategy of the DSO considering the strategic behaviour of VPPs and the operation of both DSO-owned and VPP-owned EV parking lots. This paper proposes a thorough model for EV parking lots reflecting the arrival and departure uncertainty of EVs and different existing EV classes. In addition, both DSO-owned and VPP-owned EV parking lots,

Table 1
Previous studies about active distribution system management.

Ref	Strategic VPP/MG/Agg	LAPM	LRPM	Power flow	DR	RES	EV
[9]	✓	✓	✓	✓	✓	✓	✘
[18]	✘	✘	✘	✓	✘	✘	✘
[19]	✓	✘	✘	✓	✘	✘	✘
[20]	✓	✘	✘	✓	✘	✓	✓
[21]	✓	✘	✘	✓	✘	✓	✘
[22]	✓	✘	✘	✓	✘	✓	✘
[23]	✓	✓	✘	✓	✘	✘	✘
[24]	✓	✓	✘	✓	✘	✓	✓
[25]	✓	✓	✘	✓	✓	✓	✘
[26]	✘	✓	✘	✘	✓	✓	✘
[27]	✘	✘	✘	✓	✓	✓	✘
[28]	✘	✘	✘	✓	✓	✓	✘
[29]	✓	✓	✘	✓	✓	✓	✘
Our paper	✓	✓	✓	✓	✓	✓	✓

LAPM/LRPM: Local active/reactive power market.

owing to their power electronic infrastructure, can provide RPS. This way, the DSO can reduce its operational cost by improving the system operation condition in terms of voltage and line flow, and VPPs can gain additional profit by selling their RPS in the reactive power market. Therefore, the potential of EV parking lots to act as reactive power providers is also modelled. Moreover, the Vehicle-to-Grid (V2G) mode charging has been considered and modelled for the DSO-owned EVPLs. This way, these EVPLs can serve as energy storage for some hours if it is required by the DSO to improve the system operation. The main contributions of this paper are listed below:

- Proposing a comprehensive framework for distribution system management considering the private ownership of the VPPs where the pricing strategy of the DSO, bidding strategy of the VPPs, dispatching strategy of both the DSO and VPPs, a market scheme for active and reactive power, involved uncertainties, distribution system topology and network constraints, and different VPP-owned and DSO-owned consumers, prosumers, generators such as RES, DG, EV parking lot, flexible load, demand response as well as energy storage systems are modelled.
- Modelling and investigating the potential of EV parking lots to act as flexible load, reactive power providers, and operate in the V2G charging mode in the competitive reactive and active power market framework in the distribution system to overcome the challenges resulting from their high penetration and utilize their potential capacities to improve the system operation.

The remainder of this paper is structured as follows: Section 2 describes the overall structure of the problem; Section 3 presents the problem formulation including the lower-level and upper-level problem of the bilevel optimization approach; The deployed simplification methods and equivalent single-level model is explained in Section 4. The simulation results are discussed in Section 5, and the conclusions are summarized in Section 6.

2. Overall structure of the problem

To conduct a comprehensive distribution system management, it is required to model all of the effective elements involved in the distribution system. In this regard, firstly, main energy resources and loads such as distributed generation, renewable energy resources, electric vehicles, energy storage systems, flexible and static loads, and demand response should be modelled. In this regard, the ownership of such assets could be with private sectors. In some countries, besides private sectors, the DSO itself could also own such assets. Therefore, in our model, both options of assets' ownership have been considered. However, the model can be easily modified for the cases where the DSO cannot own any asset. Besides the mentioned loads and assets, the DSO should guarantee the stable operation of the network taking care of the system voltage and power flow that has been modelled in our paper.

The other effective point that can motivate the flexible resources in the distribution system to act as active agents is the local active and reactive power markets. These markets are substantial drives for active and reactive power support from flexible agents in the distribution system. In this regard, the nodal pricing scheme for both active and reactive power can shape the incentives based on the system's needs. Because the distribution system requirements for active and reactive power support in different buses are not similar. Therefore, the different local market prices could better incentivize the agents to have a response similar to the DSO's needs and desires. Moreover, single-level optimization framework cannot model the conflict between the DSO and VPP's interests. Therefore, bilevel optimization model is used where the DSO in the upper level aims to minimize the distribution system cost while guaranteeing the stable operation of the system in terms of network constraints. In addition, at the lower level, VPPs who have different ownership try to minimize their own operational costs based on the local market prices. Finally, due to the importance of the role of the electric vehicle in the future power system, their role in acting as flexible load, energy storage system (in V2G mode), and RPS have been investigated to pave the way for increasing the EV penetration by tackling their operational challenges and making benefit from their potential active and reactive power support.

The active and reactive power price determined by DSO at the distribution level is of substantial importance to the efficient operation of the distribution-level agents and consequently the DSO-owned facilities. This way, the price should be precisely determined considering every effective parameter. In this regard, VPPs play a vital role as price-maker participants in local markets. Therefore, the DSO should accurately consider the operation of VPPs for the price determination and operation of its own facilities. To this end, as the DSO and VPPs have different ownership, the local market clearing scheme is formulated as a bilevel optimization problem where at the upper level, the DSO issues the hourly active and reactive prices and at the lower level, VPPs send the active and reactive power trade feedback to the DSO. The overall framework of the distribution system management in this paper is depicted in Fig. 1 where the DSO determines sets of optimal decisions for active and reactive power prices, its bidding plan to the upstream wholesale active and reactive markets, and dispatching of its own facilities including EVPL equipped with bidirectional and unidirectional EV chargers, ESS, DG, PV, and WT to handle the active and reactive power flow constraints considering the elaborate network topology (congestion and voltage level) and minimize its cost. To this end, the DSO utilizes the VPPs' assets' data, the wholesale active and reactive power price forecast, and the weather situation forecast. VPP managers dispatch the active and reactive power based on the active and reactive power price determined by the DSO. VPPs in this paper consist of EVPLs equipped with unidirectional chargers, DG, PV, WP, price-sensitive DR aggregators, flexible loads, and inelastic loads. Modelling all the VPP facilities is conducted considering relevant uncertainties.

It should be noted that in the bilevel optimization model, the DSO at the upper level defines its decision variables while considering the VPPs' problem at the lower level. In other words, the optimization problem of the VPPs is a constraint in DSO's optimization problem. Upper and lower-level problems are described below in detail. In this paper, it is assumed that DSO participates in the wholesale market as a price-taker player where the wholesale price is obtained from the forecast. As the main focus of the paper is regarding the local market clearing process, the uncertainty of wholesale market price has been neglected. However, the uncertainty of RES has been considered via deploying a chance-constrained formulation described in the problem formulation. In addition, the uncertainty of EVs' arrival and departure is taken into account via employing an uncertainty-observed storage model for the EV parking lot where the characteristic of the storage

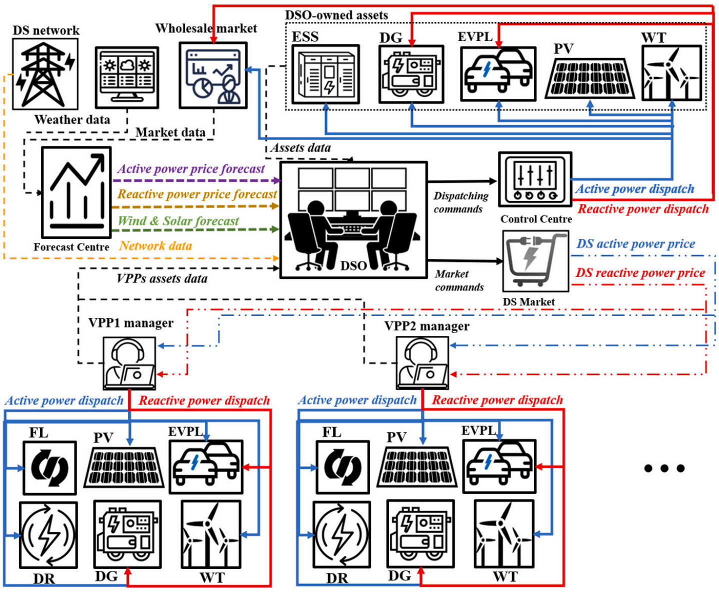

Fig. 1. Overall framework.

model is extracted from the probability distribution function of the arrival and departure pattern of EVs.

It is worth mentioning that the total demand within the distribution system is supplied by the DSO-owned resources such as RES, DG, and ESS through discharging, VPP-owned resources comprising DG, and RES, as well as the upstream grid. Under all circumstances, the value of loss of load is maintained at zero, ensuring a reliable power supply. The share of the mentioned resources for supplying the load is based on the optimization problem that models the market interaction and cost minimization involving the DSO and different VPPs. This way, it is ensured that the solution derived from our framework is the optimal power supply solution.

To summarize the market interactions, VPP agents calculate the aggregated profile of their controllable and uncontrollable assets and submit the equivalent parameters of the aggregated model to the DSO. The DSO, based on the bidding information of the market participants, sets the market prices for the VPPs, and VPPs disaggregate their dispatching plan to individual assets [9]. It is essential to emphasize that, unlike a microgrid, becoming part of a VPP is a voluntary choice for each individual asset. The main objective in establishing a VPP is aggregation, enabling increased profitability. The portion of the total VPP profit allocated to each individual asset is determined and remunerated. As a result, individual assets contribute their data to the VPP manager, enhancing market participation efficiency and profitability. Otherwise, each asset could individually participate in the market with lower profit without joining a VPP. However, it is important to note that when developing the communication infrastructure for the VPP, privacy, and cybersecurity issues related to data transactions in centralized structures must be carefully addressed.

3. Problem formulation

3.1. Upper-level problem

As mentioned in the previous section, the DSO in this paper seeks to minimize the distribution system cost by scheduling its own assets, determining its traded power with the upstream grid, and deciding on active and reactive prices in the local market. Determining the active and reactive prices empowers the DSO to have indirect control over the operation of VPPs. In this regard, the DSO's objective function is presented in (1). The first and second term in the objective function stands for the cost of active and reactive power transaction with the upstream grid. The third and fourth terms stand for the generation cost of the DSO-owned RES and DG. The last two terms are the income from selling active and reactive power to VPPs. The generation cost of the DG has been estimated with a linear formulation as represented in (2) and (3).

$$MinC_{dn} = \Delta T(\sum_{t=1}^{T} k_t^P P_t^{DN} + k_t^Q Q_t^{DN} + \sum_{i=1}^{NB}[c_i^{RES}.P_{i,t}^{RES} + F_i^{DG}(P_{i,t}^{DG})] - \sum_{k=1}^{N_{VPP}} (\pi_{k,t}^P.P_{k,t}^{VPP} + \pi_{k,t}^Q.Q_{k,t}^{VPP})) \tag{1}$$

$$F_i^{DG}(P_{i,t}^{DG}) = \sum_{n=1}^{N_i^{DG,seg}} c_{i,n}.P_{i,n,t}^{DG} \tag{2}$$

$$P_{i,t}^{DG} = \sum_{n=1}^{N_i^{DG,seg}} P_{i,n,t}^{DG} \tag{3}$$

3.1.1. Power flow equations, thermal, and voltage constraints

The DSO is responsible for supervising the active and reactive power flow in the distribution network to maintain within the allowed limits. In this regard, the linearized formulation of AC power flow for the distribution system proposed in [30] is used. It should be noted that in the mentioned linearized AC power flow, the network loss is taken into account. In addition, Eqs. (4) and (5) represent the net active and reactive power injection for all bus i and for VVP k located in bus i, accordingly. Eqs. (6) and (7) define the relation between the injected active and reactive power of each bus with the different buses' voltage magnitude and angle. Moreover, Eqs. (8) and (9) represent the constraint for voltage magnitude and branch power flow to be maintained within the allowed limits.

$$P_{i,t} = P_t^{DN} - P_{k,t}^{VPP} + P_{i,t}^{RES} + P_{i,t}^{DG} + P_{i,t}^{ESS,out} - P_{i,t}^{ESS,in} - P_{L,i,t}^{Fix} \tag{4}$$

$$Q_{i,t} = Q_t^{DN} - Q_{k,t}^{VPP} + Q_{i,t}^{DG} - Q_{L,i,t}^{Fix} \tag{5}$$

$$P_i = \sum_{j=1,i\neq j}^{N_B} P_{ij} = \sum_{j=1,i\neq j}^{N_B} (\frac{r_{ij}}{r_{ij}^2 + x_{ij}^2}(V_i - V_j) + \frac{x_{ij}}{r_{ij}^2 + x_{ij}^2}(\theta_i - \theta_j)) \tag{6}$$

$$Q_i = \sum_{j=1,i\neq j}^{N_B} Q_{i,j} = \sum_{j=1,i\neq j}^{N_B} (\frac{x_{ij}}{r_{ij}^2 + x_{ij}^2}(V_i - V_j) - \frac{r_{ij}}{r_{ij}^2 + x_{ij}^2}(\theta_i - \theta_j)) \tag{7}$$

$$P_{ij}^2 + Q_{ij}^2 \leq S_{ij}^2 \tag{8}$$

$$V_{i,min} \leq V_i \leq V_{i,max} \tag{9}$$

3.1.2. DSO-owned EV parking lot

In this paper, EVPL is modelled as energy storage where the parameters of the storage model are obtained considering the uncertain EV owners' behaviour. It is assumed that EVPL hosts several EV classes with different characteristics. Eq. (10) presents how EVPL's stored energy in each hour is calculated. The energy added to the EVPL or derived from it due to EVs' arrival and departure is obtained from the number of arriving and departing EVs in each hour. Uncertain arrival and departure of EVs in a commercial EVPL are modelled with a Truncated Normal Distribution (TND) in the related studies. This way, using the Cumulative Distribution Function (CDF) of TND, the number of arriving and departing EVs in each hour is obtained as represented in (11) and (12) where F_t^{TND} is CDF of TND. It is given that the number of EVs parking in the EVPL in a day is equal to the number of EV chargers. Such uncertainty modelling that provides a storage-based model via the CDF of arriving and departing pattern makes it a proper model for large-scale applications with a high share of EVs because of its low computational burden.

$$E_{i,t}^{PL} = E_{i,t-1}^{PL} - E_{i,t}^{dep} + E_{i,t}^{arr} + \Delta t \eta_{ch} P_{i,t}^{PL,ch} - (\Delta t/\eta_{dc}) P_{i,t}^{PL,dc} \tag{10}$$

$$N_t^{Ev,arr} = N^{EV,ent}(F_{t+0.5}^{TND,arr} - F_{t-0.5}^{TND,arr}) \tag{11}$$

$$N_t^{Ev,dep} = N^{EV,ent}(F_{t+0.5}^{TND,dep} - F_{t-0.5}^{TND,dep}) \tag{12}$$

$$N^{EV,ent} \leq N^{EV,ava} \tag{13}$$

$$F^{TND}(x) = \frac{\Phi(x,\mu,\sigma) - \Phi(a,\mu,\sigma)}{\Phi(b,\mu,\sigma) - \Phi(a,\mu,\sigma)} \tag{14}$$

$$E_{i,t}^{arr} = N_{i,t}^{Ev,arr}(\sum_{cl} Cap_{cl}^{EV} SOC_{cl}^{arr} Sh_{cl}) \tag{15}$$

$$E_{i,t}^{dep} = N_{i,t}^{Ev,dep}(\sum_{cl} Cap_{cl}^{EV} SOC_{cl}^{dep} Sh_{cl}) \tag{16}$$

EVPL's charging power should be less than the total charging capacity of the EVPL which is equal to the total charging capacity of the EV chargers as represented in (17). Moreover, EVPL's charging power in each hour is less than the summation of the nominal charging power of the parked EVs in that hour as presented in (18). Eq. (21) represents the hourly number of EVs parked in EVPL. The hourly maximum and minimum energy of EVPL is determined as shown in (22). Furthermore, (25) represents the constraint on the active and reactive power of EVPL. Finally, the output power of EVPL is equal to the summation of the charge and discharge power. However, the charge and discharge power cannot be positive at the same time as presented in (27). To prevent the non-linearity resulting from (27), the Fortuny-Amat transformation [31] is deployed according to (28) and (29).

$$0 \leq P_{i,t}^{PL,ch} \leq C_i^{PL,ins,ch} \tag{17}$$

$$0 \leq P_{i,t}^{PL,ch} \leq N_{i,t}^{EV,par}(\sum_{cl} P_{cl}^{ch,max} Sh_{cl}) \tag{18}$$

$$0 \leq P_{i,t}^{PL,dc} \leq C_i^{PL,ins,dc} \tag{19}$$

$$0 \leq P_{i,t}^{PL,dc} \leq N_t^{EV,par}(\sum_{cl} P_{cl}^{dc,max} Sh_{cl}) \tag{20}$$

$$N_{i,t}^{EV,par} = N_{i,t-1}^{EV,par} + N_{i,t}^{Ev,arr} - N_{i,t}^{Ev,dep} \tag{21}$$

$$E_{i,t}^{PL,min} \leq E_{i,t}^{PL} \leq E_{i,t}^{PL,max} \tag{22}$$

$$E_{i,t}^{PL,min} = N_{i,t}^{EV,par}(\sum_{cl} Cap_{cl}^{EV} SOC^{min} Sh_{cl}) \tag{23}$$

$$E_{i,t}^{PL,max} = N_{i,t}^{EV,par}(\sum_{cl} Cap_{cl}^{EV} SOC^{max} Sh_{cl}) \tag{24}$$

$$(P_{i,t}^{PL})^2 + (Q_{i,t}^{PL})^2 \leq (S_i^{PL})^2 \tag{25}$$

$$P_{i,t}^{PL} = P_{i,t}^{PL,ch} + P_{i,t}^{PL,dc} \tag{26}$$

$$P_{i,t}^{PL,ch} P_{i,t}^{PL,dc} = 0 \tag{27}$$

$$0 \leq P_{i,t}^{PL,ch} \leq u_t M \tag{28}$$

$$0 \leq P_{i,t}^{PL,dc} \leq (1 - u_t) M \tag{29}$$

3.1.3. DSO-owned DG and RES constraints

The power output of the DG should be within the maximum and minimum amount to satisfy the ramp rate and nominal capacity constraint as indicated in (30), (31), and (32). To take into account the uncertainty of RES generation, the chance-constrained-based formulation presented in [9] is utilized where $\Phi_a(.)$ is the CDF of the standard normal distribution. $P_{i,t}^{RES,f}$ and $\sigma_{i,t}^f$ are the mean and square difference of RES generation forecast, respectively, and η is the confidence level. The derivation of the RES chance-constrained formulation can be found in [9]. Such RES uncertainty modelling based on the chance-constrained formulation makes it an efficient approach for large-scale applications with a high share of RES owing to its low computational burden.

$$P_{i,n}^{DG,min} \leq P_{i,n,t}^{DG} \leq P_{i,n}^{DG,max} \tag{30}$$

$$\Delta_i^{DG,min} \leq P_{i,t}^{DG} - P_{i,t-1}^{DG} \leq \Delta_i^{DG,max} \tag{31}$$

$$(P_{i,t}^{DG})^2 + (Q_{i,t}^{DG})^2 \leq (S_i^{DG})^2 \tag{32}$$

$$0 \leq P_{i,t}^{RES} \leq \bar{P}_{i,t}^{RES,f} + \sigma_{i,t}^f.\Phi_a^- 1(1 - \eta) \tag{33}$$

3.1.4. ESS constraints

The operation of the DSO-owned energy storage system, considering ESS dissipation (γ), serving as a flexibility provider for the distribution system is formulated according to (37) [9]. Eqs. (34) and (35) represent the charging and discharging rate limit of the battery. Moreover, the SOC limit condition of the battery is indicated in (36).

$$0 \leq P_i^{ESS,in} \leq P_i^{ESS,in,max}.\delta_{i,t}^{ESS} \tag{34}$$

$$0 \leq P_i^{ESS,out} \leq P_i^{ESS,out,max}.(1 - \delta_{i,t}^{ESS}) \tag{35}$$

$$E_i^{ESS,min} \leq E_{i,t}^{ESS} \leq E_i^{ESS,max}, \delta_{i,t}^{ESS} \in 0, 1 \tag{36}$$

$$\begin{aligned} E_{i,t}^{ESS} = E_{i,0}^{ESS} &+ \sum_{t=1}^{j} (\gamma^{ESS})^{j,t} \eta_{in}.\Delta T.P_{i,t}^{ESS,in} \\ &- \sum_{t=1}^{j} (\gamma^{ESS})^{j,t} \eta_{out}.\Delta T.P_{i,t}^{ESS,out} \end{aligned} \tag{37}$$

3.2. Lower-level problem

As mentioned beforehand, VPPs in this paper manage the operation of their own assets in response to the active and reactive prices determined by the DSO in the lower level of the proposed bi-level optimization approach. It is noteworthy that according to the VPP definition in the introduction section, in this paper, VPP is the aggregation of different DERs that are directly connected to the same substation in the distribution system. Therefore, in our paper, there does not exist an internal network within VPPs.

3.2.1. VPPs objective function

VPPs schedule the operation of their assets consisting of EVPLs equipped with unidirectional chargers, DG, PV, WP, price-sensitive DR aggregators, flexible loads, and inelastic loads to minimize their cost as presented in (38). The first term in the VPPs' objective function stands for the utility function of the DR aggregators that is estimated with a piecewise linear function indicated in (39) [32]. The second and third terms represents the operation cost of DG and RES, and the last two terms are the cost of trading with the DSO.

$$minC^{i}_{VPP,k} = \Delta T . \sum_{t=1}^{T} -U^{DR}_{k}(P^{DR}_{k,t}) + F^{DG}_{k}(P^{DG}_{k,t}) + c^{RES}_{k} . P^{RES}_{k,t} +$$

$$(\pi^{P}_{k,t} . P^{VPP}_{k,t} + \pi^{Q}_{k,t} . Q^{VPP}_{k,t}) \tag{38}$$

$$U^{DR}_{k}(P^{DR}_{k,t}) = \sum_{n=1}^{N^{DR,seg}_{k}} d_{k,n} . P^{DR}_{k,n,t} \tag{39}$$

3.2.2. Power balance

The active and reactive power balance constraint should be satisfied for each VPP as presented in (40) and (41).

$$P^{VPP}_{k,t} + P^{DG}_{k,t} + P^{RES}_{k,t} = P^{PL}_{k,t} + P^{DR}_{k,t} + P^{AGG}_{k,t} + P^{Fix}_{L,k,t} \;:\; \lambda^{(5)} \tag{40}$$

$$Q^{VPP}_{k,t} + Q^{DG}_{k,t} = Q^{PL}_{k,t} + Q^{DR}_{k,t} + Q^{AGG}_{k,t} + Q^{Fix}_{L,k,t} \;:\; \lambda^{(6)} \tag{41}$$

3.2.3. VPP-owned EV parking lots

Equipping EVPLs with bidirectional EV chargers is very costly for private sectors, and in most cases, the investment cost of bidirectional chargers outweighs the profit resulting from the discharging capability of the bidirectional chargers. Therefore, in this paper, it is assumed that VPP-owned EVPLs are just equipped with unidirectional chargers. As a result, the discharge power of VPP-owned EVPLs is zero, and the output power of VPP-owned EVPLs is equal to EVPL's charge power as shown in (42). Except for the mentioned point, the VPP-owned EVPLs constraints are similar to DSO-owned EVPLs, as represented in (43)–(47). It is noteworthy that $E^{arr}_{k,t}$, $E^{dep}_{k,t}$, $E^{PL,min}_{k,t}$, and $E^{PL,max}_{k,t}$ are obtained similar to the DSO-owned EVPL equations.

$$P^{PL}_{k,t} = P^{PL,ch}_{k,t} \tag{42}$$

$$E^{PL}_{k,t} = E^{PL}_{k,t-1} - E^{dep}_{k,t} + E^{arr}_{k,t} + \Delta t \eta_{ch} P^{PL,ch}_{k,t} \;:\; \lambda^{(8)} \tag{43}$$

$$0 \le P^{PL,ch}_{k,t} \le C^{PL,ins}_{k} \tag{44}$$

$$0 \le P^{PL,ch}_{k,t} \le N^{EV,par}_{k,t}(\sum_{cl} P^{ch,max}_{cl} Sh_{cl}) \;:\; \mu^{(9-)}, \mu^{(9+)} \tag{45}$$

$$E^{PL,min}_{k,t} \le E^{PL}_{k,t} \le E^{PL,max}_{k,t} \;:\; \mu^{(8-)}, \mu^{(8+)} \tag{46}$$

$$(P^{PL}_{k,t})^2 + (Q^{PL}_{k,t})^2 \le (S^{PL}_{k})^2 \tag{47}$$

3.2.4. DG, RES

The operation of VPP-owned DGs and RES is similar to the DSO-owned ones as indicated in (48)–(52).

$$P^{DG}_{k,t} = \sum_{n=1}^{N^{DG,seg}_{k}} P^{DG}_{k,n,t} \;:\; \lambda^{(1)} \tag{48}$$

$$P^{DG}_{k,n,t} \ge P^{DG,min}_{k,n}, P^{DG}_{k,n,t} \le P^{DG,max}_{k,n} \;:\; \mu^{(1-)}, \mu^{(1+)} \tag{49}$$

$$\Delta^{DG,min}_{k} \le P^{DG}_{k,t} - P^{DG}_{k,t-1} \le \Delta^{DG,max}_{k,n} \;:\; \mu^{(7-)}, \mu^{(7+)} \tag{50}$$

$$(P^{DG}_{k,t})^2 + (Q^{DG}_{k,t})^2 \le (S^{DG}_{k})^2 \tag{51}$$

$$0 \le P^{RES}_{k,t} \le \bar{P}^{RES,f}_{k,t} + \sigma^{f}_{k,t} . \Phi^{-}_{a} 1(1-\eta) \;:\; \mu^{(4)} \tag{52}$$

3.2.5. DR aggregator

The operation of the DR aggregator is formulated in (53)–(55) where $\rho_{DR,N}$ is the constant power factor of DR.

$$P^{DR}_{k,n,t} \ge P^{DR,min}_{k,n}, P^{DR}_{k,n,t} \le P^{DR,max}_{k,n} \;:\; \mu^{(3-)}, \mu^{(3+)} \tag{53}$$

$$P^{DR}_{k,t} = \sum_{n=1}^{N^{DR,seg}_{k}} P^{DR}_{k,n,t} \;:\; \lambda^{(2)} \tag{54}$$

$$\zeta_{DR,N} = tan(arccos(\rho_{DR,N})) = \frac{Q^{DR}_{k,t}}{P^{DR}_{k,t}} \;:\; \lambda^{(3)} \tag{55}$$

3.2.6. Flexible load aggregator

Other flexible loads of VPPs are modelled as indicated in (56)–(59).

$$P^{AGG}_{k,t} \ge P^{AGG,min}_{k}, P^{AGG}_{k,t} \le P^{AGG,max}_{k} \tag{56}$$

$$(T^{AGG}_{start,k} \le t \le T^{AGG}_{end,k}) \;:\; \mu^{(5-)}, \mu^{(5+)} \tag{57}$$

$$E^{AGG}_{k} = \Delta T . \sum_{t=T^{AGG}_{start,k}}^{T^{AGG}_{end,k}} P^{AGG}_{k,t} \;:\; \lambda^{(7)} \tag{58}$$

$$\zeta_{AGG,N} = tan(arccos(\rho_{AGG,N})) = \frac{Q^{AGG}_{k,t}}{P^{AGG}_{k,t}} \;:\; \lambda^{(4)} \tag{59}$$

3.2.7. VPP power exchange

VPPs are limited for trading active and reactive power with the DSO due to the limitation of the connecting line (60).

$$(P^{VPP}_{k,t})^2 + (Q^{VPP}_{k,t})^2 \le (S^{VPP}_{k})^2 \tag{60}$$

4. Model simplification

4.1. Linearization of quadratic constraints

The quadratic constraints in the lower level of the problem add non-linearity to the problem which may lead to non-convexity when transforming the bilevel model to the equivalent single-level model. Therefore, the linearization approach presented in [33] is deployed. In this approach, the surrounding of the feasible region of quadratic constraints that is a circle is approximated with a polygon with the desired number of line segments. Therefore, a set of linear constraints stands for the quadratic constraint as presented in (61)–(63).

$$\begin{bmatrix} e^{PL}_{1,1} & e^{PL}_{1,2} \\ \vdots & \vdots \\ e^{PL}_{N_{seg},1} & e^{PL}_{N_{seg},2} \end{bmatrix} \begin{bmatrix} P^{PL}_{k,t} \\ Q^{PL}_{k,t} \end{bmatrix} \le S^{PL}_{k} \begin{bmatrix} f^{PL}_{1} \\ \vdots \\ f^{PL}_{N_{seg}} \end{bmatrix} \;:\; \mu^{(10)} \tag{61}$$

$$\begin{bmatrix} e^{VPP}_{1,1} & e^{VPP}_{1,2} \\ \vdots & \vdots \\ e^{VPP}_{N_{seg},2} & e^{VPP}_{N_{seg},2} \end{bmatrix} \begin{bmatrix} P^{VPP}_{k,t} \\ Q^{VPP}_{k,t} \end{bmatrix} \le S^{VPP} \begin{bmatrix} f^{VPP}_{1} \\ \vdots \\ f^{VPP}_{N_{seg}} \end{bmatrix} \;:\; \mu^{(6)} \tag{62}$$

$$\begin{bmatrix} e^{DG}_{1,1} & e^{DG}_{1,2} \\ \vdots & \vdots \\ e^{DG}_{N_{seg},2} & e^{DG}_{N_{seg},2} \end{bmatrix} \begin{bmatrix} P^{DG}_{t} \\ Q^{DG}_{t} \end{bmatrix} \le S^{DG} \begin{bmatrix} f^{DG}_{1} \\ \vdots \\ f^{DG}_{N_{seg}} \end{bmatrix} \;:\; \mu^{(2)} \tag{63}$$

4.2. Equivalent single-level model of problem

To solve the bilevel optimization problem it is required to convert the problem to a single-level problem. As the lower-level problem is a linear and convex optimization, the process of transforming the bilevel to single-level optimization is done by writing the KKT optimality condition of the lower-level problem as indicated in (64)–(65)

$$\frac{\partial L}{\partial P^{VPP}_{k,t}} = \Delta T . \pi^{P}_{k,t} - \lambda^{(5)}_{k,t} + \sum_{m=1}^{N_{seg}} \mu^{(6)}_{k,m,t} . e^{VPP}_{m,1} \tag{64a}$$

$$\frac{\partial L}{\partial P^{PL,ch}_{k,t}} = \Delta T.\pi^{P}_{k,t} - \Delta T.\lambda^{(8)}_{k,t}.\eta_{ch} + \sum_{m=1}^{N_{seg}} \mu^{(10)}_{k,m,t}.e^{PL}_{m,1} + \mu^{(9+)}_{k,t} - \mu^{(9-)}_{k,t} + \lambda^{(5)}_{k,t} \tag{64b}$$

$$\frac{\partial L}{\partial P^{DG}_{k,t}} = \lambda^{(1)}_{k,t} - \lambda^{(5)}_{k,t} + \sum_{m=1}^{N_{seg}} \mu^{(2)}_{k,m,t}.e^{DG}_{m,1} - \mu^{(7-)}_{k,t} + \mu^{(7+)}_{k,t} + \mu^{(7-)}_{k,t+1} - \mu^{(7+)}_{k,t+1} \tag{64c}$$

$$\frac{\partial L}{\partial P^{DG}_{k,n,t}} = \Delta T.c_{k,n} - \lambda^{(1)}_{k,t} - \mu^{(1-)}_{k,n,t} + \mu^{(1+)}_{k,n,t} \tag{64d}$$

$$\frac{\partial L}{\partial P^{RES}_{k,t}} = \Delta T.c^{(RES)}_{k} - \lambda^{(5)}_{k,t} - \mu^{(4-)}_{k,t} + \mu^{(4+)}_{k,t} \tag{64e}$$

$$\frac{\partial L}{\partial P^{DR}_{k,t}} = \lambda^{(2)}_{k,t} + \lambda^{(3)}_{k,t}\zeta_{DR,N} + \lambda^{(5)}_{k,t} \tag{64f}$$

$$\frac{\partial L}{\partial P^{DR}_{k,n,t}} = -\Delta T.d_{k,n} - \lambda^{(2)}_{k,t} - \mu^{(3-)}_{k,n,t} + \mu^{(3+)}_{k,n,t} \tag{64g}$$

$$\frac{\partial L}{\partial P^{AGG}_{k,t}} = \lambda^{(4)}_{k,t}\zeta_{AGG,N} + \lambda^{(5)}_{k,t} - \lambda^{(7)}_{k}.\Delta T - \mu^{(5-)}_{k,t} + \mu^{(5+)}_{k,t} \tag{64h}$$

$$\frac{\partial L}{\partial Q^{VPP}_{k,t}} = \Delta T.\pi^{Q}_{k,t} - \lambda^{(6)}_{k,t} + \sum_{m=1}^{N_{seg}} \mu^{(6)}_{k,m,t}.e^{VPP}_{m,2} \tag{64i}$$

$$\frac{\partial L}{\partial Q^{PL}_{k,t}} = \Delta T.\pi^{Q}_{k,t} + \sum_{m=1}^{N_{seg}} \mu^{(10)}_{k,m,t}.e^{PL}_{m,2} + \lambda^{(6)}_{k,t} \tag{64j}$$

$$\frac{\partial L}{\partial Q^{DG}_{k,t}} = -\lambda^{(6)}_{k,t} + \sum_{m=1}^{N_{seg}} \mu^{(2)}_{k,m,t}.e^{DG}_{m,2} \tag{64k}$$

$$\frac{\partial L}{\partial Q^{DR}_{k,t}} = -\lambda^{(3)}_{k,t} + \lambda^{(6)}_{k,t} \tag{64l}$$

$$\frac{\partial L}{\partial Q^{AGG}_{k,t}} = -\lambda^{(4)}_{k,t} + \lambda^{(6)}_{k,t} \tag{64m}$$

$$\frac{\partial L}{\partial E^{PL}_{k,t}} = \lambda^{(8)}_{k,t} - \lambda^{(8)}_{k,t+1} - \mu^{(8-)}_{k,t} + \mu^{(8+)}_{k,t} \tag{64n}$$

$$P^{DR}_{k,t} + P^{AGG}_{k,t} + P^{Fix}_{L,k,t} + P^{PL,ch}_{k,t} - P^{VPP}_{k,t} - P^{DG}_{k,t} - P^{RES}_{k,t} = 0 \tag{65a}$$

$$Q^{DR}_{k,t} + Q^{AGG}_{k,t} + Q^{Fix}_{L,k,t} + Q^{PL}_{k,t} - Q^{VPP}_{k,t} - Q^{DG}_{k,t} = 0 \tag{65b}$$

$$P^{DG}_{k,t} - \sum_{n=1}^{N^{DG,seg}_{k}} P^{DG}_{k,n,t} = 0 \tag{65c}$$

$$P^{DR}_{k,t} - \sum_{n=1}^{N^{DR,seg}_{k}} P^{DR}_{k,n,t} = 0 \tag{65d}$$

$$\zeta_{DR,N}.P^{DR}_{k,t} - Q^{DR}_{k,t} = 0 \tag{65e}$$

$$zeta_{AGG,N}.P^{AGG}_{k,t} - Q^{AGG}_{k,t} = 0 \tag{65f}$$

$$E^{AGG}_{k} - \Delta T.\sum_{t=T^{AGG}_{start,k}}^{T^{AGG}_{end,k}} P^{AGG}_{k,t} = 0 \tag{65g}$$

$$SOE^{PL,min}_{k,t} - E^{PL}_{k,t} \leq 0 \tag{66a}$$

$$E^{PL}_{k,t} - SOE^{PL,max}_{k,t} \leq 0 \tag{66b}$$

$$-\ P^{PL}_{k,t} \leq 0 \tag{66c}$$

$$P^{PL}_{k,t} - P^{ch,PL,max}_{k,t} \leq 0 \tag{66d}$$

$$P^{DG,min}_{k,n} - P^{DG}_{k,n,t} \leq 0 \tag{66e}$$

$$P^{DG}_{k,n,t} - P^{DG,max}_{k,n} \leq 0 \tag{66f}$$

$$\Delta^{DG,min}_{k} - P^{DG}_{k,t} - P^{DG}_{k,t-1} \leq 0 \tag{66g}$$

$$P^{DG}_{k,t} - P^{DG}_{k,t-1} - \Delta^{DG,max}_{k,n} \leq 0 \tag{66h}$$

$$-\ P^{RES}_{k,t} \leq 0 \tag{66i}$$

$$P^{RES}_{k,t} - \bar{P}^{RES}_{k,t} + \sigma^{f}_{k,t}.\Phi^{-}_{a}1(1-\eta) \leq 0 \tag{66j}$$

$$P^{DR,min}_{k,n} - P^{DR}_{k,n,t} \leq 0 \tag{66k}$$

$$P^{DR}_{k,n,t} - P^{DR,max}_{k,n} \leq 0 \tag{66l}$$

$$P^{AGG,min}_{k} - P^{AGG}_{k,t} \leq 0 \tag{66m}$$

$$P^{AGG}_{k,t} - P^{AGG,max}_{k} \leq 0 \tag{66n}$$

$$e^{DG}_{m,1}.P^{DG}_{k,m,t} + e^{DG}_{m,2}.Q^{DG}_{k,m,t} - S^{DG}_{k,N}.f^{DG}_{m} \leq 0 \tag{66o}$$

$$e^{VPP}_{m,1}.P^{VPP}_{k,m,t} + e^{VPP}_{m,2}.Q^{VPP}_{k,m,t} - S^{VPP}_{k,N}.f^{VPP}_{m} \leq 0 \tag{66p}$$

$$\mu^{(8-)}_{k,t}.(SOE^{PL,min}_{k,t} - E^{PL}_{k,t}) = 0 \tag{67a}$$

$$\mu^{(8+)}_{k,t}.(E^{PL}_{k,t} - SOE^{PL,max}_{k,t}) = 0 \tag{67b}$$

$$\mu^{(9-)}_{k,t}.P^{PL}_{k,t} = 0 \tag{67c}$$

$$\mu^{(9+)}_{k,t}.(P^{PL}_{k,t} - P^{ch,PL,max}_{k,t}) = 0 \tag{67d}$$

$$\mu^{(1-)}_{k,n,t}.(P^{DG,min}_{k,n} - P^{DG}_{k,n,t}) = 0 \tag{67e}$$

$$\mu^{(1+)}_{k,n,t}.(P^{DG}_{k,n,t} - P^{DG,max}_{k,n}) = 0 \tag{67f}$$

$$\mu^{(7-)}_{k,t}.(\Delta^{DG,min}_{k} - P^{DG}_{k,t} + P^{DG}_{k,t-1}) = 0 \tag{67g}$$

$$\mu^{(7+)}_{k,t}.(P^{DG}_{k,t} - P^{DG}_{k,t-1} - \Delta^{DG,max}_{k,n}) = 0 \tag{67h}$$

$$\mu^{(4-)}_{k,t}.(-P^{RES}_{k,t}) = 0 \tag{67i}$$

$$\mu^{(4+)}_{k,t}.(P^{RES}_{k,t} - \bar{P}^{RES}_{k,t} + \sigma^{f}_{k,t}.\Phi^{-}_{a}1(1-\eta)) = 0 \tag{67j}$$

$$\mu^{(3-)}_{k,n,t}.(P^{DR,min}_{k,n} - P^{DR}_{k,n,t}) = 0 \tag{67k}$$

$$\mu^{(3+)}_{k,n,t}.(P^{DR}_{k,n,t} - P^{DR,max}_{k,n}) = 0 \tag{67l}$$

$$\mu^{(5-)}_{k,t}.(P^{AGG,min}_{k} - P^{AGG}_{k,t}) = 0 \tag{67m}$$

$$\mu^{(5+)}_{k,t}.(P^{AGG}_{k,t} - P^{AGG,max}_{k}) = 0 \tag{67n}$$

$$\mu^{(2)}_{k,m,t}.(e^{DG}_{m,1}.P^{DG}_{k,m,t} + e^{DG}_{m,2}.Q^{DG}_{k,m,t} - S^{DG}_{k,N}.f^{DG}_{m}) = 0 \tag{67o}$$

$$\mu^{(6)}_{k,m,t}.(e^{VPP}_{m,1}.P^{VPP}_{k,m,t} + e^{VPP}_{m,2}.Q^{VPP}_{k,m,t} - S^{VPP}_{k,N}.f^{VPP}_{m}) = 0 \tag{67p}$$

$$\mu^{(10)}_{k,m,t}.(e^{PL}_{m,1}.P^{PL}_{k,m,t} + e^{PL}_{m,2}.Q^{PL}_{k,m,t} - S^{PL}_{k,N}.f^{PL}_{m}) = 0 \tag{67q}$$

$$\mu^{(1-)}_{k,n,t}, \mu^{(1+)}_{k,n,t}, \mu^{(2)}_{k,m,t}, \mu^{(3-)}_{k,n,t}, \mu^{(3+)}_{k,n,t}, \mu^{(4-)}_{k,t}, \mu^{(4+)}_{k,t}, \mu^{(5-)}_{k,t}, \mu^{(5+)}_{k,t}, \mu^{(6)}_{k,m,t}, \mu^{(7-)}_{k,t}, \mu^{(7+)}_{k,t}, \mu^{(8-)}_{k,t}, \mu^{(8+)}_{k,t}, \mu^{(9-)}_{k,t}, \mu^{(9+)}_{k,t}, \mu^{(10)}_{k,m,t} \geq 0 \tag{68}$$

It is worth mentioning that $\lambda^{(1-8)}$ are the Lagrange multiplier of the equality constraints (48), (54), (55), (59), (40), (41), (58), and (43), respectively. Moreover, $\mu^{(1-10)}$ are corresponding to inequality constraints (49), (63), (53), (52), (57), (62), (50), (46), (45), and (61). Therefore, (38)–(60) are replaced with the constraints resulting from the KKT condition presented in (64)–(68) and a single-level optimization is shaped to be solved.

4.3. Removing the non-linearity resulted from bilinear terms in constraints

To discard the non-linearity of bilinear terms in (67) and (27), the Fortuny-Amat transformation presented in [31] is deployed.

4.4. Bilinear terms in objective function

The objective function of the equivalent single-level problem consists of bilinear terms ($k^{P}_{t}P^{DN}_{t}$ and $k^{Q}_{t}Q^{DN}_{t}$) in which two variables of the problem are multiplied. Indeed, P^{DN}_{t} and Q^{DN}_{t} are the parameters of the upper-level problem and decision variables of the lower-level problem. However, when transforming the bilevel optimization to the single-level optimization, it is a decision variable of the equivalent single-level problem. Therefore, via the strong duality theorem, the dual objective function of the lower-level problem is used instead of the bilinear terms as represented in (69).

$$\Delta T.\sum_{t=1}^{T}(\pi^{P}_{k,t}.P^{VPP}_{k,t} + \pi^{Q}_{k,t}.Q^{VPP}_{k,t}) = \Delta T.\sum_{t=1}^{T}$$

$$
\begin{aligned}
&(U_k^{DR}(P_{k,t}^{DR}) - F_k^{DG}(P_{k,t}^{DG}) - c_k^{RES}.P_{k,t}^{RES}) + C_{VPP,k}^{i}\\
&= \Delta T.\sum_{t=1}^{T}(\sum_{n=1}^{N_k^{DR,seg}} d_{k,n}.P_{k,n,t}^{DR}\\
&- \sum_{n=1}^{N_i^{DG,seg}} c_{i,n}.P_{i,n,t}^{DG} - c_k^{RES}.P_{k,t}^{RES})\\
&+ \sum_{t=1}^{T}\lambda_{k,t}^{(5)}P_{L,k,t}^{Fix} + \sum_{t=1}^{T}\lambda_{k,t}^{(6)}Q_{L,k,t}^{Fix}\\
&+ \lambda_k^{(7)}E_k^{AGG} + \sum_{t=1}^{T}\lambda_{k,t}^{(8)}(E_{k,t}^{arr} - E_{k,t}^{dep})\\
&+ \sum_{t=1}^{T}\sum_{n=1}^{N_k^{DG,seg}} \mu_{k,n,t}^{(1-)}.P_{k,n}^{DG,min} + \mu_{k,n,t}^{(1+)}.(-P_{k,n}^{DG,max})\\
&+ \sum_{t=1}^{T}\sum_{n=1}^{N_{seg}} \mu_{k,m,t}^{(2)}(-S_{k,N}^{DG} f_m^{DG})\\
&+ \sum_{t=1}^{T}\sum_{n=1}^{N_k^{DR,seg}} \mu_{k,n,t}^{(3-)}.P_{k,n}^{DR,min} + \mu_{k,n,t}^{(3+)}.(-P_{k,n}^{DR,max})\\
&+ \sum_{t=1}^{T}\mu_{k,t}^{(4+)}.(-\bar{P}_{k,t}^{RES} + \sigma_{k,t}^{f}.\Phi_a^{-}1(1-\eta))\\
&+ \sum_{t=T_{start,k}^{AGG}}^{T_{end,k}^{AGG}} \mu_{k,t}^{(5-)}.(P_k^{AGG,min}) + \mu_{k,t}^{(5+)}.(-P_k^{AGG,max})\\
&+ \sum_{t=1}^{T}\sum_{n=1}^{N_{seg}} \mu_{k,m,t}^{(6)}(-S_{k,N}^{VPP} f_m^{VPP})\\
&+ \sum_{t=2}^{T}\mu_{k,t}^{(7-)}.\Delta_k^{DG,min} + \mu_{k,t}^{(7+)}.(-\Delta_{k,n}^{DG,max})\\
&+ \sum_{t=1}^{T}\mu_{k,t}^{(8-)}.SOE_{k,t}^{PL,min} + \mu_{k,t}^{(8+)}.(-SOE_{k,t}^{PL,max})\\
&+ \sum_{t=1}^{T}\mu_{k,t}^{(9+)}.(-P_{k,t}^{ch,PL,max})\\
&+ \sum_{t=1}^{T}\sum_{n=1}^{N_{seg}} \mu_{k,m,t}^{(10)}(-S_{k,N}^{PL} f_m^{VPP}) \qquad (69)
\end{aligned}
$$

By replacing (69) with the mentioned bilinear term in the objective function of the upper-level problem (1), a linear optimization problem is obtained that can be handled with mixed integer linear programming (MILP). The MILP problem is solved via Gorubi solver in Python.

5. Simulation results

5.1. Case study

We used the case study described in [9] as a basis for our research. However, a modification is made to the system by integrating EVPLs, as shown in Fig. 2. The location of the RES, DG, and VPPs is similar to the real-case distribution system used in [9]. However, the EVPLs are placed randomly in different buses of the system. This paper considers the presence of 10 classes of EVs with the characteristics including the battery capacity, arrival SOC, and maximum charging power of EVs outlined in Table 2, each with an equal share. Moreover, SOC_{cl}^{dep} of all EV classes are 0.85 and for DSO-owned EVPLs $P_{cl}^{dc,max}$ is equal to $P_{cl}^{ch,max}$. Additionally, as mentioned in the previous section, the uncertainty of the arrival and departure of EVs is modelled via TND. The parameters of the TND for arrival and departure are defined in Table 3. Furthermore, the values for the characteristics of the chance-constrained formulation of the uncertain available RES power are as follows: $\sigma_{i,t}^{f}$ is 10% of the forecasted RES power at that hour, and η is equal to 0.9. It is assumed that all EVPLs consist of 300 charging stations. Python is used for programming and Gurobi solver is utilized for solving the optimization problem, which is formulated as a Mixed-Integer Linear Programming (MILP) problem.

Table 2
EV classes and characteristics.

cl	1	2	3	4	5	6	7	8	9	10
Cap_{cl}	15	20	20	15	20	15	10	10	15	20
SOC_{cl}^{arr}	0.33	0.33	0.16	0.4	0.1	0.45	0.5	0.2	0.33	0.2
$P_{cl}^{ch,max}$	7	10	10	7	10	7	5	5	7	10

Table 3
TND characteristics of EVLPS.

	Min	Max	Average	Standard deviation
Arrival	5	17	8	3
Departure	11	24	16	3

5.2. Operation results of the DSO

As stated in previous sections, the DSO is in charge of determining the operation schedule of its assets. Fig. 3 shows the active and reactive power of DSO-owned DGs as well as the output power and state of energy of DSO-owned ESS. This way, the charging and discharging of the ESS system is managed based on the power price where charging is scheduled in the low-price hours and discharging is scheduled in high-price hours. Moreover, the operation of the DGs is managed based on the system's needs to provide active and reactive power in the bus where DGs are located. It is noteworthy that the active and reactive power of each DG is constrained by its rated capacity where the output active and reactive power generation is linked together. Furthermore, the available and scheduled power of DSO-owned RES is shown in Fig. 4(a) and (b). It is observed that, in all hours, the complete available RES generation is deployed. The output power and the containing energy of the DSO-owned EVPLs are depicted in Fig. 6(a) and (c), respectively. It is observed that, owing to the bidirectional EV chargers, EVPLs can operate the EVs in the V2G mode when required. In this way, EVPL 3, tend to deploy the V2G mode more than the others because of the system needs and lack of crucial grid limitation in bus 3. It should be noted that the discharging and charging profile that results in the containing energy of the EVPL satisfies the arrival and departure pattern of the EVs where the departed EVs are fully charged (with their desired SOC) upon their departure.

As mentioned in the previous sections, DSO, in addition to managing its flexible resources, is in charge of determining active and reactive power prices in the distribution system, as shown in Fig. 5(a) and (b). In this regard, the DSO is able to define different prices for VPPs located in different parts of the distribution system based on the nodal pricing scheme. This way, it is observed that the prices for different VPPs are different. The reason behind this price difference is that the distribution system prefers to have different amounts of active and reactive power in different parts of the system from VPPs due to the dissimilar generation and consumption profiles and grid constraints. In this regard, by determining different prices, the DSO motivates VPPs to operate according to the DSO's desired state. This way, the DSO has a sort of indirect control over VPPs' operation. The stable and reliable system operation is ensured as shown in Fig. 8 where the voltage and power flow all over the grid is within the permitted range.

5.3. Operation results of VPPs

Besides active power, VPPs also consume reactive power. However, owing to the DGs and EVPLs they can also provide positive (consumption) or negative (injection) reactive power for the system. This way,

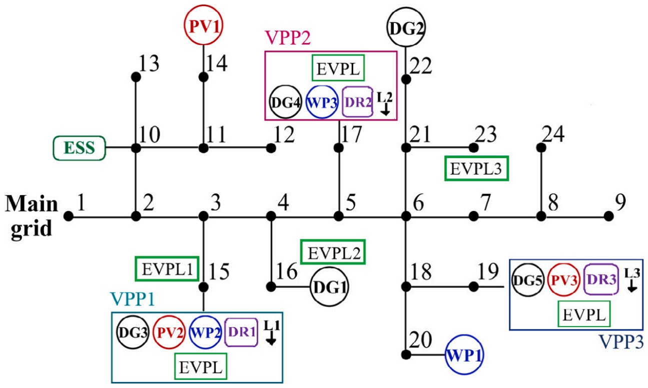

Fig. 2. Studied system.

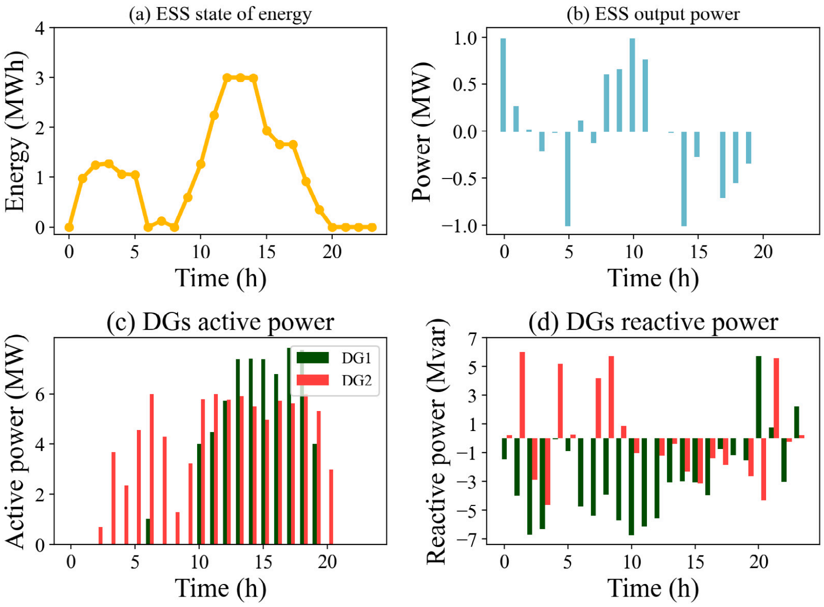

Fig. 3. Operation of DSO-owned assets.

they can benefit from this capability in the reactive market. This way, VPPs, by managing the active and reactive power of their flexible resources and loads, optimize their participation in active and reactive markets at once to have the minimum overall cost as shown in Fig. 5(c) and (d). It is worth mentioning that the limited nominal capacity of their assets links the active and reactive power management of VPPs. This way, the consumption and generation of the VPP-owned assets are scheduled according to the hourly active and reactive prices defined by the DSO. In the results, it is observed that all VPPs can deploy the whole available power of their RES without curtailment, as shown in Fig. 4(c), (d), and (e). Furthermore, the charging power and containing energy of VPP-owned EVPLs are shown in Fig. 6(b) and (d). Despite the DSO-owned EVPLS, VPP-owned EVPLs can just operate in the G2V charging mode as they are equipped with unidirectional EV chargers. The results show that the charging profile of the EVPLs is different for different VPPs as a result of the different active and reactive power prices as well as different operational limits.

5.4. Impact of the nodal pricing of local reactive and active power market

The DSO can define a unique price for VPPs all over the distribution system or determine the prices via nodal pricing where the price for active and reactive power is different for VPPs located in different buses. Table 4 presents the DSO cost in different cases for local active and reactive market pricing scheme. The lowest DSO cost is obtained when both active and reactive power prices are based on nodal pricing as depicted in Fig. 7. When just the active power price is determined based on the nodal pricing and a unique price is determined for reactive power there is 156 € increase in the DSO's cost. The DSO's cost when a unique price is determined for the active power of VPPs is 298

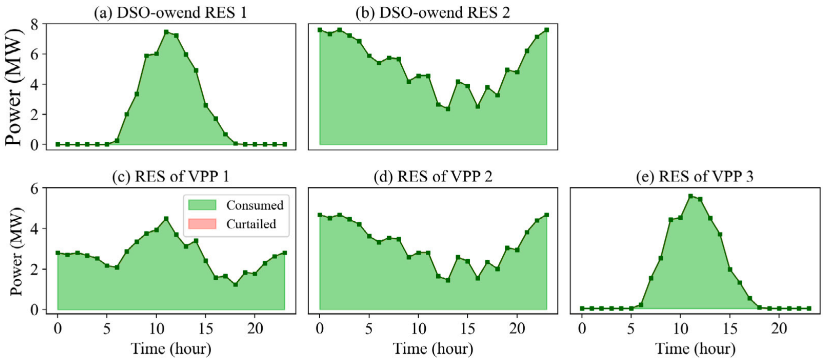

Fig. 4. RES curtailment.

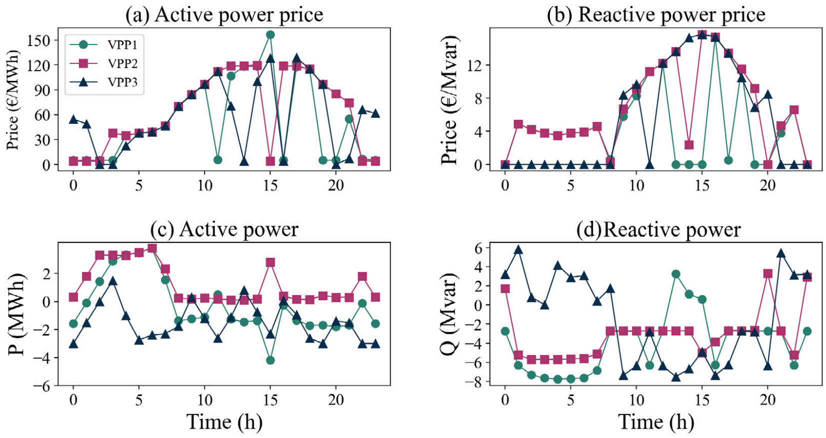

Fig. 5. Reactive and active power price for different VPPs and their consumption.

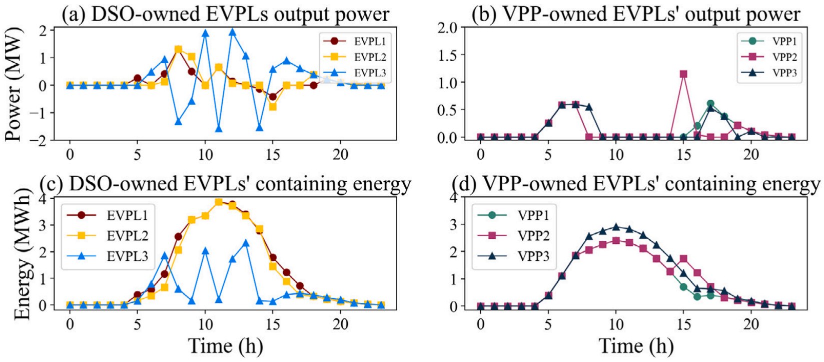

Fig. 6. The power output and containing the energy of VPP-owned EVPLs.

€ higher than case A. Finally, when none of the active and reactive power prices are determined by nodal pricing, the DSO's cost is 462 € higher than case A. The results show the effectiveness of our local market clearing via nodal pricing scheme in decreasing the cost of the distribution system. In other words, deploying the presented nodal pricing scheme for both the active and reactive power prices results in 462 € cost decrease for the DSO which is equivalent to around 4.6% profit compared to the case when nodal pricing scheme is not deployed.

Table 4
Cost of the DSO in cases A, B, C, and D (€).

Case	Nodal pricing in LAPM	Nodal pricing in LRPM	DSO cost
Case A	✓	✓	9512
Case B	✓	✘	9668
Case C	✘	✓	9810
Case D	✘	✘	9974

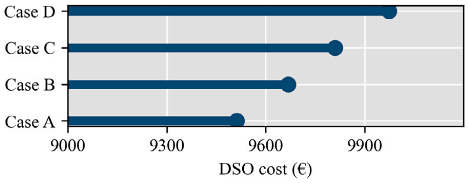

Fig. 7. Cost of the DSO in cases A, B, C, and D (€).

Table 5
Cost of the DSO in cases 1, 2, 3, and 4 (€).

Case	Reactive power	V2G charging	DSO cost
Case 1	✘	✘	9741
Case 2	✘	✓	9513
Case 3	✓	✘	9289
Case 4	✓	✓	9143

5.5. Impact of V2G charging and reactive power support from DSO-owned EVPLs

In almost all problems regarding the distribution system management, both voltage and line power constraints are established with identical limits. Nevertheless, the influence of these constraints on restricting the optimal operating point varies depending on the approach. Deploying RPS and employing V2G operation alleviate the impact of voltage and line power constraints on the optimal operating point. This is evident in the reduced overall cost of the distribution system. Deploying V2G charging from EVPLs is beneficial for the DSO according to the simulation results as presented in Table 5. It is observed that the DSO cost in case 2 where the DSO-owned EVPL can operate in V2G charging is around 2.34% less than in case 1 where the EVPL can only operate in G2V mode. Moreover, the benefit of deploying reactive power provision by EVPLs for the DSO is understood by comparing the cost of DSO for cases 1 and 3. The results show that RPS from DSO-owned EVPLs can decrease the DSO's cost by around 4.64%. It is shown that the DSO by deploying the V2G charging and RPS capability, as stated in case 4, can reduce its cost by 598 € which is equal to around 6.14% profit compared to case 1. Besides reducing the DSO's cost, RPS from EVPLs can improve the operational condition of the network in terms of voltage and branch flow. Voltage and branch flow of the system with and without RPS from DSO-owned EVPLs are shown in Figs. 8 and 9, respectively.

In order to gain a deeper comprehension of how RPS from EVPLs improves the system operation, the voltage of bus 17 (as one of the critical buses when there is a lack of RPS from DSO-owned EVPLs) has been depicted in Fig. 10(a). It is observed how RPS from EVPLs can improve the voltage of this bus by decreasing its difference with the reference voltage (equal to 1 pu). Moreover, by comparing the power flow of the line between the DS and upstream grid for the systems with and without RPS from EVPLS depicted in Fig. 10(a), it is observed that RPS via voltage improvement within the network allows for deploying a higher capacity of the line to increase the trade with the upstream grid in both directions that leads to decreasing the DS cost. This way, enhanced voltage condition alleviates constraints on determining active power consumption/generation resulting in facilitating increased trade with the upstream grid.

Table 6
Cost of VPPs in cases α, β, and γ (€).

Case	VPP1 cost	VPP2 cost	VPP3 cost
Case α	−3331	−4852	−3198
Case β	−2358	−5392	−3382
Case γ	−2842	−4562	−4128

To further investigate the role of RPS from DSO-owned EVPLs in improving the system voltage, another analysis is conducted in this section. As stated above, voltage constraint restricts the DSO from making the optimal decision for the system which leads to higher cost. Therefore, in cases where the voltage constraint is alleviated, the system could be operated with less cost. However, the overall voltage deviation within the network is increased by alleviating the voltage constraint. To evaluate the total voltage deviation within the DS, the voltage deviation (VD) index below is used that measures the summation of the absolute value of the difference between the bus voltage and reference voltage for all buses and hours as presented in Eq. (70). Our results show that with having RPS from EVPLs, when the maximum allowed voltage deviation is 0.05 (upper voltage limit equal to 1.05 and lower voltage limit equal to 0.95), the system cost is 9143 and the VD index is 16.73. However, in the case that there is no RPS from EVPLs, to have the system operation cost equal to 9143, the maximum allowed voltage deviation must be 0.0637 (upper voltage limit equal to 1.0637 and lower voltage limit equal to 0.9363) with a VD equal to 19.961. Therefore, by deploying RPS from DSO-owned EVPL's maximum allowed voltage deviation of the system could be reduced by 18%.

$$VD = \sum_{t} \sum_{bus} |V_i - 1| \tag{70}$$

5.6. Reactive power support from VPP-owned EVPLs

When EVPLs cannot provide positive and negative reactive power, the pricing strategy of the DSO differs. As a consequence, the response (scheduled active and reactive power) of VPPs varies as shown in Fig. 11. Comparing Fig. 12 and Fig. 4 shows the role of reactive power from EVPLs in improving the system operation and RES utilization. It is seen that when EVPLs can provide reactive power, there is no RES curtailment. This way, EVs that generally can make operational challenges for the DSO, improve the system operation by providing RPS. In this regard, three cases α, β, and γ are introduced to assess the benefit of reactive power provision capability for each VPP based on the VPP's cost in the cases, as outlined in Table 6. In case α, except EVPL of VPP1, none of the EVPLs in the system can provide reactive power. In case β among all EVPLs only EVPL of VPP2 can provide reactive power, and in case γ, only the EVPL of VPP3 can provide reactive power. The results show that in case α, the cost of VPP1 is lower compared to case β and case γ. Likewise, the VPP2 and VPP3 have a lower cost in the scenarios where their EVPL is the reactive power provider. However, the benefit from the reactive power capability of EVPLs is different for each VPP according to their location and the distribution system's need for the reactive power in that bus.

5.7. Discussion on opportunities and obstacles

It is essential to recognize the limitations of such a centralized approach and potential obstacles to their implementation in real systems. Challenges include the unpredictable behaviour of VPP participants, ensuring secure access to their data, and the necessity of making optimal decisions promptly, especially for real-time applications. As delineated, the primary objective of this paper is just to design the local active and reactive power market fostering the engagement of VPPs in providing services geared towards enhancing the operation and economic

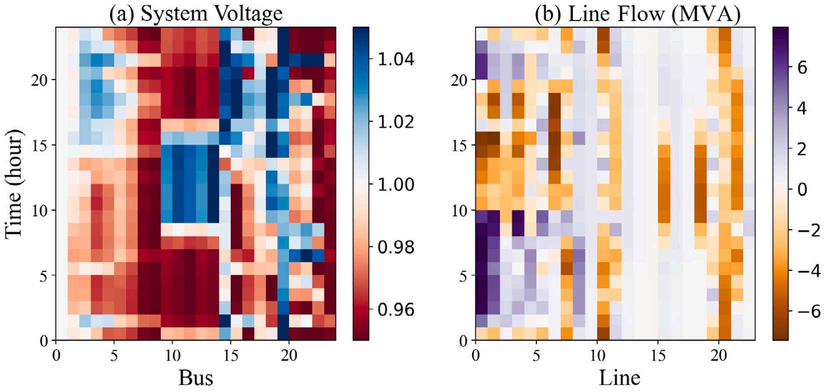

Fig. 8. Voltage and line power of the system.

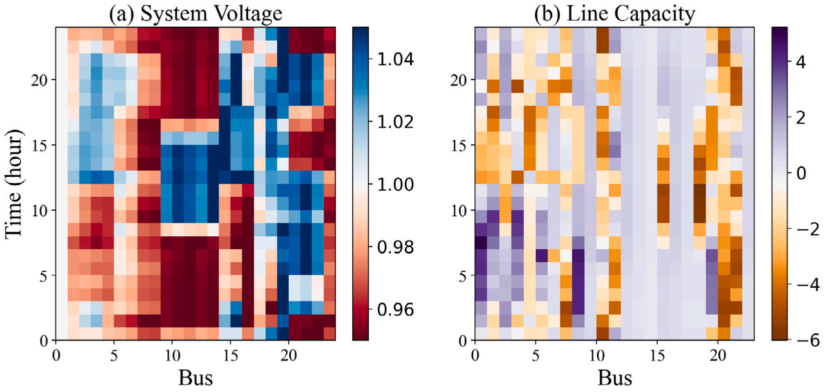

Fig. 9. Voltage and line power of the system without RPS from EVPLs.

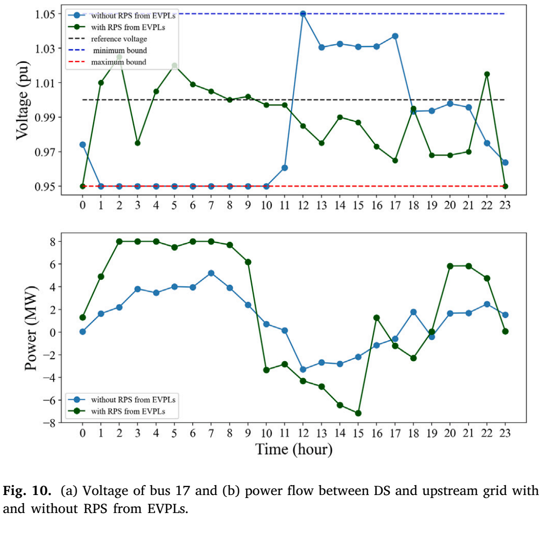

Fig. 10. (a) Voltage of bus 17 and (b) power flow between DS and upstream grid with and without RPS from EVPLs.

efficiency of ADN, focusing on the pricing mechanism within the day-ahead stage. It is imperative, however, to acknowledge that the power market constitutes a multifaceted research domain, encompassing diverse temporal scales, a variety of commodities, and communication considerations. The proposed methodology in this paper addresses the complexity of a bilevel optimization problem, involving uncertain variables, by transforming it into a deterministic MILP formulation. This transformation is achieved through the utilization of effective uncertainty modelling techniques for EVs and RES, coupled with various simplification methods. While the application of this framework is tailored for the day-ahead stage, where real-time responsiveness is not critical, it nevertheless provides fast responses, rendering it a suitable approach for large-scale systems and real-time applications. In this context, our future work will concentrate on extending the framework to couple the real-time market with the day-ahead market, encompassing services such as active and reactive power for reserve. However, the implementation of such a framework mandates a communication infrastructure ensuring the secure and efficient transmission of transaction signals during the real-time stage.

6. Conclusions

This paper proposed a bilevel optimization programming for optimal management of the distribution system based on the interaction of the DSO and the strategic VPPs through the local active and reactive power markets. The bilevel model consisting of the DSO's problem at

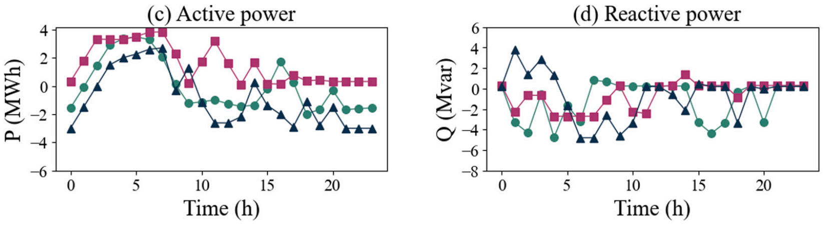

Fig. 11. Reactive and active power for different VPPs without RPS from EVPLs.

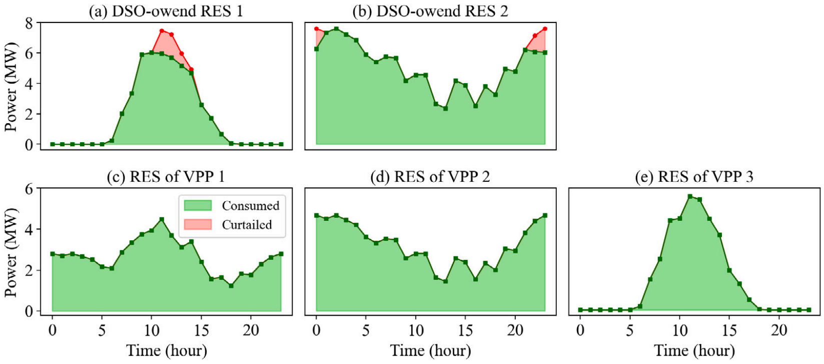

Fig. 12. RES curtailment without RPS from EVPLs.

the upper level and VPPs' problem at the lower level was transformed into a single-level optimization problem using KKT optimality conditions. Then using the strong duality theorem, piecewise linearization, and Fortuny-Amat transformation the problem was handled as a MILP problem. In this regard, it was observed that our proposed framework could ensure the optimal and stable operation of the distribution system. Our results showed that the nodal pricing scheme where the DSO defines different prices for the active and reactive power of VPPs, resulted in the lower distribution system cost. The result showed how the bidirectional EV chargers could be beneficial for the DSO to make a profit from V2G mode charging. Besides the DSO, VPPs could also benefit from the presented local market framework where their assets were scheduled based on the active and reactive prices determined by the DSO to minimize their cost strategically. In addition, the results showed that VPPs could utilize RPS from their EVPLs to reduce their cost by gaining profit in the reactive power market and facilitating their participation in the active power market via improving the local operational condition in terms of voltage and branch flow. For future work, in addition to the active and reactive power market in the day ahead stage, the role of the flexibility market will also be investigated to achieve more efficient management for the DSO.

CRediT authorship contribution statement

Mahoor Ebrahimi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mahan Ebrahimi:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Miadreza Shafie-khah:** Investigation, Conceptualization, Supervision, Writing – review & editing. **Hannu Laaksonen:** Conceptualization, Supervision, Writing – review & editing.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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Research papers

Uncertainty-observed virtual battery model for an electric vehicle parking lot enabling charger-sharing modelling

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ABSTRACT

With the increase in the penetration of electric vehicles (EVs), there is a substantial need for a proper solution to meet the EVs' charging demand. Due to the high investment cost of charging stations, the efficient operation of EV chargers is crucial. In this regard, in this paper, charger-sharing charging has been proposed to charge multiple EVs with a single EV charger. However, the existing models cannot model uncertain EV parking lots (EVPLs) with charger-sharing charging. In addition, most presented methods for uncertainty modelling of EVPLs are hard to implement in planning and large-scale system-level studies due to their complicated process and high computational burden. Therefore, in this paper, a virtual battery model has been proposed to model an EVPL enabling the charger-sharing charging modelling considering the uncertainty of arrival and departure. Our proposed approach models the EVPL as a battery with time-variant parameters obtained from EVs' arrival and departure patterns. The proposed virtual battery model has been validated by comparing its performance on day-ahead (DA) and real-time (RT) power market participation of a 24-bus distribution system owning 12 EVPLs with the scenario-based method. The results show that its performance is similar to scenario-based uncertainty modelling while its computational burden is around 2.24% of the scenario-based model. In addition, the results indicate how by employing our proposed charging-sharing charging, EVPLs can dramatically increase their profit as a result of increasing the number of hosted EVs. In this context, a sufficiently high charging tariff motivates the EVPL owner to accommodate a substantial number of EVs. With only 200 EV chargers, the EVPL can host approximately 3200 EVs, given the characteristics of EVs and EV chargers outlined in the case study section. In contrast, the exclusive charger approach allows only 200 EVs to enter the parking facility and undergo charging.

1. Introduction

1.1. Motivation

The increasing penetration of EVs in recent years makes it a principal factor in the operational and planning decisions on energy and energy-related sectors [1]. In this regard, studying the optimal operation and planning of EV charging facilities and infrastructures such as EV Parking Lots (EVPLs) and charging stations is of undeniable importance [2]. This way, the performance of the EV charging stations could be studied from different points of view; such as EV owners, parking lot or charging station owners, power system operators, potential investors, and policymakers [3]. Studies that try to model EVs from the point of view of EV owner deal with a single EV charging modelling as EV owners own single EV [4]. However, for studying EV-related problems from other agents' points of view, it is crucial to have a proper model for the aggregation of EVs such as EVPLs. In this regard, there are several papers that tried to provide a model that simulates the operation of EV aggregation. In [5], a storage model is presented to model the charging of an EVPL. In this study, the historical data of an existing parking lot is utilized to obtain the parameters of the equivalent storage model.

1.2. Research literature

In modelling electric vehicles, there are uncertain parameters such as arrival and departure time. However, some papers in the field neglected uncertainty, mainly for the sake of simplicity, to allow for the deployment of straightforward and low-computational burden approaches. For instance, Authors in [6] proposed an approach for optimal scheduling of an EV aggregator for determining charge and discharge strategy. The presented model for the EV aggregator is similar to [5] without considering uncertainty. Ref. [7] proposes an approach

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Nomenclature

Indices

cl	EV class
t	Time
w_{EV}	Scenario for arrival and departure of EVs in the scenario-based approach.
w_{RCEV}	Scenario for arrival and departure of EVs in realization.
w_{RCrt}	Scenario for RT electricity price in realization.
w_{rt}	Scenario for RT electricity price in the scenario-based approach.

Parameters

Δt	Duration of time period.
η_{ch}	Charging efficiency.
η_{dc}	Discharging efficiency.
λ_t^{DA}	DA electricity price at time t [€/kW].
$\lambda_{w,t}^{pur,rt}$	RT purchasing price at scenario w time t [€/kW].
$\lambda_{w,t}^{sell,rt}$	RT selling price at scenario w time t [€/kW].
$C_{ins}^{PL,ch}$	Total charging capacity of the installed EV chargers [kWh].
Cap_{cl}^{Ev}	Battery capacity of the EV class cl [kWh].
Sh_{cl}	Share of EVs class cl from all available EVs.
SOC_{cl}^{arr}	Arriving SOC of the EVs class cl.
SOC_{cl}^{dep}	Departing SOC of the EVs class cl.

Variables

E_t^{arr}	Added energy to EVPL due to EVs arrival at time t [kWh].
E_t^{dep}	Depleted energy from EVPL due to EVs departure at time t [kWh].
E_t^{PL}	EVPL stored energy in time t [kWh].
$E_{w,t}^{PL}$	EVPL stored energy in real time for scenario w [kWh].
$N^{EV,ent}$	Number of total arrived EVs in a day.
$N_t^{Ev,arr}$	Number of arrived EVs at time t.
$N_t^{Ev,dep}$	Number of departed EVs at time t.
$P_{cl}^{ch,max}$	Maximum charging power of the EVs class cl [kW].
$P_{cl}^{ch,min}$	Minimum charging power of the EVs class cl [kW].
$P_{cl}^{dc,max}$	Maximum discharging power of the EVs class cl [kW].
$P_{cl}^{dc,min}$	Minimum discharging power of the EVs class cl [kW].
$P_i/Q_i/V_i/\theta_i$	Active/reactive power injection/voltage amplitude/angle of bus i
$P_t^{DA,sc}$	EVPL scheduled power in DA stage at time t [kW].
$P_t^{PL,ch}$	Charging power of EVPL at time t [kW].
$P_t^{PL,dc}$	Discharging power of EVPL at time t [kW].
$P_{w,t}^{sell,rt}$	Purchasing power of EVPL in real time for scenario w [kW].
$P_{w,t}^{sell,rt}$	Selling power of EVPL in real time for scenario w [kW].

for optimal participation of an EVPL-owned microgrid in the energy and reserve market without considering EV uncertainties. EVPL modelling in this work is based on a single EV model. Ref. [8] proposed an approach for load scheduling of EVs to reduce their charging cost by optimally providing ancillary service for the grid. The uncertainty of the arrival and departure time of EVs has been neglected because of the deterministic formulation of the problem. However, neglecting uncertainty will result in unreliable analysis and inaccurate outputs.

A part of the literature attempted to consider EV uncertainties in EV-related studies. Some studies addressed the uncertainty by generating a value for uncertain parameters of each EV that is a part of the EV aggregation based on the Probability Distribution Function (PDF) of the uncertain parameters. In [9], an approach is proposed to assist the distribution system operator with the optimal operation of the system in the presence of an EVPL and demand response programme. In this paper, the EV modelling is based on a single EV. However, EV uncertainties have been taken into account by generating random values for the uncertain parameter of each EV based on truncated normal distribution. The other approach deployed in a part of literature to consider EV uncertainty is to generate a single scenario by random value generation based on parameters' pdf or random value selection among historical data. Ref. [10] studies EV aggregation's role in increasing the sustainability of the power system. It is given that number of EVs arriving at the charging station is fixed. This way, random values are generated for each EV's arrival and departure based on the PDF resulting from historical data. In [11], the impact of a PV-equipped EVPL operation on the distribution network is investigated. This paper modelled EVPLs based on the expected loading profile generated by randomly selected EVs' parking duration.

Some other papers in the literature generate multiple scenarios for uncertain EV parameters and proceed with scenario-based approaches to utilize the generated scenarios. Ref. [12], similar to [5], proposed a storage-equivalent model for EV parking addressing EV uncertainties via a scenario-based stochastic formulation. Authors in [13] presented transactive energy management for EVPLs equipped. Multiple scenarios are generated for the arrival and departure times based on the normal distribution, and energy management is performed according to the generated scenarios. The uncertainty of EVs in [14] that intends to integrate EVPLs in the distribution system, is handled via introducing 24 groups of EVs classified based on arrival and departure time. The arrival and departure times are generated from the truncated normal distribution function. In [15], authors proposed an approach for the optimal bidding strategy of EV aggregators. EV aggregator charging is modelled based on its expected strategy in the demand response programme. To consider EV uncertainties, the problem is studied in a few scenarios generated based on the type of EV. Similarly, in [16], energy management of an EVPL is conducted under a load reduction-based demand response programme. To take into account the uncertainty, eight scenarios are generated for the reference power profile of the parking lot based on the driving cycles of EVs. Authors in [17], for conducting optimal planning of EVPLs generate several scenarios for EV uncertain parameters using Monte Carlo simulation. For decreasing the simulation time Kantorovich distance technique is used to reduce the number of scenarios. Ref. [18] proposed a stochastic approach for optimal charge and discharge scheduling of a parking lot. This way, similar to [13], different scenarios are generated based on the truncated normal distribution. However, the total number of arrived EVs is given a fixed parameter. Ref. [19] utilized a scenario-based approach for formulating the uncertain smart EV charging to evaluate the profitability of compressed air energy storage. Authors in Ref. [20] investigated the flexibility potential of EV parking lots in both V2G and

G2V modes as a component of microgrids. In this regard, a stochastic programming methodology is used to address the EV uncertainty via multiple scenarios.

In addition to the mentioned approaches, parameter prediction based on historical data is the other method for considering EV uncertainties. In this regard, [21] that tries to deploy the potential of EVPLs for increasing the distribution system reliability, models an existing EVPL as available storage capacity. This way, sequential Monte Carlo simulations are utilized to determine the equivalent model based on the historical data of the parking lot. Ref. [22] presented a data-driven approach to predict EV owners' behaviour in an EVPL. Then, EVPL is modelled as an aggregation of single EVs. Authors in [23] deployed an energy storage model for EV aggregators in order to present a robust optimization approach for their participation in energy markets. EV aggregator modelling in this work is based on forecasted demand for different types of EVs under the aggregator contract. Ref. [24] presented an approach for defining the optimal operational strategy for an EVPL equipped with local photovoltaic generation. To consider the charging pattern and EV availability uncertainty, historical data from a real-case parking lot has been utilized to forecast the charging characteristic. EVs' arrival and departure uncertainty in [25] that study the optimal operation of an EVPL in a microgrid is addressed via deploying a Markov chain model for predicting the EV availability using historical data.

1.3. Research gap

EVPL (or EV aggregation) uncertainty modelling based on prediction using historical data (Refs. [5,21,23,24], and [25]) is just applicable to the studies related to existing parking lots. Such approaches cannot be employed for planning studies. Because in such approaches the core of the modelling is forecasting the uncertain parameters using the historical data of the EV charging stations, while for planning studies, historical data is not available for the Parking lots that have not yet been constructed.

In addition, there are challenges in utilizing single or multiple-scenario generation (Refs. [9] to [18]) for uncertainty modelling. Firstly, the limited number of generated scenarios cannot totally reflect the characteristics of the PDF. Moreover, it imposes complexity on the deployed approach due to stochastic aspects that add to the formulation and modelling. Furthermore, it will produce a computational burden when several uncertain parameters exist, and the number of generated scenarios is high. Besides the mentioned disadvantages of the scenario generation approach, specifically, there is a critical difficulty in deploying this approach for considering EV uncertainties in the studies related to EV aggregation charging. In this type of EV uncertainty modelling, for all EVs, based on the selected PDF, random values are generated for arrival and departure times. According to the generated values for each EV, the number of arrived EVs at the parking lot in each hour will be defined. Therefore, in such approaches, the number of arrived/departed EVs (in a day) is a parameter and predefined. This way, the scenarios are generated with regard to the total arrived/departed EVs, and then the generated scenarios are utilized in the deployed stochastic method. Consequently, scenario generation cannot work for studies where the number of EVs is unknown or is a variable of the problem, especially for some sorts of planning problems.

Furthermore, the literature review indicates that almost all papers that studies EVPLs in the power system assumed that EVPL charging in the charging stations or EVPLs is exclusive-charger based. In other words, for every single EV in the parking lot, there is one charger that is connected to an EV all the time that the EV is parked in the parking space. In such studies, it is assumed that all parking spaces in the parking lot are equipped with a separate EV charger. However, knowing that Each EV is parked in the parking for several hours while the charging process takes a few hours, there is no need to equip each parking space with a separate charger. In this regard, our paper proposes a charger-sharing approach that empowers EVPL operators to deploy one charger for multiple EV spaces. This way, more efficient operational and planning decisions could be made for EVPL owners that assist them in increasing their operational profit (for operation purposes) or decreasing investment costs (for planning purposes). It is noteworthy that the nature of our proposed virtual battery model allows us to study the EVPL with the charger-sharing approach, while the other EVPL models that have been presented yet(due to their limitations) cannot cope with the charger-sharing approach.

1.4. Contributions

Although several studies have been conducted to model the charging of aggregated EVs, a straightforward compact model with low computational burden that is able to reflect EVs arrival and departure uncertainties and model charger-sharing charging is missing. The proposed virtual battery model for modelling the EVPL (consisting of unidirectional and bidirectional EV chargers) scheduling enables the study of aggregated EV charging in interaction with other energy system components from the point of view of the charging station owner, power system operator, and all agents that intend to study the system for the operation or planning purpose. Moreover, using the virtual battery model, EV aggregation charging could be studied like a battery. This way, using the CDF of the truncated normal distribution, the number of arriving, departing, and parked EVs in each hour is calculated based on the maximum number of hosted EVs in the day, and the characteristics of the proposed virtual model are determined according to the obtained values. Therefore, the proposed modelling can be utilized for large-scale operational or planning studies that deal with aggregated EV charging when arrival and departure uncertainty is taken into consideration without imposing additional computational burden on the simulation. Furthermore, the efficient performance of the proposed virtual battery model has been validated by comparing its performance on DA and RT markets with the scenario-based method. The comparison between our paper and related papers in the literature in terms of uncertainty model, EV model, planning applicability, accuracy, computational burden, and charger-sharing modelling is presented in Table 1. It is noteworthy that the High, Mid, and Low terms used for describing the accuracy and computational burden are related to the overall EV aggregation and uncertainty model in the papers. The terms are determined in comparison with our approach, and most of the mentioned papers have resealable accuracy and computational burden.

The other contribution of this paper lies in proposing an approach that empowers the EV charging place operator to utilize the charging stations in the most efficient way. This way, the EVPL can host the most possible number of EVs. From the planning point of view, for charging a specified number of EVs, there is no need to equip each parking lot with one EV charger. Instead, multiple EVs can be charged by one EV charger as depicted in Fig. 2. Note that EV chargers in (a) exclusive charger and (b) charger-sharing are the same in terms of type and charging capacity. The idea is raised from the fact that each EV may be parked for several hours while the charging process may last a few hours. Therefore, there is no need to equip each parking space with a charging station. Instead, using the proposed charger-sharing approach, one charging station could be deployed for charging multiple Evs parked in different parking spaces. It is worth mentioning that among the EVs that share one charger, one EV is charged at each time. Therefore, the proposed model could also assist in planning decisions on the optimal number of EV charging stations for a parking lot. It should be noted that our proposed virtual battery model enables us to study and model EVPLs' charger-sharing operation, while the other EV aggregation models cannot model the charger-sharing charging. In this regard, in the charger-sharing charging mode, the maximum number of hosted EVs by EVPLs during the whole day is a decision variable of the problem that should be optimally determined in the optimization problem involving all of the EVPL and EVs constraints. The graphical abstract of our paper is depicted in Fig. 1. To summarize, the contributions of this paper are listed below.

Table 1
EV modelling in the literature.

Ref	Uncertainty model	EV model	AfP	ac	CB	CS
Ref. [4]	Parameter prediction	Single EV-based	✘	Mid	Low	✘
Ref. [5]	Parameter prediction	Storage model	✘	Mid	Low	✘
Ref. [6]	✘	Storage model	✓	Low	Low	✘
Ref. [7]	✘	Single EV-based	✓	Low	Low	✘
Ref. [8]	✘	Single EV-based	✓	Low	Low	✘
Ref. [9]	Random generation	Single EV-based	✓	High	High	✘
Ref. [10]	Random generation	Storage model	✓	High	High	✘
Ref. [11]	Random generation	Load profile	✓	High	High	✘
Ref. [12]	Scenario generation	Storage model	✓	High	High	✘
Ref. [13]	Scenario generation	Storage model	✓	High	High	✘
Ref. [14]	Scenario generation	Storage model	✓	High	High	✘
Ref. [15]	Scenario generation	Storage model	✓	High	High	✘
Ref. [16]	Scenario generation	Load profile	✓	High	High	✘
Ref. [17]	Scenario generation	Storage model	✓	High	High	✘
Ref. [18]	Scenario generation	Storage model	✓	High	High	✘
Ref. [19]	Scenario generation	Storage model	✓	High	High	✘
Ref. [20]	Scenario generation	Storage model	✓	High	High	✘
Ref. [21]	Parameter prediction	Storage model	✘	Mid	Low	✘
Ref. [22]	Parameter prediction	Single EV	✘	Mid	Low	✘
Ref. [23]	Parameter prediction	Load profile	✘	Mid	Low	✘
Ref. [24]	Parameter prediction	Storage model	✘	Mid	Low	✘
Ref. [25]	Parameter prediction	Storage model	✘	Mid	Low	✘
Our paper	PDF-based calculation	Virtual battery	✓	High	Low	✓

AfP: Applicable for Planning, ac: accuracy, CB: computational burden, CS: Charger-sharing.

- Proposing a novel charger-sharing approach for EVPL charging which defines the maximum number of EVs that an EVPL with a specified number of charging stations can host while committing to charging the EVs based on their desired final SOC upon their departure.
- Developing a straightforward compact virtual battery model for aggregated EV charging considering the uncertainty of departure and arrival enabling charging station owner, system operator, and other upper-level agents to study and model the EV parking station and its charging process (in both charger-sharing and exclusive charger mode) in interaction with other system components with a very low computational burden.
- Designing a two-stage validation framework for evaluating the performance of the proposed virtual battery model in market participation of a 24-bus distribution system with high penetration of EVs

The rest of the paper is organized as follows. In Section 2, the proposed virtual battery model is presented. Section 3 explains the process for validating our proposed virtual model for considering uncertainty. Simulation results for the presented case study are discussed in Section 4. Finally, our conclusions are presented in 5.

2. Proposed virtual battery model

In our proposed approach, the EVPL is modelled as a time-variant storage system based on EVs' arrival and departure times as presented in Fig. 3. While a battery is characterized with its constant maximum charging and discharging power ($P^{ch,max}$ and $P^{dc,max}$) as well as constant maximum and minimum SOC (SOC^{max} and SOC^{min}), the proposed virtual battery is characterized with time-variant parameters $P_t^{ch,max}$, $P_t^{dc,max}$, SOC_t^{max}, and SOC_t^{min}. For each hour, the mentioned parameters are determined based on the arriving, departing and parked EVs in that hour. In our model, the uncertainty of arrival and departure time is taken into account to define the parameters of the equivalent storage model. After determining the equivalent-storage model, energy management is done for optimal operation and planning of the parking lot. In this paper, we consider that the parking lot will host different classes of EVs with different battery capacities, charging and discharging power as well as initial and final SOCs.

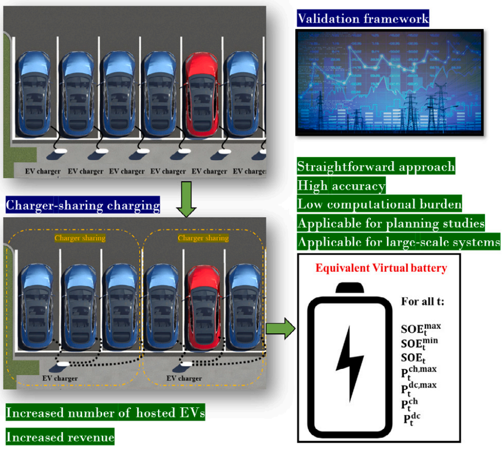
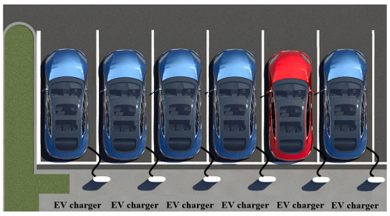


Fig. 1. The graphical abstract of our paper.

(a) Exclusive charger charging approach



(b) Charger sharing charging approach

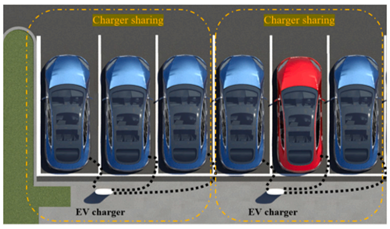


Fig. 2. (a) exclusive charger and (b) charger-sharing charging.

The stored energy in the parking lot in each hour is obtained based on the stored energy in the parking lot in the previous hour as well as stored energy in the arriving and departing EVs in that hour as represented in (1). η_{ch} and η_{dc} stand for the charging and discharging efficiency. Δt is the duration of a single time period. Δt is multiplied with the charging and discharging power to obtain the energy within the time period. Since in this paper, each single time period is equal to one hour, Δt is equal to 1. Therefore, each day consists of 24 time periods.

$$\begin{aligned} E_t^{PL} &= E_{t-1}^{PL} - E_t^{dep} + E_t^{arr} \\ &\quad + \Delta t \eta_{ch} P_t^{PL,ch} - (\Delta t/\eta_{dc}) P_t^{PL,dc} \end{aligned} \tag{1}$$

To find the containing energy of the arriving and departing EVs, it is required to find the number of arriving and departing EVs in each

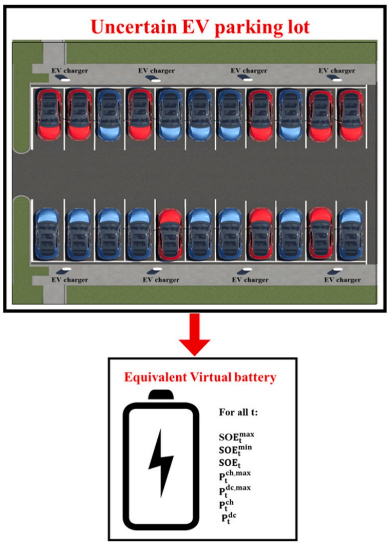


Fig. 3. Virtual battery model for an uncertain EVPL.

hour. According to the literature, the uncertainty of the arriving and departing time of the EVs is modelled with a truncated normal distribution function. It must be noted that the truncated normal distribution function has been widely used in the literature as a reliable PDF for modelling the uncertainty of arrival and departure such as [26,27], and [28]. This way, using the CDF of the truncated normal distribution, the number of arriving and departing EVs in each hour is calculated. If we consider that, $N^{EV,ent}$ EVs could be parked in the whole day, the number of arriving and departing EVs in each hour is determined as represented in (2) and (3) where F_t^{TND} is cumulative distribution function (CDF) of truncated normal distribution. Eq. (4) presents how the CDF of truncated normal distribution with the upper bound b and lower bound a is calculated based on the CDF of the normal distribution with mean μ and standard deviation σ. It should be noticed that in our proposed method, in the process of energy management, the maximum number of EVs that could be parked in the parking lot ($N^{EV,ent}$) itself is determined according to the optimal operation of the system to utilize the charging stations most efficiently. The maximum number of EVs that could be parked should be less than the number of available EVs arriving in the parking as represented in (5).

$$N_t^{Ev,arr} = N^{EV,ent}(F_{t+0.5}^{TND,arr} - F_{t-0.5}^{TND,arr}); \forall t \tag{2}$$

$$N_t^{Ev,dep} = N^{EV,ent}(F_{t+0.5}^{TND,dep} - F_{t-0.5}^{TND,dep}); \forall t \tag{3}$$

$$F^{TND}(x) = \frac{\Phi(x,\mu,\sigma) - \Phi(a,\mu,\sigma)}{\Phi(b,\mu,\sigma) - \Phi(a,\mu,\sigma)} \tag{4}$$

$$N^{EV,ent} \le N^{EV,ava} \tag{5}$$

It is clear that the numbers that (2) and (3) generate are not necessarily integer numbers. However, because the purpose of calculating the number of arriving and departing EVs in each hour is to find the containing energy of the arriving and departing EVs as well as the maximum and minimum charging and discharging power of the parking lot, in addition to the fact that the number generation is intended to model the uncertainty, there is no crucial need to convert the generated numbers to integer numbers. Eqs. (6) and (7) represent the containing energy of the arrived EVs equivalent to their initial SOC upon their arrival and the containing energy of the departed EVs equivalent to their final SOC upon their departure in each hour. Cap_{cl} refers to the battery capacity of EV class cl.

$$E_t^{arr} = N_t^{Ev,arr}(\sum_{cl} Cap_{cl}^{Ev} SOC_{cl}^{arr} Sh_{cl}), \forall t \tag{6}$$

$$E_t^{dep} = N_t^{Ev,dep}(\sum_{cl} Cap_{cl}^{Ev} SOC_{cl}^{dep} Sh_{cl}); \forall t \tag{7}$$

To obtain the EVPL's equivalent storage model, the hourly maximum and minimum bounds for charging and discharging power as well as stored energy in the EVPL should be defined. In this regard, firstly, the charging power of the parking lot for each hour should be less than the total charging capacity of the parking lot that is equal to the total maximum charging power of the charging stations in the parking lot as presented in (8). It is noteworthy that for the charger-sharing charging the number of EV chargers can be less than the number of parked EVs. Moreover, it should be noted that as the line that connects the EVPL to the grid is designed based on the capacity of the whole EV chargers existing in the parking lot, the line capacity is equal to the whole charging capacity of EV chargers. This way, as the charging power of EVPL in the charger-sharing approach is limited to the whole charging capacity of the EV chargers as represented in, the line capacity limitation will not be violated in the charger-sharing approach. In addition, the charging power should be less than the summation of the maximum charging power of the existing EVs in that hour as presented in (9). This way, the number of parked EVs in each hour is obtained according to the number of parked EVs in the previous hour and the number of EVs that arrive and depart the parking in that hour as represented in (12). Similarly, the discharging power of the EVPL is constrained as represented in (10) and (11).

$$0 \le P_t^{PL,ch} \le C_{ins}^{PL,ch}; \forall t \tag{8}$$

$$0 \le P_t^{PL,ch} \le N_t^{EV,par}(\sum_{cl} P_{cl}^{ch,max} Sh_{cl}); \forall t \tag{9}$$

$$0 \le P_t^{PL,dc} \le C_{ins}^{PL,dc}, \forall t \tag{10}$$

$$0 \le P_t^{PL,dc} \le N_t^{EV,par}(\sum_{cl} P_{cl}^{dc,max} Sh_{cl}); \forall t \tag{11}$$

$$N_t^{EV,par} = N_{t-1}^{EV,par} + N_t^{Ev,arr} - N_t^{Ev,dep}; \forall t \tag{12}$$

The stored energy in the parking lot in each hour must be less than the total allowed capacity of the parked EVs in that hour which is obtained by the maximum allowed SOC of the EVs. In addition, according to the minimum allowed SOC of the parked EVs in each hour, the lower bound of parking lot stored energy in that hour is calculated. This way, the stored energy in the Parking lot is constrained as represented in (13).

$$E_t^{PL,min} \le E_t^{PL} \le E_t^{PL,max}; \forall t \tag{13}$$

$$E_t^{PL,min} = N_t^{EV,par}(\sum_{cl} Cap_{cl}^{Ev} SOC^{min} Sh_{cl}); \forall t \tag{14}$$

$$E_t^{PL,max} = N_t^{EV,par}(\sum_{cl} Cap_{cl}^{Ev} SOC^{max} Sh_{cl}); \forall t \tag{15}$$

Moreover, the charging and discharging power cannot be nonzero simultaneously as presented in (16). To discard the non-linearity that (16) generates, the big M approach is used according to (17) and (18).

$$P_t^{PL,ch} P_t^{PL,dc} = 0; \forall t \tag{16}$$

$$0 \le P_t^{PL,ch} \le u_t M; \forall t \tag{17}$$

$$0 \le P_t^{PL,dc} \le (1 - u_t) M; \forall t \tag{18}$$

All in all, the EVPL considering the uncertainty of arrival and departure times is modelled as a virtual battery according to (1)–(18).

3. Validation approach

To evaluate our proposed virtual battery model, it is required to investigate its performance in a representative problem and compare it with other existing approaches. In this section, we have selected the optimal operation of a distribution system (DS) with high penetration of EVPLs in the DA market as a representative problem to assess the performance of our proposed approach and compare it with the scenario-based approach for EV uncertainty modelling that is widely used in this field of research. We selected the operational market participation problem for performance evaluation, as it validates the performance of our approach precisely. This way, to show the effectiveness of our virtual battery model in uncertainty modelling, the pricing of the DA and RT market has been selected in such a way that error in uncertainty evaluation imposes a cost to the EVPL. In other words, the selling price in RT is lower in comparison with the DA market, and the purchasing price in RT is higher than in RT. Therefore, if the parking lot could not consider EVs uncertainties and estimate its load profile correctly, it will be forced to trade in the RT market where both purchasing and selling in this market is more costly than in the DA market. This is the reason why we choose this kind of pricing mechanism for the evaluation of the success of our approach in uncertainty modelling. It should be noted that, because other EV uncertainty modelling methodologies cannot model the charger-sharing approach, in this section, we compare our proposed virtual battery modelling with the scenario-based modelling in the exclusive charger charging case. For the sake of simplicity, it is considered that all chargers in the parking lot are unidirectional chargers without the capability of EV discharge. In this case, the total number of the EVs that arrive in the whole day is equal to EV chargers. The market participation problems for each approach and their resulting cost calculation in realization scenarios are described in the below sections. The overall validation process flowchart is depicted in Fig. 4.

3.1. Market participation with proposed virtual battery model

Via the proposed virtual battery model, the market participation of the DS is formulated as below where DS tries to minimize its cost in the DA market. It is noteworthy that our virtual battery model does not involve any stochastic process for RT status of EVs arrival and departure, and the DA stage decisions are made based on the characteristics of the virtual battery model that are extracted considering the PDF of the uncertain parameters.

$$OF = \min \sum_t P_t^{DA} \lambda_t^{DA}$$

s.t. (1)–(18) and DS constraints

3.2. Market participation with scenario-based storage model

In the scenario-based approach for modelling EV uncertainty, based on the generated scenarios for the RT state of EVs from the truncated normal distribution function for all EVPLs, the optimal values regarding the DA market decisions of DS will be obtained via two-stage stochastic programming. This way, the parameters for the storage model of the EVPLs in each scenario are obtained by the EVs' arrival and departure in that scenario. In this regard, the number of arrived and departed EVs in each hour is generated for each scenario and based on that E_t^{arr}, E_t^{dep}, $P_t^{PL,ch,max}$, $E_t^{PL,min}$, and $E_t^{PL,max}$ are determined. Then, the optimal DA decisions of the DS will be obtained by solving (19), that is the objective function of the DS in the market participation problem, subject to (20)–(24) which are the constraints of the problem. The first term in the objective function indicates the DS cost in the DA stage, and the second term is the weighted cost of DS related to the RT stage considering the probability of each scenario. In this approach, the DA decisions are made according to the possible scenarios that may occur in RT and their expected costs. It should be noted that the RT price is also an uncertain parameter. The RT price in each hour has a normal PDF with the mean value of the DA price in that hour and the standard deviation equal to $0.3\lambda_t^{DA}$ as indicated in Fig. 5.

$$OF = \min \sum_t P_t^{DA} \lambda_t^{DA} + \sum_{w_{EV}} \sum_{w_{rt}} \pi_{w_{EV}} \pi_{w_{rt}} (P_{w_{EV},t}^{sell,rt} \lambda_{w_{rt},t}^{sell,rt} + P_{w_{EV},t}^{pur,rt} \lambda_{w_{rt},t}^{pur,rt}) \tag{19}$$

s.t. DS constraints and

$$E_{w_{EV},t}^{PL} = E_{w_{EV},t-1}^{PL} - E_{w_{EV},t}^{dep} + E_{w_{EV},t}^{arr} + \Delta t \eta_{ch} P_{w_{EV},t}^{PL,ch}; \forall t, w_{EV} \tag{20}$$

$$P_{w_{EV},t}^{PL,ch} = P_t^{DA} + P_{w_{EV},t}^{pur,rt} - P_{w_{EV},t}^{sell,rt}; \forall t, w_{EV} \tag{21}$$

$$0 \leq P_{w_{EV},t}^{PL,ch} \leq C_{ins}^{PL,ch}; \forall t, w_{EV} \tag{22}$$

$$0 \leq P_{w_{EV},t}^{PL,ch} \leq P_{w_{EV},t}^{PL,ch,max}; \forall t, w_{EV} \tag{23}$$

$$E_{w_{EV},t}^{PL,min} \leq E_{w_{EV},t}^{PL} \leq E_{w_{EV},t}^{PL,max}; \forall t, w_{EV} \tag{24}$$

3.3. Cost calculation in the realization scenarios

In this section, new realization scenarios are generated for EVs arrival and departure. Then, based on the determined DA power trade in the previous section and realization scenarios, the RT power trade are defined for each approach, and the total cost of the DS in the realization RT market is calculated according to the new scenarios generated to stand for the realization. In other words, realization scenarios are generated from the truncated normal PDF to represent the realization stage and E_t^{arr}, E_t^{dep}, $P_t^{PL,ch,max}$, $E_t^{PL,min}$, and $E_t^{PL,max}$ are determined. Then regarding the DA scheduled power of each approach, the traded power in RT is calculated, and the cost of the DS in the RT stage for realization scenarios resulting from each approach is obtained by solving (25) subject to (26)–(30). Then the total cost of the DS in the DA and RT stages are calculated and compared for the two approaches to give an overview of the performance of our proposed approach. Multiple scenarios are generated for the realization instead of single scenario to provide more reliable outputs.

$$OF = \min \sum_{w_{RCEV}} \sum_{w_{RCrt}} \pi_{w_{RCEV}} \pi_{w_{RCrt}} \cdot (P_{w_{RCEV},t}^{sell,rt} \lambda_{w_{RCrt},t}^{sell,rt} + P_{w_{RCEV},t}^{pur,rt} \lambda_{w_{RCrt},t}^{pur,rt}) \tag{25}$$

s.t. to DS constraints and

$$E_{w_{RCEV},t}^{PL} = E_{w_{RCEV},t-1}^{PL} - E_{w_{RCEV},t}^{dep} + E_{w_{RCEV},t}^{arr} + \Delta t \eta_{ch} P_{w_{RCEV},t}^{PL,ch}; \forall t, w_{RCEV} \tag{26}$$

$$P_{w_{RCEV},t}^{PL,ch} = P_t^{DA,sc} + P_{w_{RCEV},t}^{pur,rt} - P_{w_{RCEV},t}^{sell,rt}; \forall t, w_{RCEV} \tag{27}$$

$$0 \leq P_{w_{RCEV},t}^{PL,ch} \leq C_{ins}^{PL,ch}; \forall t, w_{RCEV} \tag{28}$$

$$0 \leq P_{w_{RCEV},t}^{PL,ch} \leq P_{w_{RCEV},t}^{PL,ch,max}; \forall t, w_{RCEV} \tag{29}$$

$$E_{w_{RCEV},t}^{PL,min} \leq E_{w_{RCEV},t}^{PL} \leq E_{w_{RCEV},t}^{PL,max}; \forall t, w_{RCEV} \tag{30}$$

3.4. Distribution system constraints

The constraints related to the power flow in the distribution system [29] is presented below.

$$P_{ij} = \frac{r_{ij}}{r_{ij}^2 + x_{ij}^2}(V_i - V_j) + \frac{x_{ij}}{r_{ij}^2 + x_{ij}^2}(\theta_i - \theta_j) \tag{31}$$

$$P_i = \sum_{j=1, i \neq j}^{N_B} P_{i,j} \tag{32}$$

$$Q_{ij} = \frac{x_{ij}}{r_{ij}^2 + x_{ij}^2}(V_i - V_j) - \frac{r_{ij}}{r_{ij}^2 + x_{ij}^2}(\theta_i - \theta_j) \tag{33}$$

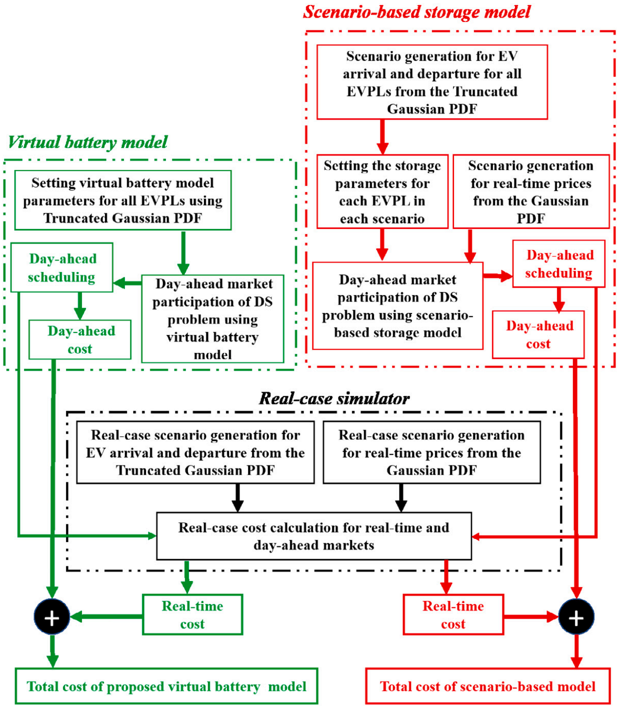


Fig. 4. Validation process flowchart.

$$Q_i = \sum_{j=1, i\neq j}^{N_B} Q_{i,j} \tag{34}$$

$$P_{ij}^2 + Q_{ij}^2 \leq S_{ij}^2 \tag{35}$$

for bus 0:

$$P_i^{RT} = P_t^{DN} - P_{L,i,t}^{Fix} \tag{36}$$

$$Q_i^{RT} = P_t^{DN} - Q_{L,i,t}^{Fix} \tag{37}$$

for EVPL buses:

$$P_i^{RT} = -P_{k,t}^{EVPL,RT} - P_{L,i,t}^{Fix} \tag{38}$$

$$Q_i^{RT} = -Q_{L,i,t}^{Fix} \tag{39}$$

for non-EVPL buses

$$P_i^{RT} = P_{L,i,t}^{Fix} \tag{40}$$

$$Q_i^{RT} = -Q_{L,i,t}^{Fix} \tag{41}$$

4. Simulation results

As presented in the previous section, to validate the performance of our proposed virtual battery model and the profitability of the charger-sharing approach, we study the problem of optimal participation of an EVPL in DA and RT markets. This way, firstly, without considering the charging-sharing approach, our proposed model is evaluated by comparing its performance with the performance of the scenario generation approach. Then, the profitability of the charger-sharing approach in comparison with the exclusive charger is presented.

Table 2
EV classes and characteristics.

cl	Cap_{cl}	SOC_{cl}^{arr}	SOC_{cl}^{dep}	$P_{cl}^{ch,max}$	$P_{cl}^{dc,max}$
1	15	0.33	0.85	7	7
2	20	0.33	0.85	10	10
3	20	0.16	0.85	10	10
4	15	0.4	0.85	7	7
5	20	0.1	0.85	10	10
6	15	0.45	0.85	7	7
7	10	0.5	0.85	5	5
8	10	0.2	0.85	5	5
9	15	0.33	0.85	7	7
10	20	0.2	0.85	10	10

4.1. Case study

In this section, the two case studies used for the validation of the proposed approach and evaluation of the profitability of the charger-sharing approach are explained. Firstly, For the validation purpose, as depicted in 6, the distribution system of our case study is the modified version of the case study used in [30] with adding EVPL to the system. The DS owns 10 EVPLs buses. Secondly, for assessing the profitability of the proposed charger sharing approach, an EVPL equipped with 100 bidirectional and 100 unidirectional EV chargers is used. It has been assumed that ten classes of EV are available where the share of each EV class from all available EVs is equal to other classes. To protect the battery, it is assumed that $SOC^{EV,min}$ and $SOC^{EV,max}$ are 0.05 and 0.95, accordingly. Different EV classes information can be found in Table 2. Moreover, the DA price and generated scenarios for the RT price (purchasing and selling) are shown in Fig. 7.

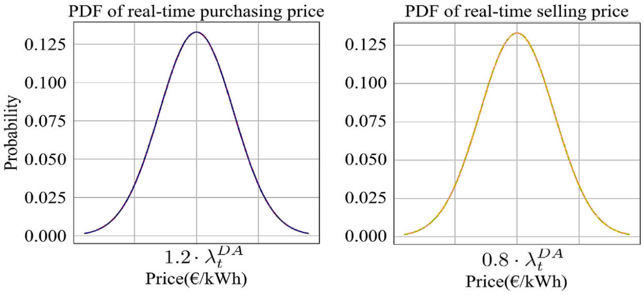


Fig. 5. PDF of RT purchasing and selling price for hour t.

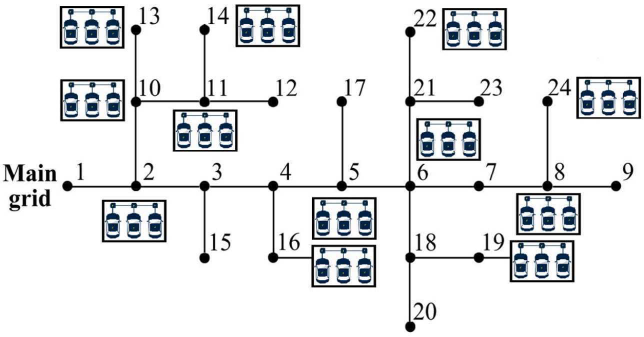


Fig. 6. Case study.

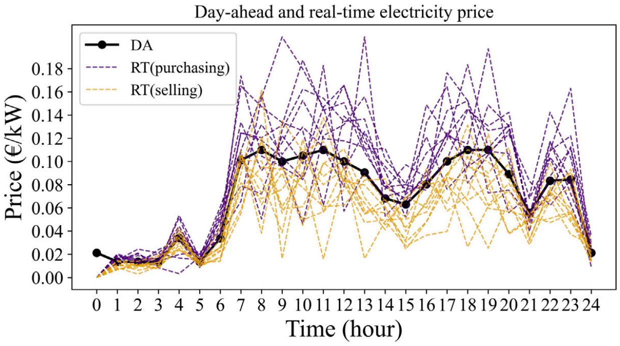


Fig. 7. DA and RT electricity price.

4.2. Validation results

As explained in the previous section, to assess the performance of our proposed virtual battery model in considering the arrival and departure uncertainty, the operation cost of the EVPL-owned DS are compared with the scenario-based approach. The results show that the performance of our virtual battery model is similar to the scenario-based approach with 21 scenarios while its computational burden is way less than the scenario-based approach. Fig. 8(a) depicts that the DA power purchased from the upstream grid is very close for two approaches. However, they are not equal as shown in Fig. 8(b) where the difference in the DA power purchased from the upstream grid for the two approaches is depicted. This different day-ahead decisions results in different real-time trades for different realization scenarios as shown in Fig. 9. However, overall the market strategy of two approaches are similar that results in similar total DS cost. Table 3 presents that the daily operational cost of the distribution system for providing power in the DA and RT markets using the scenario-based approach is 1692.06 €. While the DS operational cost with the proposed virtual batter model is 1689.78 €. The more important point is that the simulation time of our proposed approach is 4.92 s while the simulation time of the scenario-based approach is 219.53 s. This shows that the computational burden of the proposed virtual battery model is 2.242% of the computational burden of the scenario-based approach. This low computational burden of our proposed approach is of way more importance in the large scale problems where in addition to the uncertainty from numerous EVPLs,

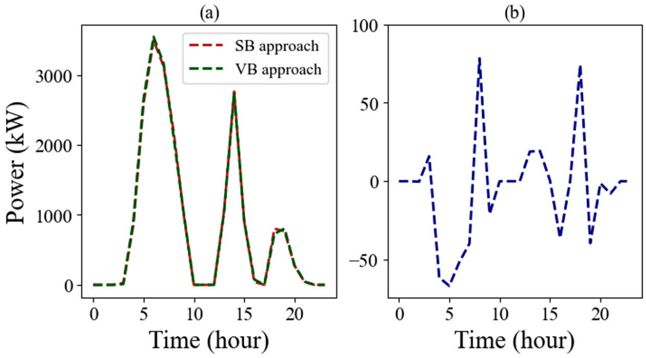


Fig. 8. (a) DA purchased power of DS for the proposed virtual battery and scenario-based approaches (b) difference of the DA purchased power for two approaches.

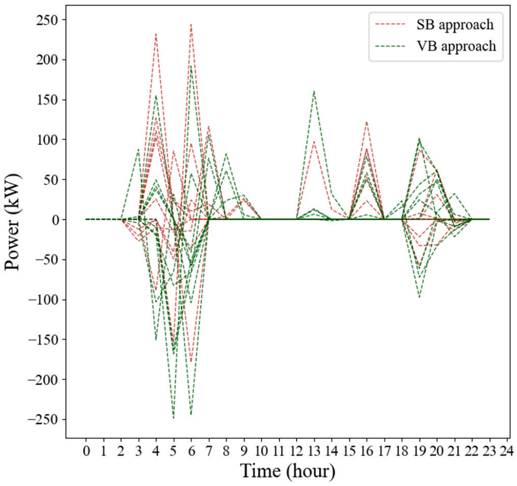


Fig. 9. RT traded power of EVPL in (a) scenario-based approach and (b) the proposed virtual battery model.

Table 3
Operational cost and simulation time of the proposed virtual battery model and the scenario-based approach.

Approach	Total cost	Simulation time
Stochastic approach	1692.06	219.53
Proposed virtual battery model	1689.78	4.92

several other uncertainty resources, such as renewable generation exist as well. This way, for large-scale problems, while using the scenario-based approach, if the number of scenarios decreases the performance of the scenario-based approach worsens. However, the proposed virtual battery model will have similar performance for such large-scale problems without imposing any additional computational burden. This way, for large-scale problems, the proposed virtual battery model has a way greater performance than the scenario-based approach. Therefore, our proposed model is efficient model for deploying in the planning problem and operational studies from the system level point of view where the penetration of EVPLs is high. owing to its simple and compact formulation.

4.3. Charger-sharing approach profitability

In this section, the profitability of the charger-sharing charging approach is shown by evaluating its role in the operation cost reduction in comparison with the existing exclusive charger charging approach. To this end, the optimal operation of an existing EVPL with a specified number of EV chargers is investigated for the exclusive charging and charger-sharing charging approach assuming that there are sufficient parking spaces to host more EVs.

4.3.1. Exclusive-charger charging

The charging and discharging power of EVPL, the maximum capacity of EV chargers for charging and discharging, and the maximum charging and discharging power possibility from parked EVs in the parking lot are depicted in Fig. 10. The maximum charging and discharging power possibility result from the number of parked EVs in each hour extracted from the arrival and departure time of EVs. The charging and discharging process is managed to meet the charging demand at the lowest cost. This way, the EVPL do the charging in the low-price hours and discharging in the high-price hours taking into account the Evs' arrival and departure behaviour ensuring that all EVs depart the parking lot at their desired departure time with their desired final SOC. As expected, in the exclusive charger charging, the big share of the EV chargers' charging and discharging capacity is not deployed. This way, the total charging capacity of the whole parking lot is 2000 kW, while in hour 14 when the charging power of the parking lot is at the highest level, the charging power is around 1100 kW which is way less than the total charging capacity. In other hours the situation is worse. In this regard, it could be understood that a big part of the charging capacity is unused. The purple arrows depict the unused charging capacity of chargers in different hours. This is the motivation for deploying the charger-sharing approach that empowers EVPLs for maximum utilization of the charging and discharging capacity of existing chargers. Moreover, the maximum charging and discharging power of the parked EVs is represented via the dotted curves. It is defined based on the number of EVs that are parked in the parking lot each hour and their nominal charging and discharging power. Therefore in the hours when no EV is parked in the parking lot, it is equal to 0, and as the number of parked EVs increases it rises. After hour 12, when the number of departed EVs is getting more than the arrived EVs, the number of parked EVs decreases resulting in a decrease the maximum charging and discharging power of the whole parked EVs.

Fig. 11 shows how the EVPL state of energy varies in each hour based on the previous hour's state of energy, energy stored from charging, energy depleted from discharging, added energy of the arrived EVs and extracted energy from departed EVs. In this regard, EVs by arriving

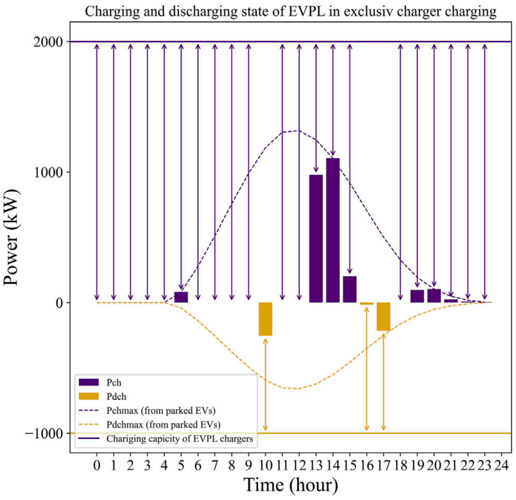


Fig. 10. Charging and discharging state of EVPL in exclusive-charger charging. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

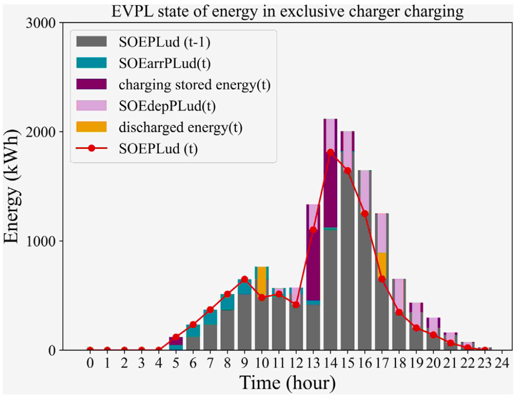


Fig. 11. EVPL state of energy in exclusive charger charging.

at the parking lot add their stored energy in their battery equivalent to their initial SOC to the containing energy of the parking lot and deplete the energy equivalent to their final SOC upon their departure from the containing energy of EVPL. Moreover, the equivalent energy of the EVs' charging/discharging is added/subtracted to/from the containing energy of EVPL. This way, the EVPL state of the energy varies in time while the energy demand of the EVs is met optimally ensuring that all EVs depart the parking lot at their desired departure time with their desired final SOC.

4.3.2. Charger-sharing charging

The performance of the charger-sharing approach in increasing the profit of EVPL is presented in this section. Firstly, Fig. 12 shows how this approach assists in better deploying the capacity of EV chargers in comparison with exclusive charger charging. In this regard, it is seen that the total capacity of the chargers is fully deployed in hours 13, 14, and 15. Comparing the results with the exclusive charger charging shows the profitability of the charger-sharing approach in utilizing the charging and discharging capacity of the chargers efficiently. This way, when it comes to using one charger for charging multiple EVs, EVPL can host more EVs (considering the parking space limitation) committing to charging the EVs based on their desired final SOC upon their departure. Therefore, it could gain more income from the efficient utilization of EV chargers. We considered seven cases with different charging tariffs assuming that in each case the tariff is acceptable by both the EVPL owner and EV owners. The results show that if there is no limitation on parking lot spaces, with the tariff of 0.09 €/kWh for charging EVs, the optimal number of hosted EVs would be 343 for the EVs that just want to be connected to UDEVCH and 221 for the EVs that are willing to be connected to BDEVCH. When the charging tariff is higher, it is profitable for EVPL to host more EVs (if EV chargers capacity allows it). Table 4 presents the optimal number of hosted EVs for different charging tariffs. It can be understood that when the charging tariff is high, hosting more EVs would be very important in comparison with the charging and discharging schedule, because just by hosting more EVs, EVPL would gain a considerable profit. This way, when the tariff increases the number of hosted EVs increases, but the limited capacity of EV chargers does not allow for accepting EVs more than a specific number. Because EVPL commits to charging the EVs based on their desired final SOC upon their departure, and with the limited number of chargers it can host a limited number of EVs. For instance, it is seen that when the tariff increases from 0.07 €/kW to 0.12 €/kW the number of accepted EVs increases, but when the tariff is 0.13 €/kW, the number of accepted EVs cannot increase due to the limitation of the EV chargers. Our charger-sharing charging approach's performance is evaluated by comparing the number of EV charges in EVPL and the number of accepted EVs. When the tariff is high enough to motivate the EVPL owner for hosting more EVs, EVPL can host around 3200 EVs with just 200 EV chargers (considering the characteristics of EVs and EV chargers explained in the case study section). However, when the exclusive charger approach is deployed, 200 EVs are accepted to enter the parking and be charged. This way, the charge-sharing approach has a substantial performance in utilizing the potential of installed EV chargers. In addition, this approach could be deployed in future EVPL planning studies to minimize the investment cost for EV chargers. In addition, Fig. 13 depicts the state of the energy of EVPL in each hour resulting from the optimal scheduling of the EVPL.

Table 4
Number of accepted EVs for connecting to unidirectional and bidirectional EV chargers for different charging tariffs.

Tariff	Accepted EVs for UDCH	Accepted EVs for BDcH
0.07	0	160
0.08	220	181
0.09	343	221
0.1	514	514
0.11	1143	1143
0.12	1601	1601
0.13	1601	1601

4.4. Discussion

While comprehensive spatial–temporal models exist for considering the location of EV charging stations, in line with the papers in the literature that aims to model the EV parking lot for the power system and energy market studies such as [31], in our paper the spatial factor and location of the EV parking lot are incorporated within the characteristics of a Truncated normal distribution. This approach simplifies the modelling complexity and reduces computational burden, particularly for large-scale system studies where various power system-related components and associated uncertainties are involved. In this context, based on the historical data of the EV owners' behaviour in each region the patterns of arrival and departure will be shaped via

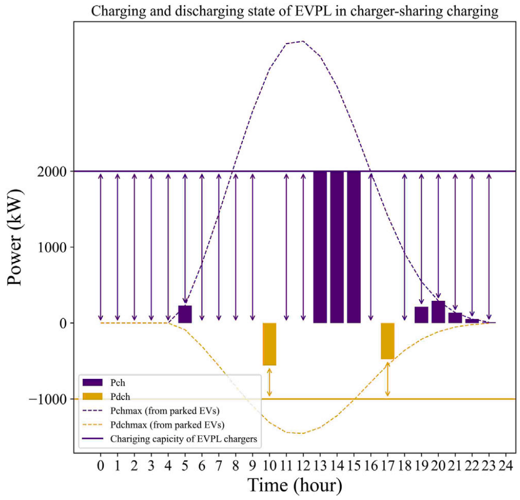


Fig. 12. Charging and discharging state of EVPL in charger-sharing charging.

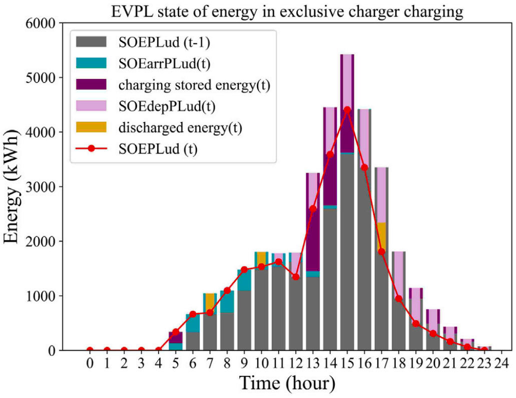


Fig. 13. EVPL state of energy in charger-sharing charging.

specific characteristics of the truncated normal distribution including mean, standard deviation, maximum value, and minimum value. In other words, it is assumed that EVs' arrival and departure behaviour for a parking lot located in a certain geographical area, for example, a district of a city, follow a certain pattern [31]. Consequently, the characteristics of the truncated normal distribution vary for EV parking lots located in different areas. Additionally, the maximum number of available EVs in the region, as represented in Eq. (5), serves as a determining factor for the maximum number of EVs that an EV parking lot can host during the whole day. This factor also varies for EV parking lots situated in different areas. In our case study, for the sake of simplicity and comparability, we have considered unique truncated normal distribution characteristics for different EV parking lots.

Another crucial aspect to note is that the proposed virtual model for the EV parking lot primarily serves power system operation and planning studies, offering a comprehensive overview of EV charging behaviour rather than exact real-time charging process management within the parking lot. Additionally, the key assumption here is that the arrival and departure patterns of EVs conform to the truncated normal distribution. In this regard, if EVs' arrival and departure in the real-case scenario, follows the truncated normal distribution, considering the containing energy of the arriving and departing EVs and Eqs. (6) and (7), it is guaranteed that all of the EVs depart the parking lot in their desired time and with their desired final SOC based on the primary optimal power consumption solution (for example in the day-ahead stage). Otherwise, if the pattern does not exactly follow the truncated normal distribution, a minor adjustment in the primary charging process decisions guarantees the service quality of EV users.

For instance, in the validation section, we demonstrate that day-ahead decisions are based on the assumption of a truncated normal distribution for EV arrival patterns. However, in real-time operations, slight modifications are made to the charging schedule to cope with the actual EV arrival and departure patterns. The charger-sharing approach has no adverse impact on the users' service quality. This is because our model ensures compliance with the requirements of EV aggregation charging, considering both departure time and final SOC. The EV parking lot operator is in charge of prioritizing the charging schedule within the parked EVs in the parking based on their departure time. This aspect of the work is not within the scope of our paper, since our main purpose is to model the charging behaviour of the EV parking lot as an EV aggregation. However by considering the mentioned constraints the feasibility of the charging solution is guaranteed.

Moreover, Our proposed charger-sharing approach does not mandate charging only one EV at a time per charger. This suggestion aims to minimize potential technical barriers and reduce investment costs associated with charging-sharing assets. Therefore, our approach allows for the simultaneous charging of multiple EVs using a single charger. Furthermore, charging a single EV at a time per charger does not result in a queue or delayed departures beyond the preferred departure times. This is because the charging schedule of the whole EV parking lot satisfies the desired final SOC of the EVs upon their departure.

If multiple EVs are charging with one charger simultaneously, the charging power of each EV is a share of the total charging capacity of that charger. Therefore, the charging process takes more time for each EV. However, when a single EV is charged via a charger at each moment, it can utilize the whole charging capacity of the charger resulting in higher charging power, and less charging time. When the EV reaches its desired SOC, charging of the next EV assigned to the same charger is started. Therefore, there is no difference in terms of the final SOC of EVs, departure time, and the charging time of the group of EVs that are sharing one charger, for the two mentioned cases. As mentioned previously, the charger-sharing approach is presented for the EV parking lots where the EVs are parked for several hours, and it is intended to make the best use of the chargers for charging the aggregation of EVs. This way, instead of dedicating one charger for each parked car in the parking lot, multiple EVs can be charged via one charger during their stay in the parking lot. Therefore, it may not be applicable for charging stations that host EVs with short stays parked just for charging, as a means of alleviating the existing queue.

5. Conclusions

In this paper, a virtual battery model was proposed for modelling EVPLs considering the uncertainty of arrival and departure enabling modelling the charger-sharing charging to use an EV charger for charging multiple EVs. For validating our proposed model to assess its performance in reflecting the uncertainty of the arrival and departure of EVs, the cost of a distribution system owning multiple EVPLs in different buses in DA and RT markets was studied. In this regard, the performance of our proposed model was compared with the scenario-based approach. Validation results indicated that the performance of our virtual battery model was similar to the scenario-based approach in terms of cost. The daily operational cost of the distribution system for providing power in the DA and RT markets using the scenario-based approach is 1692.06 €, and the DS operation cost with the proposed virtual batter model is 1689.78 €. However, its computational burden is way less than the scenario-based approach (2.24%). In addition, the performance of the EVPL with the charger-sharing charging approach was studied. The results indicated how the charger-sharing charging approach empowers the EVPL to host more EVs. According to the results, when the charging tariff increased, the EVPL could host more EVs, as hosting more EVs was profitable for EVPL. For EVPL equipped with 100 unidirectional and 100 bidirectional charging stations, when the charging tariff was high enough for EVPL to host as many EVs as possible, EVPL could host 3202 EVs. However, in the exclusive-charger charging approach, EVPL could host 200 EVs. This result showed how the charger-sharing charging approach facilitates the efficient deployment of EV chargers. Therefore, by employing charger-sharing charging, the investment cost for EVPL planning would also decrease dramatically paving the way for increasing penetration of EVs. In the future, the proposed virtual battery model will be used for modelling EV parking lots for large-scale distribution system management containing several uncertainty sources from RES. In addition, the charger-sharing approach will be further investigated to identify the possible technical difficulties.

CRediT authorship contribution statement

Mahoor Ebrahimi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Miadreza Shafie-khah:** Writing – review & editing, Supervision, Investigation, Conceptualization. **Hannu Laaksonen:** Conceptualization, Supervision, Writing – review & editing,.

Declaration of competing interest

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

Data availability

Data will be made available on request.

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RESEARCH ARTICLE

Two-Layer Game-Based Framework for Local Energy Flexibility Trading

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ABSTRACT A new configuration is required to model the behavior of customers, aggregators, the distribution system operator (DSO), and their interactions due to the active participation of customers in the local flexibility market. To this end, we propose a two-layer game-based framework that models agents' behavior and their interactions. Thus, firstly, at the inner layer, customers and aggregators set their decision variables considering the decisions of each other performing an iterative game. After the inner layer game concludes, in the outer layer, the DSO determines its decision variable according to the decision of aggregators and customers. If the convergence condition is satisfied, the game of the outer layer concludes. Otherwise, there is another inner game and subsequent outer game until the satisfaction of convergence condition. Therefor, customers, aggregators, and the DSO have similar decision-making power. Since all of them can make their own decisions and modify them according to others' decisions. To study our model, we consider three scenarios with different levels of freedom while decision-making for customers that is resulted from different levels of limitation for arbitrage avoidance. Our results illustrate that our iterative approach is converged after few iterations in both the inner and the outer layer. Moreover, customers who have a contract with the same aggregator behave similarly. Furthermore, aggregators benefit from customers' freedom, while it is very destructive for the DSO and increases its objective function.

INDEX TERMS Energy flexibility, game-based modelling, flexibility management, local electricity trading.

NOMENCLATURE

A. INDICES

t	Time intervals [h].
j	Customers.
k	Aggregators.
i	Iterations.

B. VARIABLES

L_{jt}	Real-time load for customer j at time t [kWh].
L_{jt}^{f}	Energy flexibility for customer j at time t [kWh].
OF_{k}^{ag}	Objective function for aggregator k [€].
OF^{dso}	Objective function for the DSO [€].
OF_{j}^{cu}	Objective function for customer j [€].
P_{jkt}^{L2A}	Energy flexibility traded between customer j and aggregator k at time t [kWh].
P_{t}^{rt}	Real-time energy flexibility exchanged between the DSO and the real-time electricity market (RTEM) at time t [kWh].
P_{kt}^{A2D}	Energy flexibility traded between aggregator k and the DSO at time t [kWh].
P_{jt}^{D2L}	Energy flexibility bought by customer j from the DSO at time t [kWh].
λ_{jkt}^{L2A}	Price for flexibility exchanged between aggregator k and its corresponding customers at time t [€/kWh].
λ_{kt}^{A2D}	Price for flexibility exchanged between aggregator k and the DSO at time t [€/kWh].

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

λ^{D2L}_{jt}	Price of flexibility traded among the DSO and customer j at time t [€/kWh].

C. PARAMETERS

yL^{c}_{jt}	Scheduled load for customer j at time t [kWh].
M_{jk}	Incidence matrix that maps flexibility trading between customer j and aggregator k.
ϵ	The stopping criteria in convergence condition.
λ^{rt}_{t}	Price of electricity traded among the DSO and the RTEM at time t [€/kWh].
$\underline{\lambda}^{L2A}_{kt}$	Lower band for price of flexibility traded between aggregator k and its customers.
$\overline{\lambda}^{L2A}_{kt}$	Upper band for price of flexibility traded between aggregator k and its customers.
δ_{kt}	Profit guarantee factor for aggregator k at time t ($\delta_{kt} > 1$).
γ_j	Flexibility factor for customer j ($0 \leq \gamma_j \leq 1$).

I. INTRODUCTION

A. BACKGROUND

Due to newly emerged uncertainty issues resulting from the increasing penetration of renewable energy resources in the power system, finding an efficient source for providing energy flexibility is vital to maintain the balance between generation and consumption [1]. In this way, customers can manage their energy consumption to provide positive or negative energy flexibility for distribution systems [2]. This capability of providing energy flexibility by changing the pattern of consumption, causes customers to be more engaged in the process of decision-making in the distribution system [3]. As a result, conventional models cannot cope with the active participation of market participants. Hence, novel methods are needed to model the behavior and interactions among active agents in the distribution system [4]. Some studies deployed novel approaches to facilitate the utilization of customers' flexibility in the distribution system.

In this regard, some studies investigated the flexibility trading opportunities to assist system operator. In such studies, the system operator decides on the flexibility trading among different agents in the market while other agents are not equipped with the capability of decision making. In [5], the local market operator in coordination with the DSO determines the flexibility transactions among customers in a peer-to-peer (P2P) trading platform. In [6], the DSO controls the flexibility scheduling to maximize its profit resulting from offering flexibility to the day-ahead market. Ref. [7] presented three strategies for flexibility management for electric vehicles in the distribution system. In the third presented strategy, a local coordinator manages the charging of electric vehicles and the flexibility of end-users. In [8], a methodology is presented to determine the optimal flexibility exchange strategy for improving the voltage profile and preventing line congestion. Similar to [8], in [9], a two-stage stochastic programming model is presented to assist the DSO in managing the flexibility provided in the distribution level to minimize the voltage violation and line congestion. The approach presented in [10], joins local electricity, heat, and gas systems to utilize the demand flexibility in an integrated energy system where the operation of electricity market operator, heat market operator, and gas market are coordinated. Ref. [11] presented an incentive-compatible mechanism to assist the DSO in acquiring flexibility from aggregators (who are in charge of delivering flexibility to the DSO) while they are motivated to declare their true cost.

Some other studies investigate the flexibility and energy transactions to assist other agents in the distribution system for finding the optimal strategy. Ref. [12] presented a model that enables energy communities consisting of nanogrids to provide the system with flexibility using their excess generation on the demand side. Authors in [13] presented a two-stage stochastic approach for flexibility management of large customers considering the uncertainties of solar generation and market prices. Some studies deployed a bilevel optimization approach that provides the solution for the leader of the problem based on the Stackelberg game. This approach aims to consider the actions of followers while determining the optimal strategy of the leader. In this methodology, although the optimization problem of both the leader and followers is taken into account, the problem is studied from the leader's point of view and the leader's power of autonomy is more than the followers. Because the leader is able to take into account the expected response of the followers while followers do not have similar capabilities. In this regard, authors in [14] presented a bilevel approach to consider the interdependence of the decision-making of distributed resources and aggregators to assist the aggregators in choosing the optimal strategy. Ref. [15] utilized a bilevel optimization to minimize aggregators' cost at the upper level considering the market clearing process at the lower level where independent system operator's generation cost is minimized.

Furthermore, customers have a greater potential to be involved in flexibility trading compared to energy trading, as they are a potential resource of flexibility owing to their ability to adjust their consumption. In this way, customers have a bolder role in the flexibility market compared to the energy market. Thus, it is crucial to present a trading framework that motivates customers to engage in the flexibility transaction and increase their flexibility provision. In this regard, a game-based model that serves the customers with decision-making capability could be effective in facilitating their participation in the flexibility market. In addition, customers are entitled to trade flexibility with the DSO directly. Because flexibility is derived from the demand side.

The capability for direct trading with the DSO empowers customers to play a significant role in the flexibility market. In this way, the active participation of customers will make a more competitive atmosphere in the market, and pave the way for the DSO to utilize the flexibility of customers for utilizing intermittent renewable energy resources [16].

Since different agents in a competitive market seek to gain more profit, a method should be deployed to address the competition among agents and their interactions. In this regard, game-based approaches are in the interest of some studies. As game-based approaches enable different agents in the distribution system to make decisions in a competitive market independently. Authors in [17], presented a demand response management based on a two-level game. In this regard, at the lower level, residential users define their required consumption, and at the higher level, utility companies define the price and the amount of power supply based on the consumption determined in the lower level. Ref. [18] deployed a game theory model to assist flexible consumers in finding the most profitable coalition for flexibility trading. Ref. [19] utilized a network-constrained Stackelberg game to set the price of flexibility traded by consumers. Ref. [20] deployed algorithmic game theory for energy management of communities consisting of flexible prosumers considering resources constraints. In [21], authors deployed game theory to analyze flexibility providers' strategy for selecting the best business partners in order to maximize their profit.

To simulate the real behavior of agents, iterative approaches should be utilized to reflect the agents' reactions based on a dynamic game and interactions among players in a competitive trading framework. Most of the non-iterative approaches cannot model the independent decision-making behavior of all agents and just consider a limited number of decision-maker agents in their model. Furthermore, decision-maker agents do not have similar decision-making power in the non-iterative approaches. In this way, agents' reactions to the other agents' different actions in a fair trading framework, where all agents have similar power, could be followed in iterative approaches. Moreover, the trading structure should be modeled correctly to consider and reflect behaviors of existing market players in the trading framework, otherwise, it will lead to errors in analyzing some agents' trading actions which may finally result in their failure. Authors in [22] presented a single-layer triangular iterative approach for trading flexibility in the distribution system. However, their approach converges after numerous iterations in some cases. It shows that the single-layer framework cannot model the agents' interconnections efficiently. To model the flexibility trading more realistically, by considering independent decision-making capability for the DSO, aggregators, and customers, and equipping them with the ability to update their decisions according to others actions in a two-layer structure, where all players have equal autonomy in the decision-making process, our approach analyzes flexibility transactions from the regulatory body's point of view. Therefore, our approach assists the regulator body in investigating the effects of new policies and regulations. Deploying the two-layer structure for modeling the close interconnection between customers and aggregators in the inner layer and their interaction with the DSO at the outer layer instead of considering all agents in one layer leads to fewer iterations until convergence which decreases the needed time for solving the problem.

B. AIMS AND CONTRIBUTIONS

To the best of the authors' knowledge, a two-layer framework for local flexibility trading in which the DSO, aggregators, and customers can make their own decisions independently, and the close interconnection between customers and aggregators is taken into account has not been reported in the literature. In our proposed approach, customers, who are in charge of providing energy flexibility by managing their consumption, aggregators, and the DSO intend to solve their own problems by determining their decision-making variables. In this regard, in our proposed two-layer game, in the inner layer, customers and aggregators have an iterative game until they settle on an agreement. Then, the DSO sets its decision variables in the outer layer in interaction with the inner layer. If the convergence condition of the outer layer is met after the decision of the DSO, the game is finished. Otherwise, the iterative inner game and the subsequent decision of DSO in the outer layer are repeated until the convergence condition is met. This way, considering the close interconnection between customers and aggregators in the inner layer causes the fast convergence after few iterations. Thus, the main contributions of this paper are summarized as follows:

- Proposing a framework to model the behavior of strategic agents (DSO, aggregator, and customers) in the distribution system by implementing a novel two-layer game-based model to empower agents for making their decisions regarding local flexibility trading independently and updating them in interaction with other agents considering the close interconnection between customers and aggregators.
- Developing a model that enables analyzing the competitive behavior of different agents and their interactions while considering three scenarios for validating the performance of the proposed model and evaluating the effect of the arbitrage prevention constraints in the customers' flexibility transaction with aggregators and the DSO.

The rest of the paper is organized as follows. In Section II, the formulation of the problem is described. Section III describes the structure of our proposed two-layer game-based model. Section IV explains three scenarios that are considered to study the model. Simulation results for the 33-bus test system are presented in Section V. Finally, the paper is concluded in Section VI.

II. PROBLEM FORMULATION

In this section, we explain our proposed framework of energy flexibility transaction, and different constraints for flexibility

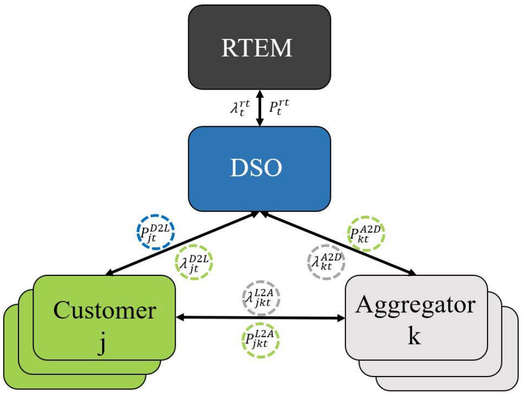

FIGURE 1. **Agents and the framework of flexibility trading.**

provision and transaction are presented. According to our model, all customers can provide either positive or negative energy flexibility by changing their scheduled consumption to participate in the flexibility market as represented in Eq. (1). In this equation, L_{jt}^f, L_{jt}^c, L_{jt} represent the amount of flexibility that customer j provides, the scheduled load for customer j, and the real-time load of customer j after providing the flexibility, respectively. In Eq. (2), the maximum and minimum amount of the energy flexibility that customers in each hour can provide are defined accordingly. Here, γ_j is called flexibility factor which can be set between 0 and 1 which is introduced in [3].

$$L_{jt} = L_{jt}^c - L_{jt}^f, \forall j, t \tag{1}$$

$$-\gamma_j L_{jt}^c \le L_{jt}^f \le \gamma_j L_{jt}^c, \forall j, t \tag{2}$$

In our proposed structure for trading energy flexibility, as illustrated in Fig. 1, customers are able to transact flexibility with their corresponding aggregator who bought their scheduled energy, P_{jkt}^{L2A}, at price λ_{jkt}^{L2A}. If a customer buys flexibility from its aggregator, P_{jkt}^{L2A} is negative. On the other hand, if a customer sells energy flexibility to an aggregator, P_{jkt}^{L2A} is positive. Furthermore, customers can also exchange flexibility with the DSO in both directions, P_{jt}^{D2L}, at price λ_{jt}^{D2L}. If a customer buys energy flexibility from the DSO, P_{jt}^{D2L} is positive. Oppositely, if a customer sells flexibility to the DSO, P_{jt}^{D2L} is negative. The flexibility provided by customers is transacted with the DSO and their corresponding aggregator. Therefore, the relation between energy flexibility provided by customers, their flexibility traded with the DSO, and their corresponding aggregators is as expressed in Eq. (3), where M_{jk} is an incidence matrix that maps flexibility trading between customer j and aggregator k. This way, customer j trades flexibility with aggregator k if $M_{jk} = 1$, otherwise, they do not trade flexibility with each other. Moreover, it is assumed that loads in this paper are interruptible to some extent. To put it another way, the sum of provided energy flexibility by each customer in 24 hours should not be necessarily zero. However, as stated in Eq. (4), this sum is limited to be more than the assigned lower band and less than the upper band. Here, α is a coefficient that defines the portion of interruptible loads. In our study, we assumed that α is 0.1.

$$L_{jt}^f = \sum_k M_{jk} P_{jkt}^{L2A} - P_{jt}^{D2L}, \forall j, t \tag{3}$$

$$-\alpha\gamma_j \sum_t L_{jt}^c \le \sum_t L_{jt}^f \le \alpha\gamma_j \sum_t L_{jt}^c, \forall j \tag{4}$$

Moreover, according to Fig. (1), the total flexibility traded between customers and aggregators is traded among aggregators and the DSO as stated in (5). Thus, as P_{jkt}^{L2A} can be either positive or negative, the flexibility exchanged among aggregators and the DSO can also be positive or negative. In addition, the DSO trades energy with the RTEM for purchasing required flexibility or selling the additional flexibility provided by customers. The relation between P_t^{rt}, P_{jt}^{D2L}, and P_{kt}^{A2D} is shown in Eq. (6).

$$P_{kt}^{A2D} = \sum_{j \in A_k} P_{jkt}^{L2A}, \forall k, t \tag{5}$$

$$P_t^{rt} = \sum_j P_{jt}^{D2L} - \sum_k P_{kt}^{A2D}, \forall t \tag{6}$$

The objectives and decision variables of the DSO, aggregators, and customers are principals of our methodology. In this way, customers define the flexibility traded with their corresponding aggregators, P_{jkt}^{L2A}, and the price of flexibility traded with the DSO, λ_{jt}^{D2L}. Their objective is to minimize their cost. The upper and lower band of P_{jkt}^{L2A} and λ_{jt}^{D2L} are presented in (7) and (8), respectively.

$$-\gamma_j L_{jt}^c \le P_{jkt}^{L2A} \le \gamma_j L_{jt}^c, \forall j, t \tag{7}$$

$$-\lambda_{jkt}^{L2A} \le \lambda_{jt}^{D2L} \le \lambda_{jkt}^{L2A}, \forall j, t \tag{8}$$

Moreover, aggregators decide on the price of their flexibility traded with the DSO, λ_{kt}^{A2D}, and the price of their flexibility exchanged with their corresponding customers, λ_{jkt}^{L2A}. They can set different prices for different customers (9). Similar to customers, the goal of aggregators is to minimize their costs. Eq. (10) and (9) describes the upper and lower bands of λ_{kt}^{A2D} and λ_{jkt}^{L2A}, respectively. Maximum and minimum values considered for λ_{jkt}^{L2A} in different hours are presented in table 1.

$$\underline{\lambda}_{kt}^{L2A} \le \lambda_{jkt}^{L2A} \le \overline{\lambda}_{kt}^{L2A}, \forall t, k \tag{9}$$

$$\delta_{kt} \lambda_{jkt}^{L2A} \le \lambda_{kt}^{A2D} \le \lambda_t^{rt}, \forall t, k \tag{10}$$

Finally, the DSO is responsible for deciding on its traded flexibility with customers, P_{jt}^{D2L}. The maximum and minimum limitations of P_{jt}^{D2L} are stated in Eq. (11).

$$-\gamma_j L_{jt}^c \le P_{jt}^{D2L} \le \gamma_j L_{jt}^c, \forall j, t \tag{11}$$

The objective functions of customers, aggregators and the DSO are presented in (12), (13) and (14), accordingly. As presented in (12), the objective function of customers consists of

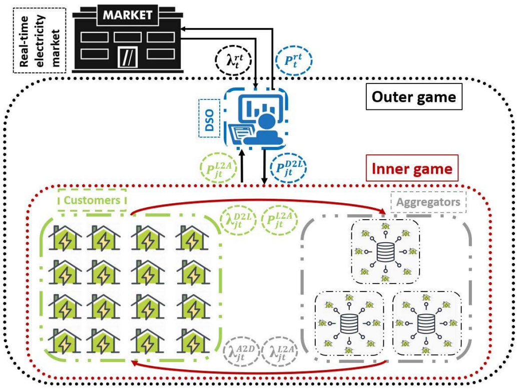

FIGURE 2. Our proposed two-layer iterative game structure.

two parts. The first part is related to the cost of trading flexibility with the DSO and the second part represents the income due to transacting flexibility with aggregators. Similar to customers, the objective function of aggregators also contains two terms which represent the cost of buying flexibility from customers and the income resulted from selling flexibility to the DSO, accordingly, which is presented in (13). However, the objective of the DSO is to minimize its financial exchange with the RTEM and increase the self-sufficiency of the distribution system as expressed by Eq. (14).

$$\begin{aligned} OF_j^{cu} &= \sum_t \lambda_{jt}^{D2L} P_{jt}^{D2L} \\ &\quad - \sum_t \lambda_{jkt}^{L2A} P_{jkt}^{L2A}, j \in A_k \end{aligned} \tag{12}$$

$$\begin{aligned} OF_k^{ag} &= \sum_t \sum_j \lambda_{jkt}^{L2A} P_{jkt}^{L2A} \\ &\quad - \sum_t \lambda_{kt}^{A2D} P_{kt}^{A2D}, \forall j \in A_k \end{aligned} \tag{13}$$

$$OF^{dso} = \sum_t \lambda_t^{rt} |P_t^{rt}| \tag{14}$$

It is also noteworthy that decision variables of an agent could be a part of the objective function of other agents. In this way, the decision variables of one agent are parameters of the decision-making problem of other agents. In this regard, we propose an iterative two-layer game-based model for trading flexibility among agents in a bottom-up approach to consider the effect of agents' decisions on others. Fig. 2 depicts interactions among agents and decision-making flow in our proposed local energy flexibility trading model.

III. GAME MODEL

In this section, we describe our proposed game model. In this regard, there are two iterative games in our proposed model; the inner game and the outer game. At the inner game, customers and aggregators reach an agreement on their decision variables after iterative games. In this regard, firstly, customers decide on their variables based on the initialized data. In the second step, aggregators make their decisions according to the decisions that came from customers. Then, customers and aggregators update their decision variables according to the decision variables of each other. This process is iterated until the first convergence condition, which is presented in (15), is met.

TABLE 1. Maximum and minimum bands for Prices of traded energy between customers and aggregators.

Time (h)	$\lambda_{k=1,t}^{L2A}$ [€/kWh]	$\lambda_{k=2,t}^{L2A}$ [€/kWh]	$\lambda_{k=3,t}^{L2A}$ [€/kWh]
1	[0.046 , 0.054]	[0.072 , 0.088]	[0.058 , 0.062]
2	[0.047 , 0.053]	[0.750 , 0.085]	[0.069 , 0.071]
3	[0.049 , 0.051]	[0.083 , 0.097]	[0.067 , 0.073]
4	[0.039 , 0.041]	[0.067 , 0.073]	[0.048 , 0.052]
5	[0.100 , 0.120]	[0.172 , 0.188]	[0.136 , 0.164]
6	[0.120 , 0.120]	[0.183 , 0.217]	[0.145 , 0.175]
7	[0.124 , 0.136]	[0.218 , 0.222]	[0.169 , 0.171]
8	[0.147 , 0.153]	[0.237 , 0.243]	[0.176 , 0.204]
9	[0.144 , 0.176]	[0.246 , 0.254]	[0.195 , 0.205]
10	[0.223 , 0.257]	[0.394 , 0.426]	[0.316 , 0.344]
11	[0.247 , 0.273]	[0.385 , 0.455]	[0.340 , 0.380]
12	[0.267 , 0.293]	[0.395 , 0.465]	[0.335 , 0.405]
13	[0.249 , 0.251]	[0.398 , 0.402]	[0.307 , 0.333]
14	[0.168 , 0.192]	[0.250 , 0.270]	[0.189 , 0.231]
15	[0.149 , 0.151]	[0.227 , 0.253]	[0.194 , 0.206]
16	[0.139 , 0.141]	[0.211 , 0.229]	[0.167 , 0.193]
17	[0.142 , 0.158]	[0.234 , 0.266]	[0.177 , 0.203]
18	[0.198 , 0.202]	[0.337 , 0.383]	[0.284 , .0316]
19	[0.193 , 0.227]	[0.349 , 0.371]	[0.270 , 0.310]
20	[0.202 , 0.238]	[0.392 , 0.428]	[0.280 , 0.320]
21	[0.223 , 0.257]	[0.419 , 0.421]	[0.324 , 0.336]
22	[0.118 , 0.122]	[0.198 , 0.242]	[0.158 , 0.162]
23	[0.103 , 0.117]	[0.187 , 0.193]	[0.135 , 0.165]
24	[0.057 , 0.630]	[0.089 , 0.091]	[0.690 , 0.710]

$$\begin{aligned} &|(OF^C(i) - OF^C(i-1))/|OF^C(i)| \\ &\quad + |(OF^A(i) - OF^A(i-1))/|OF^A(i)| < \epsilon \end{aligned} \tag{15}$$

Here, we have $OF^C = \sum_j OF_j^{cu}$ and $OF^A = \sum_k OF_k^{agg}$. Besides, ϵ is considered a small amount parameter. In our simulation, ϵ is 0.01 for all scenarios. After the convergence of the iterative inner game, the DSO determines its decision variables according to the output of the inner game. Then, the convergence condition of the outer game is checked (which is stated in (16)). In this way, if the convergence condition is not met, customers and aggregators will make their decisions at the iterative inner game again, and the DSO will update its decision according to the output of the inner game. If the convergence condition of the outer game is met, all agents reach an agreement, and the decision-making process is finished. Fig. 3 depicts the flowchart of the decision-making process in our proposed approach.

$$\begin{aligned} &|(OF^C(i) - OF^C(i-1))/|OF^C(i)| \\ &\quad + |(OF^A(i) - OF^A(i-1))/|OF^A(i)| \\ &\quad + |(OF^{dso}(i) - OF^{dso}(i-1))/|OF^{dso}(i)| < \epsilon \end{aligned} \tag{16}$$

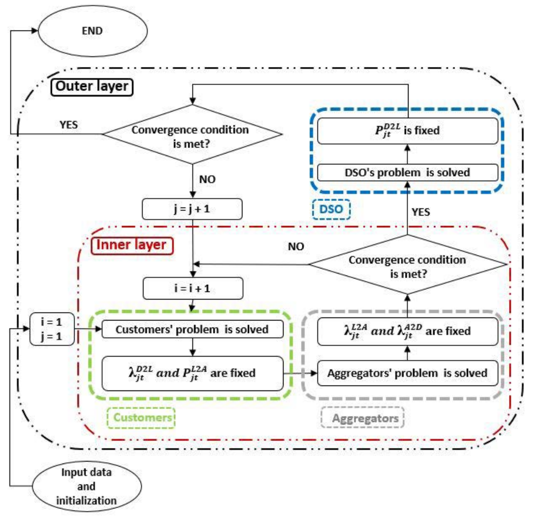

FIGURE 3. Two-layer iterative game structure.

IV. SCENARIOS DEFINITION

In this section, three different scenarios considered for our study are discussed. In these three scenarios, the DSO and customers have dissimilar levels of freedom for defining their decision variables. Different levels of freedom result from the presence or absence of two constraints. Despite the DSO and customers, aggregators have a similar level of freedom in all scenarios. Table. 2 describes the constraints of customers, aggregators, and the DSO's problem in different scenarios. In scenario 1, the problem of customers includes Eq. (7) in its constraint. In fact, there is a constraint for the amount of flexibility traded between customers and their corresponding aggregator (P^{L2A}_{jkt}) in the problem of customers. This amount should not be bigger than $\gamma_j L^c_{jt}$. This constraint is for arbitrage prevention in the flexibility trading between customers and aggregators. In addition, the problem of the DSO includes Eq. (11) in its constraints. As a matter of fact, there is a constraint for the amount of flexibility traded between customers and the DSO (P^{D2L}_{jt}) in the problem of the DSO. This amount should also not be bigger than $\gamma_j L^c_{jt}$. The presence of this constraint means that arbitrage is prevented in the flexibility transaction between the DSO and customers. Thus, the DSO and customers have a lower level of freedom, due to having one more constraint while solving their own problems. Problems of customers, aggregators, and the DSO in scenario 1 are presented below:

- Customers' problem (Problem E):
  $Min.\ OF^E$
  $s.t.$ (2), (3), (4), (7), (8).
- Aggregators' problem (Problem A):
  $Min.\ OF^A$
  $s.t.$ (5), (10), (9).

TABLE 2. Constraints of customers, aggregators and the DSO's problem in different scenarios.

Scenario	Problem E $Min.\ OF^E$	Problem A $Min.\ OF^A$	Problem D $Min.\ OF^{dso}$
Scenario 1	(2),(3),(4),(7),(8)	(5),(9),(10)	(2),(3),(4),(11)
Scenario 2	(2),(3),(4),(8)	(5),(9),(10)	(2),(3),(4),(11)
Scenario 3	(2),(3),(4),(7),(8)	(5),(9),(10)	(2),(3),(4)

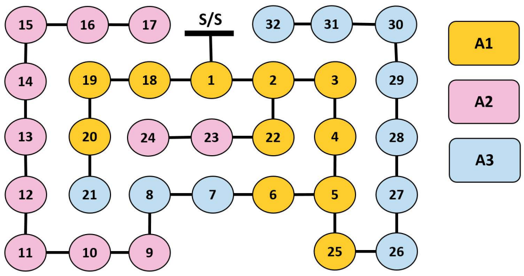

FIGURE 4. 33-bus test system and aggregators [23].

- DSO's problem (Problem D):
  $Min.\ OF^{dso}$
  $s.t.$ (2), (3), (4), (11).

In scenario 2, the DSO's constraints are similar to scenario 1. However, Eq. (7) is removed from customers' constraints. It means that there is not any constraint onP^{L2A}_{jkt}, and the possibility of arbitrage is not prevented. However, it should be noted that the amount of flexibility provided by customers is constrained by Eq. (2). But, (P^{L2A}_{jkt}) is not constrained by separate constraint. Therefore, customers in scenario 2, are freer for deciding on their decision variables. On the other hand, in scenario 3, constraints of customers' problem are similar to scenario 1, while Eq. (11) is removed from the DSO's constraints. It implies that there is not any constraint on P^{D2L}_{jt} and arbitrage is possible in the customers' flexibility transaction with the DSO and aggregators. Hence, the DSO'S level of freedom in scenario 3, is more than scenarios 1 and 2.

V. SIMULATION RESULTS

A. CASE STUDY

We used a 33-bus test system from [3] and [16] to evaluate our proposed method. As shown in Fig. 4, each customer in this system is related to one of the three aggregators. Besides, we persume that $\gamma_j = 0.1$, and $\delta_{kt} = 1.1$ according to [3] and [16], accordingly.

B. GAME INTERACTIONS

As mentioned beforehand, we have considered three scenarios with different levels of freedom for the DSO and customers to decide and determine their decision variables. Our results show that in scenarios 1 and 2, in both the inner and outer layer, the convergence condition is met after few iterations. However, in scenario 3, the convergence condition of the outer layer is met after 18 iterations, while there are few

TABLE 3. Number of iterations of game in outer layer for different scenarios.

Scenario	1	2	3
Number of outer iterations	5	4	18

TABLE 4. Number of iterations of inner games in different iterations of game in outer layer for different scenarios.

iteration of outer layer	scenario 1	scenario 2	scenario 3
iteration 1	5	3	3
iteration 2 to last iteration	2	2	2

iterations for the inner layer. Number of iterations of outer layer and their corresponding inner iterations are presented in tables 3 and 4 respectively.

In scenario 1, there are five iterations in the outer layer. In the first iteration in the outer layer, there are five inner games between customers and aggregators. They modify their decisions in each inner game, and finally, the first condition convergence is fulfilled at the end of 5th inner game. In 2nd to 5th outer game, there are just two inner games between customers and aggregators. It shows that, except the first iteration in the outer layer, in which customers and aggregators reach an agreement after five iterations, in the following iterations in the outer layer, they reach an agreement immediately. Finally, in the 5th iteration in the outer layer, the convergence condition of the outer layer is fulfilled, and the decision-making process is finished. The final objective functions for customers, aggregators, and the DSO, in scenario 1, are 1752 €, -2608 €, and 18.89 €, respectively. Aggregators can set their variables in such a way that obtain a negative objective function. Hence, flexibility trading makes profit for them. On the other side, customers' objective function is positive. Therefore, flexibility trading is loss-making for them.

In scenario 2, the decision-making process is finished after four iterations in the outer layer. In the first iteration of the game in the outer layer, aggregators and customers settle on an agreement after three iterations in the inner layer. Iterations two to four in the outer layer consist of just two iterations in their inner layer. Unlike scenarios 1 and 2, in scenario 3, there are several iterations in the outer layer. The complete agreement among agents results after 18 iterations in the outer layer. However, in each game in the outer layer, there are few iterations in the inner layer (3 iterations for the first outer game and just two iterations for all other outer games). Therefore, our proposed two-layer iterative game-based framework is very efficient in scenarios 1 and 2 due to the few iterations in both layers. In addition, Although in scenario 3, there are 18 iterations in the outer layer, aggregators and customers reach an agreement immediately after few iterations in the inner layer.

As mentioned before, in scenario 1, both customers and the DSO are more limited for defining their decision variables. Moreover, in scenario 2, owing to fewer constraints, customers are freer for making their decisions. The amount of objective function of customers, aggregators, and the DSO in different inner and outer games for scenarios 1 and 2 are presented in the Figures 5 and 6, accordingly. It is observed that, while customers in the first outer game obtain income owing to the negative objective function, the DSO's decisions push them to achieve a positive objective function in other outer iterations. The negative objective function in the first outer game is owing to the initialized value of P_{jt}^{D2L}. However, after the DSO determines P_{jt}^{D2L} to solve its problem, in the next outer iterations, customers are not able to gain income regarding the limitations that P_{jt}^{D2L} assigned by the DSO imposes on the upper and lower band of P_{jkt}^{L2A} based on Eqs. (3) and (4).

In scenario 2, at the first outer game, customers' objective function is -2245 € due to decisions they made according to initialized data. However, in the next outer game, the decision of the DSO at the end of the first outer game pushes customers' objective function to be -537 €. In the third outer game, customers' objective function increases to -434 €. Finally, it settles on -444 € at the last outer game. On the other hand, aggregators' objective function increases from -2583 € in the first outer game to -5179 € in the third outer game. It shows that in the first to third iterations of the game in the outer layer, the decision of the DSO restricts customers but paves the way for aggregators to gain more income. At the last iteration in the outer layer, aggregators' objective function increases insignificantly.

C. BEHAVIOUR ANALYSIS OF AGENTS

1) CUSTOMERS

Customers in our game model compete with aggregators in the inner game. Our results show that P_{jkt}^{L2A} for customers with the same aggregators have a similar pattern. It is reasonable since there is no constraint to couple customers with each other, therefore customers who have a contract with the same aggregator should have similar behavior. Fig. (7) illustrates P_{jkt}^{L2A} in 24 hours for 6 customers who have contract with aggregator 2. It is shown that P_{jkt}^{L2A} is the same for customers 11 and 14, and customers 23 and 24 because their real-time load, L_{jt}, is the same. Furthermore, it is seen that the 24-hour curve of P_{jkt}^{L2A} is similar for all six customers. It means that the ratio of their traded flexibility is almost equal in all hours. Therefore, as expected, their behavior is completely alike.

2) AGGREGATORS

As mentioned in section II, according to our model, each aggregator can determine different prices for trading flexibility with their corresponding customers. Our results show that each aggregator sets an equal price for trading flexibility with its customers as seen in Fig. (8). In this way, the price of flexibility traded between all customers and their corresponding aggregators in hours 5, 9, 14, and 22 are plotted. It is observed that customers with the same aggregator have a similar price for trading flexibility. The reason behind this issue can be understood from the behavior of customers. As mentioned

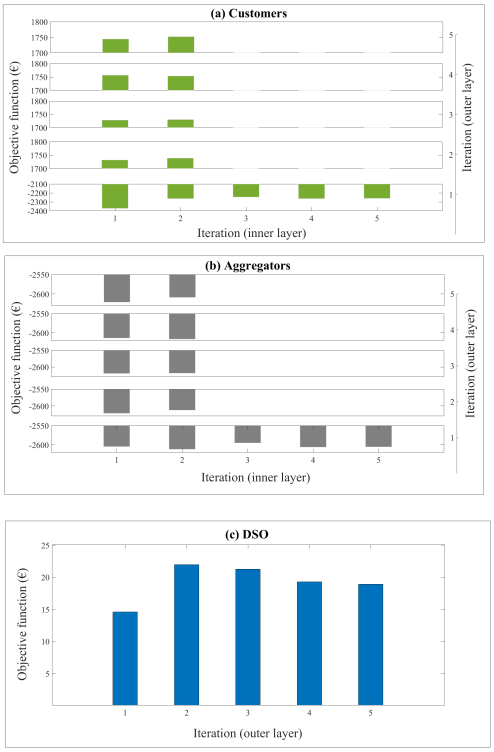

FIGURE 5. Objective function of (a) customers, (b) aggregators, and (c) the DSO in scenario 1.

in the previous section, customers who have a contract with the same aggregator have similar behavior. Therefore, each aggregator behaves similarly to all of its customers and sets equal prices for them in each hour.

3) DSO

In this section, in order to investigate the behavior of the DSO, its flexibility exchanged with the RTEM in three scenarios that are shown in Fig. 9 are studied. It can be seen that in scenario 3, where the DSO is freer for determining its decision variable, in all hours, P_t^{rt} is near zero. Similarly, in the first scenario in which both customers and the DSO's level of freedom is lower, P_t^{rt} is near zero in most hours. However, in comparison with scenario 3, P_t^{rt} is more in all hours in scenario 1. On the other hand, in scenario 2, where customers can solve their problem freer, and the DSO is more limited, P_t^{rt} is very big in all hours. This trend corresponds to the DSO's objective function in different scenarios. It shows that customers' freedom causes the DSO's objective function to be very high. Therefore, customers' freedom has a very destructive effect on the performance of the DSO.

D. SCENARIO DISCUSSION

In this section, the performance of the DSO, aggregators, and customers in different scenarios are studied, and the impact of customers and the DSO's freedom on their performance is discussed. As mentioned before, we considered three scenarios with dissimilar levels of freedom for customers and the DSO due to the presence and absence of arbitrage prevention

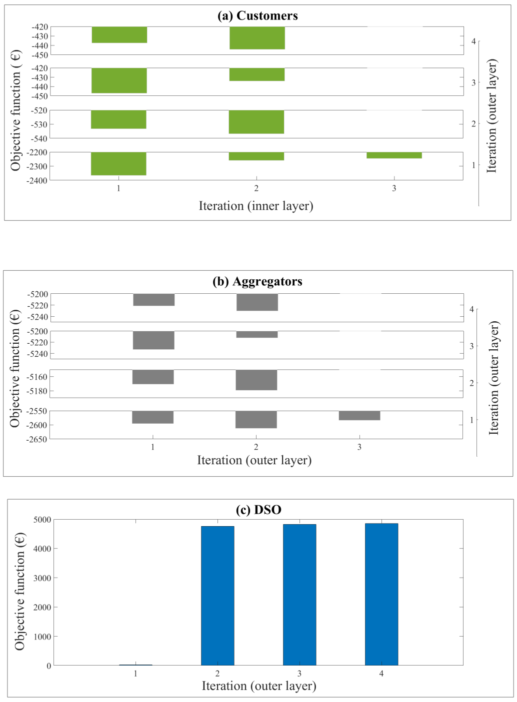

FIGURE 6. Objective function of (a) customers, (b) aggregators, and (c) the DSO in scenario 2.

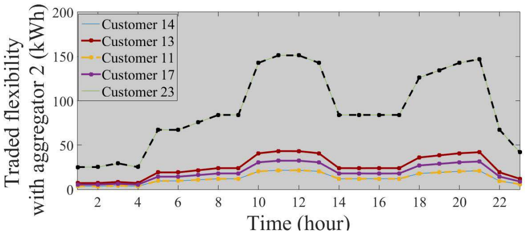

FIGURE 7. Traded flexibility between aggregator 2 and customers.

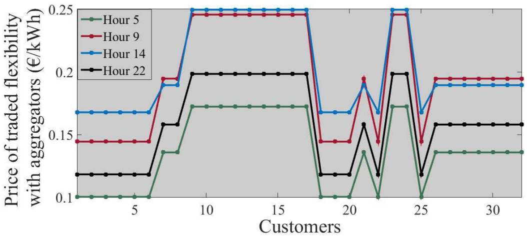

FIGURE 8. Price of traded flexibility between customers and their corresponding aggregator.

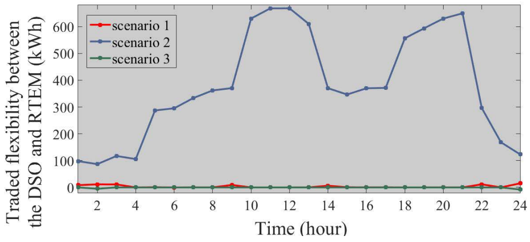

FIGURE 9. Real-time energy traded among the DSO and the RTEM.

TABLE 5. Objective function for customers, aggregators and the DSO in different scenarios.

Scenario	OF^E [€]	OF^A [€]	OF^{dso} [€]
1	1752.33	-2608.33	18.89
2	-444.24	-5230.7	4851.80
3	1799.99	-2607.64	1.78

constraints in the customers' flexibility transaction with aggregators and the DSO as described in Table 2. Thus, it is expected that customers' objective function in the second scenario, and the DSO's Objective function in the third scenario, be less than other scenarios. Table 5 represents customers, aggregators, and the DSO's objective function in different scenarios. As expected, OF^E in scenario 2 is less than two others scenarios, and OF^{dso} in the third scenario is minimum. By deciding more freely, customers can reduce their objective function from 1752.33 € to -444.24 € ($\approx$ 125% reduction). The decrease of the DSO's objective function owing to omitting one of its constraints is about 90.5% (from 18.89 € to 1.78 €). Moreover, it is observed that OF^A in the second scenario is less than in scenarios 1 and 3. Therefore, aggregators benefit from the freedom of customers. Aggregators' objective function in scenario 1 is -2608.33 €, while it decreases to -5230.7 € in scenario 2 ($\approx$ 100.5 % decrease). Additionally, the freedom of customers is very destructive for the DSO because its objective function in scenario 2 (4851.8 €) is about 256 times more than scenario 1. However, the impact of the DSO's freedom on customers' objective function is not as intense as the impact of customers' freedom on the DSO. Since customers' objective function in scenario 3 (1799.99 €) is just about 2.7 % more than scenario 1. In addition, it is interesting that, although aggregators benefit from the freedom of customers, the freedom of the DSO does not worsen their performance. As their objective function in scenario 3 is similar to scenario 1.

VI. CONCLUSION

In this paper, a novel two-layer game-based framework has been presented for local flexibility transaction in distribution systems. We also considered three scenarios with dissimilar levels of freedom while decision-making for customers and the DSO due to the presence and absence of arbitrage prevention constraints in the customers' flexibility transaction with aggregators and the DSO. The proposed model enabled us to analyze the performance of customers, aggregators, and the DSO as well as their interactions in different scenarios where arbitrage is possible or prevented. According to the simulation results, our iterative approach is converged after few iterations in both the inner and the outer layers. Besides, it has been found that all customers who have a contract with the same aggregator behave similarly while determining the flexibility traded with their corresponding aggregator. Moreover, each aggregator sets a similar price for trading flexibility with all of its customers. Furthermore, the removal of arbitrage avoidance constraint in the flexibility transaction between customers and aggregators is very destructive for the DSO as its objective function increases significantly. In addition, customers can reduce their objective function while determining their decision variables more freely. The impact of the DSO's freedom (due to removal of arbitrage avoidance constraint in the flexibility transaction between the DSO and customers) on the objective function of customers is not as destructive as the impact of customers' freedom (due to removal of arbitrage avoidance constraint in the flexibility transaction between customers and aggregators) on the DSO. Similar to customers, aggregators also benefit from the customers' freedom for solving their problems, and their objective function decreases. Finally, it is found that the freedom of the DSO for determining its decision variables does not have a significant effect on the objective function of aggregators.

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Iterative Game Approach for Modeling the Behavior of Agents in a Competitive Flexibility Trading

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ABSTRACT The potential of end-users to modify their consumption pattern makes them an interesting resource for providing energy flexibility in energy communities. Thus, active end-users require sufficient incentives and automated trading and management schemes. In order to enable increased small-scale end-users participation for flexibility service provision, a new design for flexibility trading is required to model the behavior of different agents and their interactions in energy communities. The novelty of our work lies in proposing an iterative game-based approach in which all agents – consisting of the distribution system operator (DSO), aggregators, and customers– can determine their decision variables to optimize their own objective functions and interact with others to modify their decisions according to others' decisions. In addition, three scenarios are considered to study the effects of agents' freedom while setting their decision variables (by removing one of their constraints in their corresponding decision-making problem). Moreover, the impact of the presence of interruptible loads in comparison with shiftable loads is investigated in this paper. According to the simulation results, it is found that in the scenario where end-users have fewer constraints, in presence of interruptible loads, end-users gain greater income compared to the absence of interruptible loads.

INDEX TERMS Aggregators, energy community, flexibility management, game-based approach, local energy trading.

I. INTRODUCTION

A. BACKGROUND

Due to the increase in the utilization of renewable energies as variable and non-dispatchable resources, the power system is facing new problems related to the balance between demand and generation [1]. In this regard, new resources for providing the required balance management and other flexibility services are needed [2]. End-users can provide energy flexibility for the power system due to their ability to modify their consumption [3]. For instance, by adjusting their loads, utilizing the energy storage systems, or making use of the thermal inertia of buildings, end-users can provide flexibility for the system [4]. As a consequence, they are more engaged in the decisions related to the local community [5]. Therefore, conventional centralized approaches are not efficient enough to model the active participation of end-users [6]. In this regard, new approaches are needed to model the new type of energy transactions and interactions among different agents in the local communities. Several works proposed new models to follow the active behavior of end-users in energy and flexibility markets. In [7], a theoretical and mathematical foundation for the decentralized participation of consumers in the energy market has been presented. Moreover, challenges related to

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the specific characteristics of decentralized participation of flexible demands have been addressed in [7]. Furthermore, authors in [8] proposed an energy management mechanism to pave the way for residential buildings with distributed resources to trade energy in the distribution system. Ref. [9] proposed a decentralized mechanism to manage the operation of electric vehicles in charging mode and energy flexibility provided by end-users.

Some papers in the literature concentrated on the novel frameworks for flexibility trading in the distribution system. In [10], the authors proposed a two-stage approach that enables end-users to trade flexibility and energy in a peer-to-peer (P2P) platform that is supervised by the local market operator and the DSO. The authors in [11], presented a chance-constrained approach to manage uncertainties in the flexibility transaction among microgrids and the DSO. In [12], a pricing and bidding mechanism is proposed for the local flexibility market to boost its coupling with other markets such as retail, ancillary service, and the wholesale market. Ref. [13] proposed a stochastic model for optimal bidding strategy of aggregated prosumers to facilitate their flexibility provision. In this way, the uncertainty related to the PV generation, loads, outdoor temperature, and end-users' behavior has been considered by deploying scenario-based programming. In [14], a distributed local flexibility market is proposed where the uncertainty of demand and network congestion have been considered to assist the DSO in reserving and utilizing the demand flexibility most efficiently.

It is crystal clear that Handling the power system consisting of a large number of prosumers who are in charge of providing the system flexibility is very difficult. Therefore, an agent e.g aggregator is needed to aggregate energy and flexibility provided by prosumers. Authors in [15] presented a model for local flexibility market where aggregators control different devices for providing various services in the distribution system. In [16], the authors presented a decentralized market design in which aggregators are in charge of motivating prosumers to provide energy flexibility for the DSO. Authors in [17] proposed a two-stage stochastic optimization to facilitate the engagement of aggregators in energy and ancillary service markets. In ref. [18], the performance of aggregators for delivering the provided flexibility by residential end-users to the DSO in presence of large uncertainties is evaluated. In [19], authors proposed a control strategy based on a decentralized bottom-up approach to utilize the flexibility potentials of virtual power plants. Authors in [20] presented a cooperative market mechanism to determine energy transaction and price for micro-grids in isolated and connected modes considering the uncertainty of renewable energy sources and demand.

In addition to the necessity of the presence of an agent to aggregate the provided flexibility on the demand side, it should be noted that prosumers have a right to trade flexibility with the DSO directly owing to their important role in providing flexibility [21]. In this way, flexibility trading in the distribution system will be more competitive. Thus, an approach is needed to model the competition between different agents and their interactions. In this respect, a part of the literature deployed the models based on the game theory. Game-based approaches allow modeling the behavior of strategic agents and interactions among them by presenting a mathematical framework [22]. This characteristic makes the game-based approach an ideal method for modeling the energy and flexibility trading in energy communities. The proposed approach in [22] is based on a game theory analysis to investigate the behavior of the flexibility providers and their optimal strategy for choosing the best business partner that maximizes their profit. In [23], the demand response management problem has been studied using a game among utility companies and end-users. The proposed approach in [23] deployed the Stackelberg game between utility companies and end-users. The goal of utility companies and end-users is to optimize their income and payment, respectively. In [24], monopolistic and game-based approaches for trading energy flexibility are presented and compared. In this regard, in the monopolistic method, just aggregators or consumers decide on flexibility management. In addition, two scenarios are considered for the game-based approach, where in the first scenario, the DSO and aggregators are strategic agents and in the second scenario, the DSO and aggregators are the decision-maker agents.

Additionally, in [25], authors proposed a generic model for the geographical and economic evaluation of the flexibility potentials of the alternative flexibility providers using cooperative game theory. In [26], a two-level game is used for demand response management. In this regard, in the bottom level, households determine their purchased demand from utility companies according to the power price, and utility companies define their generation and price according to the power demand of residential users at the higher level. Ref. [27] presented a decentralized approach scheme for energy transactions among microgrids based on a game. In [28], an event-driven approach is proposed for energy trading between microgrids. For this sake, in their game-based model, authors deployed the concept of reward to make an incentive for the transaction. In [29], a design based on contributions is used for energy trading among microgrids in a competitive market. In this regard, energy is collected from providers and distributed to the consumers according to their historical contributions. Ref. [30] proposed a game-theoretic model in which aggregators compete with each other to maximize their profit by selling the demand response to the distribution system company. In [31], a novel scheme has been proposed for a non-convex community energy management problem based on the game theory and the constraints of resources. Ref. [32] presented a stochastic multi-layer model to investigate the behavior of different players in the electricity market. In their proposed approach, consumers are in charge of selecting their supplying agent using a game-theoretic model. Therefore, supplying agents should compete with each other to maintain their customers.

B. CONTRIBUTION

In the literature, numerous studies have been performed to propose an ideal framework for transacting energy flexibility in energy communities. Among all proposed solutions, game-based approaches are more applicable and realistic because they model the behavior of agents to empower them to make a decision independently. An important point in this approach is that the interaction among all agents should be considered while making decisions. However, complete interaction among the DSO, aggregators and end-users has not been modeled in the literature. To the best of the authors' knowledge, a framework in which all agents including end-users, aggregators, and the DSO can decide independently and modify their decisions has been proposed in none of the papers in the literature. In this paper, we propose an iterative game for modeling the rational behavior of all agents (end-users, aggregators, and the DSO) in a competitive flexibility trading in which agents can play their role and change their decisions according to the other agents' decisions. The contribution of this paper can be summarized as follows:

- A novel iterative game-based algorithm is proposed for modeling the flexibility transaction in the energy community considering interactions among all agents.
- Effects of shiftable and interruptible loads based on the portion of interruptible loads are studied.
- Three flexibility scenarios are considered (by removing one of their constraints in their corresponding decision-making problem) for assessing the impact of the freedom of agents on their decisions and validating the simulation results.

Our proposed iterative game-based approach has some advantages compared to other methods used in the literature. Firstly, it provides a competitive trading framework where all players have their decision variables and can solve their problems independently to find their optimal solutions. All agents in our proposed approach are engaged in the decision-making process, while there are limited decision-maker agents in other approaches. Secondly, our approach provides an equal power for all agents to update their decisions based on the last decisions of others, because the trading problem is solved from all agents' points of view considering their optimal strategies. For instance, bilevel optimization methodology solves the optimization problem from the leader's point of view. The autonomy of the followers in the bilevel optimization model is way less than the leader of the problem, as the leader can consider the objective function and constraints of the followers as a constraint in its optimization problem, to anticipate the logical actions of followers, while followers do not have a similar ability. In this regard, our proposed approach considers a similar power for all agents to make and update their decisions and prevents monopoly in the transaction process to serve the players with a competitive trading platform.

Furthermore, since our approach empowers all agents for making their decisions independently and modifying them based on others' decisions, it can simulate the real behavior of agents for flexibility trading where all agents have their optimal strategies. In this way, the energy sector policy-maker can study the trading behaviors and interactions of agents. This will enable the policy-maker to investigate the impacts of new regulations and rules on the agents' behavior and trading platform.

The rest of the paper is organized as follows. In Section II, the problem formulation is presented. Section III explains three scenarios for studying the impact of agents' decision-making freedom. Section IV describes our iterative game-based algorithm which is deployed for energy flexibility management. Simulation results for the 33-bus test system are discussed in Section V. Finally, our conclusions are presented in VI.

II. PROPOSED MODEL

A. PROBLEM FORMULATION

In this section, we explain our proposed model for transacting energy flexibility between agents in the energy community, i.e. end-users, aggregators, and the DSO, as illustrated in Fig. 1. In our model, end-users, aggregators, and the DSO transact flexibility in a hierarchical structure. In this way, the total energy transacted among end-users and aggregators is traded through aggregators and the DSO. In addition, end-users can trade flexibility with both their corresponding aggregator and the DSO. In this way, the monopoly is prevented, and the freedom of agents for participation in flexibility trading is promoted. Moreover, when end-users have the opportunity to trade flexibility with both the aggregators and the DSO, they are motivated to be more involved in the flexibility provision [21]. These factors can pave the path toward a competitive trading framework. It is considered that each aggregator has a bilateral contract with its corresponding end-users. In this way, end-users and aggregators can transact flexibility in both directions. Each end-user can adjust its load to provide positive or negative energy flexibility as represented in Eq. (1). Here, L_{jt}^{f} is the amount of flexibility provided by end-user j at time slot t, and L_{jt}^{c} is the scheduled load of end-user j. Besides, L_{jt} represents the

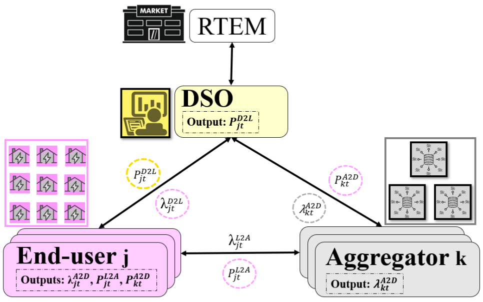

FIGURE 1. Interaction among agents in our proposed local flexibility trading model.

load of end-user j after providing the flexibility in real-time. Accordingly, Eq. (2) presents the upper and lower bounds for provision flexibility of end-users. Here, γ_j represents the flexibility factor which is introduced in [24]. The flexibility provided by an end-user is traded with the DSO or aggregator or both of them. The relation between the energy flexibility provided by an end-user (L_{jt}^{f}) and its flexibility traded with the DSO (P_{jt}^{D2L}) and its corresponding aggregator (P_{jt}^{L2A}) is represented in (3).

$$L_{jt} = L_{jt}^{c} - L_{jt}^{f}, \forall j, t \tag{1}$$

$$-\gamma_j L_{jt}^{c} \leq L_{jt}^{f} \leq \gamma_j L_{jt}^{c}, \forall j, t \tag{2}$$

$$L_{jt}^{f} = P_{jt}^{L2A} - P_{jt}^{D2L}, \forall j, t \tag{3}$$

Furthermore, Loads of end-users have been categorized into three general classifications; non-flexible, shiftable, and interruptible loads. Thus, shiftable and interruptible loads have the potential to be a source of flexibility, while end-users cannot adjust non-flexible loads for the sake of flexibility provision. The portion of interruptible and shiftable loads of consumers is described in (4) and Fig. 2. In this way, the portion of interruptible loads is determined by setting α. If $\alpha = 0$, energy consumption after providing flexibility over a time horizon, e.g. 24 hours, should be equal to the energy of scheduled load in the assumed time horizon. In other words, the sum of provided flexibility over a time horizon must be equal to zero by setting $\alpha = 0$. In this case, all flexible loads are shiftable. As the amount of α increases, the difference between the sum of scheduled load and the sum of the real-time load over a time horizon can be bigger which increases the portion of the interruptible load of end-user j. In addition, as mentioned before, end-users can trade flexibility with aggregators. In this way, if end-user j sells energy flexibility to its corresponding aggregator, P_{jt}^{L2A} is positive. However, if end-user j buys energy flexibility from its corresponding aggregator, P_{jt}^{L2A} is negative. Moreover, the relation between flexibility traded among aggregator k and its end-users (P_{jt}^{L2A}), and flexibility traded among aggregator k and the DSO (P_{kt}^{A2D}) is presented in (5).

$$-\alpha\gamma_j \sum_{t} L_{jt}^{c} \leq \sum_{t} L_{jt}^{f} \leq \alpha\gamma_j \sum_{t} L_{jt}^{c}, \forall j \tag{4}$$

$$P_{kt}^{A2D} = \sum_{j \in A_k} P_{jt}^{L2A}, \forall k, t \tag{5}$$

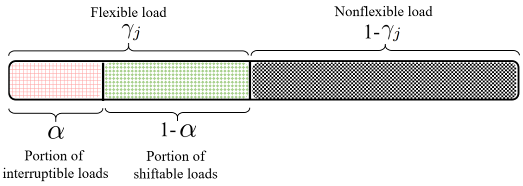

FIGURE 2. **Definition of interruptible and shiftable portions for flexible loads.**

In our proposed structure, the DSO and end-users are also able to trade flexibility in both directions. The positive sign of P_{jt}^{D2L} is considered for the trade of flexibility from the DSO to the end-user j, whereas if the DSO buys flexibility from end-user j, P_{jt}^{D2L} is negative. Additionally, end-users determine the amount of flexibility traded with their corresponding aggregators, P_{jt}^{L2A}, and the price of flexibility which is exchanged with the DSO, λ_{jt}^{D2L}. To prevent the possibility of arbitrage in the flexibility transaction between end-users and aggregators, upper and lower limits are considered for P_{jt}^{L2A} which is represented in (6). In addition, maximum and minimum limits related to λ_{jt}^{D2L} which is the decision variable of end-users is presented in (7).

$$-\gamma_j L_{jt}^{c} \leq P_{jt}^{L2A} \leq \gamma_j L_{jt}^{c}, \forall j, t \tag{6}$$

$$-\lambda_{kt}^{L2A} \leq \lambda_{jt}^{D2L} \leq \lambda_{kt}^{L2A}, \forall j, t \tag{7}$$

On the other hand, aggregators determine the price of their flexibility transacted with the DSO, λ_{jt}^{A2D}. The upper and lower bands of λ_{jt}^{A2D} are presented in (8).

$$\delta_{kt}\lambda_{kt}^{L2A} \leq \lambda_{kt}^{A2D} \leq \lambda_{t}^{rt}, \forall t, k \tag{8}$$

Finally, the DSO sets the flexibility traded among the DSO and end-users, P_{jt}^{D2L}. A limitation is considered for P_{jt}^{D2L}, in both directions, to prevent the possibility of arbitrage in flexibility trading among end-users and the DSO as presented in Eq. (9). Moreover, the DSO transacts flexibility with the RTEM and all agents as expressed in (10).

$$-\gamma_j L_{jt}^{c} \leq P_{jt}^{D2L} \leq \gamma_j L_{jt}^{c}, \forall j, t \tag{9}$$

$$P_{t}^{rt} = \sum_{j} P_{jt}^{D2L} - \sum_{k} P_{kt}^{A2D}, \forall t \tag{10}$$

B. AGENTS' OBJECTIVE FUNCTIONS

In this section, we introduce objective functions of end-users, aggregators and the DSO which are presented in (11), (12) and (13), respectively. As seen in (11), the objective function of end-user j consists of two parts. The first term represents the cost of buying flexibility from the DSO and the second term expresses the income of selling flexibility to its corresponding aggregator. The objective function of aggregators also consists of two parts consisting of the cost of exchanging flexibility with end-users and the income of flexibility exchanging with the DSO, accordingly. However, the DSO is in charge of minimizing the trade with the RTEM to increase the self-sufficiency of the distribution system. Fig. 1 shows interactions among agents and decision-making flow in our proposed energy flexibility trading model.

$$\begin{aligned} OF_{j}^{eu} = & \sum_{j}\sum_{t} \lambda_{jt}^{D2L} P_{jt}^{D2L} \\ & - \sum_{t}\sum_{j} \lambda_{kt}^{L2A} P_{jt}^{L2A}, j \in A_k \end{aligned} \tag{11}$$

$$OF_{k}^{ag} = \sum_{t}\sum_{j} \lambda_{kt}^{L2A} P_{jt}^{L2A}$$

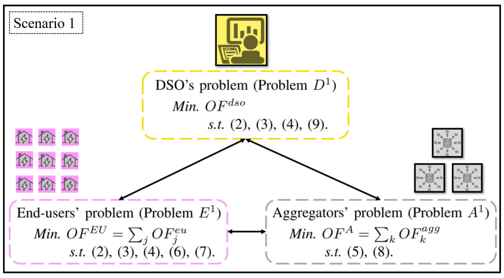

FIGURE 3. **Problems of agents and their constraints in scenario 1.**

$$-\sum_t \lambda_{kt}^{A2D} P_{kt}^{A2D}, \forall j \in A_k \tag{12}$$

$$OF^{dso} = \sum_t \lambda_t^{rt} |P_t^{rt}| \tag{13}$$

III. SCENARIOS DEFINITION

In this paper, three different scenarios are defined in which the DSO and end-users have different levels of freedom for determining their decision variables due to the presence or absence of the constraint on the amount of the traded flexibility between end-users and the DSO (Eq. (9)), as well as the constraint on the amount of the traded flexibility between end-users and their corresponding aggregator (Eq. (6)). On the other hand, the freedom of aggregators is constant in all scenarios. In this regard, the freedom of end-users and the DSO is increased by removing one of their constraints in their corresponding decision-making problem. As mentioned in Section II, (6) and (9) were the constraints related to preventing the possibility of arbitrage. Therefore, with their absence and presence, there are different levels of arbitrage avoidance. we consider three scenarios to analyze the behavior of the agents in the presence or absence of the arbitrage prevention constraints. Our proposed scenarios are explained in the following:

- Scenario 1: In scenario 1, the constraints of end-users' problem is composed of (2), (3), (4), (6), and (7). Aggregators problem consists of 2 constraints; (5) and (8). In addition, (2), (3), (4), and (9) are the constraints of the DSO's problem in this scenario. Presence of ((6)) in the problem of end-users, indicates that a restriction is set to prevent the possibility of arbitrage in the flexibility transaction between end-users and their corresponding aggregators. Furthermore, a limitation is imposed by (9) in the problem of the DSO to prevent the possibility of arbitrage in the flexibility transaction among end-users and the DSO. The objective function and constraints of all agents in scenario 1 is shown in Fig. 3
- Scenario 2: In scenario 2, problems of aggregators and the DSO are the same as scenario 1. However, in this scenario, (6) is removed from the constraints of end-users' problem. Therefore, an arbitrage may occur in the flexibility transaction between end-users and aggregators. However, owing to the presence of (9) in the constraints of the DSO's problem, the possibility of arbitrage in the flexibility transaction among the DSO and end-users is prevented. The objective function and constraints of all agents in scenario 2 is shown in Fig. 4.
- Scenario 3: In scenario 3, the problems of end-users and aggregators are similar to scenario 1. However, in this scenario, (9) is removed from the constraints of the DSO's problem. Therefore, an arbitrage may occur in the flexibility trading between end-users and the DSO. However, owing to the presence of (6) in the constraints of the end-users' problem, the possibility of arbitrage in the flexibility transaction among aggregators and end-users is prevented. Agents' objective functions and constraints in scenario 3 are presented in Fig. 5.

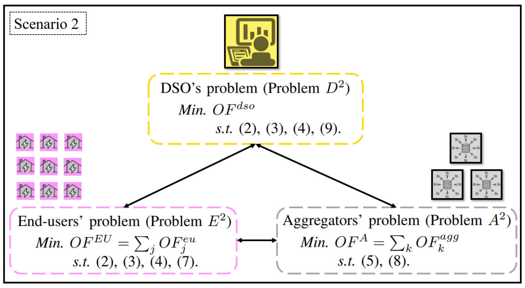

FIGURE 4. **Problems of agents and their constraints in scenario 2.**

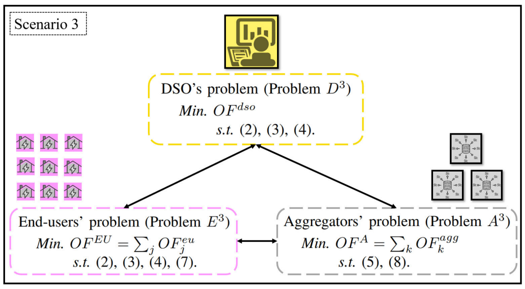

FIGURE 5. **Problems of agents and their constraints in scenario 3.**

IV. PROPOSED FLEXIBILITY TRADING

In this paper, we proposed an iterative game-based approach that enables players to make and update their decisions, as shown in Fig. 6. Since the decision variables of one agent may be a parameter in the objective function of other agents, the decision of each agent influences the optimal decision of other agents. In this regard, all agents are able to make their optimal decisions by optimizing their objective functions and finding the optimal value for their assigned decision variables. Then, in the next iteration, they can update their decision variables based on the last decisions of other agents. In this way, firstly, end-users solve their problem

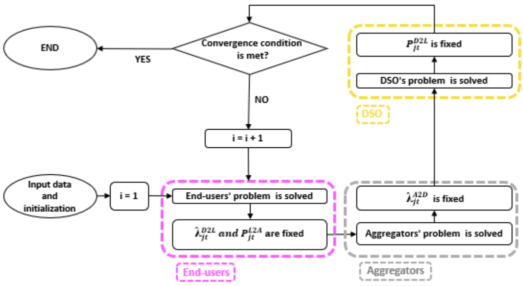

FIGURE 6. Flowchart of the proposed iterative game-based algorithm.

(problem E), and set their decision variables, P_{jt}^{L2A} and λ_{jt}^{D2L}, according to the initialized inputs and parameters. In the next step, aggregators find an optimal solution for their problem (problem A), and determine the amount of λ_{kt}^{A2D}. Moreover, P_{kt}^{A2D} is calculated according to P_{jt}^{L2A} determined in the previous step by end-users. Finally, the DSO solves its problem (Problem D) and determines the amount of P_{jt}^{D2L}. It is clear that the decision of the DSO depends on the previous decisions of end-users and aggregators in each iteration. Hence, the amount of P_{jt}^{L2A} affects the optimal amount of P_{jt}^{D2L} for Problem D. After P_{jt}^{D2L} is obtained, the decision-making procedure will be ended if the convergence condition is met as presented by (14). On the other hand, if Eq. (14) has not been met, the proposed game procedure will be iterated. This way, end-users make their decisions according to the updated value of P_{jt}^{D2L} which is determined by the DSO. Then, P_{jt}^{D2L} affects both decisions of end-users. Furthermore, it impacts on the constraints of P_{jt}^{L2A} according to (2) and (3). Moreover, the direction of the flexibility traded between the DSO and end-users influences the optimal value of λ_{jt}^{D2L}.

In this paper, we proposed an iterative game-based approach where the decision of each agent influences the decision of other agents as shown in Fig. 6. Thus, all agents are able to make their optimal decisions and update their decision variables in an iterative interaction with other agents. In this way, firstly, end-users solve their problem (problem E), and set their decision variables, P_{jt}^{L2A} and λ_{jt}^{D2L}, according to the initialized inputs and parameters. In the next step, aggregators find an optimal solution for their problem (problem A), and determine the amount of λ_{kt}^{A2D}. Moreover, P_{kt}^{A2D} is calculated according to P_{jt}^{L2A} determined in the previous step by end-users. Finally, the DSO solves its problem (Problem D) and determines the amount of P_{jt}^{D2L}. It is clear that the decision of the DSO depends on the previous decisions of end-users and aggregators in each iteration. Hence, the amount of P_{jt}^{L2A} affects the optimal amount of P_{jt}^{D2L} for Problem D. After P_{jt}^{D2L} is obtained, the decision-making procedure will be ended if the convergence condition is met as presented by (14). On the other hand, if Eq. (14) has not been met, the proposed game procedure will be iterated. This way, end-users update their decision variables based on the last value of P_{jt}^{D2L} which was determined by the DSO. As, P_{jt}^{D2L} affects both decisions of end-users, and impacts on the constraints of P_{jt}^{L2A} according to (2) and (3). Moreover, the direction of the flexibility traded between the DSO and end-users influences the optimal value of λ_{jt}^{D2L}. After end-users update their decisions, the aggregators and the DSO update their decision variables based on the last decision of end-user. This procedure is repeated and agents update their decisions until the convergence condition is met. In general, iterative approaches do not have deterministic convergence criteria. We considered a convergence criterion that is represented in Eq. 14. The convergence criterion of our approach is based on the difference between agents' objective functions in two consecutive iterations. In this way, the summation of variations of the agents' objective functions in two consecutive iterations must be less than a sufficiently small value.

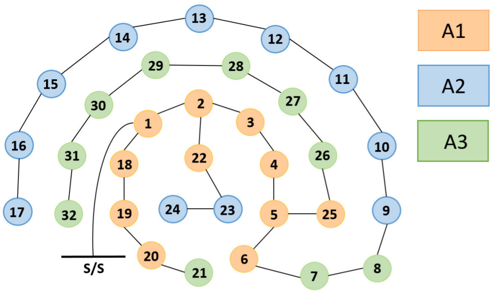

FIGURE 7. 33-bus test system [21], [24].

$$
\begin{aligned}
&(|OF^{EU}(i) - OF^{EU}(i-1)| \\
&\quad +|OF^{A}(i) - OF^{A}(i-1)| \\
&\quad +|OF^{dso}(i) - OF^{dso}(i-1)|)/(|OF^{EU}(i)| \\
&\qquad\qquad +|OF^{A}(i)| + |OF^{dso}(i)|) < \epsilon \qquad (14)
\end{aligned}
$$

V. SIMULATION RESULTS

A. CASE STUDY

In this paper, a 33-bus test system is used from [21], [24] to assess our proposed flexibility trading algorithm between agents in the energy community as shown in Fig. 7. Three regions have been considered which are managed by their corresponding aggregators. The price data of energy traded between end-users and aggregators is came from [21]. Besides, we assume that $\gamma_j = 0.1$, and $\delta_{kt} = 1.1$ according to Refs. [21], [24], respectively. In addition, it is considered that loads are totally shiftable ($\alpha = 0$). Our proposed flexibility management problem is solved in MATLAB using particle swarm optimization (PSO) for determining the optimal decision of each agent in each iteration. Thus, agents solve their problem in each iteration independently via PSO.

B. SCENARIOS DISCUSSION

1) SCENARIO 1

In this scenario in which none of the constraints of end-users and the DSO is removed, and both the DSO and end-users are

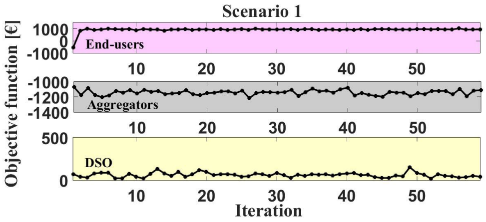

FIGURE 8. Objective function of end-users, aggregators, and the DSO in different iterations (Scenario 1).

TABLE 1. Objective function for end-users, aggregators and the DSO in different scenarios [€].

Scenario	End-users' OF	Aggregators' OF	DSO's OF
1	943.62	−1110.42	41.65
2	525.46	−2426.83	3253.48
3	1228.74	−1145.49	16.21

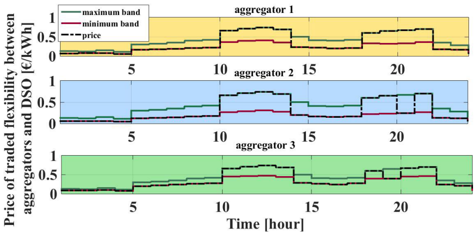

FIGURE 9. Price of flexibility transacted between aggregators and the DSO (Scenario 1).

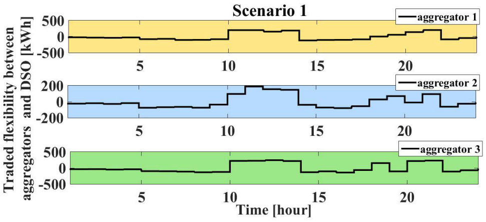

FIGURE 10. Flexibility traded between aggregators and the DSO (Scenario 1).

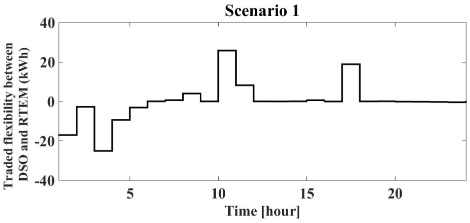

FIGURE 11. Real-time energy exchanged between the DSO and the RTEM (Scenario 1).

more restricted for making their decisions, after 59 iterations the convergence condition is met. Fig. 8 shows the amount of objective function of end-users, aggregators, and the DSO in different iterations. As shown in this figure, aggregators are able to achieve a negative value for their objective function which means that flexibility trading is profitable for them. On the other hand, while end-users in the first iteration can gain income due to the negative value of their objective function, decisions of other agents push them to have a positive objective function in other iterations. It can also be realized that like aggregators, fluctuation of end-users' objective function in different iterations is very low. However, the fluctuation of DSO's objective function is considerable. It shows that decisions of end-users have a significant effect on the maximum and minimum band of P_{jt}^{D2L}, according to Eq. 9, 2, and 3. Therefore, the objective function of the DSO fluctuates with different decisions of end-users.

Figs. 10 and 9 shows the flexibility traded between aggregators and the DSO and their price accordingly. It is obvious that when an aggregator buys energy flexibility from the DSO ($P_{kt}^{A2D} < 0$), it sets the minimum band for λ_{kt}^{A2D} based on Eq. (8) which is $\delta_{kt}\lambda_{kt}^{L2A}$. On the other hand, when aggregators k sells energy flexibility to the DSO ($P_{kt}^{A2D} > 0$), λ_{kt}^{A2D} is set on its maximum band (λ_t^{rt}). Fig. 11 shows energy flexibility traded among the DSO and the RTEM. It is observed that, in most hours, the amount of P_t^{rt} is near zero. Consequently, the amount of the objective function of the DSO is not considerable according to (13). Table 1 presents the amount of the objective function of end-users, aggregators, and the DSO in all three scenarios. The objective function of end-users, aggregators, and the DSO in scenario 1 are 943.62 €, −1110.42 € and 41.65 €, accordingly.

2) SCENARIO 2

In the second scenario where one of the constraints of end-users is removed and they can decide more freely, the convergence condition is met after 11 iterations. The amount of objective function of end-users, aggregators, and the DSO in different iterations is shown in fig. 12. Our results show that, in scenario 2, aggregators are more successful in gaining income in comparison with scenario 1, since they can reduce their objective function from −1110.42 in scenario 1 to −2294.28 in scenario 2. Figs. 14 and 13 show the flexibility traded between aggregators and the DSO and their price in scenario 2 accordingly. It can be understood that the amount of flexibility traded between aggregators and the DSO is more than its amount in scenario 1. So, aggregators are able to increase their income. In all iterations, end-users' objective function is positive except the first iteration, and finally, in the last iteration, their objective function is 522.46 €. Therefore, it is less in comparison with scenario 1 (943.62 €), in which they are more restricted while determining decision variables. Moreover, The objective function of the DSO in the second scenario (3253.48 €) is much more than its value in scenario 1 (41.65 €). Hence, the objective function of the DSO is about 77 times bigger than scenario 1. Therefore, it can be concluded that the freedom of end-users in scenario 2 is very

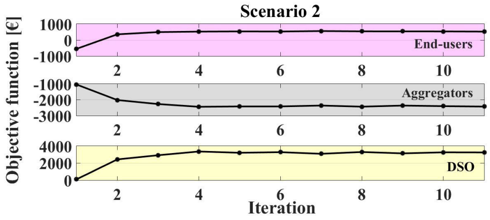

FIGURE 12. Objective function for end-users, aggregators, and the DSO in different iterations (Scenario 2).

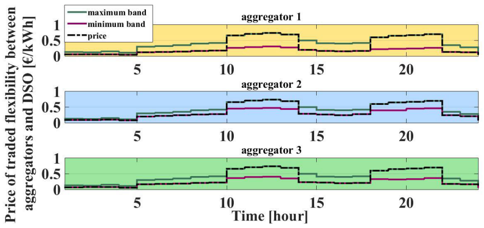

FIGURE 13. Price of flexibility transacted between aggregators and the DSO (Scenario 2).

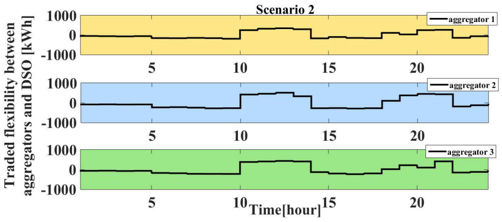

FIGURE 14. Flexibility traded between aggregators and the DSO (Scenario 2).

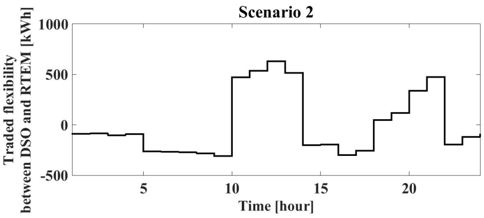

FIGURE 15. Real-time energy exchanged between the DSO and the RTEM (Scenario 2).

destructive for the DSO in such a way that the loss of the DSO is way more than the benefit of end-users and aggregators. Fig. 15 shows the energy flexibility traded among the DSO and the RTEM. It is seen that its amount is much more than its amount in scenario 1, which causes the objective function of the DSO to increase dramatically according to (13).

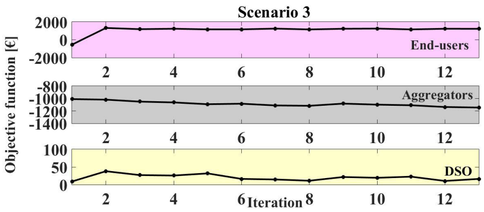

FIGURE 16. Objective function for end-users, aggregators, and the DSO in different iterations (Scenario 3).

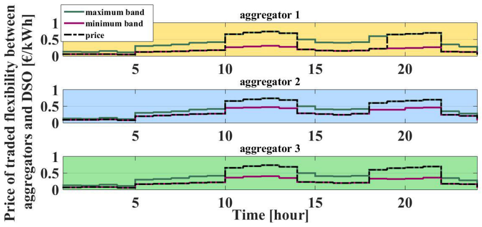

FIGURE 17. Price of flexibility transacted among aggregators and the DSO (Scenario 3).

3) SCENARIO 3

In this scenario in which one of the constraints of the DSO is removed and it can decide more freely in comparison with scenarios 1 and 2, after 13 iterations the problem is solved. fig. 16, shows the amount of objective functions for end-users, aggregators, and the DSO in different iterations. In Scenario 3, the DSO is able to improve its performance by decreasing its objective function from 41,65 in scenario 1 to 16,21 in scenario 3 (about 60%). Fig. 15 shows that in most hours the energy flexibility traded among the DSO and the RTEM in scenario 3 is less than its amount in scenario 1. On the other hand, the objective function of end-users in scenario 3 (1228.74 €) is more than scenario 1 (943.62 €) and scenario 2 (525.46 €). Therefore, end-users' performance in scenario 3 is worse compared to Scenarios 1 and 2. Moreover, aggregators' objective function in scenario 3 (−1145.49 €) is about identical to its objective function in the first scenario (−1110.42 €). Figs. 18 and 17 show the flexibility traded between aggregators and the DSO and their price in scenario 3 accordingly. It is noticeable that the adverse effect of end-users' freedom on the DSO's objective function is much more than the adverse impact of DSO's freedom on end-users' objective function. Because the objective function of the DSO in scenario 2 (3253.48 €) is about 7700 percent more than its objective function in scenario 1 (41.65 €). However, the objective function of end-users in scenario 3 (1228.74 €) is just 30% more than their objective function in scenario 1 (943.62 €).

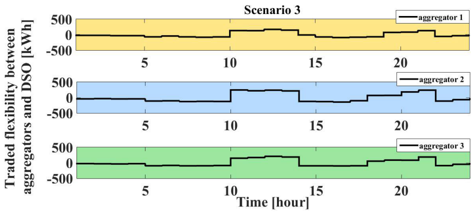

FIGURE 18. Flexibility traded between aggregators and the DSO (Scenario 3).

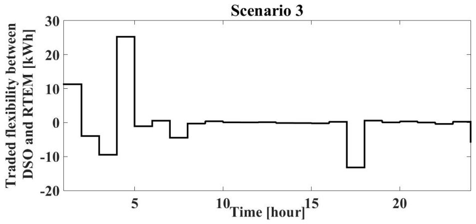

FIGURE 19. Real-time energy exchanged between the DSO and the RTEM (Scenario 3).

TABLE 2. Objective functions for end-users, aggregators and the DSO in different scenarios for interruptible loads ($\alpha = 0.1$) [€].

Scenario	End-users' OF	Aggregators' OF	DSO's OF
1	1286.67	−2294.28	222.91
2	−387.97	−4666.51	4224.48
3	1559.55	−2333.99	18.02

C. PRESENCE OF INTERRUPTIBLE LOADS

In the previous sections, it has been assumed that loads of end-users only consist of shiftable loads ($\alpha = 0$). In this section, the behavior of different agents in presence of interruptible loads is assessed. Tables 2 and 3 show the amount of objective functions of agents for $\alpha = 0.1$ and $\alpha = 0.15$ accordingly. Fig. 20, using a radar plot, depicts the objective function of end-users and aggregators in different scenarios in presence of shiftable loads ($\alpha = 0$) and interruptible loads ($\alpha = 0.1$ and $\alpha = 0.15$). As seen in scenario 2, the amount of objective function of end-users decreases as α increases. On the other hand, in scenario 3, the objective function of end-users increases as α increases. However, in scenario 1, with increasing α from 0 to 0.1 objective function of end-users increases, and with increasing α from 0.1 to 0.15 objective function of end-users decreases. In addition, aggregators' objective function in scenarios 1 and 2 decreases as α increases. This trend is not similar in scenario 3. Because with increasing α from 0 to 0.1 objective function of aggregators decreases and with increasing α from 0.1 to 0.15 objective function of aggregators increases. Unlike aggregators and end-users, the DSO has a similar trend in all scenarios. The objective function of the DSO increases with increasing α.

TABLE 3. Objective function for end-users, aggregators and the DSO in different scenarios for interruptible loads ($\alpha = 0.15$) [€].

Scenario	End-users' OF	Aggregators' OF	DSO's OF
1	1260.54	−2333.75	227.75
2	−442.09	−4698.11	4321.04
3	1669.54	−2220.78	32.46

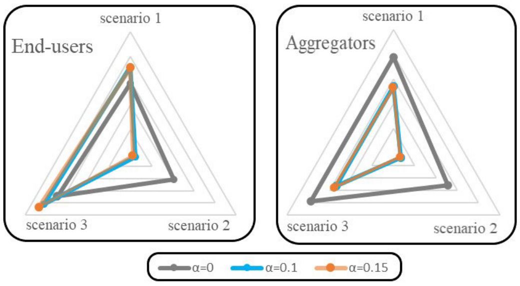

FIGURE 20. Objective functions for end-users and aggregators in different scenarios for $\alpha = 0$, $\alpha = 0.1$, and $\alpha = 0.15$.

D. CHALLENGES

The challenges of our proposed model should be taken into account in our future works to improve the quality of our proposed trading framework. For instance, Peer-to-peer (P2P) flexibility trading possibility that can incentivize peers to be actively involved in flexibility provision for the local energy communities, will be addressed in our future works. However, there will be serious scalability issues in the P2P trading platform as there are complex interactions among end-users. While in our approach, there is no interaction between end-users. Therefore, increasing the scale of the distribution system has no serious impact on the performance of our proposed approach. In addition, as there is no coupling constraint between end-users' flexibility trading, the computational burden of our approach is very low. Therefore, our approach does not require high computational units. In addition, the distribution network topology and optimal power flow that is missing in our work can be considered for shaping an energy flexibility market platform.

VI. CONCLUSION

In this paper, we proposed a novel iterative game-based algorithm based on a complete interaction among agents for trading energy flexibility in the energy community. We considered three scenarios assigning different levels of freedom to end-users and the DSO in presence of both shiftable and interruptible loads for evaluating our proposed model. According to the simulation results, it is found that:

- In almost all situations end-users and aggregators have a similar performance in the presence of shiftable loads.
- The removal of one of end-users' constraints has a destructive effect on the performance of the DSO.

- The presence of interruptible loads causes the objective function of end-users to be less when they have fewer constraints.
- With increasing the portion of the interruptible loads, the condition of aggregators improves in almost all of the situations.
- As the portion of interruptible loads increases the objective function of the DSO increases.

In this work, peer-to-peer energy trading among end-users have not been addressed. In our future work, we will study a flexibility market considering distribution network constraints where end-users can transact flexibility through peer-to-peer sharing. In addition, we will study the potential of end-user for providing flexibility such as adjusting the loads, utilizing energy storage systems, and making use of the thermal inertia of the buildings in more detail by considering a comprehensive model for each of them.

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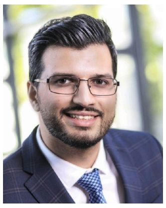

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The Role of EV Parking Lots for Supporting the Distribution System Operation Considering EV Uncertainties

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Abstract

Due to the dramatic increase in the penetration of the Electric Vehicle Parking Lots (EVPLs) in future, there will be a crucial challenge in the operation of the distribution systems. In this regard, the potential of the EVPLs for acting as a flexible load can be employed besides their capability to support the system with positive or negative reactive power if they are equipped with the required power electronic facilities. Our results show that EVPLs can modify their charging schedule to provide positive or negative reactive power support to improve the system condition in terms of congestion and voltage to let for deploy the cheaper generation sources that result in a decrease in total system cost. In this regard, EVPLs' location has a very important impact on the optimal operation of the system and the amount of benefit from their active and reactive power support.

Keywords: Electric vehicle parking lot; EV uncertainty, distribution system, reactive power support

1. Introduction

Distribution system management can be impacted both positively and negatively by Electric Vehicles (EVs). It is possible to obtain different results by charging and discharging EVs in controlled and uncontrolled modes. Uncontrolled charging could develop an increase in loss and demand, unbalancing of the distribution system loads, and a decrease in the life span of distribution system infrastructures, as they are assessed in the works of Shariff et al.

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(2022), Kütt et al. (2013), and Shukla, Verma, and Kumar (2019), respectively. On the other hand, taking advantage of controlled charging and discharging technologies such as vehicle-to-grid (V2G) Guille et al. (2009) will grant the distribution system the ability to manage its production-consumption balancing. In other words, peak load shaving Solanke et al. (2020), a decrease in emissions Vidhi et al. (2018), and voltage regulation Hu et al. (2021) could be mentioned as the main advantages of the controlled charging and discharging of EVs. Several studies have been performed to investigate the EVPL's impact on the distribution system and how they can support its operation. In general, researchers have studied the impact of EV charging on the distribution system, including the impact of charging schedule on the distribution system and the potential need for reinforcement and upgrading of the network Ramadhani et al. (2020). Moreover, some articles have also studied the optimization of EV charging in parking lots to improve the overall efficiency of the system Chippada and Reddy (2022); Ebrahimi et al. (2022). Integration of renewable energy sources into EVPLs has also been assessed to reduce the carbon footprint of charging EVs and to improve energy security Al-Thani et al. (2022). Researchers have also studied the integration of smart grid technologies into EVPLs, including advanced metering, demand response, and energy storage systems, to improve the distribution system's efficiency and reliability Judge et al. (2022). User behavior and adoption of EVs, including the impact of incentives and tariffs on user behavior are also investigated in Von Bonin et al. (2022).

Authors in Shahbazitabar et al. (2018) solved a stochastic unit commitment problem considering EVPLs and renewable generations. Similarly, a bi-level method has been presented in Sadati et al. (2019) that incorporates EVPLs in energy and reserve markets. In this research, a novel approach for minimization of costs and addressing the distribution grid constraints was deployed. Authors in Wenzel et al. (2017) proposed a two-level model for charge-scheduling of EVs in order to facilitate frequency regulation services inside the distribution grid. In Zheng et al. (2018) an EV charging scheduling model is presented. In this research, an AC power flow is used to reach the most efficient scheduling in the case of energy cost and EV demand supply. Similar purposes have persuaded the authors of Latifi et al. (2018) to present a game theory-based decentralized model for EV charging strategies. Ref Ahmad et al. (2022) investigated the influences that several EV charging lot allocation strategies have on the distribution system. Authors in Ahmadi et al. (2022) presented a decentralized optimization approach for optimizing the operation of multi-agent microgrids in presence of sector coupling. The authors aim to address the challenges associated with coordinating the decisions of multiple agents, uncertainty in energy demand and supply, and the integration of multiple energy storage technologies. The article Hamidan et al. (2022) focuses on the integration of battery energy storage systems (BESS) and EV charging stations into smart distribution networks to enhance the flexibility and reliability of the electricity grid and presents a flexible planning approach optimizing the deployment and operation of BESS in a way that balances the trade-off between energy storage capacity and energy storage utilization, and considers the uncertainties in load demand and renewable energy sources. Authors in Pirouzi et al. (2019) discussed the potential use of single-phase EVs for power conditioning in distribution networks to enhance the stability and reliability of distribution networks. The proposed approach considers the impact of EV charging and discharging dynamic behavior on the distribution network. Ref Baherifard et al. (2022) explored the impact of intelligent charging planning for EVs on distribution network's imbalance indices.

This paper tries to fill the gap in the literature to investigate the role of EV parking lots in supporting the distribution system with a focus on reactive power support considering the uncertain arrival and departure of EVs. This way the optimal operation of the distribution system components like EVPLs, renewable energy resource, distributed generation units, and energy storage are conducted based on the hourly active and reactive power prices as well as the network topology, lines capacity, and the fixed active and reactive loads by deploying a linearized AC power flow formulation.

2. Problem Formulation

As stated in previous section, the main aim of this paper is to study the operation of distribution system that is equipped with EVPL. This way the optimal energy management of the distribution system operator in presence of EVPL, Renewable Energy Sources (RES) and Distributed Generation (DG) is investigated in this paper.

2.1. Objective function

The objective of the DSO is to minimize its operational cost as stated in (1) where the first and second terms stand for the cost of trading active and reactive power with the upstream grid. The third and fourth terms are related to the generation cost of RES and DGs. $P_t^{DN}, Q_t^{DN}, P_{i,t}^{RES}, and\ P_{i,n,t}^{DG}$ stand for active and reactive power traded between the distribution system and the upstream power system as well as generated power by RES and segment n of the DG generation, respectively.

$$Min\ C_D = \Delta T \sum_{t=1}^{T} \left(k_t^P . P_t^{DN} + k_t^Q . Q_t^{DN} + \sum_{i=1}^{NB} \left[c_i^{RES} . P_{i,t}^{RES} + \sum_{n=1}^{N_i^{DG,seg}} c_{i,n} . P_{i,n,t}^{DG} \right] \right) \tag{1}$$

2.2. Constraints

The operational constraints of the different DSO-owned facilities are explained below.

2.2.1 Grid constraints

The linear active and reactive power flow equations are adopted from Yuan et al. (2016) as stated in (2)-(7). $P_{i,t}^{EVPL}$, $Q_{i,t}^{EVPL}$, $P_{i,t}^{ESS,dc}$, $P_{i,t}^{ESS,ch}$, $P_{L,i,t}^{Fix}$, $Q_{L,i,t}^{Fix}$, P_i, Q_i, P_{ij}, Q_{ij} stand for active and reactive power of EVPL, discharging and charging power of the ESS, nonflexible active and reactive load, active and reactive injection power at bus i as well as active and reactive power in the line between bus i and j.

$$P_{ij} = \frac{r_{ij}}{r_{ij}^2 + x_{ij}^2} \left(V_i - V_j \right) + \frac{x_{ij}}{r_{ij}^2 + x_{ij}^2} \left(\theta_i - \theta_j \right) \tag{2}$$

$$P_i = \sum_{j=1, i \neq j}^{N_B} P_{i,j} \tag{3}$$

$$Q_{ij} = \frac{x_{ij}}{r_{ij}^2 + x_{ij}^2} \left(V_i - V_j \right) - \frac{r_{ij}}{r_{ij}^2 + x_{ij}^2} \left(\theta_i - \theta_j \right) \tag{4}$$

$$Q_i = \sum_{j=1, i \neq j}^{N_B} Q_{i,j} \tag{5}$$

$$P_i = P_t^{DN} - P_{i,t}^{EVPL} + P_{i,t}^{RES} + P_{i,t}^{DG} + P_{i,t}^{ESS,dc} - P_{i,t}^{ESS,ch} - P_{L,i,t}^{Fix} \tag{6}$$

$$Q_i = Q_t^{DN} - Q_{i,t}^{EVPL} + Q_{i,t}^{DG} - Q_{L,i,t}^{Fix} \tag{7}$$

2.2.2 EV parking lot

EVPL in this paper is modelled as energy storage where the parameters are obtained via the characteristics of different EV classes hosted by EVPL and the PDF of the arrival and departure of EVs. In this paper, similar to most of the papers in the literature, the EV arrival and departure pattern is modelled with a Truncated Normal Distribution (TND) in the related studies. This way, using the cumulative distribution function (CDF) of TND, the number of arriving and departing EVs in each hour is obtained. Then, EVPL's charging and discharging power, EVPL's stored energy, and EVPL's active and reactive power constraints are represented in (8)-(18).N, E, Cap, cl, arr, and dep denotes the number of EVs, level of energy, capacity of the EV Battery, EV class, arrival, and departure. Moreover, Sh_{cl} and $C_i^{PL,ins,ch}$ stand for share of the EV class and installed capacity of the EV chargers in the EVPL.

$$E_{i,t}^{PL} = E_{i,t-1}^{PL} - E_{i,t}^{dep} + E_{i,t}^{arr} + \Delta t \eta_{ch} P_{i,t}^{PL,ch} \tag{8}$$

$$N_t^{Ev,arr} = N^{EV,ent} \left(F_{t+0.5}^{TND,arr} - F_{t-0.5}^{TND,arr} \right) \tag{9}$$

$$N_t^{Ev,dep} = N^{EV,ent} \left(F_{t+0.5}^{TND,dep} - F_{t-0.5}^{TND,dep} \right) \tag{10}$$

$$E_{i,t}^{arr} = N_{i,t}^{Ev,arr}\left(\sum\nolimits_{cl} Cap_{cl}^{Ev}\, SOC_{cl}^{arr} Sh_{cl}\right) \tag{11}$$

$$E_{i,t}^{dep} = N_{i,t}^{Ev,dep}\left(\sum\nolimits_{cl} Cap_{cl}^{Ev}\, SOC_{cl}^{dep} Sh_{cl}\right) \tag{12}$$

$$0 \le P_{i,t}^{PL,ch} \le C_{i}^{PL,ins,ch} \tag{13}$$

$$0 \le P_{i,t}^{PL,ch} \le N_{i,t}^{EV,par}\left(\sum\nolimits_{cl} P_{cl}^{ch,max}\, Sh_{cl}\right) \tag{14}$$

$$N_{i,t}^{EV,par} = N_{i,t-1}^{EV,par} + N_{i,t}^{Ev,arr} - N_{i,t}^{Ev,dep} \tag{15}$$

$$E_{i,t}^{PL,min} \le E_{i,t}^{PL} \le E_{i,t}^{PL,max} E_{i,t}^{PL,min} = N_{i,t}^{EV,par}\left(\sum\nolimits_{cl} Cap_{cl}^{Ev}\, SOC^{min} Sh_{cl}\right) \tag{16}$$

$$E_{i,t}^{PL,max} = N_{i,t}^{EV,par}\left(\sum\nolimits_{cl} Cap_{cl}^{Ev}\, SOC^{max} Sh_{cl}\right) \tag{17}$$

$$\left(P_{i,t}^{PL}\right)^2 + \left(Q_{i,t}^{PL}\right)^2 \le \left(S_{i}^{PL}\right)^2 \tag{18}$$

2.2.3 RES and DG

The generated power by DGs should satisfy the ramp rate and nominal capacity constraint as indicated in (19)-(21). In addition, the uncertainty of RES generation is modelled by the chance-constrained-based formulation presented in (Yi et al. 2020) as represented in (22). $\Phi_{\mathrm{a}}(.)$ is the CDF of the standard normal distribution, η is the confidence level, and $\sigma_{i,t,fore}$ is the standard deviation.

$$P_{i,n,min}^{DG} \le P_{i,n,t}^{DG} \le P_{i,n,max}^{DG} \tag{19}$$

$$\Delta_{i,min}^{DG} \le P_{i,t}^{DG} - P_{i,t-1}^{DG} \le \Delta_{i,max}^{DG} \tag{20}$$

$$\left(P_{i,t}^{DG}\right)^2 + \left(Q_{i,t}^{DG}\right)^2 \le \left(S_{i,t}^{DG}\right)^2 \tag{21}$$

$$0 \le P_{i,t}^{RES} \le \overline{P_{i,t,fore}^{RES}} + \sigma_{i,t,fore}.\, \Phi_{a}^{-}1(1-\eta) \tag{22}$$

2.2.4 Energy storage system

The operation of energy storage system (ESS) is modelled as represented in (23)-(26). $\delta_{i,t}^{ESS}$is a binary variable for defining the charging/discharging status of the ESS. $\eta_{in}$and η_{out} are the charge and discharge efficiency.

$$0 \le P_{i,t}^{ESS,ch} \le P_{i,max}^{ESS,ch}.\, \delta_{i,t}^{ESS} \tag{23}$$

$$0 \le P_{i,t}^{ESS,dc} \le P_{i,max}^{ESS,dc}\left(1 - \delta_{i,t}^{ESS}\right) \tag{24}$$

$$E_{i,min}^{ESS} \le E_{i,t}^{ESS} \le E_{i,max}^{ESS} \tag{25}$$

$$E_{i,t}^{ESS} = E_{i,0}^{ESS} + \Delta T \sum\nolimits_{t=1}^{j} \eta_{in}.\, P_{i,t}^{ESS,ch} - \eta_{out}.\, P_{i,t}^{ESS,dc} \tag{26}$$

2.3. Linearization

There are quadratic constraints in the power flow, EVPL, and DG modelling. To remove the nonlinearity the linearization method presented in Yang et al. (2017) is deployed where the circle feasible area of the quadratic constraint is approximated with a polygon. Therefore, the optimization problem is handled via mixed integer linear programming.

3. Simulation results

3.1. Case study

We used the case study of Yi et al. (2020) and modified it by adding EVPLs to the system as depicted in Fig. 1. This way, we have considered two systems for our simulations with different locations of EVPLs in the grid. In the first system, EVPLs are located at the margins of the network, while in the second system, EVPLs are located in the central areas. In this paper, we considered that there are 10 EV classes with the characteristics presented in Table 1. For all EV classes $SOC_{cl}^{dep}$is equal to 0.85 and $P_{cl}^{dc,max}$is equal to $P_{cl}^{ch,max}$. Moreover, the share of each EV class in total available EVs is 0.1. Furthermore, the parameters of TND for arrival are as follows: the minimum and maximum EVs arrival times are 5 and 17, the average arrival time is 8 and the standard deviation is 3. In addition, the parameters of TND for departure are as follows: the minimum and maximum EVs departure times are 11 and 24, the average departure time is 16 and the standard deviation is 3. Finally, the number of charging stations in all EVPLs is 3000.

Table 1. EV classes and characteristics

cl	1	2	3	4	5	6	7	8	9	10
$P_{cl}^{ch,max}$ (kW)	7	10	10	7	10	7	5	5	7	10
Cap_{cl}^{Ev} (kWh)	15	20	20	15	20	15	10	10	15	20
SOC_{cl}^{arr}	0.33	0.33	0.16	0.4	0.1	0.45	0.5	0.2	0.33	0.2

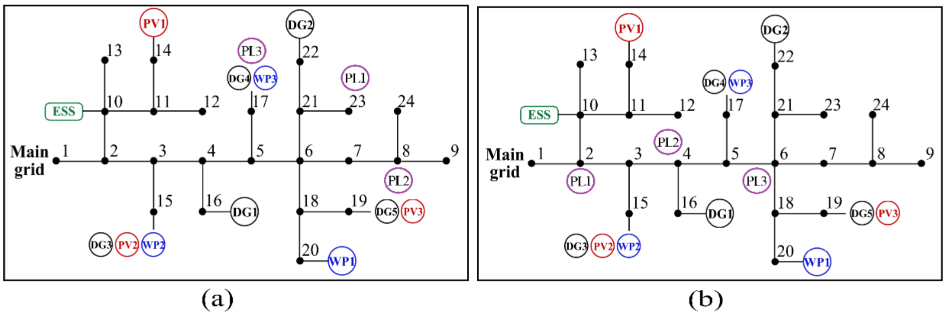

Fig. 1 Distribution system topology in (a) Case 1 and (b) Case 2

3.2. Results and discussion

We have studied the system operation in two cases to study the impact of the reactive power support capability of EVPL, coordinated operation of EVPL, deploying bidirectional EV chargers, and location of EVPL on the optimal system operation in terms of operational cost. As EV chargers in EVPLs are equipped with power electronic facilities to convert the AC current to DC current, there is a possibility to provide reactive power support Paudyal et al. (2017). This way, by investing in the power electronic facilities in the EV chargers, there will be a reactive power support capability in EV chargers. The impact of reactive power support capability on system operation has been investigated in two cases with the same system but different EV locations. The results show that in both cases the EVPLs' reactive power support capability will result in a decrease in the system cost. Moreover, EVPLs based on their location provide the system with different positive and reactive power support during the day as represented in Fig. 2 which is related to case 1 and Fig. 3 which is relayed to case 2. In these figures, the operation of EVPLs with and without reactive power capability is investigated to assess the impact of reactive power support capability and the location of the EVPLs on their operation. In this regard, when there is no reactive power support from EVPLs, their charging schedule is managed like a flexible load to reduce the system cost. However, when there is a reactive power support capability, EVPLs can modify their charging schedule to provide positive or negative reactive power support to improve the system condition in terms of congestion and voltage to let for deploy the cheaper power sources. In this regard, the

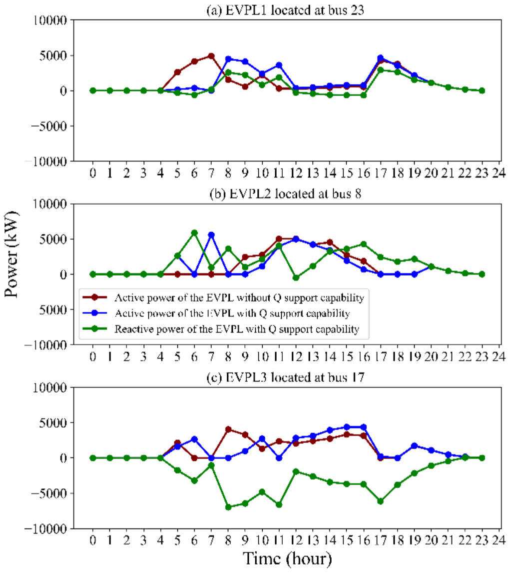

Fig. 2 The active and reactive power of (a) EVPL1, (b) EVPL 2, and (c) EVPL3 in case 1 (EVPLs are located in buses 2, 4, and 6)

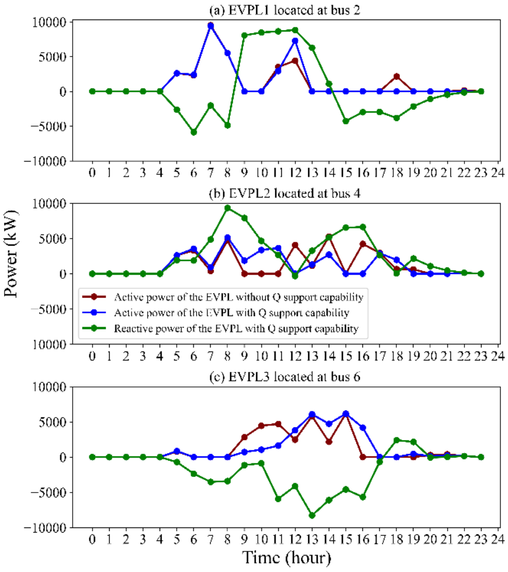

Fig. 3 The active and reactive power of (a) EVPL1, (b) EVPL 2, and (c) EVPL3 in case 2 (EVPLs are located in buses 23, 8, and 17)

operation of EVPLs 1, 2, and 3 are different in cases 1 and 2 as their locations are different in these two cases. Therefore, EVPLs location has a very important factor in the optimal operation of the system for two reasons. Firstly, the active power load would be different in different system buses and secondly, the reactive power support capability is also different in different buses. Therefore, the impact of the EVPLs on the distribution system operation depends on the distribution system topology and active and reactive loads and different assists in different parts of the system besides the characteristics and capabilities of EVPLs. In addition, it is understood that when EVPLs are equipped with reactive power support, their optimal charging schedules are changed to enable them for reactive power support. This way, the system voltage at that bus would be regulated to let for optimal active and reactive power flow to reduce the active power cost.

Table 2. The whole system cost for cases 1 and 2

Case	*Case 1*		*Case 2*	
Q support capability	✓	×	✓	×
System cost	18955.68 €	19468.06 €	18369.03 €	18395.24 €

The other important point is that the cost reduction amount is different for the two cases. For case 1, the whole system cost with and without Q support is 18369.03 €and 18395.24 €, accordingly. Therefore, the cost reduction from EVPLs' reactive power support is 26.21€ in case 1. However, the whole system cost with and without Q support is 18955.68 € and 18468.06 €, accordingly. Hence, the cost reduction from EVPLs' reactive power support is 512.36 € in case 2. This shows that deploying Q support from EVPLs in case 1 is way more beneficial due to the system topology than in case 2. The different benefits from reactive power support can be understood by noticing the operation of DGs and RES for case 1 and case 2 in the presence and absence of reactive power support as depicted in Fig. 4, Fig. 5, Fig. 6, and Fig. 7. Fig. 4 shows that in case 1, reactive power support capability allows for more RES generation in some hours, while as depicted in Fig. 5, reactive power support from EVPLs has not any impact on the RES generation in case 2. Similar behaviour can be seen in DGs' operation in cases 1 and 2. In case 1, when reactive power support from

EVPLs is available, the DG generation pattern can be totally modified to let for reducing the system cost, as shown in Fig. 6, while in case 2, the change in the DG generation pattern is way less compared to case 1. This way, deployment of reactive power support from EVPLs is more beneficial in case 1 compared to case 2.

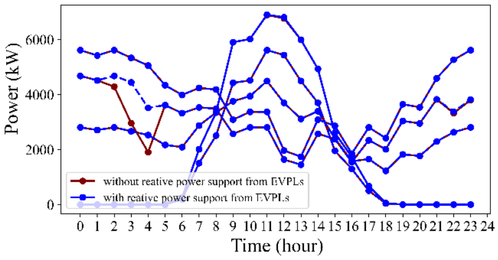

Fig. 4 RES generation in case 1

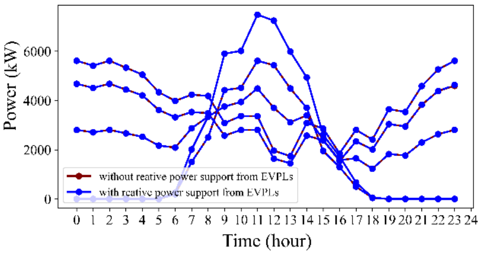

Fig. 5 RES generation in case 2

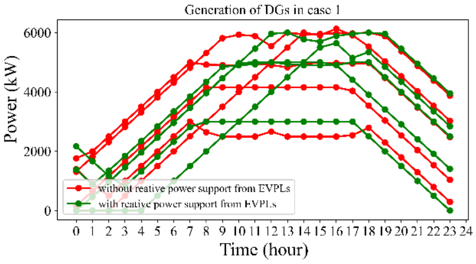

Fig. 6 Generation of DGs in case 1

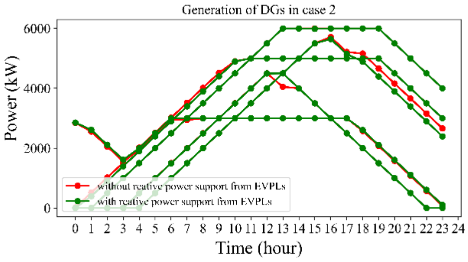

Fig. 7 Generation of DGs in case 2

4. Conclusion

In this paper, the impact of the commercial EVPL on the optimal distribution system operation was investigated. The results show that EVPLs can modify their charging schedule to provide positive or negative reactive power support to improve the system condition in terms of congestion and voltage to let for deploy the cheaper power sources. In this regard, EVPLs' location has a very important impact on the optimal operation of the system for two reasons. Firstly, the active power load would be different in different system buses and secondly, the reactive power support capability is not similar in different buses. Therefore, the location of the EVPLs and their situation in the distribution system is an important factor in deciding on the investment in equipping them with reactive power support facilities. In future studies, the effect of residential EV chargers can also be studied to assist decision-makers to define the proper locations for both residential and commercial EVPLs. In addition, the voltage violation cost should be considered in the whole system cost to better highlight the impact of the reactive power support from EVPLs in improving the distribution system operation.

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Impact of Voltage Violation Penalty Cost on Distribution System Operation Considering Electric Vehicle

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***Abstract*—In the future, the widespread adoption of electric vehicle parking lots (EVPLs) may introduce operational challenges like voltage limit violations in distribution networks. However, EVPLs can potentially relieve these voltage limit violations by acting as flexible loads and providing reactive power support. In this paper, the impact of EVPLs on the optimal operation of the distribution network is investigated with a focus on their potential capability for reactive power support in a scenario that the distribution system operator (DSO) is committed to pay a penalty cost to customers if voltage limits are violated. Our results show that flexible charging of Electric Vehicles (EVs) and reactive power support from EVPLs, especially in the case where there exists a penalty cost for voltage violation, has a major impact on reducing the system cost. It can also pave the way for deploying more generation from distributed generation (DG) and renewable energy sources (RES) as well as reducing the voltage violation penalty costs.**

***Keywords*—EV Parking Lot, Reactive Power Support, Voltage Violation Cost, Distribution System Operation**

I. INTRODUCTION

The charging and discharging of electric EVs can have significant impacts on the distribution system management. On the positive side, EVs can provide a source of distributed energy storage that can be used to balance the variability of renewable energy sources [1]. EV charging can be managed to coincide with periods of excess renewable generation, which can help to reduce curtailment and increase the utilization of renewable energy sources [2]. Additionally, EVs can provide voltage support and reactive power compensation through smart charging strategies that respond to system needs [3]. However, on the negative side, high levels of uncoordinated EV charging can lead to the overloading of distribution transformers and other distribution system components, which can result in voltage instability and equipment damage [4]. To mitigate these negative impacts, distribution system operators need to develop effective strategies for managing EV charging and discharging, including the use of smart charging algorithms, the deployment of advanced monitoring and control systems, and the development of appropriate policies and regulations [5].

The impacts on the distribution system, which could be resulted from the charging and discharging patterns of EVs is the main concept of several studies [6]. In this regard, authors in [7] proposed an optimized pattern for the charging and discharging of EVs with the aim of maximizing the efficiency of the distribution system. Energy security and the independency concept can also be the benefit of EV charging integration into the distribution system, as investigated in [8]. In [9] EV parking lots have been incorporated into energy and reserve markets using a bi-level method. This research aimed to minimize costs and address distribution grid constraints using an innovative approach. Authors in [10] proposed a charging and discharging scheduling plan for small-scale parking lots in order to achieve frequency stability inside the distribution system. A similar scheduling plan has been investigated in [11] using operating envelopes.

Authors in [12] presented a model for scheduling EV charging, which employs an optimal AC power flow to achieve the most efficient scheduling in terms of energy cost and EV demand supply. To achieve comparable objectives, [13] proposes a decentralized model for EV charging strategies based on game theory. In [14], various EV charging lot allocation strategies are studied to analyze their impact on the distribution system. The authors of [15] put forth a novel approach that employs a decentralized bi-level stochastic optimization technique to optimize the operation of multi-agent multi-energy networked microgrids with the integration of various energy storage technologies. By addressing the coordination of multiple agents, managing uncertainty in energy demand and supply, and incorporating multiple energy storage technologies, the authors aim to overcome the challenges associated with microgrid operation. In [16] the authors proposed an approach for EV parking lot charging/discharging in which both the demand response and energy consumption cost are considered in their objective function formulation.

Although there are several studies to investigate the role of EV charging stations and parking lots, their potential role in providing reactive support to the power system has not been investigated thoroughly. Moreover, a formulation that can quantify the voltage violation penalty cost that DSO should pay to the consumers as compensation for an unsatisfied power quality index has not been proposed in the literature. This paper tries to fill the mentioned gap by investigating the role of EVPLs in decreasing the distribution system costs and improving the system voltage condition by acting as a flexible active load and providing the system with reactive power support when the voltage violation penalty cost is included in the system cost besides the other operational costs.

II. PROBLEM FORMULATION

The problem of the DSO is conceived as an optimization problem where the objective function is minimizing the operational cost considering the operational constraints of the whole system such as grid, EVPL, DG, RES, and loads. Objective function as well as constraints are explained below.

A. Objective Function

The DSO's objective function, as represented in (1), is minimizing the total operational cost consisting of the DGs and RES generation cost, the cost of trading reactive and active power with the upstream grid as well as the cost for voltage violation that the DSO is committed to paying to consumers. The DSO is committed to supplying the consumers with an acceptable voltage range. In this regard, there are different compensation mechanisms if the voltage is not within the acceptable range [17] and [18]. In this paper, we assumed that there is two range of voltage violation. The first range is within 0 and VV^a (proper voltage range) where the DSO should not pay any compensation to consumers. The second range is within VV^a and VV^{max} (critical voltage range) where the DSO must pay compensation to consumers according to (2) and (3). $S^L_{i,t}$ is the nominal load of consumers. VV^a and VV^{max} can be set based on the distribution system voltage requirements and standards. For our study, we assumed that $VV^{max} = 0.1$ and voltage violation cannot be exceeded from this amount anyway. VV^a in our study is equal to 0.05 meaning that for voltage violation more than this value the DSO should perform a monetary compensation.

$$Min\ C_D = \Delta T \sum_{t=1}^{T} \Big(k_t^P . P_t^{DN} + k_t^Q . Q_t^{DN} + \sum_{i=1}^{NB} \Big[c_i^{RES} . P_{i,t}^{RES} + \sum_{n=1}^{N_i^{DG,seg}} c_{i,n} . P_{i,n,t}^{DG} + C_{i,t}^{vv} \Big] \Big) \tag{1}$$

$$VV_{i,t} = |V_{i,t} - 1| \tag{2}$$

$$C_{i,t}^{vv} = \begin{cases} 0 & : if\ VV_{i,t} < VV^a \\ (VV_{i,t} - VV^a)\, S_{i,t}^L\, c^{VV} & : if\ VV_{i,t} > VV^a \end{cases} \tag{3}$$

B. Constraints

The constraints of the optimization problem are the operational constraints of different DSO-owned facilities. The constraints related to the distribution grid (reactive and active power flow), DG & RES, and Energy Storage System (ESS) have been extracted from [19] as represented in (4)-(9), (12)-(15), and (16)-(19), accordingly. $Q_{i,t}^{EVPL}$, $P_{i,t}^{EVPL}$, $P_{i,t}^{ESS,ch}$, $P_{i,t}^{ESS,dc}$, $Q_{L,i,t}^{Fix}$, $P_{L,i,t}^{Fix}$ indicate reactive and active EVPL power, ESS charge and discharge power, nonflexible reactive and active nonflexible load in different buses.

$$P_{ij} = \frac{r_{ij}}{r_{ij}^2 + x_{ij}^2}(V_i - V_j) + \frac{x_{ij}}{r_{ij}^2 + x_{ij}^2}(\theta_i - \theta_j) \tag{4}$$

$$P_i = \sum_{j=1, i \neq j}^{N_B} P_{i,j} \tag{5}$$

$$Q_{ij} = \frac{x_{ij}}{r_{ij}^2 + x_{ij}^2}(V_i - V_j) - \frac{r_{ij}}{r_{ij}^2 + x_{ij}^2}(\theta_i - \theta_j) \tag{6}$$

$$Q_i = \sum_{j=1, i \neq j}^{N_B} Q_{i,j} \tag{7}$$

$$P_i = P_t^{DN} - P_{i,t}^{EVPL} + P_{i,t}^{RES} + P_{i,t}^{DG} + P_{i,t}^{ESS,dc} - P_{i,t}^{ESS,ch} - P_{L,i,t}^{Fix} \tag{8}$$

$$Q_i = Q_t^{DN} - Q_{i,t}^{EVPL} + Q_{i,t}^{DG} - Q_{L,i,t}^{Fix} \tag{9}$$

$$V_{min} \leq V_i \leq V_{max} \tag{10}$$

$$(P_{ij})^2 + (Q_{ij})^2 \leq (S_{ij})^2 \tag{11}$$

DGs generation must meet the ramp rate and capacity limitations as indicated in (12)-(14). In addition, RES uncertainty is modelled via the chance-constrained formulation as represented in (15). $\delta_{i,t}^{ESS}$ is a binary that stands for ESS discharging/charging status. and η_{dc} and η_{ch} indicate the discharge and charge efficiency.

$$P_{i,n,min}^{DG} \leq P_{i,n,t}^{DG} \leq P_{i,n,max}^{DG} \tag{12}$$

$$\Delta_{i,min}^{DG} \leq P_{i,t}^{DG} - P_{i,t-1}^{DG} \leq \Delta_{i,max}^{DG} \tag{13}$$

$$(P_{i,t}^{DG})^2 + (Q_{i,t}^{DG})^2 \leq (S_{i,t}^{DG})^2 \tag{14}$$

$$0 \leq P_{i,t}^{RES} \leq \overline{P_{\iota,t,fore}^{RES}} + \sigma_{i,t,fore} . \Phi_a^- 1(1 - \eta) \tag{15}$$

ESS operational constraints are as represented in (16)-(19). $\delta_{i,t}^{ESS}$ is a binary that defines the charging/discharging status of the ESS. η_{in} and η_{out} are the charge and discharge efficiency.

$$0 \leq P_{i,t}^{ESS,ch} \leq P_{i,max}^{ESS,ch} . \delta_{i,t}^{ESS} \tag{16}$$

$$0 \leq P_{i,t}^{ESS,dc} \leq P_{i,max}^{ESS,dc}(1 - \delta_{i,t}^{ESS}) \tag{17}$$

$$E_{i,min}^{ESS} \leq E_{i,t}^{ESS} \leq E_{i,max}^{ESS} \tag{18}$$

$$E_{i,t}^{ESS} = E_{i,0}^{ESS} + \Delta T \sum_{t=1}^{j} \eta_{in} . P_{i,t}^{ESS,ch} - \eta_{out} . P_{i,t}^{ESS,dc} \tag{19}$$

The operation of EVPL has been modeled via (20)-(30). In this regard, the EVPL is modeled similarly to a battery. The parameters for this model are derived from the characteristics of various EV classes parked in the EVPL, as well as the Probability Density Function (PDF) describing the arrival and departure patterns of EVs. Similar to previous studies in the field, Truncated Normal Distribution (TND) stands for the arrival and departure of EVs to determine the number of arriving and departing EVs during a day. Equations (20)-(30) represent the charge and discharge power of the EVPL, the energy stored in the EVPL, and the output active and reactive power of the EVPL. Positive sign of reactive power of EVPL stands for the reactive power consumption. In these equations, N, E, Cap, cl, arr, and dep represent the number of EVs, energy level, EV capacity, EV class, and arrival and departure, respectively. Additionally, Sh_{cl} and $C_i^{PL,ins,ch}$ indicate the share of the EV class within the EVPL and the capacity of total installed EV chargers, respectively.

$$E_{i,t}^{PL} = E_{i,t-1}^{PL} - E_{i,t}^{dep} + E_{i,t}^{arr} + \Delta t \eta_{ch} P_{i,t}^{PL,ch} \tag{20}$$

$$N_t^{Ev,arr} = N^{EV,ent}(F_{t+0.5}^{TND,arr} - F_{t-0.5}^{TND,arr}) \tag{21}$$

$$N_t^{Ev,dep} = N^{EV,ent}(F_{t+0.5}^{TND,dep} - F_{t-0.5}^{TND,dep}) \tag{22}$$

$$E_{i,t}^{arr} = N_{i,t}^{Ev,arr}(\sum_{cl} Cap_{cl}^{Ev}\, SOC_{cl}^{arr} Sh_{cl}) \tag{23}$$

$$E_{i,t}^{dep} = N_{i,t}^{Ev,dep}\left(\sum_{cl} Cap_{cl}^{Ev}\, SOC_{cl}^{dep} Sh_{cl}\right) \tag{24}$$

$$0 \leq P_{i,t}^{PL,ch} \leq C_{i}^{PL,ins,ch} \tag{25}$$

$$0 \leq P_{i,t}^{PL,ch} \leq N_{i,t}^{EV,par}\left(\sum_{cl} P_{cl}^{ch,max}\, Sh_{cl}\right) \tag{26}$$

$$N_{i,t}^{EV,par} = N_{i,t-1}^{EV,par} + N_{i,t}^{Ev,arr} - N_{i,t}^{Ev,dep} \tag{27}$$

$$E_{i,t}^{PL,min} \leq E_{i,t}^{PL} \leq E_{i,t}^{PL,max} E_{i,t}^{PL,min} = N_{i,t}^{EV,par}(\sum_{cl} Cap_{cl}^{Ev}\, SOC^{min} Sh_{cl}) \tag{28}$$

$$E_{i,t}^{PL,max} = N_{i,t}^{EV,par}(\sum_{cl} Cap_{cl}^{Ev}\, SOC^{max} Sh_{cl}) \tag{29}$$

$$\left(P_{i,t}^{PL}\right)^2 + \left(Q_{i,t}^{PL}\right)^2 \leq (S_{i}^{PL})^2 \tag{30}$$

III. SIMPLIFICATION

Equations (2) and (3) in the problem formulation section, make it necessary to proceed with the optimization via metaheuristic algorithm. However, such algorithms, due to their weakness and lack of correctness proof are not in the interest these days. In this regard, firstly to write (2), which uses the absolute value function, in another form, the binary variable $u_{i,t}^1$ is used as represented in (31) where $u_{i,t}^1 = 1$ stands for $V_{i,t} > 1$ and $u_{i,t}^1 = 0$ stands for $V_{i,t} < 1$. Its proof is obtained if $u_{i,t}^1$ is equal to 0 and 1 in the (31). Then $VV_{i,t}$ is obtained via (32). (31) and (32) have been written in another form according to (33) and (34), respectively.

$$\left(2u_{i,t}^1 - 1\right).\left(V_{i,t} - 1\right) >= 0 \tag{31}$$

$$VV_{i,t} = \left(2u_{i,t}^1 - 1\right).\left(V_{i,t} - 1\right) \tag{32}$$

$$2u_{i,t}^1 V_{i,t} - V_{i,t} - 2u_{i,t}^1 + 1 >= 0 \tag{33}$$

$$VV_{i,t} = 2u_{i,t}^1 V_{i,t} - V_{i,t} - 2u_{i,t}^1 + 1 \tag{34}$$

The proof is obtained via setting $u_{i,t}^1$ equal to 1 and 0. If $u_{i,t}^1 = 1$ from (31) and (34) we will have:

$$\begin{cases} 2V_{i,t} - V_{i,t} - 2 + 1 >= 0 \\ VV_{i,t} = 2u_{i,t}^1 V_{i,t} - V_{i,t} - 2u_{i,t}^1 + 1 \end{cases}$$

Therefore;

$$\begin{cases} V_{i,t} >= 1 \\ VV_{i,t} = V_{i,t} - 1 \end{cases}$$

In addition, if $u_{i,t}^1 = 0$ from (31) and (34) we will have:

$$\begin{cases} 0 - V_{i,t} - 0 + 1 >= 0 \\ VV_{i,t} = 0 - V_{i,t} - 0 + 1 \end{cases}$$

Therefore;

$$\begin{cases} V_{i,t} <= 1 \\ VV_{i,t} = 1 - V_{i,t} \end{cases}$$

This way, it has been shown that (31) and (34) stand for (2). Then, to remove the if-condition from (3), the binary variable $u_{i,t}^2$ is utilized where $u_{i,t}^2 = 1$ stands for $VV_{i,t} > VV^a$ and $u_{i,t}^2 = 0$ stands for $VV_{i,t} < VV^a$. Its proof is obtained if $u_{i,t}^2$ is equal to 0 and 1 in (35). Then $VV_{i,t}$ is obtained via (36). (31) and (36) have been written in another form according to (37) and (38)(34), respectively.

$$\left(2u_{i,t}^2 - 1\right).\left(VV_{i,t} - VV^a\right) >= 0 \tag{35}$$

$$C_{i,t}^{vv} = u_{i,t}^2.\left(VV_{i,t} - VV^a\right) S_{i,t}^L\, c^{VV} \tag{36}$$

$$2u_{i,t}^2 VV_{i,t} - VV_{i,t} - 2u_{i,t}^2 VV^a + VV^a >= 0 \tag{37}$$

$$C_{i,t}^{vv} = (u_{i,t}^2 VV_{i,t} - u_{i,t}^2 VV^a)\, S_{i,t}^L\, c^{VV} \tag{38}$$

The proof is obtained via setting $u_{i,t}^2$ equal to 1 and 0. If $u_{i,t}^2 = 1$ from (37) and (38) we will have:

$$\begin{cases} 2VV_{i,t} - VV_{i,t} - 2VV^a + VV^a >= 0 \\ C_{i,t}^{vv} = (VV_{i,t} - VV^a)\, S_{i,t}^L\, c^{VV} \end{cases}$$

Therefore;

$$\begin{cases} VV_{i,t} >= VV^a \\ C_{i,t}^{vv} = (VV_{i,t} - VV^a)\, S_{i,t}^L\, c^{VV} \end{cases}$$

In addition, if $u_{i,t}^2 = 0$ from (37) and (38) we will have:

$$\begin{cases} 0 - VV_{i,t} - 0 + VV^a >= 0 \\ C_{i,t}^{vv} = (0 - 0)\, S_{i,t}^L\, c^{VV} \end{cases}$$

Therefore;

$$\begin{cases} VV^a >= VV_{i,t} \\ C_{i,t}^{vv} = 0 \end{cases}$$

This way, it has been shown that (37) and (38) stand for (3). In addition, quadratic constraints (11), (14), and (30) are written in a linearized form. To this end, the circle that stands for the quadratic constraint is replaced with a polygon inside the circle. This way, the new feasible area would be similar to the previous one, while set of linear constraints are replaced with quadratic constraint. After conducting the simplifications above, the DSO's problem is formulated via Mixed Integer Non-Linear Programming (MINLP).

IV. SIMULATION RESULTS

A. Case study

We utilized the case study from [19] and made modifications by incorporating EVPLs into the system, as shown in Fig. I. This paper considers that there are 10 classes of EVs with an equal share as described in TABLE. I including their respective characteristics. Additionally, we define the parameters for TND as represented in TABLE. II. Moreover, we have considered two cases and two scenarios for our simulation. In case (a), it is assumed that there is no voltage violation penalty cost for the DSO, while in case (b) the voltage violation penalty cost is considered in the objective function of the DSO. Furthermore, in scenario 1, EVPL chargers cannot provide reactive power support, while in scenario 2, EVPL chargers are fully able to provide reactive power. Lastly, there are 3000 charging stations available across all EVPLs and it is assumed that every charger will be used by one car in the day.

The DSO's optimization problem that is formulated as MINLP is coded in Python and solved via the Apopt solver.

TABLE. I EV CLASSES AND CHARACTERISTICS

class	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
$P_{cl}^{ch,max}$ (kW)	7	10	10	7	10	7	5	5	7	10
Cap_{cl}^{Ev} (kWh)	15	20	20	15	20	15	10	10	15	20
SOC_{cl}^{arr}	0.33	0.33	0.16	0.4	0.1	0.45	0.5	0.2	0.33	0.2

TABLE. II TND CHARACTERISTICS OF EVLPS

EVPL type		**Min**	**Max**	**Average**	**Standard deviation**
Residential	Arrival	16	23	20	3
	Departure	6	11	8	3

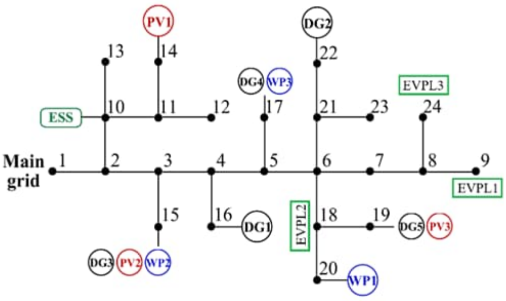

Fig. I. Distribution system topology

B. Result and Discussion

The charging power scheduling of the EVPL in scenario 1, where EVPLs cannot provide reactive power support, is depicted in Fig. II. It can be seen that the charging schedules of EVPLs are different from each other in both cases. This is because of their different locations in the power system where different network constraints result in different charging schedules. This way, the EVPLs charging schedule is determined based on the hourly power price and the power generation of DGs and RES meeting the voltage conditions all over the system to be within the maximum and minimum allowed values. Moreover, for each EVPL the charging schedule in case (a) is different from its charging schedule in case (b). In case (b), in which there is a voltage violation cost, decreasing voltage violation level is of more importance compared to case (a).

This way, the charging schedule is determined to assist the DSO in reaching a lower voltage violation level, as depicted in Fig. III, since modification in the charging schedule results in a change in hourly generation and trading power. This way, EVPL, by acting as a flexible load, will support the DSO to decrease the voltage violation all over the power system as represented in the TABLE. III. It is also seen that if the DSO must pay the voltage violation penalty, there will be a meaningful increase in its cost even with the modification in the charging schedule of EVPLs that results in a lower voltage violation in the whole system.

TABLE. III TOTAL SYSTEM COST IN SCENARIO 1

Case	VV	System cost
Case (a)	27.3365	18597.12
Case (b)	23.3558	21623.89

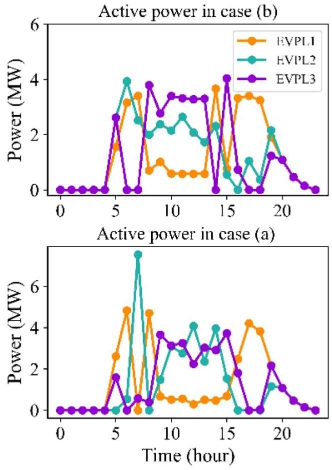

Fig. II. The active power of EVPLs for case (a) and case (b) in scenario 1

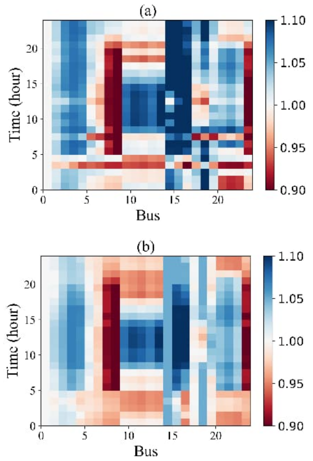

Fig. III System voltage for case (a) and case (b) in scenario 1

In scenario 2, EVPLs are equipped with reactive power support for the DSO. It is observed that the total system cost in this scenario for case (a) is 1.37% less than the system cost for the same case in scenario 2. This lower cost is expected as reactive power support from EVPL could result in a cheaper power supply mix due to improving the voltage situation in the system that enables DGs to generate more. This way, the total system cost is reduced. The reactive power support in scenario 2 has a higher impact on improving the system operation in case 2 where the total system cost in scenario 2 for case (b) is 11.23% less than the system cost for the same case in scenario 2. This highlights the importance of reactive power support from EVPLs when we consider the cost of voltage violation penalty cost for the DSO. Fig. IV shows the active and reactive power of EVPLs for case (a) and case (b) in scenario 2. It can be seen that in this scenario, for both cases, EVPLs modify their charging schedule (compared to scenario 1 in Fig. II) to provide reactive power support for a major improvement in the system voltage situation as shown in Fig. V that leads to lower voltage violation and consequently lower system cost. From TABLE. IV, it is observed that when DSO commits to pay for the voltage violation of more than 0.05, the total voltage violation of the system will decrease by around 34%. This meaningful voltage violation reduction shows EVPLs can have a decent performance in supporting the system to improve the voltage situation.

TABLE. IV TOTAL SYSTEM COST IN SCENARIO 2

Case	VV	System cost
Case (a)	28.19	18352.35
Case (b)	18.63	19194.94

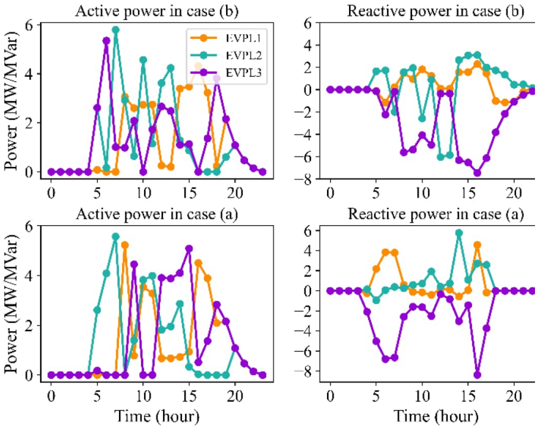

Fig. IV. The active and reactive power of EVPLs for case (a) and case (b) in scenario 2

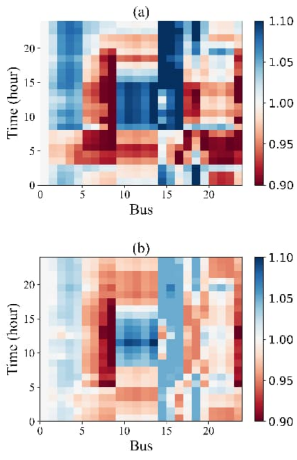

Fig. V System voltage for case (a) and case (b) in scenario 2

V. CONCLUSION

This paper examined how commercial EVPLs affected the distribution system operation, specifically by assessing their ability to provide reactive power support while considering the penalty cost incurred by DSO due to unauthorized voltage violations. This way, a new linear formulation was deployed to quantify the voltage violation index. Our findings demonstrated that EVPLs in the different parts of the system had different responses for supporting the DSO based on the network limitation in that area. In addition, the results showed that by equipping the EVPLs with the reactive power support capability the system cost decreased 1.37% for case (a) where the voltage violation penalty cost was neglected and 11.23% for case (b) where voltage violation penalty cost was considered. Therefore, the reactive power support provided by EVPLs had a significant influence on decreasing the overall system cost and on improving system voltage specially when DSO was committed to paying the voltage violation penalty to consumers. For future studies, it is needed to investigate the role of residential EVPLs in supporting the distribution system. In addition, the effect of EVPLs' size (capacity) and location should also be studied.

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OPTIMAL PLANNING OF A VIRTUAL POWER PLANT HOSTING AN EV PARKING LOT

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ABSTRACT

With the increasing penetration of electric vehicles (EV) in the future, VPPs can take some actions for meeting their demand. This way, VPPs can increase their income by selling electric power to EVs and utilizing the battery of EVs as energy storage to facilitate the deployment of renewable energy resources. However, investing too much in charging stations may not have an acceptable return on investment. In this paper, we study the optimal operation and planning of a VPP which is located to certain part of the network and is composed of wind turbines, PV units, as well as unidirectional and bidirectional EV charging stations. In our proposed approach, optimal planning is done considering that the system will be operated optimally. According to the simulation results, EV owners' behavior could have a significant impact on the optimal planning decision of the VPP. In addition, optimal number of the unidirectional and bidirectional EV charging stations depend on the share of the PV and wind generation and the capacity of the line between the VPP and upstream grid.

INTRODUCTION

Recently, due to environmental reasons, interest towards the exploitation of renewable energy resources in electricity networks has been constantly increasing. Nonetheless, the high penetration of renewable-based units and their intermittent behavior have caused several technical, economic, and regulatory challenges [1]. The mentioned issues could be addressed by jointly operating non-dispatchable renewable units with different types of dispatchable resources, including conventional generation units, flexible loads, and energy storage devices [2]. To facilitate the coordination of these energy sources in a single platform, a concept called virtual power plant (VPP) has been raised. Accordingly, the VPP aggregates a wide range of distributed energy resources (DERs) and systematically controls them to not only compensate for the uncertain nature of renewable energy generation but also pave the way for the participation of the integrated DERs in different energy markets or providing system support services [3]. It is clear that VPPs are willing to find a solution for promoting their profit, and in this context, an optimal planning strategy assists them to reach the highest possible amount of income.

On the other hand, over the past few years, the number of electric vehicles (EVs) has been increasing notably, having also growing effects on power systems [4]. Thanks to the high deployment of EVs at the distribution level, VPPs can take some actions to meet their demands. In this way, VPPs are able to increase their income by selling electric power to EVs and utilizing their batteries as energy storage systems to mitigate the power fluctuation resulting from the stochastic generation of renewable energy resources [5]. Thus, by adding charging stations and hosting EVs, VPPs can improve the optimal utilization of renewable-based resources. However, investing too much in charging stations may not have an acceptable return on investment. As a result, it is highly required to find the optimal operational planning for VPPs equipped with EV charging stations as well.

Various research works have been conducted to evaluate the planning strategy of VPPs taking into account operational constraints. In this regard, a bi-level programming framework has been provided in [6] to determine the optimal location and capacity of an energy storage system within the VPP. The upper level of the model deals with the planning problem aimed at maximizing the net profit of the VPP, while the lower level deals with its operational strategy. A risk-based stochastic method has been utilized in [7] for investigating the investment planning of a VPP trading power in the electricity market. In this study, the objective is to maximize the profit of the VPP, which comprises conventional and renewable generation units, storage systems as well as flexible demands. A multi-objective optimization approach has been employed in [8] for the optimal capacity allocation of the VPP, which includes EVs. The capacity allocation of the considered VPP is implemented in a way to not only promote its net revenue but also reduce pollution and overcome environmental concerns. An optimization framework has been developed in [9] for the optimal operational planning of an integrated system that aggregates multiple renewable-based resources, energy storage systems, and EV charging stations for providing services to the upstream grid. The primary objective of this study is to determine the optimal configuration of the system and maximize its profit while considering operational constraints. A mixed-integer linear programming model has been exploited in [10] for the optimal planning of an aggregator that integrates a wide range of disparate DER technologies at the distribution level. This work aims to maximize the aggregator's net present value income from providing services to the upstream network over the planning horizon. Finally, a bi-level stochastic model has been suggested in [11] for the capacity allocation of an energy storage system within a VPP. Accordingly, at the upper level, the VPP's planning problem is modeled to minimize its investment and maintenance costs. At the lower level, the VPP's operating problem is formulated to minimize the power fluctuation of the existing renewable units.

Given the importance of making strategic decisions over the planning horizon of VPPs and according to the high penetration rates of EVs, the present article focuses on the operational planning of a VPP that possesses renewable-based energy resources as well as EV charging stations which are located at a certain part of the grid. Accordingly, the main goal of the paper is to determine the optimal number of unidirectional and bidirectional EV charging stations and renewable-based units within the VPP and in the presence of operational constraints of each component. On the other hand, this research seeks to assess how the investment in the charging stations differs for VPPs with different shares of renewable generations. This analysis will pave the path toward more deployment of renewable energy resources as well as EVs and provide a green and sustainable energy sector in the future.

The rest of the paper is organized as follows: the structure of the considered VPP and the problem formulation are explained in more detail in section 2. A typical case study is implemented in section 3. Ultimately, the study is concluded in section 4.

PROPOSED VPP MODEL

In this section, we intend to explain the formulation used for modelling a VPP consisting of electric vehicle charging station, wind and photovoltaic generation, as well as load. This way, the VPP's problem is composed of its objective function for minimizing its operational cost and the constraints related to the operation of all components.

The operational objective function of the VPP is presented in (1).

$$OF_{op} = -((SOC_{ex} - SOC_{en}).\boldsymbol{\lambda}_{EVch}.(\mathbf{N}_{UDCS} + \mathbf{N}_{BDCS}) + \sum_t P_{grid}(t).\boldsymbol{\lambda}_{DA}(\mathbf{t})) \quad (1)$$

The objective function of the problem is the operational cost of the VPP. The first term in the objective function is the income gained from electric vehicle owners for charging their vehicles. $\boldsymbol{\lambda}_{EVch}$ is the price tariff for charging EVs. The second term is the total cost of the VPP for buying power from the power system.

We have considered two types of electric vehicle charging stations. The first type is the unidirectional charging station in which the electric vehicle can just be charged while it cannot be discharged to inject the power into the grid. The second type is the bidirectional charging station in which the vehicle can be both charged and discharged. Therefore, the flow of power can be both from the grid to the vehicle (G2V) and vehicle to grid (V2G).

The battery of the EVs that are located at unidirectional and bidirectional charging stations are modelled as represented in (2-6) and (7-12), respectively.

$$P^n_{ch_{min}}(t) \le P^n_{ch}(t) \le P^n_{ch_{max}}(t) \quad (2)$$

$$SOC^n(t+1) = SOC^n(t) + P^n_{ch}(t).\boldsymbol{\eta}_{ch} \quad (3)$$

$$SOC^n_{min}(t) \le SOC^n(t) \le SOC^n_{max}(t) \quad (4)$$

$$SOC^n(t_{en}) = SOC_{initial} \quad (5)$$

$$SOC^n(t_{ex}) = SOC_{final} \quad (6)$$

$$P^m_{ch_{min}}(t) \le P^m_{ch}(t) \le P^m_{ch_{max}}(t) \quad (7)$$

$$P^m_{dch_{min}}(t) \le P^m_{dch}(t) \le P^m_{dch_{max}}(t) \quad (8)$$

$$SOC^m(t+1) = SOC^m(t) + P^m_{ch}(t).\boldsymbol{\eta}_{ch} - P^m_{dch}(t)/\boldsymbol{\eta}_{dch} \quad (9)$$

$$SOC^m_{min}(t) \le SOC^m(t) \le SOC^m_{max}(t) \quad (10)$$

$$SOC^m(t_{en}) = SOC_{initial} \quad (11)$$

$$SOC^m(t_{ex}) = SOC_{final} \quad (12)$$

The output power of the wind turbines and the photovoltaic cell can vary between 0 and the maximum possible generation according to the hourly wind speed and solar radiation (13, 14). The maximum possible generation of the PV and wind turbine is calculated as represented in (15) and (16).

$$0 \le P_{PV}(t) \le P^{max}_{PV}(t) \quad (13)$$

$$0 \le P_{wind}(t) \le P^{max}_{wind}(t) \quad (14)$$

$$P^{max}_{PV}(t) = G_{PV}(t).\boldsymbol{\eta}_{PV}.A_{PV} \quad (15)$$

$$P^{max}_{wind}(t) = \begin{cases} 0 & if\ v(t) < v_{cutin} \\ \frac{(v(t)-v_{cutin})}{(v_{rated}-v_{cutin})}.P^{max}_{w} & if\ v_{cutin} \le v(t) \le v_{rated} \\ P^{max}_{w} & if\ v_{rated} \le v(t) \le v_{cutout} \\ 0 & if\ v_{cutout} \le v(t) \end{cases} \quad (16)$$

The power balance of the VPP is formulated as presented in eq. (17). In addition, the traded power between VPP and the upstream grid (in both directions) in each hour must not exceed the capacity of the line between the VPP and the grid (18).

$$P_{wind}(t) + P_{PV}(t) - \sum_m P^m_{dch}(t) + \sum_m P^m_{ch}(t) + \sum_n P^n_{ch}(t) - Load(t) = P_{grid}(t) \quad (17)$$

$$-P^{max}_{grid} \le P_{grid}(t) \le P^{max}_{grid} \quad (18)$$

In addition, the charge and discharge power of each bidirectional charging station cannot be nonzero simultaneously in each hour (19). This constraint causes the problem to be nonlinear. To prevent nonlinearity, by utilizing the big M method, equations (20) and (21) are used instead of (19) where M is a large enough number and $u(t,m)$ is a binary variable. Then the problem would be converted to mixed-integer linear programming (MILP).

$$P^m_{ch}(t).P^m_{dch}(t) = 0 \quad (19)$$

$$P^m_{ch}(t) \le u(t,m).M \quad (20)$$

$$P^m_{dch}(t) \le (1 - u(t,m)).M \quad (21)$$

For the planning problem, the objective function is the total cost of the plan that equals the summation of the investment cost and the net present value of the total operational cost of the VPP over its lifecycle (22). In addition, all of the mentioned constraints for the operational problem are also the constraints of the planning problem. Because the optimal planning is done considering that the system will be operated optimally.

$$OF_{pl} = NPV(\textstyle\sum_{lifecycle} OF_{op}) + \mathbf{N}_{UDCS}.\mathbf{C}_{UDCS} + \mathbf{N}_{BDCS}.\mathbf{C}_{BDCS} + \mathbf{N}_{WT}.\mathbf{C}_{WT} + \mathbf{N}_{PV}.\mathbf{C}_{PV} \quad (22)$$

The net present value of the operational cost of the year i is calculated using Eq. (23), in which IR is the interest rate, and C_i is the operation cost at year i. Therefore, the net present value of the operation cost should be calculated for all years of the lifecycle separately. The summation of the net present value of each year gives the net present value of the total operational cost over the lifecycle.

$$NPV(C_i) = C_i/(1 + IR)^{\,i} \quad (23)$$

SIMULATION RESULTS

This section consists of four subsections. At first, the case study used for the simulation is introduced. Then, the operational performance of the VPP for scheduling the charging of EVs is investigated. The third subsection studies the optimal planning of the VPP for hosting unidirectional and bidirectional EV charging stations. The fourth part investigates the comprehensive planning of the VPP for adding the capacity of wind power plants and PV units as well as unidirectional and bidirectional EV charging stations.

Case study

The data related to the wind speed, solar radiation, the day-ahead (DA) electricity price, and load pattern is presented in Table. 1. In addition, the technical characteristics of the wind turbine and PV are available in Table. 2. Moreover, the data related to the maximum charging and discharging power, the initial and final state of charge (SOC), as well as the entrance and exit time of the EVs are represented in Table. 3. Furthermore, the investment costs used in our simulation are presented in Table 4. We simulated the operational problem by coding in Python. The solver Ipopt has been used for optimization. Then, for the planning, the objective function of each planning scenario is calculated using Ipopt solver, and the planning scenario with the least planning objective function is the optimal planning decision. It is noteworthy that the plan's life cycle in our case study is 15 years. Moreover, for the planning problem, it has been assumed that the data for all days in the lifecycle is similar to the data presented in Table 1.

Table. 1. Hourly wind, solar, DA price, and load data

Hour	Wind speed	Solar radiation	DA price	Load
1	19.60	0	0.031	68.35
2	13.50	0	0.025	57.7
3	22.00	0	0.021	57.94
4	6.80	0	0.012	44.74
5	9.60	0	0.015	66.18
6	11.50	0	0.022	78.51
7	9.90	0.052	0.056	103.55
8	7.10	0.272	0.078	125.28
9	9.90	0.329	0.108	129.3
10	15.40	0.45	0.128	143.39
11	11.00	0.519	0.12	131.91
12	11.90	0.53	0.135	145.22
13	5.30	0.601	0.128	149.07
14	8.80	0.638	0.104	130.58
15	11.20	0.551	0.068	119.98
16	9.20	0.427	0.039	110.71
17	2.00	0.22	0.034	128.15
18	4.20	0.052	0.046	118
19	13.20	0	0.064	120.62
20	7.50	0	0.073	129.06
21	14.20	0	0.066	116.3
22	11.20	0	0.055	101.47
23	8.00	0	0.044	92.94
24	12.60	0	0.034	83.35

Table. 2. The technical characteristics of the wind turbine and PV

P_w^{max}	V_{cutin}	V_{rated}	V_{cutout}	A_{PV}	$\boldsymbol{\eta}_{PV}$
150	5	14	25	700	0.14

Table 3. Data related to the EVs

P_{ch}^{max}	P_{dch}^{max}	t_{en}	t_{ex}	SOC_{init}	SOC_{final}	Battery capacity
20	20	7	16	50%	100%	20

Table. 4. Investment costs and interest rate data

$\mathbf{C}_{UDCS}$	$\mathbf{C}_{BDCS}$	$\mathbf{C}_{WT}$	$\mathbf{C}_{PV}$	IR
5000€	13000€	1475€/kW	1625€/kW	0.02

Optimal Operation of the VPP hosting EV charging stations

In this subsection, the operational performance of the VPP in presence of one unidirectional and bidirectional charging station is studied. The charge and discharge power of the bidirectional station, the charge power of the unidirectional charging station, as well as the day-ahead electricity price are shown in Fig. 1. As expected, charging at the unidirectional and bidirectional stations is done at those hours when the electricity price is low. Accordingly, discharging at the bidirectional charging station is done in hours that electricity price is high. Therefore, the bidirectional EV charging station acts as an energy storage system and gains income by smart charging and discharging. The total operational cost of the VPP over the lifecycle is 258097 €. We also did the simulation for 3 other scenarios to study the impact of EV entrance and exit time on the total operational cost of the VPP over a 15-year lifecycle. The results are presented in Table. 5.

When EVs enter the parking earlier and quit later, the total operation cost is less because EVs charging and discharging could be scheduled with more freedom. In addition, indicate that earlier entrance is more effective than later exit in reducing the cost. Because when EVs enter at 7 and leave at 15, the total operational cost is 258478 €, which is less than the operational cost when EVs enter at 8 and leave at 16, while the staying time of the EVs in the two scenarios are similar. Therefore, for the VPP owner, it is preferred that EVs enter earlier in the day. Furthermore, it is clear that the entrance and exit time has a major impact on the results. In future studies, the behavior of the EV owners (entrance and exit time) and potential uncertainties and risks should be further studied and modelled in a probabilistic manner.

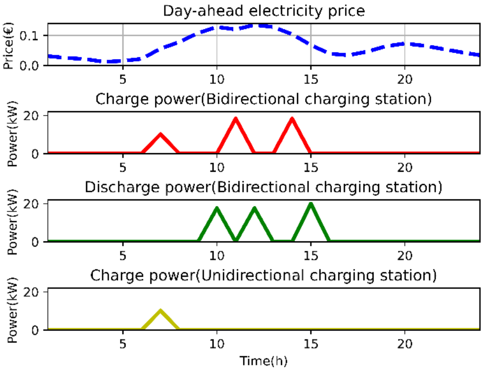

Fig. 1. Charge and discharge power as well as day-ahead electricity price

Table. 5. Operational cost for different entrance and exit time of the EVs

t_{en}	t_{ex}	Total operational cost
7	16	258097 €
7	15	258478 €
8	15	261636 €
8	16	263704 €

Optimal Planning of a VPP for hosting EV charging stations

In this part, we want to define the optimal number of unidirectional and bidirectional charging stations to be utilized at the EV parking lot owned by the VPP. We consider that VPP possesses one wind turbine and one PV introduced in the section "Case study". At first, we consider five different VPPs with different capacities of the line between the VPP and the upstream grid (all other characteristics are the same). Fig. 2. shows that for VPPs with the greater capacity of the line between the VPP and the grid the number of optimal bidirectional charging stations is more. The reason is that when the VPP can trade more power to the grid in each hour, the possibility of buying power in low price hours by charging and selling power in high price hours by discharging in bidirectional EV charging stations increases. Therefore, bidirectional EV charging stations could gain more benefits.

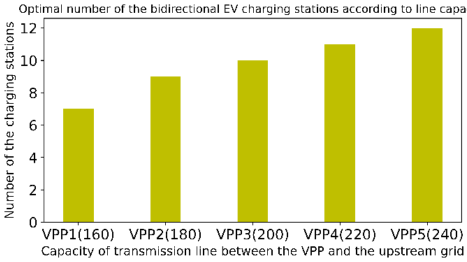

Fig. 2. Optimal number of the bidirectional EV charging stations for different line capacities

In addition, seven scenarios have been considered for the initial SOC of the EVs entering the VPP. As shown in Fig.3, if the initial SOC of the VPP is 10% and 20%, the optimal number of the unidirectional and bidirectional EV charging stations are 2 and 10, respectively. If it is 30%, 40%, or 50% the optimal number of the unidirectional and bidirectional EV charging stations are 0 and 10. For the more initial SOC the optimal number of bidirectional charging stations decreases. The reason behind this is that when the initial SOC is low, there is more potential for gaining income from EV owners for charging their EVs, and the greater initial SOC will result in less potential for gaining income. Therefore, EV charging stations would have a less return on investment as the initial SOC increases.

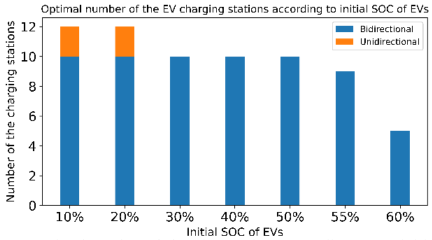

Fig. 3. Optimal number of charging stations according to EV initial SOC

Comprehensive Planning of a VPP for defining the capacity of wind and PV generation as well as EV charging stations

In this section, we intend to investigate the optimal planning of the VPP when the number of PV units, wind turbines, and EV charging stations are the decision variables of the planning problem. To this end, we have considered five different VPPs with different capacities of the line between the VPP and the upstream grid (all other characteristics are the same) and found the optimal plan for each VPP. The results are illustrated in Fig. 4.

The results depict that for VPP1, with the 180kW line capacity, the optimal number for wind turbines, PV units, and unidirectional as well as bidirectional EV charging stations would be 2, 4, 6, and 5, respectively. However, for the VPP2 (the line capacity is 200kW), the optimal number of unidirectional and bidirectional EV charging stations would be 1 and 7, respectively, while the optimal number of wind turbines and PV units are similar to the VPP1.

From these results, it can be understood that the greater line capacity of VPP2 makes the bidirectional EV charging station a more profitable option than the unidirectional EV charging station. Because the possibility for utilizing from bidirectional EV charging station as an energy storage system to charge at low price hours and discharge at high price hours is more available. This operational profit outweighs its high investment cost. Furthermore, VPP3 (with 220kw capacity line) allows for the deployment of one more PV unit, and subsequently, the optimal number of the unidirectional EV charging station would be 10, which is more than VPP3. These results reveal that more PV generation paves the way for the deployment of the more unidirectional EV charging station. In this regard, the additional PV generation could be used for EV charging.

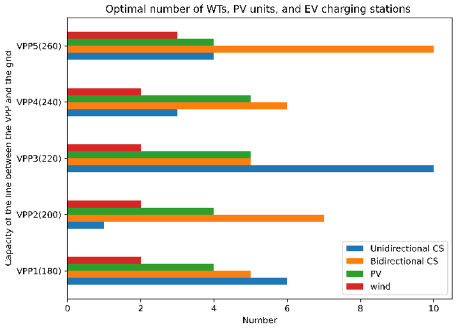

Fig. 4. Optimal number WTs, PV units, and EV charging stations

Comparing VPP4 and VPP3 shows that the optimal number of PV units and wind turbines is similar, while unidirectional EV charging stations are a more profitable choice for VPP4 compared to VPP3. This is similar to what has been described in the comparison between VPP1 and VPP2. The other important point is that the 260kw capacity line in VPP5 makes wind turbines more profitable and makes PV a less profitable planning option compared to VPP4. The results show that the higher share of wind generation in VPP5, causes the bidirectional EV charging station to be a more profitable planning option than the unidirectional EV charging station. In fact, the results show that when the share of the wind generation is more, the bidirectional EV charging station is of more interest to the VPP owner.

CONCLUSION

In this paper, we investigated the optimal operation and planning of the VPP for the deployment of unidirectional and bidirectional EV charging stations. In this way, comprehensive planning has been done where the optimal number of PV units, wind turbines, and EV charging stations have been defined for our case study VPP. The results of our case study show that when the share of PV generation increases, the profitability of the PV cells may also increase. On the other hand, the greater share of wind generation encourages the deployment of the bidirectional EV charging station. The other important point is that the behavior of EV owners for entering and exiting the parking lot and the initial SOC of the EV while entering the parking have a major impact on the results. Therefore, the uncertainty related to the mentioned issues should be considered in future studies to make a more reliable planning decision.

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