Evaluating Local Energy Trading for Massive Integration of Distributed Energy Resources

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STUDENT DECLARATION

I, **Morsy Abdelkader Morsy Mohammed Nour**, the undersigned, hereby declare that the present Ph.D. thesis work has been prepared by myself and without any unauthorized help or assistance. Only the specified sources (references, tools, etc.) were used. All parts taken from other sources, word by word or after rephrasing but with identical meaning, were unambiguously identified with explicit reference to the sources utilized.

Madrid, 17 July 2024

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Morsy Abdelkader Morsy Mohammed Nour

DEDICATION

To my beloved parents, wife, sons, family, friends, colleagues, and professors.

Thanks for your love, support, help, and inspiration.

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Abstract

Electricity generation from renewable energy sources (RESs) is increasing rapidly worldwide due to environmental, economic, and energy security challenges. A considerable percentage of RESs generation is produced by a small generation connected to the distribution network, being part of distributed energy resources (DERs). At a fast pace, other DERs are being deployed at the distribution level, such as electric vehicles (EVs), battery energy storage (BES), flexible loads, etc. It is estimated that 83% of houses in the European Union will have DERs by 2050. The high number of DERs could cause many technical challenges in the power system, especially at the distribution level, unless they are adequately managed. Indeed, appropriate management is required to maximize the benefits of the DER owners and the power system.

Many management approaches have been proposed to efficiently integrate DERs and provide ancillary services such as home energy management systems (HEMS), building management systems, microgrid management systems, and virtual power plants. One of the recent promising approaches to integrating DERs is local energy trading (LET), also known as local electricity markets (LEMs) or peer to peer (P2P) energy trading. LET enables energy trading between end customers to maximize their economic benefits. However, the LET approach is still in the early stage of research, and many fundamental questions need further research to enable large-scale adoption. For instance, what are the benefits of LET compared to other DER management approaches? What are the possible impacts of LET on unbalanced distribution networks? How do we minimize LET impacts on unbalanced distribution networks? What are the DER investment options in the LET framework that maximize the benefits and minimize the costs of DER owners? What are the most suitable market designs and technology for LET? How to relieve any congestion in the distribution networks using market-based solutions? These important questions must be answered before the real implementation of LET. This thesis aims to answer these research questions.

Given this context, this thesis compares LET with the HEMS in terms of energy community (EC) operation costs and interaction with the retailer in a Spanish case study. Moreover, this thesis is

the first study to focus on assessing the impacts of LET and HEMS on unbalanced LVDN, considering DERs' flexibility. The results show that LET reduces the EC operation cost compared to the corresponding HEMS scenarios. LET results in better self-generation and self-sufficiency. However, LET increases the community peak demand from the retailer and causes higher impacts on the unbalanced LVDN than HEMS.

Next, the effect of considering contracted power costs in the LET optimization model in reducing the impacts on unbalanced LVDN is studied for the first time in the literature. The proposed approach does not require the consideration of grid constraints in the LET model and, therefore, requires low computational power. The results showed that the proposed approach reduces the peak demand of the EC by 34.3% without affecting its economic performance, energy exchange with the retailer, and amount of energy traded locally. Moreover, the proposed approach prevents violations of LVDN limits that occur in the LET scenario that does not consider contracted power cost in the optimization model.

Then, since DERs have a high investment cost, there is a need to optimally size DERs of LET participants to maximize the benefits, minimize the costs of DER owners, and reduce the payback period. Therefore, an optimization model is developed for optimal photovoltaic (PV) and BES sizing to minimize the total annual costs. Uncertainties of demand, PV generation, electricity prices, and EVs are considered. The results showed that optimal planning achieved a 10.95% reduction in annual costs compared to the scenario without optimal planning.

Previous studies in the thesis assumed the presence of a central entity responsible for managing the LET between participants. However, the centralized management of LET has a few challenges, such as a single point of failure, participants' privacy concerns, lack of participants' autonomy, etc. Therefore, many studies have used blockchain technology to implement distributed LET and address these challenges. However, limited focus in the literature was given to comparing the performance and economic viability of different technologies that could be used to implement LET. Therefore, the thesis compares several market models for LET developed on various technologies, such as a centralized server and a distributed ledger (i.e., blockchain). The output-based

quantitative comparison highlights the limitations and advantages of different market models and implementations. Technical constraints on the power system through a congestion market are also analyzed. Results show that there is not a single best solution of general validity. A centralized double auction market is faster, while a distributed continuous double auction market guarantees larger energy traded locally. Moreover, it is found that public blockchain technology still has several limitations for the tested application and assumed conditions that do not allow its efficient applicability to LET.

Resumen

La generación de electricidad a partir de fuentes de energía renovables está aumentando rápidamente en todo el mundo debido a desafíos ambientales, económicos y de seguridad energética. Un porcentaje considerable de la generación renovable se produce mediante pequeñas unidades conectadas a la red de distribución, formando parte de los recursos energéticos distribuidos (DER, por sus siglas en inglés). Otros DER se están conectando a nivel de distribución, como vehículos eléctricos (VE), almacenamiento de energía en baterías, cargas flexibles, etc., a un ritmo acelerado. Se calcula que el 83% de las viviendas de la Unión Europea dispondrán de DER en 2050. El alto número de DER podría causar muchos desafíos técnicos en el sistema eléctrico, especialmente a nivel de las redes de distribución, a menos que se gestionen adecuadamente. De hecho, se requiere una gestión adecuada para maximizar tanto los beneficios de los propietarios de DER como del sistema eléctrico.

Se han propuesto muchos enfoques de gestión para integrar eficientemente los DER y proporcionar servicios auxiliares como sistemas de gestión de energía doméstica (SGED), sistemas de gestión de edificios, sistemas de gestión de microrredes y unidades de energía virtuales. Uno de los enfoques recientes y prometedores para integrar los DER es el intercambio de energía a nivel local, también conocido como mercados locales de electricidad (MLE) o intercambio de energía entre pares (P2P). El MLE permite el intercambio de energía entre usuarios finales para maximizar sus beneficios económicos. Sin embargo, el enfoque de intercambio de energía local aún está en una etapa temprana de investigación, y muchas preguntas fundamentales necesitan más investigación para permitir una adopción a gran escala. Por ejemplo, ¿cuáles son los beneficios del MLEen comparación con otros enfoques de gestión de DER? ¿Cuáles son los posibles impactos del MLE en redes de distribución desequilibradas? ¿Cómo se minimizan los impactos del MLE en redes de distribución desequilibradas? ¿Cuál es el tamaño óptimo de los DER en el marco del MLE que maximiza los beneficios y minimiza los costes de los propietarios de DER? ¿Cuáles son los diseños de mercado y tecnologías más adecuados para el intercambio de energía P2P? ¿Cómo solucionar congestiones en

las redes de distribución con soluciones de mercado? Estas preguntas se deben responderse antes de la implementación real del MLE. Esta tesis pretende responder a estas preguntas.

Dado este contexto, la tesis compara la gestión de MLE con el SGED en cuanto a los costes de operación y la interacción con el comercializador en un caso de estudio español. El primer estudio se centra en evaluar los impactos del MLE y el SGED en el desequilibrio de la red de baja tensión (RDBT). Los resultados muesstran que el MLE reduce el coste de operación de la MLE en comparación con los escenarios correspondientes de SGED. El MLE resultó en una mejor auto-generación y autosuficiencia. Sin embargo, el MLE aumenta la demanda máxima de la comunidad del minorista, causando así mayores impactos en la RDBT que el SGED.

Para evitar estos problemas, se considera los costes de potencia contratada en un modelo de optimización para reducir los impactos del MLE en la RDBT. El enfoque propuesto no requiere la consideración de restricciones de red en el modelo MLE y, por lo tanto, requiere baja potencia computacional. Los resultados muestran que el enfoque propuesto redujo el pico de potencia de los MLE en un 34.3% sin afectar su rendimiento económico, el intercambio de energía con la comercializadora y la cantidad de energía intercambiada localmente. Además, el enfoque propuesto previene violaciones de los límites de la RDBT en sobrecarga de la línea, el desequilibrio de tensiones y la magnitud de tensiones que ocurren en el escenario con MLE que no considera el coste de potencia contratada en la función objetivo.

Adicionalmente, existe la necesidad de dimensionar óptimamente los DER de los participantes del MLE que maximicen los beneficios, minimicen los costes de los propietarios de DER y reduzcan el período de recuperación de la inversión. Se desarrolla un modelo de optimización para el dimensionamiento óptimo de fotovoltaicos (PV) y baterías con el objetivo de minimizar los costes anuales totales. Se consideraron incertidumbres de demanda, generación PV, precios de la electricidad y VE. Los resultados muestran que la planificación óptima logró una reducción del 10.95% en los costes anuales de inversión y operación en comparación con el escenario sin planificación óptima.

Los estudios anteriores de la tesis suponían la presencia de una entidad central encargada de gestionar el MLE entre los participantes. Sin embargo, la gestión centralizada del MLE presenta algunos retos, como un único punto de fallo, preocupaciones sobre la privacidad de los participantes, falta de autonomía de los participantes, etc. Por lo tanto, muchos estudios han utilizado la tecnología blockchain para implementar el MLE descentralizado y abordar estos desafíos. Sin embargo, en la bibliografía se ha prestado poca atención a la comparación del rendimiento y la viabilidad económica de las distintas tecnologías que podrían utilizarse para implantar el MLE. Finalmente, se compara varios modelos de mercado para el intercambio de energía en MLE desarrollados por diversas tecnologías, como un servidor centralizado y tecnologías de registro distribuido como Blockchain o cadena de bloques. La comparación cuantitativa destaca las limitaciones y ventajas de diferentes modelos de mercado e implementaciones. También se analizan las restricciones técnicas en el sistema eléctrico a través de un mercado de restricciones técnicas. Los resultados muestran que no hay una única solución que sobresalga en todos los indicadores de evaluación. Un mercado de subasta bilateral centralizado es más rápido, mientras que un mercado de subasta bilateral continua distribuido garantiza una mayor energía comercializada localmente. Además, la tecnología Blockchain todavía tiene varias limitaciones para la aplicación estudiada y bajo las consideraciones asumidas no resulta atractiva su aplicabilidad al MLE.

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List of Abbreviations

AC	Alternating current
AMI	Advanced metering infrastructure
BES	Battery energy storage
CDA	Continuous double auction
CHP	Combined heat and power
CMM	Congestion management market
CP	Contracted power
CSC	Community self consumption,
CQR	Clear quantity ratio
CS	Charging station
DA	Double auction
DC	Direct current
DER	Distributed energy resource
DG	Distributed generation
DLT	Distributed ledger technology
DNs	Distribution networks
DSO	Distribution system operator
EC	Energy community
ESS	Energy storage system
EV	Electric vehicle
EVM	Ethereum virtual machine
EWC	Energy Web Chain
FACTS	Flexible AC transmission systems
FIT	Feed in tariff
FSP	Flexibility service provider
G2V	Grid to Vehicle
GA	Genetic algorithm
GT	Game theory
HEMS	Home energy management system
ICTs	Information and communication technologies
IEC	International Electrotechnical Commission
IOTA	Internet of Things Application
KPI	Key performance indicator
kV	Kilo volt
kVA	Kilo volt ampere
kW	Kilowatt
kWh	Kilowatt hour
kWp	Kilowatt peak

LEM	Local electricity market
LET	Local energy trading
LFM	Local flexibility market
Li-ion	Lithium-ion
LP	Linear Programmig
LV	Low voltage
LVDN	Low voltage distribution network
LW	Local welfare
MCP	Market clearing price
MILP	Mixed integer linear programming
MV	Medium voltage
O&M	Operation and maintenance
OPF	Optimal power flow
P2P	Peer-to-Peer
P2P-ET	Peer-to-Peer energy trading
PBFT	Practical byzantine fault tolerance
PCDA	Pseudo-continuous double auction
PoAu	Proof of Authority
PoW	Proof of work
PSO	Particle Swarm Optimization
PTDF	Power transfer distribution factor
PV	Photovoltaic
RES	Renewable energy source
SoC	State of Charge
TE	Transactive energy
ToU	Time of Use
TSO	Transmission system operator
V2G	Vehicle to Grid
VPP	Virtual power plant
VUF	Voltage unbalance factor
WCT	Waiting clearing time
WG	Wind generation
ZI	Zero intelligence

List of Publications

Publications included in the thesis.

[1] **M. Nour**, J. P. Chaves-Ávila, G. Magdy, and Á. Sánchez-Miralles, "Review of Positive and Negative Impacts of Electric Vehicles Charging on Electric Power Systems," *Energies*, vol. 13, no. 18, p. 4675, Sep. 2020.

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[4] **M. Nour**, J. P. Chaves-Avila, M. Troncia, and A. Sanchez-Miralles, "Mitigating the Impacts of Community Energy Trading on Distribution Networks by Considering Contracted Power Network Charges, " in *IEEE Access*, vol. 12, pp. 26991-27004, 2024.

[6] **M. Nour**, A. Ali, J. P. Chaves-Avila, M. Troncia, and A. Sanchez-Miralles, "Optimal Planning and Operation of Energy Community DERs Considering Local Energy Trading and Uncertainties,". Sustainable Energy Grids and Networks. **[Submitted].**

[5] **M. Nour**, M. Galici, M. Troncia, J. P. Chaves-Avila, F. Pilo, and A. Sanchez-Miralles, "Techno-economic Assessment of Local Market Models Deployed using Bockchain-Based Platforms,". Sustainable Energy Grids and Networks. **[Submitted].**

[7] **M. Nour**, J. P. Chaves-Avila, and A. Sanchez-Miralles, "Review of Local Electricity Markets: Current Status and Future Prospects,". Alexandria Engineering Journal. [**Submitted].**

Publications not included in the thesis.

[1] **M. Nour**, G. Magdy, J. P. Chaves-Ávila, Á. Sánchez-Miralles, and F. Jurado, "A new two-stage controller design for frequency regulation of low-inertia power system with virtual synchronous generator," *J. Energy Storage*, vol. 62, no. February, 2023.

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[3] **M. Nour**, G. Magdy, A. Bakeer, A. Telba, A. Beroual, U. Khaled, H. Ali, "A New Fractional-Order

Virtual Inertia Support Based on Battery Energy Storage for Enhancing Microgrid Frequency Stability". *Fractal Fract.* **2023**, *7*, 855.

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[6] M. Zedan, **M. Nour**, G. Shabib, Z. M. Ali, A. Alharbi and A. -A. A. Mohamed, "Techno-Economic Assessment of Peer to Peer Energy Trading: An Egyptian Case Study," in *IEEE Access*, vol. 12, pp. 58317-58337, 2024.

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[9] M. Zedan, **M. Nour**, G. Shabib, and A.A. Ali, "Review of Peer to Peer Energy Trading Advances and Challenges," e-Prime - Advances in Electrical Engineering, Electronics and Energy. **[Submitted].**

[10] **M. Nour**, G. Magdy, and H. Ali, "Enhancing Frequency Stability of a Low Inertia Power System Using a New Controller and a Fractional Virtual Inertia Control," Journal of Energy Storage. **[Will be submitted]**.

Chapter 1
Introduction

1.1 Background and motivation

Electric power systems were centralized for decades, with big central generation plants supplying electricity to consumers via transmission and distribution networks. The flow of power from generation plants to consumers was unidirectional, as was the movement of money from consumers to generation plants. Because of the growing installation of distributed energy resources (DERs) [1], [2] like small distributed generation, battery energy storage (BES), and flexible devices such as electric vehicles (EV) and other flexible loads (i.e., heat pumps, water heaters, refrigerators, etc.) at the distribution level, the power system structure and business model are currently facing enormous transformations. [3]–[5]. This will increase the power system management and control complexity, requiring many active actors to coordinate for cost-effective and reliable power system operation. [6]–[8].

As a result, research studies, pilot projects, and industry have shown a lot of interest in DER coordination to enable the integration of a large number of DERs to maximize DER owners' financial benefits and comfort without sacrificing power system stability and quality of supply [9]. Many approaches have been developed for managing DERs effectively in future power systems while maximizing the benefits of all involved stakeholders [9]. One well-known approach is home energy management systems (HEMS). In HEMS, every home optimizes its DERs to meet particular objectives such as lowering energy bills, increasing revenue, maximizing consumption of local generation of small renewable energy sources (RESs), maximizing comfort, etc. HEMS is simple and appropriate for low levels of DER penetration. Similarly, building management systems are used to manage different types of buildings to decrease energy costs, and increase efficiency and comfort [10].

Another feasible approach for harmonizing DERs into a single power plant is known as a virtual power plant (VPP) to attain a common objective. The grouped DERs in VPP can be spread across a wide geographical region and are not required to be connected to the same distribution network. VPPs may participate in wholesale energy markets or provide different grid services to distribution system operators (DSOs) or transmission system operators (TSOs). Moreover, DERs could be integrated into a microgrid connected to the grid or operating in an islanded mode [11], [12].

Another promising approach for effectively integrating DERs into future power systems is local energy trading (LET). LET attempts to bring the principles of liberalized wholesale electricity markets to end customers. [13]. LET empowers customers by allowing them to sell excess energy to their neighbors (i.e., peers) in the energy community (EC) or sell it to retailers if no neighbor is interested in the purchase. LET benefits energy sellers by increasing their revenues and energy buyers by reducing energy costs. Many studies proved that LET could decrease the energy bought from the grid (i.e., increase EC self-sufficiency), decrease energy sold to the grid (increase EC self-generation), and decrease energy costs considering different types of participants (i.e., houses, buildings, microgrids, and VPP) [14]–[17]. The results of many pilot projects support these findings [8], [18].

LET could empower end customers and provide many environmental, economic, and technical benefits. However, it brings many challenges and open questions that must be answered before large-scale adoption. For instance, there is a need for a comprehensive comparison of the technical and economic performance of LET with other DER management approaches considering different DERs, participants, pricing schemes, and distribution network characteristics. Do the LET benefits outweigh the costs of required infrastructure upgrades to manage such a complex system?

LET could impact different levels of the physical grid (i.e., generation, transmission, and distribution), especially the distribution networks, due to the change in power flow and end users' energy utilization patterns [19]. Therefore, the impacts of LET on distribution networks must be evaluated. Moreover, computationally efficient techniques such as efficient tariff design and market-based solutions for mitigating LET impacts on distribution networks must be developed.

Existing literature assumes the ratings of DERs installed in LET studies [20], [21]. Despite the fast decay in DER costs, technologies like BES still have a high price and short lifespan, which raises questions about their economic viability for end customers. Many countries have subsidies for BES to increase their sales. It is unclear if the DERs' large ratings are needed and if they are used optimally in LET. Therefore, studies need to be conducted to optimize the planning of DERs in LET to maximize the benefits, minimize costs, minimize the payback period, and avoid installing unnecessary DERs or oversized DERs.

Choosing suitable technology for LET is a significant challenge. Previous studies developed centralized LET platforms managed by central entity computation resources and distributed LET platforms managed by distributed ledger technologies like blockchain without a central entity [22]. Their main objective is proof of concept and that the technologies could be used for LET applications or to improve the performance of the used technologies [8]. However, limited research has focused on comparing the performance of the technologies used (i.e., centralized servers or blockchains) in LET. Therefore, a comprehensive comparison between technologies that could be used for LET is needed. All these challenges should be tackled before LET becomes a reality and achieves a considerable adoption rate.

1.2 Objectives

The previous section presents many challenges facing LET. This thesis aims to address a few challenges facing this approach. The following are the thesis objectives:

- Review LET existing studies and pilot projects and identify the research gaps that require further research.
- Evaluate the techno-economic performance of LET compared to HEMS considering different DER installations.
- Assess the impacts of LET and HEMS on an unbalanced low voltage distribution network (LVDN) considering DERs flexibility.
- Assess the effect of grid tariff design on LET economic performance and the impacts on unbalanced LVDN considering DERs flexibility.

- Evaluate DER investment options in LET and evaluate the impacts on unbalanced LVDN.
- Compare the performance of blockchain-based and centralized LET.
- Mitigate any congestion that could occur from LET on LVDN using a market-based solution.

1.3 Contribution of the thesis

The contributions that follow are developed in this thesis to achieve the study objectives:

(1) Local energy trading: current status and future prospects.

- Provide a critical overview of LET regarding market design, market clearing approaches, grid representation, and enabling technologies.
- Identify LET research gaps that require further investigation.

(2) Impacts of local energy trading on unbalanced LVDNs.

- A comprehensive techno-economic comparison of LET-based coordinated DER management and HEMS, where houses manage their DERs individually.
- Develop a joint optimization and network model for assessing the impacts of LET and HEMS on unbalanced LVDN.
- The first study that evaluates the impacts of LET on unbalanced LVDN considering DERs flexibility.

(3) Mitigating the impacts of local energy trading on LVDN by considering contracted power cost.

- The first study that compares LET economic and technical performance when contracted power is or is not considered in the LET model.
- The first study to analyze how considering the contracted power cost could mitigate the impacts of LET on unbalanced LVDN.

(4) Optimal planning and operation of energy community DERs considering local energy trading and uncertainties.

- The first study of optimal planning and operation of DERs in LET that considers PV, EV, electricity prices, and house demand uncertainties and the associated impacts on unbalanced LVDN.
- Sensitivity analysis of PV and BES optimal planning to cost of BES investments, electricity prices, and electricity selling prices.

(5) Techno-economic assessment of local market models deployed using blockchain-based platforms.

- The first study to compare two blockchain-based LET with a central LET, based on several key performance indicators (KPIs).
- Eliminate any congestion in LVDN through the congestion management market.

(6) General conclusions and Implications for stakeholders

- Derive general conclusions from the thesis findings and research gaps that need further research.
- Identify the thesis findings' implications for stakeholders and propose recommendations for implementing LET.

1.4 Thesis structure

This thesis is divided into seven chapters. What follows is the arrangement of these chapters, with a brief summary of every chapter. Figure 1.1 illustrates what each chapter addresses and how the thesis chapters are connected to give a better understanding of the thesis content.

The thesis is organized as follows:

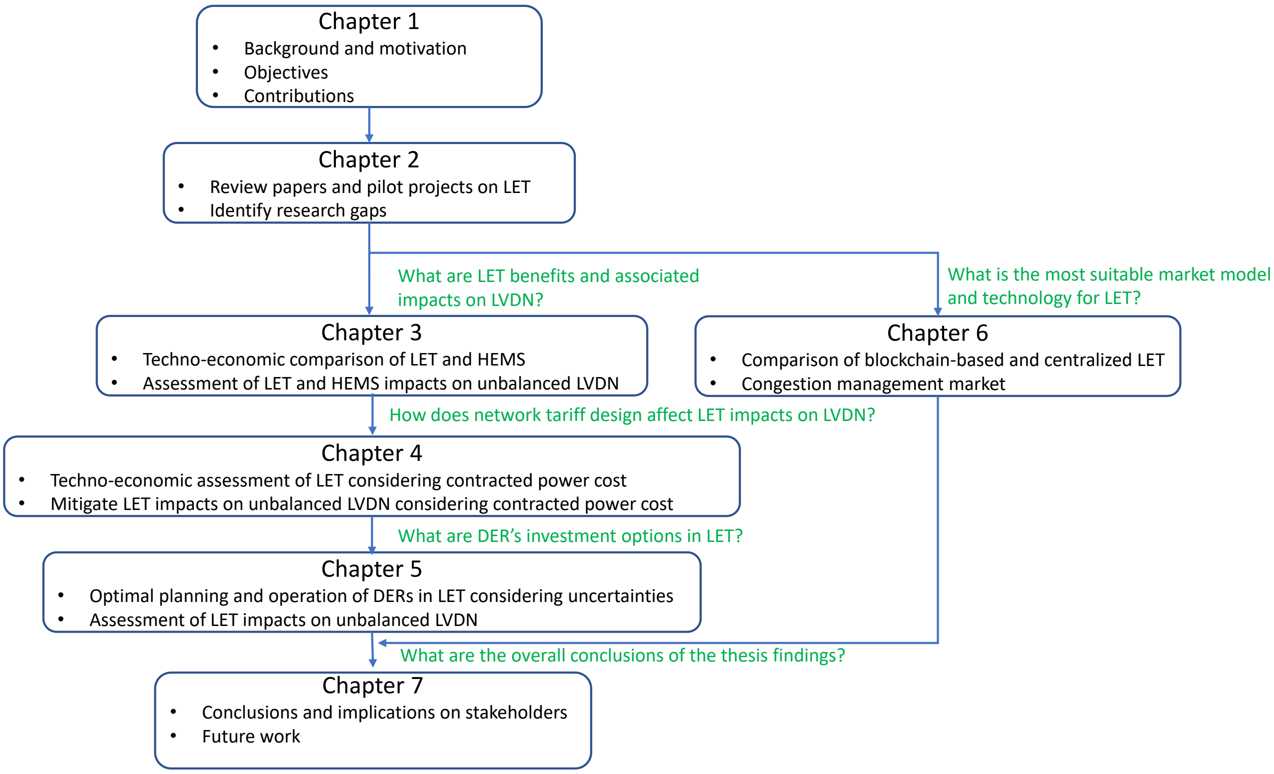

Figure 1.1. Structure of the thesis and connections between chapters.

Chapter 1 provides background about the thesis research topic and the motivations to investigate the studied research questions. Moreover, it presents the objectives and contributions of the thesis in addition to the thesis structure and a summary of every chapter.

Chapter 2 provides a critical overview of different DER management approaches and discusses vital aspects of LET, such as market designs, market clearing approaches, and grid representation. Moreover, it presents the enabling technologies for the real implementation of LET, such as distributed ledger technologies, information and communication technologies, smart meters, etc. Furthermore, a few pilot projects studying LET are presented. Finally, it identifies research gaps addressed in the thesis and others that need more study in future studies.

Chapter 3 introduces the modeling of centralized LET and the details of the Spanish case study. Moreover, it compares the performance of LET and HEMS regarding EC operation costs and interaction with the retailer. Furthermore, the study focused on assessing the impacts of LET on the voltage unbalance, transformer loading, lines loading, and voltage deviations of unbalanced LVDN considering different DERs.

Chapter 4 studies the effectiveness of considering contracted power costs in LET model in mitigating the impacts of LET on unbalanced LVDN. The proposed approach does not require the consideration of grid constraints in the LET model. It compares the techno-economic performance of LET with contracted power cost with LET without considering contracted power cost.

Chapter 5 proposes a model for optimal planning and operation of PV and BES installed in a residential EC, enabling LET between participants. The objective is to minimize the EC's total annual costs, including investment, maintenance, and operation costs (i.e., energy and contracted power costs). Uncertainties of demand, PV generation, electricity prices, and EVs are considered. Moreover, the impacts of LET on unbalanced LVDN are assessed.

Chapter 6 proposes a comparative analysis of three different market models: double auction (DA), continuous double auction (CDA), and pseudo-continuous double auction (PCDA). The DA market model is proposed as a centralized version, while the CDA and PCDA market models are realized in a distributed manner via the blockchain platform. The three market models include a congestion management market, which is solved using a centralized optimization problem that involves distribution system operator.

Chapter 7 outlines the conclusions of the thesis results, discusses the thesis findings' implications for different stakeholders, and presents future work related to the studies presented in this thesis.

Chapter 2
Literature Review

There is a rapid uptake of distributed energy resources (DERs). Many approaches are developed to efficiently manage a large number of DERs that maximize the benefits of all stakeholders while maintaining power system reliability. Local energy trading (LET) is an emerging approach that could be used to manage DERs. Many academic studies and pilot projects investigated different aspects of this promising approach. This chapter starts by comparing different DERs management approaches and their strengths and challenges. Next, it provides a critical overview of LET regarding market design, market clearing approaches, and grid representation. Then, it presents the enabling technologies required for the real implementation of LET. Finally, it presents Identify LET research gaps that require further investigation

2.1 Introduction

The electricity sector is undergoing massive changes to achieve energy security while considering environmental challenges. Renewable energy sources (RESs) are being deployed at a fast pace to meet these objectives. Figure 2.1 shows that the globally installed PV generation capacity is expected to exceed coal, natural gas, and hydropower capacity by 2027. Moreover, wind generation capacity will exceed the hydropower capacity by 2027 [23]. This high integration of intermittent and stochastic RESs could result in many challenges in the operation and control of power systems and negatively impact power system stability [24]. Therefore, many solutions were proposed to handle these challenges, such as grid-scale energy storage systems (ESSs) [25]–[27]. Besides integrating large-scale RESs power plants and ESSs, small-scale distributed energy resources (DERs) such as small RESs such as photovoltaic (PV) generation, small ESSs, heat pumps, and electric vehicles (EVs) are being deployed at the distribution level. The high penetration of DERs could result in operation issues, especially in the distribution network, unless they are optimally managed.

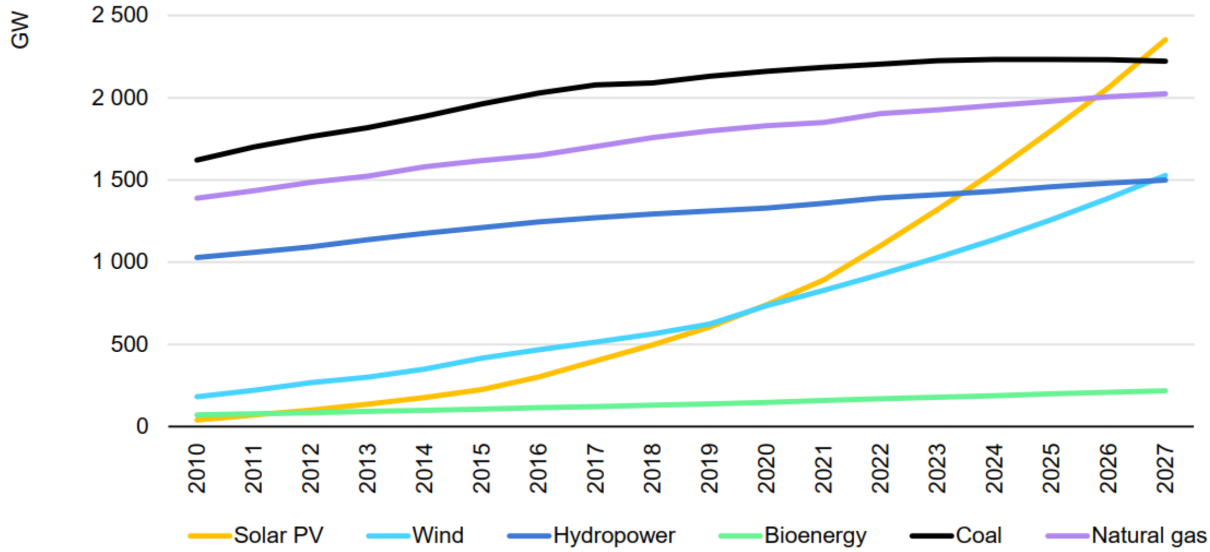

Figure 2.1. Global cumulative power capacity by technology, 2010-2027 [23].

For example, uncontrolled charging of EVs with high penetration levels is anticipated to have undesired adverse impacts on the power system [28]–[30]. Increased peak demand, overloading of power system equipment, voltage variation from permitted limits, increased phase imbalance (i.e., unbalance) owing to single-phase EV chargers, increased power system power losses, and harmonics injection might all come from uncontrolled charging of EVs. [31]. A wide number of research studies have explored these aspects since estimating the adverse effect of EV charging on grids is reliant on multiple parameters [31] and involves numerous uncertainties that should be addressed and modeled appropriately in the research to assess the effect of EV charging on power grids effectively.

On the contrary, EVs remain parked for many hours of the day [20] and remain connected to the charger for longer than the necessary recharging period. As a result, EV batteries may be utilized to deliver grid services and generate revenues for EV owners by providing power to the power system to maintain a demand-supply balance or by managing charging power and time to lower charging costs and energy bills. Numerous research studies have proven that controlled EV charging may boost power system efficiency, reduce operating costs, and reduce RES curtailment. Furthermore, EVs with controlled discharge might offer extra benefits and grid services. [32]. However, this could reduce EV batteries lifetime [33].

Because of the rapid response of EV chargers, EVs could offer short-time scale grid services such as primary frequency control and medium-time scale grid services such as secondary frequency control. Moreover, they could provide long-time scale grid services such as minimizing power loss, voltage deviations, and congestion management owing to the high kWh capacity of EV batteries. [34]. Figure 2.2 depicts a classification of the positive and negative impacts of EVs charging/discharging on electric grids. More details about the probable adverse effects of EV charging on electric grids, essentially owing to uncontrolled charging, and how such adverse effects can be minimized and even turned positive through smart charging and discharging could be found in our published article [35].

Similarly, the high penetration of small rooftop PV could cause many negative impacts on the distribution networks [36]. The high PV penetration will reduce the demand from the main grid or even cause a reverse power flow during hours of high generation and low demand. This high local PV generation could increase voltage above permitted limits (i.e., overvoltage). Moreover, since the small PV generation is a single phase, it could increase the voltage unbalance above the acceptable limits [37]. The voltage issues resulting from PV generation will require more installations of voltage regulation devices at the distribution system. Additionally, it will increase the operation frequency of voltage regulation devices, which means more maintenance costs and a reduction in expected life. To mitigate these impacts, a limit on PV generation could be imposed (i.e., generation curtailment). This solution results in economic and environmental losses because of wasting renewable generation. Many studies investigated conventional methods like grid upgrades, on-load tap changers, etc., in addition to new techniques like PV inverters VAR control, ESS, and distributed flexible AC transmission systems (FACTS) for mitigating the impacts of PV on distribution networks [37].

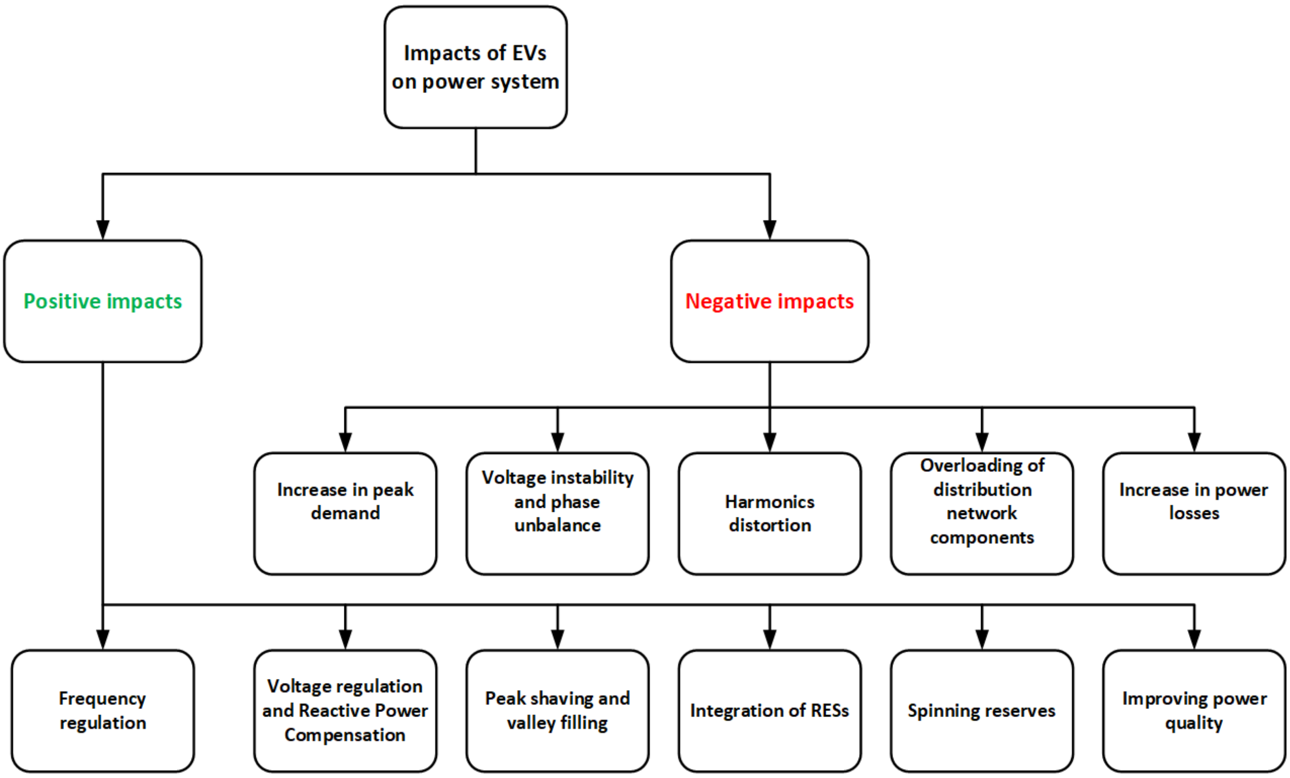

Figure 2.2. Classification of EVs charging impacts on electric power systems.

To deal with the mentioned challenges of high penetration of DERs, several management approaches are being tested for efficient DERs integration to the power system while maximizing the benefits for DERs owners and other stakeholders while maintaining power systems within acceptable operation limits [9]. Another recent approach that received significant interest in the last years for DERs integration is local energy trading (LET), which is also known as peer to peer energy trading (P2P-ET) or local electricity market (LEM). In LET, customers with energy surplus can trade energy with other customers that need energy and receive financial remuneration. This chapter reviews LET current status and future prospects.

The contributions of this chapter are the following:

- Discuss different DER management approaches and their strengths and challenges.

- Provide a critical overview of LET market design, market clearing approaches, grid representation, enabling technologies, and pilot projects.
- Identify LET research gaps addressed in this thesis and research gaps that future studies and pilot projects should address.

This chapter is organized in the following manner. An overview of different DER management approaches is given in section 2.2. Section 2.3 discusses key aspects of LET, such as market designs, market objectives, market clearing approaches, and grid representation. Section 2.4 presents the enabling technologies for the real implementation of LET, such as distributed ledger technologies, information and communication technologies (ICTs), smart meters, etc. Social aspects regarding LET are presented in section 2.5. A few pilot projects studying LET are presented in 2.6. Section 2.7 presents research gaps addressed in this thesis and research gaps that future studies and pilot projects should address.

2.2 Approaches for the management of DERs

Many approaches were proposed to efficiently manage DERs in future power systems and maximize the benefits of DER owners, system operators, and other stakeholders. The management approaches can be classified as uncoordinated approaches, coordinated approaches, and LET [9], as shown in Figure 2.3. The uncoordinated approaches consider the individual interests of end users without any coordination between them and are classified as home energy management systems (HEMS) and HEMS with operating envelopes [9]. In HEMS, each home optimizes its DERs to achieve individual objectives such as reducing electricity costs, maximizing revenues, maximizing comfort, etc [38]. HEMS is suitable for low DER penetration levels. However, this approach lacks coordination between DERs, and grid limits are not considered. As a result, grid limits may be violated as the number of DERs increases. A HEMS with operating envelopes that considers the grid constraints set by the distribution system operator (DSO) has been proposed to address this [9]. The operating envelopes will result in individual management of DERs while considering the grid constraints. The uncoordinated approaches are simple and do not require sophisticated ICT infrastructure compared to the other DER management approaches. In uncoordinated approaches, DER owners sell their excess energy to retailers and receive wholesale market prices.

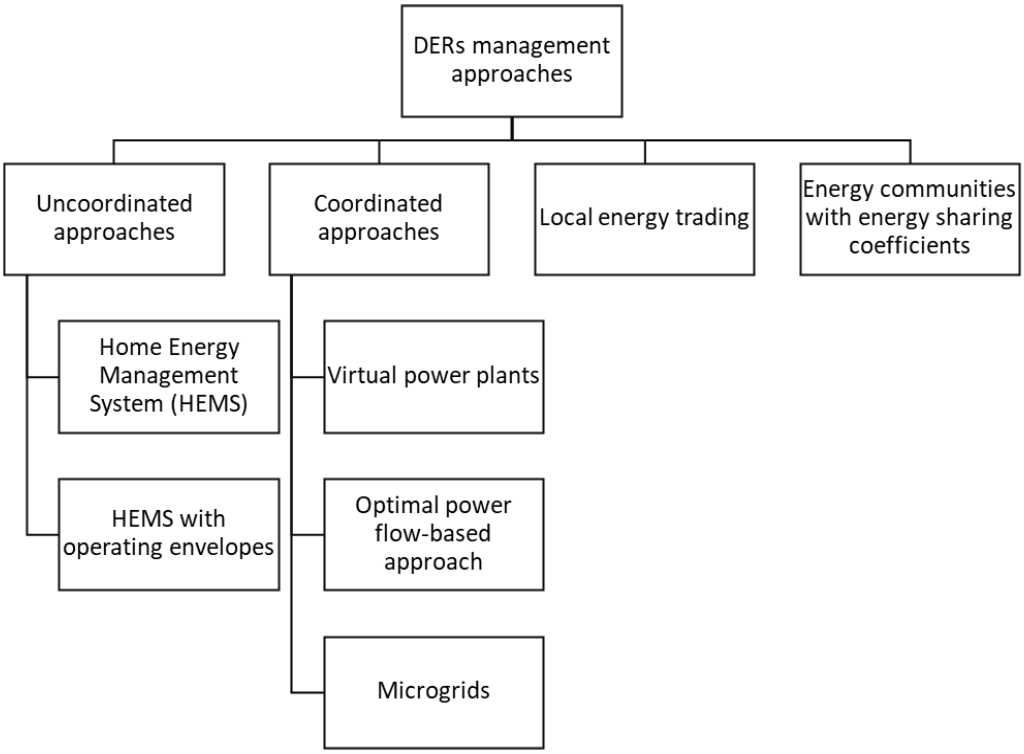

Figure 2.3. Classification of DERs management approaches.

The coordinated approaches aggregate end users' DERs to achieve a common objective for end customers. They are classified into virtual power plants (VPP) and the optimal power flow-based approach (OPF-BA). Small DERs still have limitations to participate in wholesale energy markets [39]. One viable approach is to harmonize DERs into a single power plant known as a VPP. The aggregated DERs in VPP could be scattered in a very large geographical area and do not need to be connected to the same distribution network. VPPs might engage in wholesale electricity markets and provide various grid services to transmission system operators (TSOs) or DSOs. [40], [41]. Usually, an entity called an aggregator interacts with and manages the DERs of the VPP. The aggregator is responsible for participating in different markets on behalf of the aggregated DERs. The VPP objective is to maximize revenues and reduce the cost of the aggregated DERs, and usually, VPP does not consider the grid constraints in the DERs management. The aggregator could have direct control of DERs or indirect control using price signals that make end users change their generation and consumption habits.

OPF-BA is similar to the conventional OPF used in wholesale markets in terms of objective function and consideration of grid constraints. However, OPF for DERs will manage a large number of small DERs instead of the finite number of large generators in conventional OPF. Therefore, the OPF-BA for DER management could face scalability challenges due to the large number of DERs to be managed. One of the proposed solutions is to use distributed optimization that reduces the computational complexity of the OPF optimization problem. Moreover, DERs could be integrated into a microgrid connected to the grid or operating in an islanded mode [11], [12], [42]. The coordinated approaches enable more efficient management of DERs, gain higher economic benefits for DERs, and provide more grid services than uncoordinated approaches. However, they are more complex and require sophisticated ICT infrastructure than uncoordinated approaches.

LET is another viable strategy for integrating DERs into future electricity networks. LET allows customers to sell excess energy to neighbors who need energy. Figure 2.4 demonstrates the power system's energy flow change in the past, present, and future with the adoption of LET [43]. In the past, the electricity was generated by central power plants and supplied to consumers, as seen by black arrows. Currently, the energy is supplied from central power plants, and the customers with DERs can supply the excess generation to the grid (i.e., sell extra energy to retailers), as seen by green arrows. In the future, in addition to central generation and energy supply from DERs to the grid, active electricity customers will be able to interact with each other in a P2P manner. The customers can supply energy surplus to the nearby customers with energy deficit and get financial remuneration, as seen by the blue arrows (i.e., P2P-ET).

The LET could be applied to residential homes, as shown in Figure 2.4. Moreover, the same approach could be used to trade energy between different types of buildings (i.e., residential, commercial, industrial, educational, etc.). In [16], LET between a group of industrial buildings was studied. LET decreased the electricity costs and maximized the self-generation. In addition, microgrids can communicate with one another in a P2P fashion, exchanging energy and information to form interconnected microgrids. This communication may allow better utilization of local assets than standalone microgrids and decrease customer energy bills. Furthermore, it gives greater flexibility during severe conditions like distribution network outages or congestions by altering microgrid demand and generation to address these conditions. [17]. Reference [44], for example, developed a blockchain-based method for bidirectional LET between microgrids. The method was evaluated using data from an actual distribution network containing 14 microgrids in Guizhou, China. According to the findings, the suggested method boosted RES generation utilization and microgrid revenues.

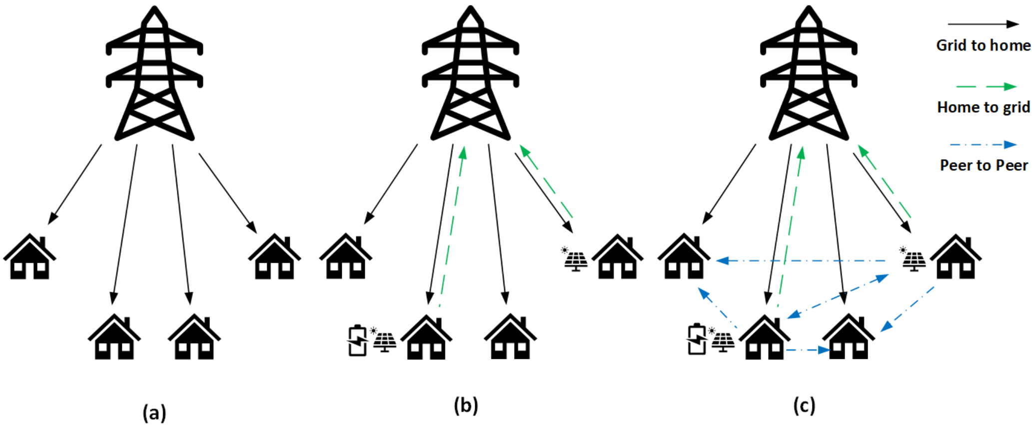

Figure 2.4. Energy flow in the power system (a) Past, (b) Present, and (c) Future (i.e., LET).

From the customers' perspective, the LET approach could be considered a sharing economy similar to Airbnb or Uber to maximize the benefits of underutilized assets. Since, in many countries, the price for selling energy to the grid by wholesale price is lower than the retail price at which they buy energy, LET could create a win-win situation for sellers and buyers in the local community, but not necessarily for the overall system. The seller can receive prices higher than the wholesale prices, and the buyers can pay prices lower than the retail prices. From power system operators' perspective, LET could be a practical approach to managing DERs since centralized management of many DERs is costly and impractical [45]. LET has the potential to promote competition among small DERs and retailers [46], achieve local supply-demand equilibrium, boost self-generation of local RES production, and minimize purchases from the retailer. Furthermore, it could increase customers' economic gains by getting better pricing in LET compared to retailer prices [47]. This might accelerate the adoption of DERs that could reduce grid infrastructure upgrades. LET faces many challenges that hinder real implementation such as regulations that do not allow free local trade between customers, and advanced ICT infrastructure that is usually not installed at the consumer level, among others. More details about LET are provided in the next sections.

Coordinated DER management approaches could provide many benefits. However, they require complex algorithms and advanced ICT infrastructure, which are currently uncommon at the distribution level [48]. On the contrary, legislation in many countries enables the use of energy-sharing coefficients in energy communities (ECs) [49], [50]. Energy sharing coefficients determine how the local RESs generation is distributed between EC members. Energy sharing coefficients could be classified into static and dynamic [48]–[50]. Static coefficients are fixed based on an agreement between community members, such as distributing the local generation equally between members. Dynamic coefficients are variable, and the local generation could be distributed based on the percentage of demand of each participant of the total members' demand at any instant. Energy sharing coefficients are used in many European countries like Austria [50], Portugal [49], Italy [50], Spain [51], [52], etc. Many studies proved the superiority of dynamic coefficients over static coefficients in decreasing members' energy costs and increasing self-generation [48]–[50]. However, dynamic coefficients are more complex than static coefficients [50]. Table 2.1. compares the discussed DER management approaches. This thesis considers several methods for dynamic energy sharing at the ditribution level that allows different dynamic rules and will provide more flexibility for participants to get to tailored and advanced arrangements.

2.3 Overview of local energy trading

Based on the reviewed research in LET, it was found that the studies focus on Policy, market participants' social behavior, power system, ICT infrastructure, trading platforms, and market design, as shown in Figure 2.5 [45]. In the following sections, a few of these aspects that are relevant to the thesis scope are explained.

Table 2.1. Comparison between DER management approaches.

	Main features	Advantages	Disadvantages
HEMS	Individual optimization of DERs without coordination (network unaware).	Simple with low cost. Suitable for low DER penetration levels. Low ICT needs. High autonomy.	No coordination of DERs. Could cause network issues. Limited remuneration schemes (i.e., only tariffs).
HEMS with operating envelopes	Individual optimization of DERs without coordination (network aware by DSO limits signals).	Low cost but more complex than HEMS. Suitable for low DER penetration levels. Low ICT needs. Medium autonomy. Lower network issues than HEMS	No coordination of DERs. Requires accurate estimation of network state. Limited remuneration schemes.
VPP	Coordinated optimization of DERs (network unaware).	Efficient coordination of Medium DER penetration. Participation in different electricity markets.	Could cause network issues due to neglecting network constraints. Advanced ICT needs.
OPF-BA	Coordinated optimization of DERs (network aware)	Efficient coordination of high DER penetration while respecting network constraints.	Computational issues. Hard to integrate into existing markets. Advanced ICT needs.
Microgrids	Coordinated optimization and control of DERs.	Efficient coordination of DERs. Could operate in grid-connected or islanded mode.	Expensive infrastructure upgrades especially if it could operate in islanded mode. Advanced ICT needs.
LET	Decentralized energy sharing between nearby participants.	Maximize the benefits of underutilized DERs. Economic benefits for buyers and sellers. Increase competition between DERs and retailers.	Fully decentralized sharing results in suboptimal coordination. Advanced ICT needs.
Energy communities with energy-sharing coefficients	A simple approach for sharing local energy between participants.	Simple approach compared to LET. Efficient coordination of medium DERs penetration. Medium ICT needs.	Lower level of coordination than LET. May not achieve the optimal solution.

2.3.1 Market design

The market design includes the centralization level, the market products, stability, interactions with other markets (wholesale and retail), and game theory approaches. From a centralization-level perspective, LET can be classified into centralized, decentralized, and distributed markets [45], [53]. The structure of these markets is presented in Figure 2.6 [45].

2.3.1.1 Centralized Markets

In centralized markets, the market participants (peers) communicate with a central entity (i.e., coordinator, aggregator, market operator, etc.) that manages the market and controls all flexible resources in the community. As shown in Figure 2.6(a), the coordinator receives measurements from different peers about their consumption, production, and different DERs status, such as batteries SoC. Based on this information, the coordinator controls the community DERs to achieve a community objective, such as maximization of social welfare or minimizing imports from retailers to decrease costs. The coordinator distributes the revenues to the peers based on their participation in LET [54]. This design is also known in the literature as community-based markets.

The advantages of centralized markets are that the coordinator knows the production and consumption of different peers, so there is less uncertainty regarding peers' patterns [55], which is not the case for decentralized and distributed markets. Moreover, since the coordinator has direct control of DERs, maximizing social welfare is ensured [56]. On the other hand, the centralized markets structure has a few disadvantages. Centralized markets require high computational power and high communication infrastructure to manage a large number of DERs. These requirements increase with the number of DERs to be managed, representing a scalability issue [57]. Moreover, privacy concerns exist since the coordinator can access peers' data [8]. Furthermore, the direct control of the coordinator of peers' DERs undermined the autonomy of peers [57]. Finally, the centralized markets coordinator is vulnerable to a single point of failure, which endangers the market security [45]. The use of distributed optimization enables overcoming these disadvantages.

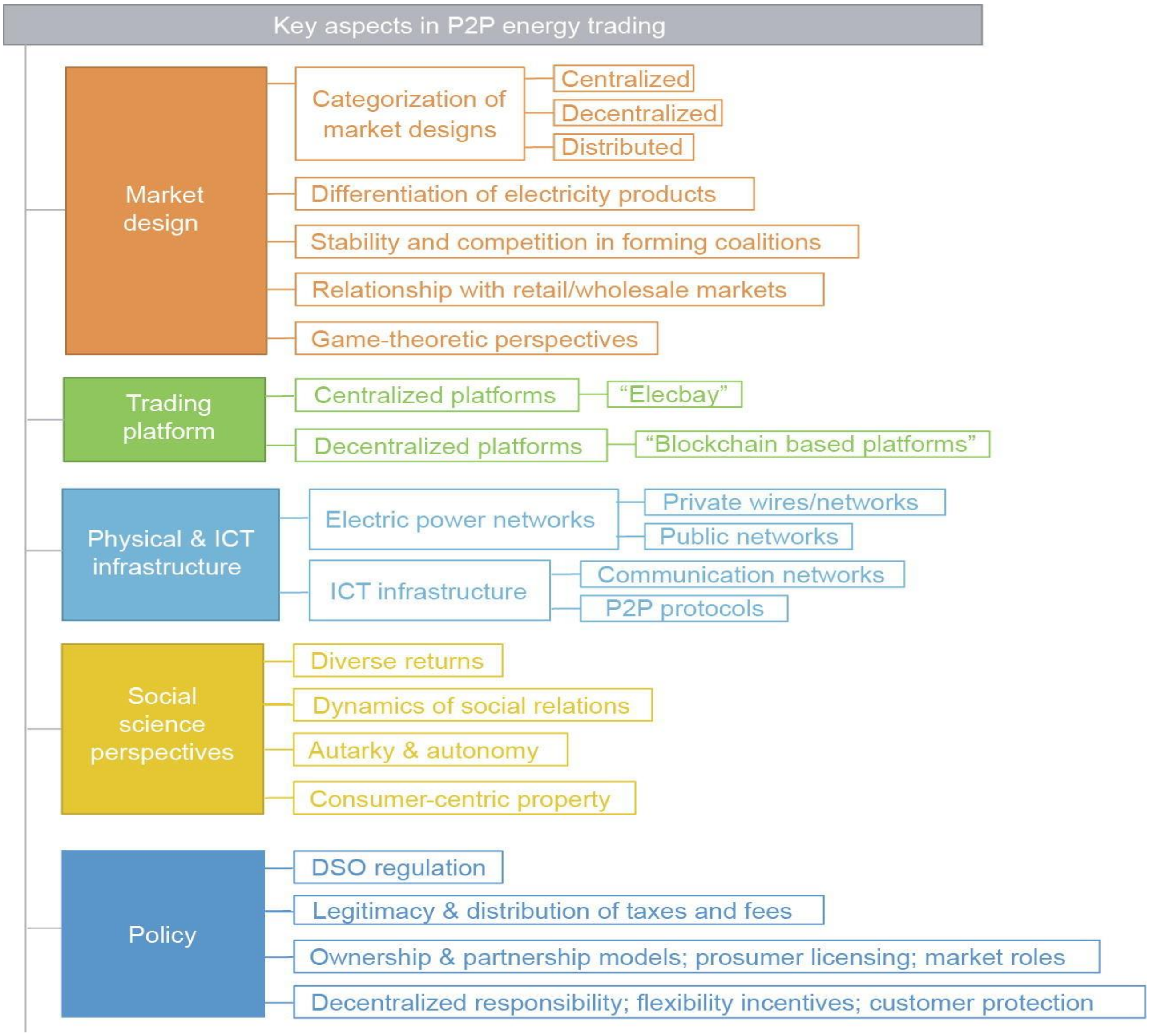

Figure 2.5. Overview of key aspects of local energy trading [45].

2.3.1.2 Decentralized Markets

No central coordinator exists in decentralized markets, and the peers interact and trade directly without an intermediary, as shown in Figure 2.6(b). The advantages of this market design are increasing the autonomy of peers since they have full control of their devices, increasing peers' data privacy since they do not need to share their data with intermediaries, and improving scalability [58], [59].

On the other hand, decentralized markets have lower efficiency and lower social welfare than centralized markets. This market design makes maintaining grid constraints and power system operation more complex because the LET is invisible to power system operators. Furthermore, peers are subject to more uncertainties in the decentralized markets [58], [59].

2.3.1.3 Distributed Markets

Distributed markets features are between centralized and decentralized markets. The coordinator in this design has no direct control over peers but influences their behavior by price signals, as shown in Figure 2.6(c). Peers have higher autonomy and privacy level than centralized markets since the coordinator does not have direct control over peers' devices and limited information is received from peers. Distributed markets have better efficiency than decentralized markets due to the presence of a coordinator [60], [61]. This market design requires accurate forecasts to enable efficient pricing and achieve the coordinador aimed behavior by peers. This market design is also known in the literature as hybrid markets. Table 2.2 compares the main features of the three market designs discussed.

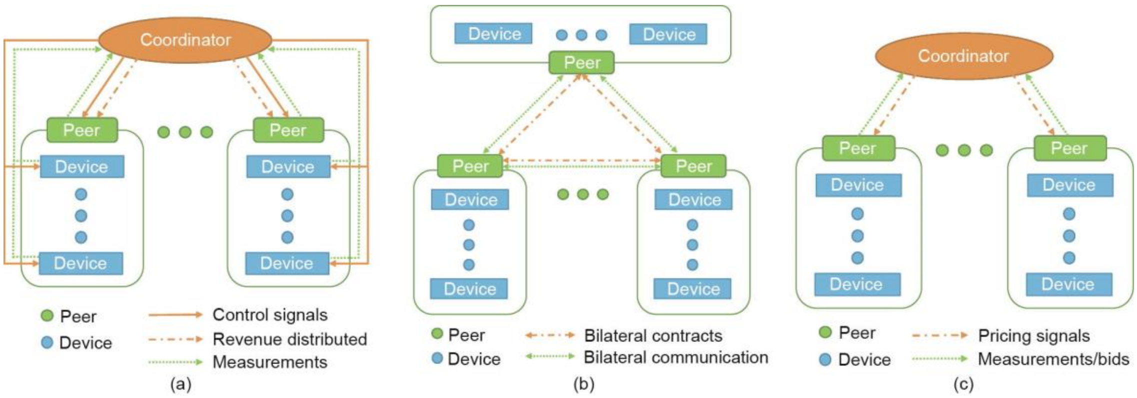

Figure 2.6. Classification of local energy trading market designs: (a) Centralized, (b) Decentralized, and (c) Distributed [45].

Table 2.2. Comparison of different market designs in LET.

	Advantages	Disadvantages
Centralized markets	High level of peers coordination.	Scalability issues for large DER numbers.
	Low uncertainty of peers' patterns.	Peers' privacy concerns.
	Ensures social welfare maximization.	Low peers autonomy.
	Easy to respect grid constraints.	Single point of failure.
		Low market transparency.
Decentralized markets	High peers autonomy and data privacy.	High uncertainty of peers' patterns.
	No intermediaries.	Does not ensure social welfare maximization.
	No single point of failure.	Difficult to maintain grid constraints.
	High market transparency.	Lower level of peers coordination.
	High scalability.	
Distributed markets	Provides a balance between centralized and decentralized markets.	Requires accurate forecasts to enable efficient pricing.
	Intermediate level of peers data privacy.	Complex pricing mechanism.
	Good scalability.	

2.3.2 Market objectives

LET usually has a main objective and may have a secondary objective. The most common main objectives are social welfare maximization, profit maximization, or cost minimization. The secondary objective could be to respect grid constraints, respect participants' preferences, increase self-generation, and decrease CO2 emissions, among others [21], [62].

2.3.3 Market clearing approaches in local energy trading

In LET, the objective optimization or market clearing was performed in various methods such as auction, optimization problem, bilateral negotiations, or game theory depending on system modeling (i.e., market rules, the behavior of market participants, market structure, and assumptions) [62] as shown in Figure 2.7. This subsection briefly introduces the main approaches for LET market clearing.

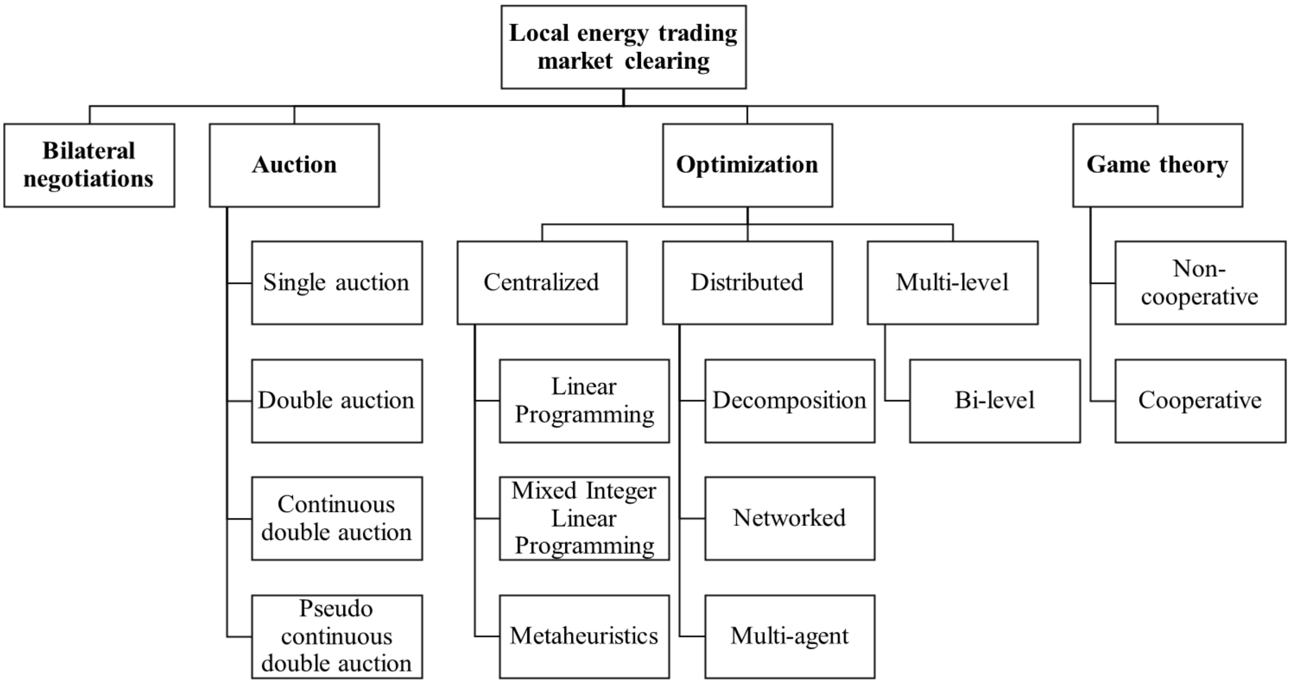

Figure 2.7. Market clearing approaches in local energy trading.

2.3.3.1 Auction

Auction is a negotiation mechanism and is usually managed by an intermediary. DLTs, such as blockchain, can substitute the intermediary and perform the auction in a decentralized manner by writing the market rules as a smart contract. The auction can be a single auction, where only one side of the market participants send bids [21]. This is common when one agent represents one side of the market. For example, one buyer receives asks bids from several sellers. There is also a double auction, where buyers send their bids and sellers send their asks bids [62]. Auction mechanisms were widely used in LET literature. In auction-based LET, each peer willing to participate in the market submits his bid to buy in case of energy deficit or asks to sell in case of energy surplus to the aggregator or auctioneer that runs the market. Each buyer's bid contains the energy quantity and the maximum price he is willing to pay. Each seller's ask contains the energy quantity and the minimum price he is willing to get.

Two approaches were used in previous studies for bidding representation: strategic and non-strategic bidding. Strategic bidding accurately represents market participants' competitive behavior, but it requires the use of game theory. Few studies use metaheuristic optimization algorithms such as the vortex search algorithm, ant colony optimization, and differential evolution variant for optimal bidding in LET [63]. In non-strategic bidding, the market participants randomly bid. Therefore, it does not accurately represent market participants' competitive behavior [64], [65].

Figure 2.8 shows the matching between buying bids and selling asks in LET for a double auction where the market is cleared in a definite time. The buyers are ordered in descending order (i.e., demand curve) based on the bid price, and the sellers in ascending order (i.e., supply curve) based on the ask price. The intersection between the demand and supply curves represents the market equilibrium point. The market outputs are the market clearing quantity and market clearing price. The settlement in this case, is based on a uniform price where the price is the same for all energy traded in LET at this period (i.e., 15 min., 30 min., or 1 hour). The objective of the auction is social welfare maximization. Social welfare is the area between the demand curve and the supply curve. Another method for pricing the energy in LET (besides uniform pricing) is pay as bid. In this method, each local energy trade has a different price. Many other auction methods, such as continuous double auction and pseudo continuous double auction, were tested by previous studies for LET.

2.3.3.2 Optimization

The LET was modeled as an optimization problem in many previous studies. The optimization method can be centralized, distributed, and multi-level. A central intermediary solves the market clearing optimization problem using the centralized method. A linear model was proposed in [55] for LET in a local residential community in England, UK, where a central entity manages the LET. Linear programming was used to solve the optimization problem. Another study [56] used mixed integer linear programming (MILP) to solve the LET optimization problem for a community of 500 houses equipped with PV and batteries. The objective is to minimize the energy cost. Few studies used metaheuristic algorithms for LET [63], [66].

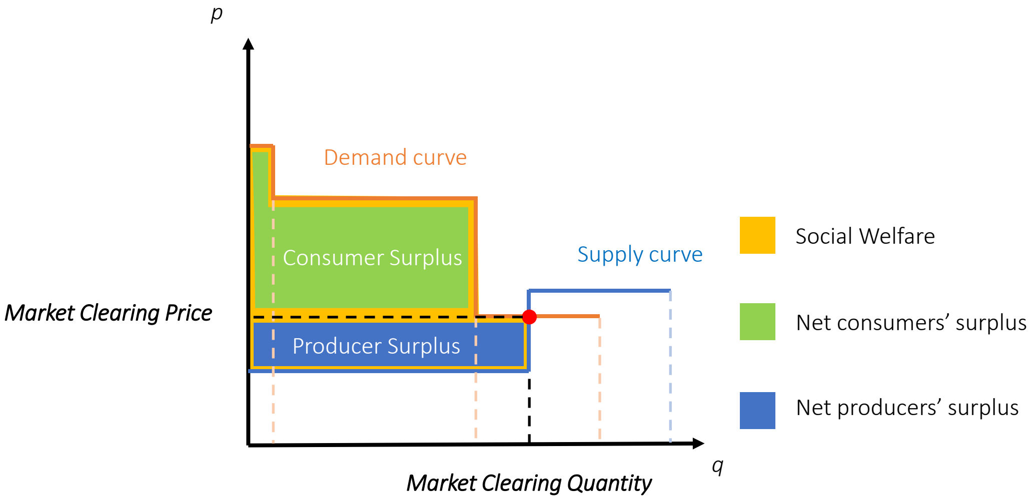

Figure 2.8. Market clearing for double auction in local energy trading.

There are scalability and privacy issues in the optimal management of a large number of DERs in a centralized structure. Therefore, many distributed optimization algorithms were proposed in previous studies for LET, and they can be classified as decomposition and networked optimization [62]. In the decomposition method, the large complex optimization problem is divided (i.e., decomposed) into many easier subproblems, and each subproblem is separately solved. A coordinator is present in this method to ensure reaching global optimum. Its main types are primal decomposition and dual decomposition. The coordinator is unnecessary in the networked optimization method, and each participant coordinates with immediate neighbors. In multi-level optimization, the problem is divided into several sections. For example, in bi-level optimization, one optimization problem is constrained by another optimization problem. The bi-level model enables solving the problem without an iterative process as in the Stackelberg game.

2.3.3.3 Game theory

Game theory is a tool to analyze the decision-making of rational market participants where each participant's strategic action affects and is affected by the other participants' actions in a competitive situation. Game theory was applied in many LET studies to capture the participants conflicting interests [67], [68]. Game theory can be categorized into non-cooperative games and cooperative games. Non-cooperative games analyze the decision-making of rational market participants with conflicting interests without interaction (i.e., cooperation) between participants. On the other hand, cooperative games focus on the decision-making of the rational market participants collectively. A cooperative game is also known as a coalition game [15].

2.3.4 Grid representation

After the negotiation in LET through different methods such as auction, optimization, or game theory, a specific amount of energy based on the market outcomes will be delivered from the sellers to the buyers through the distribution network. The grid constraints should not be violated during the local energy trade between peers. This free local trade at the distribution network is challenging because of the different nature of distribution networks compared to transmission networks at which the energy trading of large power plants conventionally occurs. The distribution networks have a radial topology, limited monitoring devices, limited control devices, simple protection schemes, etc. Therefore, LET should ensure no constraint violation to be feasible for practical implementation.

Previous research on LET focused on the market design and enabling technologies challenges compared to the challenges associated with the physical network at which the energy trading will occur. There are mainly two methods to consider the distribution networks in LET. The first method incorporates the grid constraints in the market model, using sensitivity coefficients (i.e., loss sensitivity factors, voltage sensitivity coefficients, and power transfer distribution factors) or power flow equations (i.e., AC or DC). However, these methods have limitations, such as being approximate in the case of sensitivity coefficients and DC power flow equations or requiring high computational power in the case of AC power flow equations due to the non-convexity of the optimization problem. The second method assesses the impacts of LET on distribution networks after market clearing. These methods try to avoid any possible issues that LET could cause on distribution networks.

Considering the early stage of the development of LET and the lack of knowledge of its possible effects on power system operation, few studies assessed the impacts of LET on distribution networks if the grid constraints were not considered in the market model. The following points introduce the challenges associated with LET on the distribution networks operation that were studied in previous research.

2.3.4.1 Voltage limit violation

Due to their radial architecture and lack of voltage control devices, LVDNs are more vulnerable to voltage fluctuations than the rest of the power system. Therefore, researchers paid close attention to the effects of the high penetration of DERs on voltage variations at the LVDNs. Particularly in rural locations with lengthy feeders, the end nodes of the feeders typically have more voltage variation than other nodes close to the transformer. When the local demand is high, the LVDNs may experience a high voltage drop, and when the local generation is high, they may experience a voltage rise. Recent studies have examined the impact of LET on voltage deviations at LVDN. For example, [47] examined the effect of LET on voltage deviation on LVDN. The study concluded that voltage surpassed the lower limits for several nodes in the LET (PV+ESS) scenario during the winter. Furthermore, because of excessive PV generation, the voltage surpassed the upper limits (i.e., overvoltage) for several nodes in the summer LET (PV) scenario. This voltage increase is caused by surplus PV generation and has nothing to do with LET. With the consideration of ESS, the overvoltage problem was resolved.

2.3.4.2 Phase unbalance

Although small consumers at the low voltage distribution networks are single-phase loads, roughly all LET studies model them as three-phase loads for the sake of simplicity. Hence, the phase unbalance was disregarded. Previous studies paid little attention to the unbalanced nature of DERs in LET and only looked at a small subset of operational possibilities in the LVDN. Based on this, it is crucial to evaluate the effects of LET interactions among customers in the energy community on phase unbalance [69]. The effect of LET on the phase imbalance of the LVDN was examined in [46] for just one day and one operational scenario. The study solely took into account the existence of PV and EVs that were in the charging mode; V2G was not taken into account. Furthermore, ESS was not taken into account in this study. In comparison to the reference scenario with no LET, the study's findings revealed a small change in phase unbalance for the low degree of LET.

2.3.4.3 Congestion problems

The loading of different power system components should be kept below the maximum limits. Integrating DERs such as EVs without proper management could increase peak demand and consequently create grid congestion problems. Therefore, it is important to understand the possible impacts of LET on the loading of different components (i.e., transformers, lines, regulation devices, etc.) in all levels of the power system, especially the distribution level. Ref [70] studied the impacts of LET on LVDN line loading, voltage deviation, and losses in the presence of PV, EV, and combined heat and power (CHP). EVs are operating in the charging mode. In contrast to many studies, LET resulted in the elimination of constraint violations of LVDN. The reason is CHP's participation in supplying local loads through LET since CHP receives a price higher than FIT when the generated energy is sold locally. Without LET, the operation cost of CHP is higher than FIT. Therefore, it does not produce any energy.

2.3.4.4 Power losses

When electricity flows in the power system, a considerable percentage of the energy is lost on its way to consumers due to the resistance of different grid components (i.e., lines, transformers, etc.). The power losses change based on the behavior of DERs. Therefore, a few articles studied the effect of LET on power losses in distribution networks. Ref. [71] investigated the effect of LET on power losses in large-scale LVDN. Compared to the scenario with no LET, LET generated a minimal increase in losses for the entire day (less than 0.5%). Because only 25% of customers have PV, and less than 12.5% of customers have ESS or controlled loads, this study explored a limited LET. A recent study looked at the effect of LET on LVDN losses [72]. In comparison to other situations, LET caused larger energy losses in winter with the presence of PV and ESS.

2.4 Enabling technologies for local energy trading

In LET, consumers will have a more active role, and many technologies need to be adopted to achieve this. The following subsections introduce the main enabling technologies required for the real implementation of LET, such as DERs, DLTs, ICT, smart meters, and user interface. Figure 2.9 shows a schematic diagram of the LET main components [73].

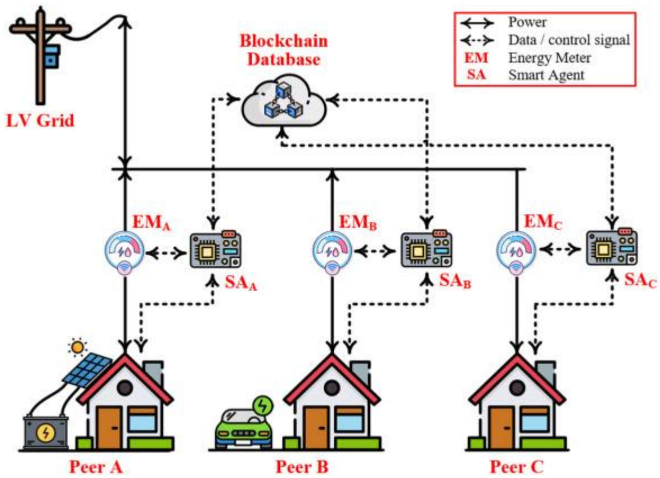

Figure 2.9. Schematic diagram of local energy trading components [73].

2.4.1 Assets of market participants

Many types of DERs are being deployed at the distribution level. The DERs can be PV, wind generator (WG), ESS, EV, controllable load, etc. Other assets are present in LET, such as non-controllable loads, and they are usually represented by demand profiles. PV represents the majority of small generation due to the continuous reduction in its capital cost and low maintenance cost due to its static nature. Moreover, PV can be easily installed on the rooftop or in the yard of a residential home or building. However, it only generates energy during day hours. Therefore, the PV generation peak is usually different from the demand peak, which is usually at night. Therefore, ESS could be used to store excess PV generation to supply the load at hours with high electricity prices and increase the self-generation of generated energy from PV.

EV numbers are increasing worldwide due to their environmental advantages over gasoline vehicles. EVs can behave as a controllable load where their charging power can be controlled or stopped for a definite time. Moreover, it can act as ESS and control the charging and discharging power [35], [74], [75]. Controllable loads include thermal loads whose power can be controlled, such as water heaters, or shiftable loads whose start could be delayed but, once started, cannot be stopped, such as washing machines. Small penetration levels of DERs will not cause any issues in power system operation and might not require coordination. However, with the increase in DERs penetration level, coordination of DERs is a must to maximize the economic benefits of DERs and avoid issues in power system operation.

2.4.2 Distributed ledger technologies and blockchain

Blockchain is a P2P system that enables distributed computation, data sharing, and storage of data among network users. A blockchain is a network of blocks that store transactions or data. Blocks are linked via cryptography to provide attack opposition and security. Blockchain is a decentralized database, also known as a distributed ledger, that is spread on nodes (i.e., computers) that validate transactions. All validated transactions are saved on each node. This avoids the single point of failure problem that can occur in central databases due to cyber-attacks or technological issues. [76]. Blockchain is unchangeable, and it is significantly hard to modify or delete a block after it has been produced and inserted into the chain [76]. Moreover, there are no or few middlemen engaged, allowing for quick transactions with no or little transaction costs. Because participants can observe every modification, transparency is a significant merit of blockchain. Blockchain is open, and anybody (in the case of public blockchain) can contribute.

As illustrated in Figure 2.10, each block is made up of a block header and a block body. The block header contains the prior block hash, which connects the present block to the former one, as well as the current block hash and a timestamp indicating the moment of block generation. The block body includes saved data or transactions. Each transaction includes the sender's and receiver's public keys, the amount of money to be sent, the time, and so on [77].

Blockchain's main application was cryptocurrencies (i.e., Bitcoin). After that, Ethereum added innovative features of smart contracts and decentralized applications (DApps). The smart contract is similar to traditional contracts, but it is digital (i.e., code) and stored in blockchain (i.e., distributed ledger). DApps are decentralized applications or blockchain-enabled websites that run on top of the blockchain. Smart contact and DApps can be written or programmed in Ethereum using solidity programming language and can run on an Ethereum virtual machine (EVM). They are written in other languages on different blockchain platforms. Smart contacts are decentralized, which means no single entity controls them

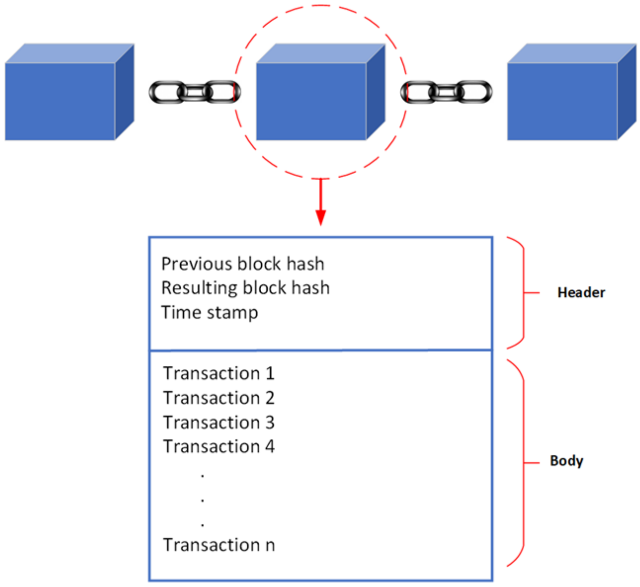

Figure 2.10. Blockchain general structure.

DLTs and blockchain have been advertised as potential technologies that might play an important role in smart grids. Many decision-makers in the electrical industry, utilities, and researchers think that blockchain and its desirable qualities can aid in the transition to the smart grid and accomplish digitization, democratization, decentralization, and decarbonization of electricity systems. Blockchain can also lower transaction fees, enhance processes, improve data security, and improve transparency. Based on the scope of activity, blockchain applications in the electricity industry may be categorized into nine sectors, as illustrated in Figure 2.11. More information about blockchain applications in the electricity industry may be found in our previously published publications [8]. The next paragraphs will concentrate on the use of blockchain in LET. Among other blockchain applications in the electricity industry, LET has gained the most interest.

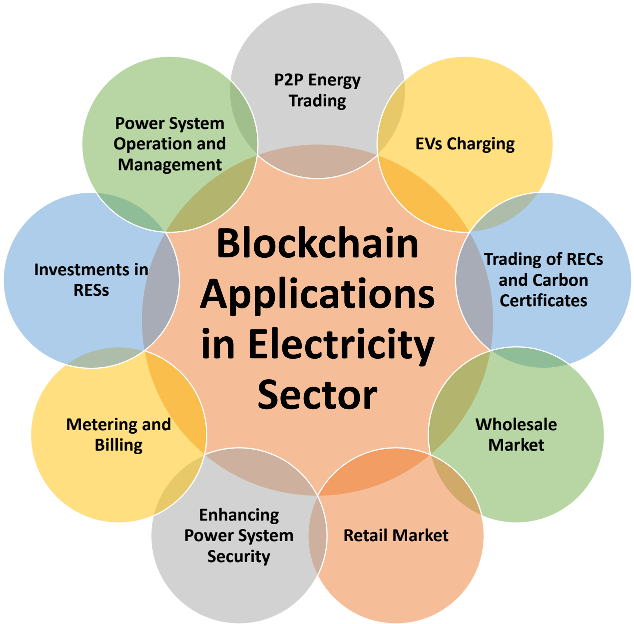

Figure 2.11. Classification of blockchain applications in the electricity sector.

Several projects and studies investigated the viability of the LET using various technologies [78], [79]. Blockchain technology has been introduced as an attractive technology that could be utilized to set up LET to match demand and supply bids, trade energy among neighbors, and conduct money transactions quickly, securely, and at low cost. Blockchain can track all parties' energy consumption and production, as well as the corresponding money everyone should pay or receive. Based on the architecture, it can perform transactions automatically without the involvement of intermediaries such as retailers or banks.

Reference [55] developed LET in a small community with PV using a private blockchain, enabling customers to exchange energy without an intermediary. This study utilized the Ethereum platform to govern energy trade, record transactions, and conduct payments. The main grid supplies the deficit when the community PV production is inadequate to serve all users. Furthermore, the study performed a security analysis and demonstrated system protection against threats. Another research evaluated LET using the IOTA DLT platform to solve the shortcomings of blockchain technology, such as the necessity for miners and scalability [80]. The simulation findings demonstrated the feasibility of IOTA for LET, and they advised that the platform should be implemented practically in the future to prove its viability.

A central entity, such as an aggregator or auctioneer, could also perform all these functions that blockchain performs in a decentralized way. Each method has strengths and weaknesses, and the most suitable method for LET is still being researched.

2.4.3 Information and communication technology (ICT) infrastructure

LET requires many information exchanges during bidding, market clearing, energy delivery, and financial settlements. In decentralized markets, there is a lot of bilateral communication between peers. In centralized and distributed markets, there is a lot of communication between the coordinator and peers. ICT infrastructure is required to communicate between stakeholders in LET [45]. ICT is a crucial component in LET. Therefore, ICT infrastructure for LET should have high reliability, enough bandwidth, high security, and low latency.

2.4.4 Smart meter

Each participant of the LET must be equipped with a smart meter that can provide the following function. (a) record demand, (b) record PV or WG production, (c) record energy storage SoC, (d) estimate the home demand deficit or generation surplus, (e) record the amount of energy traded in LET and its price, (f) record the amount of energy exchanged with retailer and its price [81]. The smart meter readings are used for financial settlement between peers in LET and can be used by the retailer for energy cost or revenue determination [15]. A smart agent can perform the previous functions and more, as discussed in [73] and as shown in Figure 2.9 [73]. The smart agent is a microcomputer that enables the peer to perform computational tasks like optimization or forecasting of demand and generation.

2.4.5 User interface

LET enables more freedom for customers. They can specify their energy requirements, offered prices, preferences, etc. Moreover, they will need to monitor their assets' condition, demand, generation, retailer prices, demand forecast, and generation forecast, among others. Therefore, a friendly user interface like a mobile app is needed to enable the end user to perform these functions easily and efficiently. Many pilot projects and startups of LET developed simple apps for users to perform the previous functions and have a more active role in maximizing their benefits. In Quartierstrom pilot project [18], a mobile app was developed so that participants may track their own and the community's consumption and production. They may also determine the price for which they intend to purchase or sell energy.

2.5 Social aspects

In LET, producers and consumers interact to reach an agreement on LET at an accepted price for all. Therefore, the success of the LET concept in reality depends on the willingness of end users to participate in the local trade of energy and adoption of these systems. One of the most significant risks to the LET concept is an insufficient level of end-user participation [14]. However, limited research focused on the behavior of end users and their preferences in the LET context, and the previous research primarily focused on the economic and technical aspects of LET.

In [82], 830 participants from four European countries were surveyed, and 79% of them favored participating in LET. Another article studied German house owners' willingness to participate in LET in a simulated environment [83]. They found that 77% of house owners are willing to participate. The end customers' behavior in LET was studied in the real world in a pilot project [84]. The LET happens in EC in Switzerland, containing two commercial entities and 35 houses. The study investigated the interaction of participants with the LET app, which displays each participant's production and consumption data and where they can set price limits for LET. Moreover, the study interviewed the participants to investigate if they check the data provided in the app, how they understand it, and how they act based on their understanding. The study showed a high engagement of participants with the LET app during the study duration, which lasted for 4.5 months. Moreover, 30% of participants set their prices for LET, 35% choose that the prices are set automatically, and 35% are non-respondents or non-users. Further research is needed to consider different socio-economic contexts, larger communities, and different types of participants (i.e., residential, industrial, commercial, or buildings with different purposes).

2.6 Pilot projects

Besides the academic studies investigating different aspects of LET, many pilot projects and startups developed LET solutions for the integration of DERs. This section introduces a few of these pilot projects and startups. In April 2016, the LO3 Energy firm in New York, USA, launched the first blockchain-based LET pilot project for LET of energy among customers (i.e., Brooklyn Microgrid). In this project, the prosumers are enabled to sell their excess PV energy to adjacent community consumers. Customers may take part in the local market after installing smart meters that track and store electricity, and they can sell surplus production locally or to the grid via the feed-in tariff. Customers may cover their demand from the main grid, RESs anywhere, or local PV production using the Brooklyn microgrid app. They may also bid on the price they are ready to pay for local PV production. The Brooklyn microgrid gives customers control over the origin of their electricity. Furthermore, it provides more possibilities to customers while improving the local economy. [85]. It must be noted that this application has infrastructure and scalability concerns. In the Brooklyn microgrid, for example, all participants in energy trading required a computer to function as a blockchain node. LO3 worked on several more projects in the United States and other countries. [86]. LO3 and eMotorWerks worked on a project in 2018 that links the eMotorWerks EV charging technology and the LO3 platform to facilitate the trading of local RESs production and EVs. The LO3 platform handles LET transactions and pricing signals, while the eMotorWerks platform handles matching local production demand of houses and EVs and managing energy flow. [87]. The Brooklyn microgrid initiative inspired several projects and businesses that leverage blockchain for LET.

In January 2019, a trial initiative known as Quartierstrom 1.0 was launched in the Swiss town of Walenstadt to create a blockchain-based LET [18]. The project's goals are to evaluate the technological feasibility, user behavior, and market design of LET. They used the private blockchain Tendermint [88], and a smartphone app that allows users to monitor their own and the community's consumption and generation. They can also establish the rate at which they are prepared to purchase or sell energy. Each participant's smart meter automatically submits a bid every 15 minutes, and the market is cleared based on a double auction method.

The study lasted a year, and the findings indicated that the community's self-generation and self-sufficiency nearly doubled using the blockchain-based local market. Furthermore, it was shown that participants are usually against charging higher costs for energy generated locally than grid rates. [18], [84]. The private blockchain utilized requires very little computational power. The blockchain program established its reliability, but it was plagued by hardware issues. Furthermore, they required a smart meter with an application processor that was not present in market smart meters. As a result, they employed self-created modules on the Raspberry Pi. Furthermore, scalability concerns plagued the project. They discovered that the system is capable of supporting up to 600 users while staying stable [89]. Recently, Quartierstrom 2.0 was initiated [90], and it was announced that the number of participants in the local market would increase to 63 and that the blockchain-based platform would be replaced with a centralized platform. The new platform will enable market participants to perform bilateral trading contracts.

Power Ledger, an Australian enterprise, created a blockchain-based platform that allows several applications and services in the electricity sector. The platform's primary application is LET. The platform enables neighbors to trade locally generated or stored energy in a trustless environment while getting money in real-time. In their initial experiment in Australia, they demonstrated significant potential profits for energy generators by selling their energy at higher rates than the feed-in tariff and lowering consumer bills by purchasing electricity at lower rates than retailer charges. Many additional initiatives outside of Australia have joined with Power Ledger. They collaborated with Vector Energy to create a LET platform for the Auckland distribution system in New Zealand. Power Ledger also has initiatives in Thailand, India, Japan, and USA [91].

Grid Singularity created an open-source blockchain technology for LET in a local community. This P2P local market has the potential to minimize congestion at distribution networks, boost self-sufficiency, and lower the community's energy bill. [92]. Prosume blockchain-based network facilitates peer-to-peer trade of energy with the cooperation of an existing provider or aggregator. The neighbors might earn money by trading their generated or stored energy. [93]. SunContract, a Slovenian enterprise, created a blockchain-based LET market platform. The platform maximizes consumer advantage by linking suppliers and customers in an open marketplace without mediators. The platform enables small local producers to sell excess production by trading on the market, boosting their profit. Customers may pick their energy source and choose from various rates and the opportunity to check daily electricity use [94].

Spectral has collaborated with Dutch DSO Alliander to create a blockchain-based LET platform. The platform is named Jouliette, and it contains a token to support local energy trade and P2P financial transactions among members' wallets [95]. ToBlockChain, a Dutch enterprise, created a blockchain-based network for LET. The platform is called PowerToShare and was tested at the green village at TU Delft. [96]. Many other firms have established or are developing blockchain-based LET projects. Most of the discussed projects in this section used blockchain to implement LET. Blockchain may be appropriate for this application since it grants numerous important advantages, such as low operation costs by automating processes while eliminating or decreasing middlemen fees for transactions, preserving end-users data privacy, cyber attacks immunity, transparency, decentralization, etc. Since the legislation defining this sort of market remains unavailable, accepting the LET idea will likely require time before we see it deployed in electricity networks on a widespread basis. Furthermore, unique smart metering (i.e., hardware) with higher-level characteristics beyond currently operational smart meters and distributed ICT are required for effective LET deployment, which entails significant capital and operational expenses. Moreover, there is a need for more studies on scalability issues, even when using private blockchains in this application. In addition, even after the usage of private blockchains in this application, additional research into scalability difficulties is required. Also, grid operational limits restrict the feasibility of free trade of energy between buyers and sellers. Furthermore, the technology must demonstrate that the advantages it brings to LET exceed the development costs. Due to these challenges, blockchain-based LET is currently in its early stages and has not progressed to large-scale deployments [8].

Besides LET, end customers can provide flexibility services [97]. There are many platforms for local flexibility markets (LFM) [98]. For instance, Piclo Flex, a LFM platform, enables DSOs to procure flexibility services from various market participants. Flexibility services involve adjusting the supply or demand of electricity in response to signals, which helps balance the grid and manage congestion [99]. This is crucial as the energy system integrates more renewable energy sources, which are often intermittent and decentralized. Moreover, The Iremel flexibility market within OMIE (Iberian Electricity Market Operator) offers various grid services by managing DERs and controllable loads [100]. These services help balance supply and demand, manage congestion, and ensure grid reliability. Flexibility services are procured through a competitive auction system. Providers submit bids to offer their services at specific prices, and the market operator selects the most cost-effective bids to meet the grid's needs.

Table 2.3 summarises the key facts regarding the initiatives and startups addressed in this section. [101]–[103]. It can be observed that startups are putting in the most effort in establishing LET platforms, while incumbents (such as utilities, system operators, and so on) are attempting to keep up with these rapid advances through pilot projects and collaborations with startups. [104].

2.7 Research gaps

LET is still at an early stage of research, and many open questions need to be addressed before reaching real implementation at a large scale. This section presents a few research gaps that are addressed in this thesis and a few that need to be addressed in future studies.

2.7.1 Research gaps addressed in the thesis

2.7.1.1 Grid representation and Impacts on the grid

High integration of DERs could affect the operation of all levels of power systems due to uncertainties associated with many of these DERs, like small RESs, EVs, etc., and the bidirectional power flow that results from excess supply of DERs. Considering that the LET happens on the low voltage/medium voltage distribution networks. There is a higher need to assess the possible impacts of LET on the operation of distribution networks. Moreover, the impacts of LET on generation and transmission levels operation need to be assessed. Many studies have proposed different methods to consider grid constraints in market designs to avoid any issues on the grid due to LET. However, in [21], they found that only 20% of the reviewed papers comprehensively represent grid constraints in the market designs. Therefore, more research is needed to develop efficient methods with low computational complexity to incorporate the grid constraints in the market design.

Table 2.3. Summary of projects and startups that have developed local energy trading applications.

#	Project or company	Country	Year Founded	Type	Application	Consensus mechanism	Platform
1	Grid Singularity	Austria	2016	Startup	LET	PoAu	EWC
2	LO3 Energy (Brooklyn Microgrid)	US	2016	Startup	LET	PBFT	Tendermint
3	LO3&eMotorWerks	US	2018	Pilot by companies	LET	PBFT	Tendermint
4	Power Ledger	Australia	2016	Startup	LET, Grid operation, Trading of RECs and carbon credits	PoAu	Ethereum
5	Prosume	Switzerland	2016	Startup	LET, Grid operation, Investment in RESs, Metering and billing	NA	NA
6	Quertierstrom 1.0	Switzerland	Jan 2019 – Jan 2020	Pilot project	LET	PBFT	Tendermint
7	Quertierstrom 2.0	Switzerland	NA	Pilot project	LET	-	No blockchain (centralized)
8	Restart Energy	Romania	2015	Company	LET, Retail Markets	NA	NA
9	Spectral (Jouliette)	Netherlands	2017	Startup	LET	PoW	MultiChain
10	SunContract	Slovenia	2016	Startup	LET	NA	NA
11	ToBlockChain	Netherlands	2016	Startup	LET	NA	NA
12	Piclo Flex	UK	2019	Company	LFM	-	-
13	IREMEL	Spain	2019	Company	LFM	-	-

In addition, the studies that assessed the impacts of LET on distribution networks are deterministic. Therefore, future studies must consider uncertainties of demand, RESs, EVs, etc. Furthermore, future research must evaluate the effects of LET on different distribution networks due to the varying characteristics of distribution networks (i.e., topology, kind of loads, loading condition, installed DERs, and so on). Chapter 3 addresses this research gap by assessing the impacts of LET on distribution networks. Moreover, chapter 4 studies how power-based network charges (i.e., contracted power costs) could decrease the impacts of LET on distribution networks.

2.7.1.2 Optimal size of DERs for local energy trading

Most LET studies concentrated on operating costs, with little attention paid to investment costs. For example, there is concern regarding BES's financial viability because of its high initial cost and short lifetime. Few papers investigated the optimal planning of DERs while considering LET, as discussed in chapter 5 in detail. Therefore, future research must focus on the optimal planning of energy communities DERs and optimize their operation to maximize the benefits for all stakeholders. Chapter 5 studies the optimal planning of PV and BES in a Spanish energy community while considering LET between participants.

2.7.1.3 Comparison of technologies

Blockchain and DLTs have been presented as a promising technology for LET. Many studies and pilot projects developing blockchain for LET focused on demonstrating the functionality of blockchain for various LET and enhancing blockchain effectiveness in this particular application. Nevertheless, little emphasis was placed on comparing centralized versus blockchain-based LET. [8]. For instance, regarding computation time, the authors of [105] evaluated centralized LET against blockchain-based LET. The study concluded that blockchain-based LET required much more computational time than centralized LEM. They did not, however, investigate more indicators that may provide a more quantitative evaluation of the situation. Nonetheless, the researchers present a qualitative assessment of a blockchain-based LET. The results of the study highlights that under some situations, a centralized structure is more easily scalable and cheaper for LET participants. As a result, there still exists a necessity for a full comparison of centralized and blockchain-based LET that takes into account aspects other than computation time which is addressed in chapter 6.

2.7.2 Research gaps not addressed in the thesis

2.7.2.1 Size, scalability, and replicability of the market

LET is proposed as a management approach for the large number of participants with DER installations. However, most of the previous studies considered a small number of participants. Ref [21] analyzed 117 journal papers on LET and concluded that most studies considered small LET with up to 100 participants, as shown in Figure 2.12. Moreover, studies with more than 500 participants considered a short study duration of up to one day. The reviewed studies' main focus was on evaluating the performance of their proposed market mechanisms. This provides limited insights into scalability and a real implementation of the market. Therefore, more research is needed for LET with a large number of participants and a longer study duration. The replicability concept in LET refers to replicating the market design in different locations and contexts, considering different grid structures, assets, participants, and regulations [21]. Future research should address the replicability of the proposed market designs.

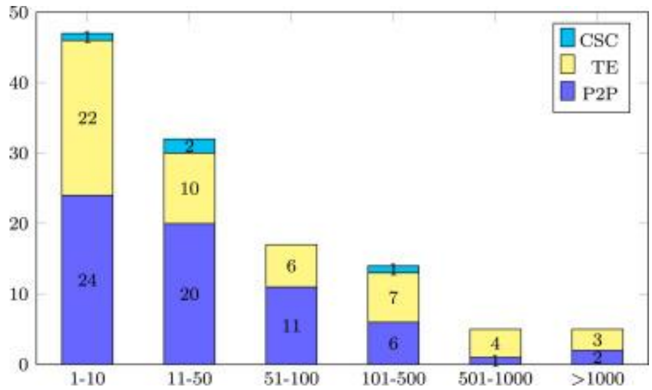

Figure 2.12. Number of participants in LETs reviewed in [21]. CSC: Community Self Consumption, TE: Transactive Energy, and P2P: Peer to Peer Energy Trading.

2.7.2.2 Infrastructure and degradation costs

LET studies assume the presence of assets and infrastructure required for LET, such as DERs, ICT infrastructure, smart metering, etc., and do not consider their initial investment costs in assessing the economic benefits of LET compared to other management approaches that require fewer initial investments such as HEMS. Therefore, there is a need to assess the infrastructure upgrades required for LET, assess their initial investment and life cycle, and, based on that, evaluate the actual economic benefits of LET. Moreover, the participation of some assets like ESS and EVs in LET requires more charging and discharging, which may degrade them and reduce their life period. Most of the LET studies neglect degradation costs. Degradation costs should be assessed and compared to the revenues gained by the participation of these assets in LET.

2.7.2.3 Penalty mechanism and energy losses allocation

Most of the LET studies assume that the market participants are able to supply/consume the energy they promised to sell/buy at the negotiation stage. However, it is expected that deviations from the contracted energy will occur at the energy delivery stage due to prediction errors, issues with the production or consumption devices, etc. Therefore, there is a need to develop efficient incentives and/or penalization methods for the participants who deviate from their agreements [106]. Furthermore, the LET between different market participants will result in energy losses due to the flow of energy through the distribution network. Most of the studies do not consider the cost of losses resulting from the local trade and how it can be assigned to different participants. Therefore, there is a need to develop efficient and fair methods to allocate the cost of losses to market participants [106].

2.7.2.4 Behavior of end users in local energy trading

Existing studies mainly focus on the techno-economic evaluation of LET, considering different participants, technologies, market design, etc. There has been little research on end users' preferences and behavior in the context of LET [84]. Additional studies are required to take into account various socio-economic conditions, larger communities, and various participant kinds (such as residential, industrial, commercial, or buildings with various purposes).

Chapter 3
Impacts of Local Energy Trading on Low Voltage Distribution Networks

Because of the widespread of distributed energy resources (DERs), the passive consumer has been transformed into an active prosumer. Local energy trading (LET) is one of the emerging techniques for effective DER management and maximizing benefits for the energy community (EC) and individual customers. LET provides customers the freedom and flexibility to trade excess energy within the EC to maximize their economic benefits while increasing local consumption of renewable energy sources production. Despite the economic benefits of LET for the whole EC and individual end users, it may influence the low voltage distribution network (LVDN). As a result, a full assessment of the possible effects of LET on LVDN is required.

This chapter compares LET with the home energy management system (HEMS) in terms of community operation expenses and interaction with the retailer. Furthermore, this chapter examined the effects of LET between customers on the voltage unbalance, transformer loading, line loading, and voltage variations of LVDN. The results show that LET decreases EC energy costs by up to 31% when compared to similar HEMS scenarios. LET increased self-generation by 93% by lowering sales to retailers and increased self-sufficiency by fulfilling up to 54% of EC demand by DERs. However, LET increased community peak demand, resulting in more impacts on the LVDN. The transformer has low loading for LET and HEMS. LET caused loading limit violations in several lines despite the majority being lightly loaded. At some LVDN nodes, the voltage unbalance and voltage magnitude exceeded permitted limits.

Nomenclature

Positive variables	**Description**
$G_{t,h}$	Energy purchased from the retailer at instant t for house h

$I_{t,h}$	Imports (purchase) from other houses (i.e., peers) to house h at instant t
$E_{t,h}^{\mathrm{BES}}$	BES stored energy at time t and house h
$D_{t,h}^{\mathrm{BES}}$	BES discharge power at time t and house h
$D_{t,h}^{\mathrm{EV}}$	EV discharge power at time t and house h
$X_{t,h}$	Exports (selling) to other houses (i.e., peers) from house h at instant t
$E_{t,h}^{\mathrm{EV}}$	EV stored energy at time t and house h
$F_{t,h}$	Energy sold to the retailer at instant t from house h
$C_{t,h}^{\mathrm{BES}}$	BES charge power at time t and house h
$C_{t,h}^{\mathrm{EV}}$	EV charge power at time t and house h
$I_{t,h\leftarrow p}^{p}$	Energy imported (i.e., purchased) to house h from its peer p at instant t
$X_{t,h\rightarrow p}^{p}$	Energy exported (i.e., sold) from house h to its peer p at instant t
Parameters and scalars	**Description**
$dem_{t,h}$	Demand at time t and house h
$P_{t,h}^{PV}$	PV production at time t and house h
p_t^b	Purchase price at instant t
p_t^s	Selling price at instant t
p_{per}^{cp}	Contracted power cost for period per
η_C^{BES}	Efficiency of BES charging
η_D^{BES}	Efficiency of BES discharging
$P_{t,h}^{d}$	Net power demand at time t and house h
η_C^{EV}	Efficiency of EV charging
η_D^{EV}	Efficiency of EV discharging
$\bar{C}_{BES}$ and $\bar{D}_{BES}$	Upper limits of BES charging and discharging powers
$\bar{C}_{EV}$ and $\bar{D}_{EV}$	Upper limits of EV charging and discharging powers
$\underline{E}_{BES}$ and $\bar{E}_{BES}$	BES storage level lower and upper limits
$\underline{E}_{EV}$ and $\bar{E}_{EV}$	EV storage level lower and upper limits
$E_{\min}^{\mathrm{EV}}$	Lowest threshold of EV energy at departure time
b_t	Binary parameter value and time t. It indicates if the EV is connected to the charger or not.
μ^{loss}	Loss factor due to P2P energy trade within EC
Sets	**Description**
$t \in T$	Time instant t in time horizon T
$h, p \in H$	House h and peers p in a community of H Houses
$k \in K$	k is the day number in a set of days K

3.1 Introduction

Local energy trading (LET) is a promising method of incorporating distributed energy resources (DERs) into power systems [21]. LET allows customers to offer their surplus energy output to neighbors who have an energy shortage. The LET might stimulate competition among retailers and DERs [46], attain a supply-demand equilibrium in the energy community (EC), raise self-generation of local production from renewable energy sources (RESs), lower purchases from the retailer, and enhance the financial gains of EC participants by obtaining better prices in the LET than the retailer prices for both buyers and sellers [47]. Consequently, the installation of DERs may proceed more quickly.

Numerous studies addressed LET. For instance, a LET in a residential EC in London, UK, was studied in [55]. Numerous DERs exist in the EC, including photovoltaic (PV) generation, wind generation, and battery energy storage (BES). The findings demonstrated the value of LET among EC homes in lowering reliance on the main grid, boosting local self-sufficiency, and lowering overall community energy expenses. Another research evaluated the performance of LET in an EC of industrial buildings in Norway [16]. LET minimized the cost of energy and maximized the consumption of local generation. The authors of [107] presented an auction-based LET among residential buildings in Spain.

These studies took into account the existence of a central body that controls LET. LET, under central management, promotes the maximization of social welfare. It does have a few weaknesses, though, including a single point of failure and participants' privacy issues [8]. Many research articles suggested using distributed ledgers to control LET in a decentralized manner such that no central body is necessary to run the market to overcome the weaknesses of centralized markets [8], [108]. Ref. [109] presented an iterative double auction on a blockchain for LET amongst EVs in an EC. LET allows EVs with extra energy in their batteries to exchange it with adjacent EVs needing energy for financial gain. The findings demonstrated that the suggested blockchain-based LET maximized social welfare while preserving EV privacy and enhancing the security of transactions.

Other than academic research, pilot projects and start-ups showed much interest in LET. In an EC in New York, USA, the LO3 firm was the first company to establish a blockchain-based LET so neighbors could exchange energy [85], [110]. Another pilot project named Quertierstrom developed a blockchain-based LET in a Swiss EC. [18]. The market is cleared every 15 minutes based on a double auction after the market players make their bids. A blockchain-based platform created by the start-up Powerledger facilitates LET among neighbors. [91]. They were involved in several LET projects across various countries, including Australia, Japan, and the USA. [111].

The majority of LET studies and pilot projects concentrated on the market design (i.e., bidding strategy, market clearing approach, centralized or decentralized architecture, etc.), scalability of the market, the installed DERs in the studied EC, and technologies that allow the execution of such markets, like blockchain. A minimal focus was paid to the impact of LET on grid limits [69]. Recent research suggested a variety of approaches to take the grid into account in the market model. Various sensitivity coefficients, such as voltage sensitivity coefficients, loss sensitivity factors, or power transfer distribution factors, have been utilized in the studies [112]. Other studies used DC power flow equations [113], [114], or AC power flow equations [115] for grid representation. Whenever the grid is taken into account in the LET model, only energy transactions that do not exceed grid constraints are permitted. However, each of these approaches has some drawbacks [72]. For instance, the coefficients approximate the physical grid. DC power flow is more suitable for the transmission level and inaccurate at the distribution level [116]. AC power flow needs a high computational power because of the non-linear power flow equations, and the optimum solution is not guaranteed because of the non-convexity of the optimization problem.

These studies provided several methods to incorporate the physical grid limits in the market model and prevent any constraint violations rather than studying the effects of LET on the physical grid. Additionally, earlier research recommended the use of dynamic pricing signals, network tariffs, and power loss signals to express grid limits. [69]. Furthermore, a few studies run a power flow to evaluate the impact of LET on the distribution network as a second step after clearing the market [71], [72].

The impacts of high DER integration in low voltage distribution networks (LVDNs) received significant attention from many studies [35] [117]. They studied the impacts of EVs, PVs, etc., on peak demand, transformer loading, lines loading, voltage deviation, and power losses [29], [74], [118]. Many articles have studied the impacts of single-phase DERs on phase unbalance at LVDNs. The impacts of EVs charging on LVDN phase unbalance were assessed in [119]. The results found that the voltage unbalance limit is exceeded at the 50 % EV penetration level. Many smart charging strategies were developed to mitigate the impacts of EVs charging on the power system [35]. The impacts of single-phase PV generation on phase unbalance of LVDNs in two countries were assessed in [120]. The results found that PV generation caused a violation of voltage unbalance limits for a few studied scenarios.

Considering that most of the suggested market designs do not consider the grid limits in the LET model. Few studies have examined how LET among residential users affects LVDN constraints while considering various DERs, market designs, and operational settings. For instance, it was evaluated how LET affected LVDN's voltage deviation in [47]. The study found that voltage surpassed the lower limits for some nodes in winter for LET (PV+BES) scenario. In addition, the voltage surpassed the upper limits (i.e., overvoltage) for some nodes in summer for LET (PV) scenario because of high PV production. Excess PV generation causes this voltage rise, and it is not due to anything related to LET . This overvoltage problem was eliminated when BES was connected. Another study assessed the impact of LET on voltage deviation and losses on LVDN [72]. The findings demonstrated that LET resulted in higher undervoltage and energy losses in winter with the presence of PV and BES compared to other scenarios.

The impact of LET on power losses and voltage in large-scale LVDN was investigated in [71]. LET caused a negligible increase in losses for the whole day (less than 0.5%) compared to the scenario with no LET. Moreover, the voltage was within acceptable limits during hours with high LET. This study considered a limited LET since only 25% of consumers have PV (i.e., prosumers), and less than 50% of the prosumers have BES or controllable loads. The impacts of LET on peak demand, losses, and voltage levels of LVDN in Norway were evaluated in [121]. The LVDN has 52 prosumers with PV, BES, and EVs connected. The study concluded that LET resulted in higher energy losses and voltage fluctuations compared to the scenario with HEMS. Moreover, LET increased peak demand and voltage fluctuations compared to the reference scenario (i.e., no LET and no DERs). However, this study did not consider the connection of BES and EVs simultaneously at the LVDN. Ref [122] assessed the impact of LET on LVDN voltage considering the presence of PV, WG, BES, and EVs. The study found that the voltage was within acceptable limits.

At the LVDN, the DERs are connected to a single phase; however, for simplicity, most of the LET studies assume the DERs are connected as a three-phase, so the phase unbalance was neglected. Based on that, assessing the impacts of local energy interactions between EC customers on voltage unbalance is important. In previous studies, limited attention was given to the unbalanced nature of DERs in LET [69], and they studied a limited number of possible operation scenarios in the LVDN. For instance, ref. [46] studied the impact of LET on the voltage unbalance of LVDN for only one day and considered one operation scenario. The study only considered the presence of PV and EVs operating in the charging mode and did not consider V2G. Moreover, BES was not considered in this study. The study results showed a negligible variation in voltage unbalance due to the moderate level of LET compared to the reference scenario with no LET. Furthermore, LET shows a negligible effect on energy losses, voltage variation, and peak demand. Table 3.1 provides an overview of related studies that evaluated the impacts of LET on LVDNs.

The contributions of this chapter are the following:

- A techno-economic comparison of LET-based coordinated DERs management with HEMS, where customers manage their DERs individually. The studied approaches are compared in terms of energy exchange with the retailer, locally traded energy, the total operation cost of the community, and the percentage of demand covered by community DERs.
- Develop a joint optimization and network model for assessing the impacts of LET and HEMS on unbalanced LVDN.
- The first study that evaluates the impact of LET on the transformer loading, lines loading, voltage deviation, and voltage unbalance of LVDN considering DERs flexibility.

Table 3.1. Comparison of relevant studies that assessed the impacts of LET on LVDNs.

Reference	Data	DERs	G2V	V2G	Study duration	voltage unbalance	Evaluated impacts
[47]	Ireland	PV, BES	X	X	January, June	X	Voltage
[72]	Ireland	PV, BES	X	X	January, June	X	Voltage, Losses
[71]	Australia	PV, BES, controllable loads	X	X	1 day	X	Voltage, Losses
[121]	Norway	PV, BES/EV	✓	X	21 days (summer)	X	Voltage, losses, peak demand,
[122]	England	PV, WG, BES, EV	✓	✓	1 month	X	Voltage
[46]	England	PV, EV	✓	X	1 day	✓	Voltage, losses, peak demand
Chapter 3 [19]	Spain	PV, BES, EV	✓	✓	1 month July	✓	Voltage, peak demand, components loading

The rest of the chapter is organized as follows. The LET model and HEMS model are presented in section 3.2. Section 3.3 describes the studied LVDN, load profiles, generation profiles, DERs characteristics, retailer prices, and the studied scenarios. Section 3.4 presents the results of comparing the seven studied scenarios, the operation of houses with different DERs, and assessing the impacts on the unbalanced LVDN. The conclusion is provided in section 3.5.

3.2 Problem formulation

This study is divided into two cascaded stages. The first stage executes a LET optimization of the studied EC, resulting in the energy dispatch of houses for the studied time horizon T (i.e., one month). Every 1 hour interval t, participants' decisions are optimized. The market model is created using MATLAB. The second stage involves performing a power flow to assess the effects of LET on the LVDN based on the market outcomes from the first phase. Pandapower software is used for executing power flow [123], [124]. It is an open-source tool based on Python for power system studies. Because the case study is an unbalanced LVDN, a 3-phase AC power flow is executed. Figure 3.1 depicts a schematic layout of the LET impacts evaluation procedure. As inputs, the MATLAB

LET model (first stage) gets houses uncontrollable demand profiles, PV production profiles, import prices, export prices, and DERs characteristics. The LET output is the dispatch of customers' DERs and the net demand profile required for power flow. LVDN data and LET results are inputs to Pandapower (second stage), which performs 3 phase power flow every 1 hour. Pandapower outputs the voltage unbalance value at the house nodes, component loadings, and voltage magnitude at various phases of the LVDN.

3.2.1 Local energy trading model

The LET is modeled as a linear multi-period optimization problem for a trading period T and considering h houses. Recent studies have developed a similar model for LET [47], [55], [121]. EC's objective is to minimize the expenses of EC energy purchased from the retailer while maximizing the revenue generated from selling the EC energy excess to the retailer. This is accomplished by rewarding local energy trading within the EC and the flexibility of EVs and BES. Equation (3.1) states the EC objective function, which is bounded by DERs operating limits, power balance limits, and local energy trading (i.e., P2P-ET) limits within the EC. For LET scenarios, it is assumed that the sum of EC houses revenues from selling energy equals the sum of EC houses purchase payments for locally traded energy. As a result, they are excluded from the EC objective function. p_t^b and p_t^s are the import price and the export price at time instant t. $G_{t,h}$ is the energy bought energy from the retailer at time instant t for house h. $F_{t,h}$ is the energy sold to the retailer at time instant t from house h. The LET problem is optimized by linear programming.

$$min \sum_t \sum_h (p_t^b \times G_{t,h} - p_t^s \times F_{t,h}) \, \Delta t \tag{3.1}$$

At every house node, the supply and demand must be balanced at every instant t as indicated in (3.2). It means that the sum of imports from the retailer (i.e., grid) $G_{t,h}$, imports from peers in the EC $I_{t,h}$, PV production $P_{t,h}^{PV}$, BES discharge $D_{t,h}^{\text{BES}}$, and EV discharge $D_{t,h}^{\text{EV}}$, must equals the sum of exports to peers in the EC $X_{t,h}$, house demand $dem_{t,h}$, exports to the retailer $F_{t,h}$, BES charge $C_{t,h}^{\text{BES}}$, and EV charge $C_{t,h}^{\text{EV}}$. This equation models a house equipped with PV, BES, and EVs. The power balance equation will be different for houses with other DERs or no DERs installations by eliminating some terms from (3.2).

$$G_{t,h} + I_{t,h} + P_{t,h}^{PV} + D_{t,h}^{\mathrm{BES}} + D_{t,h}^{\mathrm{EV}} = X_{t,h} + dem_{t,h} + F_{t,h} + C_{t,h}^{\mathrm{BES}} + C_{t,h}^{\mathrm{EV}} \quad (3.2)$$
$$\forall t \in T, \forall h \in H$$

The deployed BES must function between its limits. The power capacity of the power electronic converter, which links the BES to the LVDN limits the charging $C_{t,h}^{\mathrm{BES}}$ and discharging $D_{t,h}^{\mathrm{BES}}$ power of BES. The lower bounds of charging and discharging powers are zero. The upper bounds of charging and discharging powers are $\bar{C}_{BES}$ and $\bar{D}_{BES}$, respectively, as given in (3.3) and (3.4). Moreover, the BES has lower and upper bounds of energy stored $E_{t,h}^{\mathrm{BES}}$ in kWh as given (3.5).

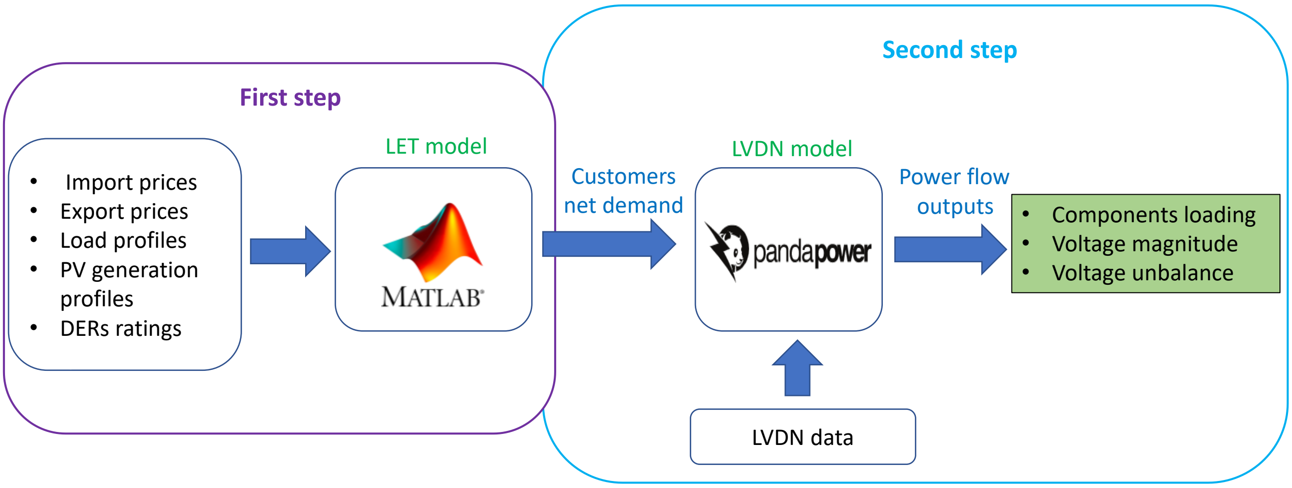

Figure 3.1. Schematic diagram of LET impacts assessment.

$$0 \leqslant C_{t,h}^{\mathrm{BES}} \leqslant \bar{C}_{BES} \qquad \forall t \in T, \forall h \in H \quad (3.3)$$

$$0 \leqslant D_{t,h}^{\mathrm{BES}} \leqslant \bar{D}_{BES} \qquad \forall t \in T, \forall h \in H \quad (3.4)$$

$$\underline{E}_{BES} \leqslant E_{t,h}^{\mathrm{BES}} \leqslant \bar{E}_{BES} \qquad \forall t \in T, \forall h \in H \quad (3.5)$$

Equation (3.6) calculates the amount of energy stored at every BES $E_{t,h}^{\mathrm{BES}}$ in a time instant t for a house h. Where, η_C^{BES} is charging efficiency and η_D^{BES} is discharging efficiency of BES. The energy stored at BES at time instant $t-1$ is designated as $E_{t-1,h}^{BES}$. The final values of the BES SoC on the first day are used as the SoC of the first hour on the second day. Every other day of the simulation period is analogous in this regard, as stated in (3.7).

$$E_{t,h}^{\mathrm{BES}} = E_{t-1,h}^{BES} + \eta_C^{BES} \times C_{t,h}^{\mathrm{BES}} \Delta t - \left(\frac{1}{\eta_D^{BES}}\right) \times D_{t,h}^{\mathrm{BES}} \Delta t \qquad \forall t \in T, \forall h \in H \tag{3.6}$$

$$E_{t_1,k+1,h}^{\mathrm{BES}} = E_{t_{24},k,h}^{\mathrm{BES}} \qquad \forall t \in T, \forall h \in H, \forall k \in K \tag{3.7}$$

Similarly, the deployed EV must function within its limits. The EV charging power $C_{t,h}^{\mathrm{EV}}$ and discharging power $D_{t,h}^{\mathrm{EV}}$ are bounded by the bidirectional EV charger power capacity that links the EV to the LVDN. Zero is the lower bound for both charging and discharging powers. $\bar{C}_{EV}$ and $\bar{D}_{EV}$ refer to the EV upper bounds of charging and discharging, respectively, as stated in (3.8) and (3.9). Moreover, $E_{t,h}^{\mathrm{EV}}$ refers to the EV lower and upper bounds of energy stored in kWh as stated (3.10) [16].

$$0 \leqslant C_{t,h}^{\mathrm{EV}} \leqslant \bar{C}_{EV} \times b_t \qquad \forall t \in T, \forall h \in H \tag{3.8}$$

$$0 \leqslant D_{t,h}^{\mathrm{EV}} \leqslant \bar{D}_{EV} \times b_t \qquad \forall t \in T, \forall h \in H \tag{3.9}$$

$$\underline{E}_{EV} \leqslant E_{t,h}^{\mathrm{EV}} \leqslant \bar{E}_{EV} \qquad \forall t \in T, \forall h \in H \tag{3.10}$$

The status of EV (i.e., connected to LVDN for charging or not) at the time instant t is defined by a binary parameter b_t as stated in (3.11). When the EV is linked to the LVDN, the value of b_t is 1, and when the EV is not connected to the LVDN, the value of b_t is 0.

$$b_t = \begin{cases} 1, & if\ EV\ is\ connected\ to\ the\ LVDN\ at\ time\ instant\ t \\ 0, & otherwise \end{cases} \qquad \forall t \in T \tag{3.11}$$

Equation (3.12) calculates the amount of energy stored at every EV $E_{t,h}^{\mathrm{EV}}$ in a time instant t for a house h when the EV is connected to the charger. Where η_C^{EV} is charging efficiency and η_D^{EV} is discharging efficiency of EV. Equation (3.13) calculates the amount of energy stored at every EV when it is used for mobility. The energy stored at EV at time instant $t-1$ is designated as $E_{t-1,h}^{\mathrm{EV}}$. The final values of the EV SoC on the previous day are used as the SoC of the first hour of the next day. Every other day of the simulation period is analogous in this regard, as stated in (3.14). To ensure that EV owners' mobility and comfort requirements are met, the energy of any EV battery at departure time every day must be greater than or equal to E_{min}^{EV}, as stated in (3.15).

$$E_{t,h}^{\mathrm{EV}} = E_{t-1,h}^{\mathrm{EV}} + \eta_C^{EV} \times C_{t,h}^{\mathrm{EV}} - \left(\frac{1}{\eta_D^{EV}}\right) \times D_{t,h}^{\mathrm{EV}} \qquad \forall t \in T, \forall h \in H, \forall b_t = 1 \tag{3.12}$$

$$E_{t,h}^{\mathrm{EV}} = E_{t-1,h}^{\mathrm{EV}} - 0.06 * E_{t-1,h}^{\mathrm{EV}} \qquad \forall t \in T, \forall h \in H, \forall b_t = 0 \tag{3.13}$$

$$E_{t_1,k+1,h}^{\mathrm{EV}} = E_{t_{24},k,h}^{\mathrm{EV}} \qquad \forall t \in T, \forall h \in H, \forall k \in K \tag{3.14}$$

$$E_{t_{dep},h}^{\mathrm{EV}} \geq E_{min}^{\mathrm{EV}} \qquad \forall t \in T, \forall h \in H \tag{3.15}$$

Within the EC, the purchase of house h from peer p equals the export of p to h at every time t taking into account the losses at LVDN because of LET, as stated in (3.16). μ^{loss} refers to the LVDN energy losses caused by LET within the EC.

$$I_{t,h\leftarrow p}^{p} = \mu^{loss} \times X_{t,p\rightarrow h}^{p} \qquad \forall p \neq h \tag{3.16}$$

Each house with DERs is able to export energy to any house (i.e., peer) in the EC. The total energy exported $X_{t,h}$ from house h at time t is the sum of exported energy $X_{t,h\rightarrow p}^{p}$ from house h to peer p, as stated in (3.17).

$$X_{t,h} = \sum_{p\neq h} X_{t,h\rightarrow p}^{p} \qquad \forall t \in T, \forall h \in H \tag{3.17}$$

In a similar way, the total energy imported $I_{t,h}$ by house h at time t is the sum of imported energy $I_{t,h\leftarrow p}^{p}$ by house h from peer p, as stated in (3.18).

$$I_{t,h} = \sum_{p\neq h} I_{t,h\leftarrow p}^{p} \qquad \forall t \in T, \forall h \in H \tag{3.18}$$

Since LET takes place inside the EC, the sum of houses' energy sales and purchases must equal each other, taking into account the losses at LVDN because of LET, as stated in (3.19).

$$\sum_{h} \mu^{loss} \times X_{t,h} = \sum_{h} I_{t,h} \qquad \forall t \in T \tag{3.19}$$

In order to ensure that LET within the EC is beneficial for all market players (i.e., buyers and sellers), The LET price is estimated to be constrained between the retailer import and export prices. Energy is purchased from peers in the EC at a lower price than the retailer import price, while energy is sold to peers in the EC at a higher price than the retailer export price.

Each home independently dispatches its DERs under the HEMS scenarios, which do not include local trade of energy to minimize the cost of energy purchased from the retailer and maximize the profits from selling it to the retailer. The objective function of each house is provided in (3.20). The objective function is subjected to power balance limit for each house (3.21), and DERs operation limits (3.3) to (3.15).

$$min\sum_{t}\left(p_t^b \times G_t - p_t^s \times F_t\right)\Delta t \qquad \forall t \in T \tag{3.20}$$

$$G_t + P_t^{PV} + D_t^{\mathrm{BES}} + D_t^{\mathrm{EV}} = dem_t + F_t + C_t^{\mathrm{BES}} + C_t^{\mathrm{EV}} \qquad \forall t \in T \tag{3.21}$$

3.2.2 Impacts of local energy trading on LVDN

Equation (3.22) is used to determine the net power demand $P_{t,h}^d$ at each time instant t of each house h. The equation does not include the BES and EV charging and discharging because they are assumed to occur behind the node connection point. Pandapower software receives $P_{t,h}^d$ as an input to run the power flow.

$$P_{t,h}^d = G_{t,h} + I_{t,h} - F_{t,h} - X_{t,h} \tag{3.22}$$

The load connected to the three phases is even in perfect operation conditions. Under such circumstances, the neutral line has zero current flow, and the power losses are reduced. However, there is always unbalance between the load connected to each phase at the LVDNs. This unbalance must be maintained within certain values to ensure the normal operation of LVDNs and the 3-phase loads that require a balanced 3-phase supply [125]. It was easy to keep the phase unbalance level within acceptable limits by distributing the loads evenly at each phase since the consumers in a geographical area have relatively similar consumption habits. This situation is expected to change significantly with deploying various single-phase DERs (i.e., PV, BES, EV, etc.). Therefore, many studies were executed to evaluate the impacts of single-phase DERs on LVDNs phase unbalance. LET could change DER owners' consumption and production habits based on the retailer and local trade prices. Therefore, assessing the impacts of LET on voltage unbalance is crucial. The voltage unbalance factor $VUF\%$ has many definitions, and in this study, it is calculated by (3.23). $VUF\%$ can be defined as a ratio between the negative sequence component and the positive sequence component, as given in (3.23) [126]. The maximum allowed limit of $VUF\%$ is 2 %.

$$VUF\% = \frac{V_2}{V_1} * 100 \leqslant 2\% \qquad (3.23)$$

3.3 Low voltage distribution network, DERs characteristics, and retailer prices

This section provides an overview of the LVDN that is utilized as a case study. Furthermore, it presents the characteristics of the loads and DERs. In addition, it discusses the energy selling/purchasing prices to/from the energy retailer in Madrid, Spain.

3.3.1 Low voltage distribution network

The single-line diagram of the examined imbalanced LVDN is displayed in Figure 3.2. It is a commonly used IEEE European test system for DER integration studies [127]. It has a radial topology, which is very common in LVDN in Europe. The test grid is connected to the main grid through MV/LV transformer with 800 kVA rating that steps down the voltage from 11 kV to 416 V with delta/grounded star winding connections. The windings resistance and reactance are 0.4% and 4%, respectively.

The LVDN connects 55 one-phase residential customers, each with a unique connection point. Each customer's phase of connection is distinguished by the color of the customer number (i.e., phase A in blue, phase B in green, and phase C in orange). Phase A has 21 customers connected, phase B has 19 customers connected, and phase C has 15 customers connected. The number of customers connected to each phase is given in [127]. The profiles are anonymized actual measurements for customers in Madrid, Spain, given by i-DE, an Iberdrola Group DSO. Each customer has a unique consumption profile, chosen randomly from the collected measurements of Madrid residents. The load profiles in this study are sampled at a 1-hour resolution. Figure 3.3 depicts the aggregated demand of the 55 consumers over two days. The first day displayed is a weekend day (i.e., Sunday), and the second day is a business day (i.e., Monday).

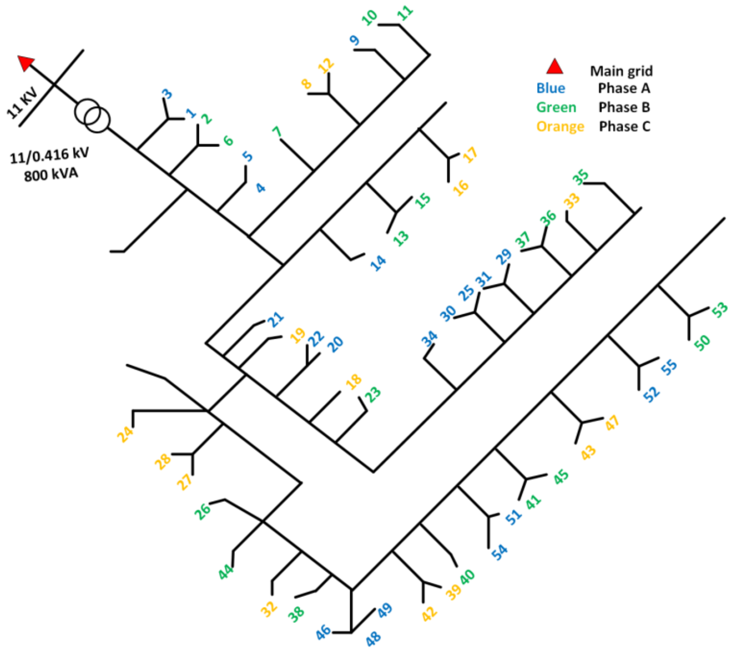

Figure 3.2. single line diagram of the IEEE European test system.

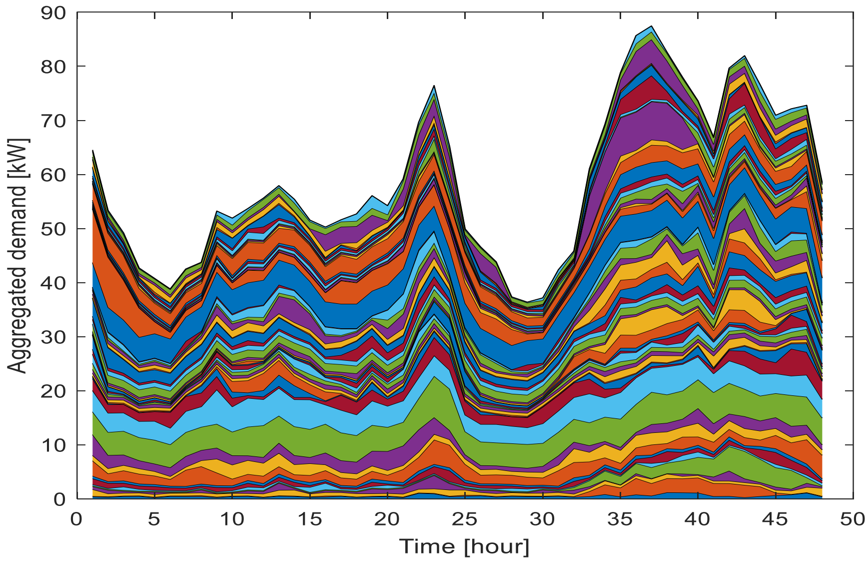

Figure 3.3. Aggregated demand profiles of 55 houses in Madrid, Spain.

The LET optimization model solely examines active power trading and ignores reactive power. As a result, the loads in the load flow are considered to have a fixed power factor of 0.95 pu.

The power factor of the end customer is a crucial parameter that measures the efficiency of the power usage in the system. It is defined as the ratio of the active power to the apparent power. A power factor value can range from 0 to 1, with a higher value indicating more efficient use of electrical power. A high power factor value results in lower current flow in the power system, leading to lower loading of power system components, voltage deviations, and losses. The evaluation of the power factor effect on the LET impacts on LVDN is out of the scope of this thesis.

This study is particularly pertinent in the European context, where policymakers support forming ECs that install DERs and exchange energy locally. Various legal and functional bodies, such as the Citizen Energy Community (Directive 2019/944) and the Renewable Energy Community (Directive 2018/2001), are being established [128], [129].

Table 3.2. The DERs deployed at each house in the EC.

house	PV	BES	EV	house	PV	BES	EV	house	PV	BES	EV	house	PV	BES	EV
1	✓	✓	-	**15**	✓	✓	-	**29**	-	-	-	**43**	✓	-	-
2	✓	✓	✓	**16**	✓	-	✓	**30**	✓	✓	-	**44**	-	-	-
3	✓	✓	-	**17**	-	-	-	**31**	-	-	✓	**45**	✓	✓	-
4	-	-	-	**18**	✓	✓	-	**32**	✓	-	-	**46**	-	-	✓
5	✓	✓	-	**19**	-	-	-	**33**	✓	✓	-	**47**	-	-	-
6	-	-	-	**20**	✓	✓	✓	**34**	✓	-	-	**48**	✓	✓	-
7	✓	-	✓	**21**	-	-	-	**35**	-	-	✓	**49**	✓	-	✓
8	✓	-	-	**22**	-	-	-	**36**	-	-	-	**50**	✓	✓	✓
9	✓	✓	✓	**23**	✓	✓	-	**37**	✓	✓	-	**51**	-	-	-
10	-	-	-	**24**	✓	-	-	**38**	-	-	-	**52**	✓	✓	-
11	-	-	-	**25**	✓	-	✓	**39**	✓	-	✓	**53**	✓	✓	✓
12	✓	✓	✓	**26**	-	-	-	**40**	✓	✓	-	**54**	✓	✓	✓
13	-	-	-	**27**	✓	✓	-	**41**	✓	-	✓	**55**	✓	✓	✓
14	-	-	-	**28**	-	-	✓	**42**	-	-	-				

3.3.2 DERs characteristics and retailer prices

PV, BES, and EV are among the DERs linked to the investigated LVDN. Any customer can have one or more of these DERs, while some users do not have any DERs present. The DERs placed at each house are shown in Table 3.2. PV generating has a power rating of 5 kWp. In the EC, 33 PV systems have been deployed (representing 60% of the houses). Figure 3.4 depicts the generation profile of one PV over two days. PV generation profiles for Madrid, Spain, are acquired from Renewables Ninja [130].

The BES energy and power capacities are 13.5 kWh and 5kW, respectively, and the charging and discharging efficiencies are 95%. The BES state of charge (SoC) lower and upper bounds are 20% and 100%, respectively. On the first day of the studied period, the initial SoC of any BES is a random value equal to or greater than 2.7 kWh (i.e., 20%). In the EC, 22 BES are deployed (representing 40% of houses).

As in the Nissan Leaf, EVs of the studied EC have 24 kWh batteries and a 3.6 kW charging rate. The efficiency of charging and discharging for EVs is 96%. The EV chargers are bidirectional, allowing energy injection (V2G) or absorption (G2V). On the first day of the studied period, the initial SoC of any EV is a random value equal to or greater than 4.8 kWh (i.e., 20%). It is assumed that the EVs are linked to the LVDN for charging/discharging from 5 p.m. to 8 a.m. on the next day and are utilized for mobility throughout the other hours of the day. When an EV is used for mobility, the SoC of the battery is assumed to drop by 6% for each hour. When the EV begins charging, the initial value of the SoC relies on the SoC when the vehicle is unplugged from the LVDN and the distance traveled. It is estimated that the SoC of the EV battery will stay between 20% and 100% when connected to the charger. The energy stored in any EV battery at 8 a.m. (i.e., departure time) every day must be greater than or equal to E_{min}^{EV} (i.e., 75%). In the EC, 18 EVs have been deployed (representing 33% of houses). LET within the EC results in 5% energy losses (i.e., $\mu^{loss} = 0.95$).

The Spanish pricing for purchasing or selling energy from/to the retailer is utilized in this analysis. Customers in Spain buy based on retailer tariffs and sell based on self-consumption surplus energy price for the regulated tariff (PVPC) used in Spain. The purchasing and selling prices in Madrid for July 2021 are acquired from Red Eléctrica (i.e., the Spanish TSO) [131]. Figure 3.5 depicts the retail pricing on July 1st and 2nd. The scenarios investigated consider potential DERs and penetration levels that might be achieved in the near future. In this chapter, we examined a summer month with significant PV production and, as a result, high local energy trade inside the EC.

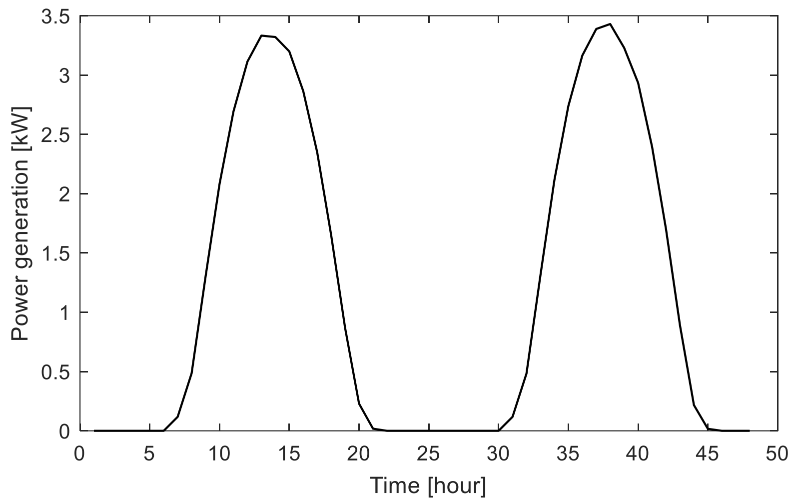

Figure 3.4. PV generation profile of 1 house.

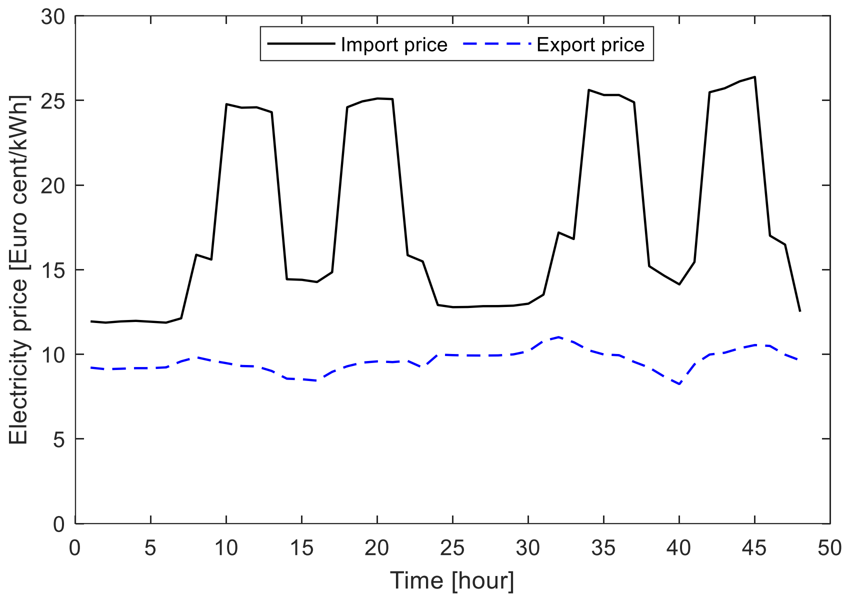

Figure 3.5 Houses import and export prices for the 1st and 2nd of July.

3.3.3 Studied scenarios

Many operating scenarios are explored in this chapter, in which various DERs are linked to the grid and scheduled based on LET or HEMS individual optimization without LET. The following paragraphs outline the key characteristics of these scenarios, which are summarised in Table 3.3.

Table 3.3. Summary of the seven studied scenarios.

#	Scenario	DERs management	DERs	Description
1	Reference	No	No DERs	None of the houses possess DERs, and the houses purchase all their electricity needs from retailer.
2	PV	No	PV (60% of houses)	PV is installed in certain houses for self-generation. The retailer buys the excess production.
3	LET(PV)	LET	PV (60% of houses)	PV is installed in certain houses for self-generation. The excess generation is sold to other houses or retailer.
4	HEMS(PV, BES)	HEMS	PV (60% of houses) BES (40% of houses)	Certain houses possess PV and BES. Each house DERs are optimally controlled to minimize the electricity cost of the house.
5	LET(PV, BES)	LET	PV (60% of houses) BES (40% of houses)	Certain houses possess PV and BES, and owners may exchange excess PV production or energy stored with peers in the EC (i.e., LET) or sell it to the retailer.
6	HEMS(PV, BES, EV)	HEMS	PV (60% of houses) BES (40% of houses) EV (33% of houses)	Certain houses possess PV, BES, and EV. Each house DERs are optimally controlled to minimize the electricity cost of the house.
7	LET(PV, BES, EV)	LET	PV (60% of houses) BES (40% of houses) EV (33% of houses)	Certain houses possess PV, BES, and EV, and owners may exchange excess PV production or energy stored with peers in the EC (i.e., LET) or sell it to the retailer

The first scenario represents the reference case, in which no DERs are deployed, and houses purchase their whole energy needs from retailers at the import price. In this chapter, this scenario is referred to as a reference.

Certain houses in the second scenario have PV installed. The consumption of the houses is met by their PV production or by the retailer, and if there is excess PV production, they sell it to the retailer and acquire the export price. In this scenario, houses with PV cannot exchange their excess generation with other houses in the EC. In this chapter, this scenario is referred to as PV.

In the third scenario, certain houses have PV installed. The demand of the houses is covered by their PV generation, other EC houses (i.e., peers), or the retailer. Each house's surplus PV generation is sold to other houses, and if there are no other houses in EC eager to purchase energy at that time instant, PV owners can sell excess production to the retailer. This scenario is referred to as LET(PV) in this chapter.

PV and BES are installed in certain houses in the fourth scenario. HEMS optimizes the PV and BES of each house to minimize the energy cost and maximize revenues, and no local trade of energy within EC is permitted. In this chapter, this scenario is referred to as HEMS(PV, BES).

In the fifth scenario, PV and BES are installed in certain houses, and owners can exchange excess PV production or energy stored with other houses in the EC (i.e., LET) or sell it to the retailer if no peers want to buy energy at that time instant. BES could be charged by the house PV, energy purchased from other houses, or energy purchased from the retailer. This scenario is referred to as LET(PV, BES) in this chapter.

In the sixth scenario, PV, BES, and EV are installed in certain houses. HEMS optimizes each house's PV, BES, and EV to minimize energy costs and maximize revenues, and no local trade of energy is permitted. In this chapter, this scenario is referred to as HEMS(PV, BES, EV).

In the seventh scenario, PV, BES, and EV are installed, and owners have the option of trading excess PV production or energy stored in BES or EV with other houses in the EC (i.e., LET) or selling it to the retailer if no neighbors want to buy energy at that moment. The house PV production, purchasing from peers, or purchasing from the retailer are all options for charging BES and EV. This scenario is referred to as LET(PV, BES, EV) in this chapter.

3.4 Results and discussions

The findings are divided into three sections. The first section compares the analyzed scenarios according to the energy trade with the retailer, energy traded locally, operation cost of EC, and amount of demand covered by EC DERs. The second section explains how different types of houses (without DERs, with PV, etc.) cover their energy demand and manage DERs in the studied scenarios. The third section examines the effects of the studied scenarios on transformer loading, line loading, voltage deviations, and voltage unbalance of the LVDN.

3.4.1 Comparison of studied scenarios

This section compares the LET scenarios and other scenarios. Table 3.4 shows a comparison between the seven studied scenarios. In all of the scenarios analyzed, the use of LET decreased the quantity of energy exported to the retailer by up to 93% compared to the corresponding HEMS scenarios and increased EC self-generation by encouraging EC demand to be covered through LET exchange. When LET was used, most of the local production was exchanged locally. Furthermore, when BES and EV (i.e., flexible devices) are included, a significant portion of demand is covered by DERs of EC. This means that LET increased EC self-sufficiency by covering a high percentage of demand by local DERs. DERs cover approximately 54% of EC demand in the LET(PV, BES) scenario and around 44% of EC demand in the LET(PV, BES, EV) scenario. These percentages are much higher than the corresponding HEMS scenarios.

The simulation period in this chapter is one month. However, we presented only three days in Figure 3.6 for better visibility of the results. Figure 3.6(a) depicts the total amount of energy purchased from the retailer by all EC houses for the scenarios analyzed. It demonstrates that there are hours with no energy imports from the retailer for LET scenarios. Customers meet their demand during these hours with their own DERs or purchase from other EC houses at a lower price than the retailer price. Similarly, Figure 3.6(b) demonstrates that a small quantity of energy is typically sold to the retailer in LET scenarios. Customers would rather sell surplus energy to their peers at a higher price than the retailer price. This demonstrates that LET can strengthen ECs' independence from the main grid electricity supply. It can be seen that the amount of energy traded with the retailer differs between the PV and the LET(PV) scenarios. Nevertheless, the physical flow of electricity in the grid is identical in both scenarios. Houses in LET(PV) can trade energy with one another in addition to trading with the retailer. As a result, the LET(PV) scenario displays lower energy trade values with the retailer than the PV scenario.

Figure 3.6(c) and Table 3.4 illustrate the total quantity of exchanged energy under LET scenarios for all houses in the EC. When BES and EV are installed, the quantity of traded energy and the trading hours between peers in the EC rise since customers are able to charge BES or EV during hours with high PV production and sell it later during hours with low or no PV production. When compared to other LET scenarios, the LET(PV) scenario has a longer duration with no LET. This happens when the PV production is limited and the house uses it locally, or when there is no PV production at night.

Table 3.4. Comparison of the seven studied scenarios for July.

	No DERs	PV		PV+BES		PV+BES+EV	
	Reference	**PV**	**LET**	**HEMS**	**LET**	**HEMS**	**LET**
Imports from retailer (kWh)	47228.78	35123.66	24567.22	32810.24	21873.91	38723.78	26620.64
Exports to retailer (kWh)	0	15692.07	4580.02 (-70%)	12820.15	851.91 (-93.35%)	14039.55	927.17 (-93.39%)
Total LET (kWh)	0	0	11112.05	0	15687.87	0	16796.28
Demand by retailer (%)	100	74.37	52.02	69.47	46.31	81.99	56.37
Demand by DERs (%)	0	25.63	47.98	30.53	53.69	18.01	43.63
Peak of grid consumption (kW)	105.91	88.36	88.36	125.92	164.16	159.84	228.96
Total operation Costs (€)	7622.45	4140.09	3324.76	3743.65	2592.33	4165.58	3007.29
LET cost reduction (%)	-	-	-19.69	-	-30.75	-	-27.81
Costs of imports from retailer (€)	7622.45	5543.45	3741.71	4938.34	2672.87	5486.30	3095.71
Revenue of exports to retailer (€)	0	1403.36	416.95	1194.69	80.55	1320.73	88.42

The findings revealed that DERs decrease the amount of energy purchased from the retailer and the EC's energy cost. Compared to all other equivalent scenarios (i.e., with HEMS and the identical DERs deployed), the LET scenarios lowered the EC energy cost. LET decreased EC energy costs by around 20% in the LET(PV) scenario, 31% in the LET(PV, BES) scenario, and 28% in the LET(PV, BES, EV) scenario compared to the equivalent HEMS scenarios.

Nevertheless, BES and EVs energy arbitrage (charging at low price hours and discharging at high price hours for house self-generation or selling to other houses in the EC) raised the peak of grid consumption (i.e., energy imports from the retailer) as illustrated in Table 3.4 and Figure 3.6(a) at hour 25 for scenarios with BES installation or EV, and peak demand is greater in LET scenarios than the corresponding HEMS scenarios.

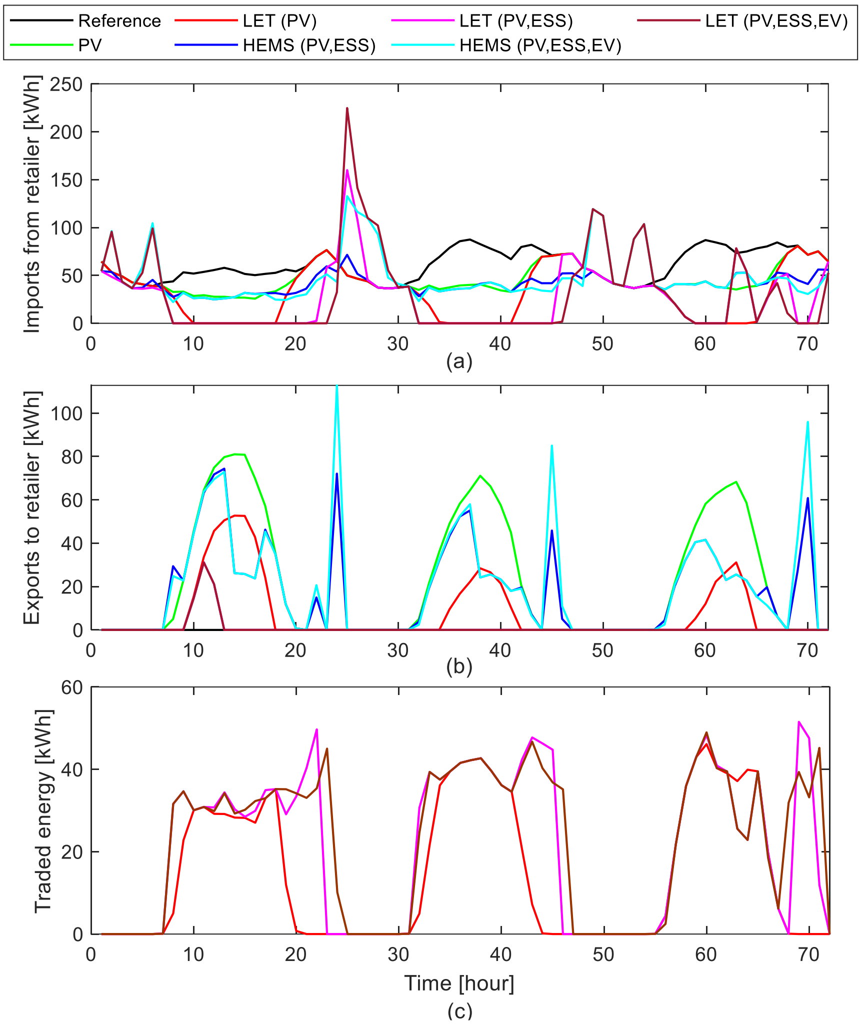

Figure 3.6. Comparison of the studied scenarios in terms of (a) Imported energy from the retailer, (b) Exported energy to the retailer, and (c) Traded energy within the EC for LET scenarios.

This chapter focused on studying a summer month where a high generation from PV is expected and, consequently, a high LET within the EC. The performance of LET and HEMS are compared during 1 month in Winter (i.e., January) to understand the seasonal variation effect on the obtained results. Table 3.5 compares the LET scenarios and HEMS scenarios for winter (i.e., January). For all the studied scenarios, the introduction of LET significantly reduced the amount of energy sold to the retailer by up to 99% and increased EC self-consumption by incentivizing local consumption to be covered through exchange between peers in the EC. A negligible amount of energy is usually sold to the retailer for LET scenarios. The producers prefer to sell excess energy to peers at a higher price than the retailer price, and the consumers prefer to buy energy from peers at a lower price than the retailer price. Therefore, most of the local generation was traded locally within the community when LET was introduced. However, DERs covered a lower percentage of demand for January than for July. This is due to the low PV production and high demand in January compared to July.

The results show an increase in the amount of traded energy between peers in the community when ESS and EV are installed because prosumers can charge ESS or EV when there is high PV generation and sell it at hours with less or no PV generation.

The results showed that DERs reduce the energy bought from the retailer and the electricity cost for the community. The LET scenarios reduced the community electricity cost compared to all the corresponding scenarios (i.e., with HEMS and the same DERs installed). LET reduced the community electricity cost by about 5% for LET (PV) scenario, 7% for LET (PV, ESS) scenario, and 8% for LET (PV, ESS, EV) scenario. LET scenarios recorded a lower cost reduction for January compared to July.

Table 3.5. Comparison of the seven studied scenarios for January.

	No DERs	**PV**		**PV+ESS**		**PV+ESS+EV**	
	Reference	**PV**	**LET**	**HEMS**	**LET**	**HEMS**	**LET**
Imports from retailer (kWh)	58498.57	48503.58	41060.18	46524.57	40949.712	52236.36	45812.59
Exports to retailer (kWh)	0	9208.60	1373.43 (-85.09%)	6475.33	26.16 (-99.60%)	7546.58	135.32 (-98.21%)
Total LET (kWh)	0	0	7835.16	0	12153.78	0	13615.13
Demand by retailer (%)	100	82.91	70.19	79.53	70	89.30	78.31
Demand by DERs (%)	0	17.09	29.81	20.47	30	10.70	21.69
Total operation Costs (€)	17050.43	12409.27	11773.45	11652.65	10789.19	12501.92	11511.31
LET cost reduction (%)	-	-	-5.12%	-	-7.41%	-	-7.92%
Costs of imports from retailer (€)	17050.43	14178.29	12041.08	12980.30	10794.18	14089.97	11542.63
Revenue of exports to retailer (€)	0	1769.02	267.63	1327.65	4.99	1588.05	31.32

3.4.2 Operation of houses under different scenarios

The operation of several houses is analyzed for the investigated scenarios to demonstrate how the various houses cover their energy needs and how BES and EVs operate in various scenarios. House number 10 has no DERs, house number 32 has PV installed, house number 15 has PV and BES installed, and house number 53 has PV, BES, and EV installed. The simulation period in this study is one month. However, we presented only two days in Figures 3.7-3.10 for better visibility of the results.

As illustrated in Figure 3.7(a), house 10 met its demand by importing from the retailer in all scenarios without LET (i.e., reference, PV, HEMS(PV, BES), and HEMS(PV, BES, EV)). When LET is used, purchases from other EC houses (i.e., peers) meet a percentage of the demand since LET prices are lower than retailer pricing. In the LET(PV) scenario, purchases from peers occur when they have excess PV production, while demand is met by the retailer at night when there is zero PV production, as seen in Figure 3.7(b). The purchases from peers occur for a longer period in the LET(PV, BES) scenario than in the LET(PV) scenario because of the existence of BES installed at other houses in EC that charges at hours of high PV production or low prices and discharges at hours of high prices, as illustrated in Figure 3.7(c). Similarly, purchases from peers take longer periods in the LET(PV, BES, EV) scenario represented in Figure 3.7(d) due to the existence of BES and EV in other houses in EC. Even though House 10 does not have DERs, it may actively engage in LET and decrease its energy cost by purchasing inexpensive local electricity from other peers in the EC.

For scenarios with no LET, house 32 sells any surplus PV production to the retailer and purchases the required energy from the retailer when demand exceeds PV production and during the night hours, as illustrated in Figure 3.8(a). Because the price of energy trading within the EC is higher than the price of selling to the retailer, in the LET(PV) scenario, the local energy trade in the EC takes precedence over selling to the retailer. As a result, as shown in Figure 3.8(b), house 32 sells surplus PV power to other peers eager to purchase energy and to the retailer when none of its peers want to buy. Furthermore, house 32 purchases surplus energy from other peers since their prices are lower

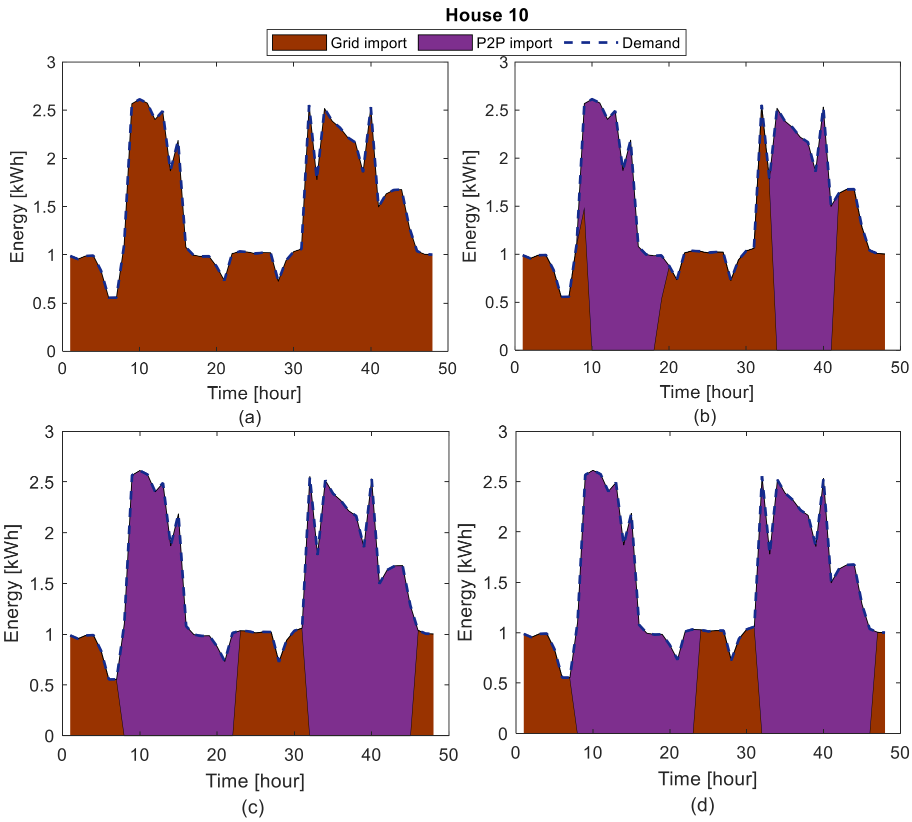

Figure 3.7. Operation of house 10. (a) no LET scenarios, (b) LET(PV) scenario, (c) LET(PV, BES) scenario, (d) LET(PV, BES, EV) scenario.

than the retailer price. As demonstrated in Figure 3.8(c), the LET(PV, BES) scenario exhibited a distinct behavior of house 32 owing to the BES owned by other EC houses, which increases the period that house 32 may meet its demand from other houses. Similarly, in the LET(PV, BES, EV) scenario, house 32 fulfilled more demand from peers than all other scenarios due to the existence of BES and EV in the EC, as seen in Figure 3.8(d).

As shown in Figure 3.9(a), for both HEMS (PV, BES) and HEMS (PV, BES, EV) scenarios, house 15 satisfies nearly all of its demand using PV production at the day hours and BES discharge at hours with low PV production and night. House 15 imported a very small amount of electricity from the retailer during the days shown. Excess PV production is either charged to BES or sold to the retailer. Similarly, in both LET(PV, BES) and LET(PV, BES, EV) scenarios, house 15 meets nearly

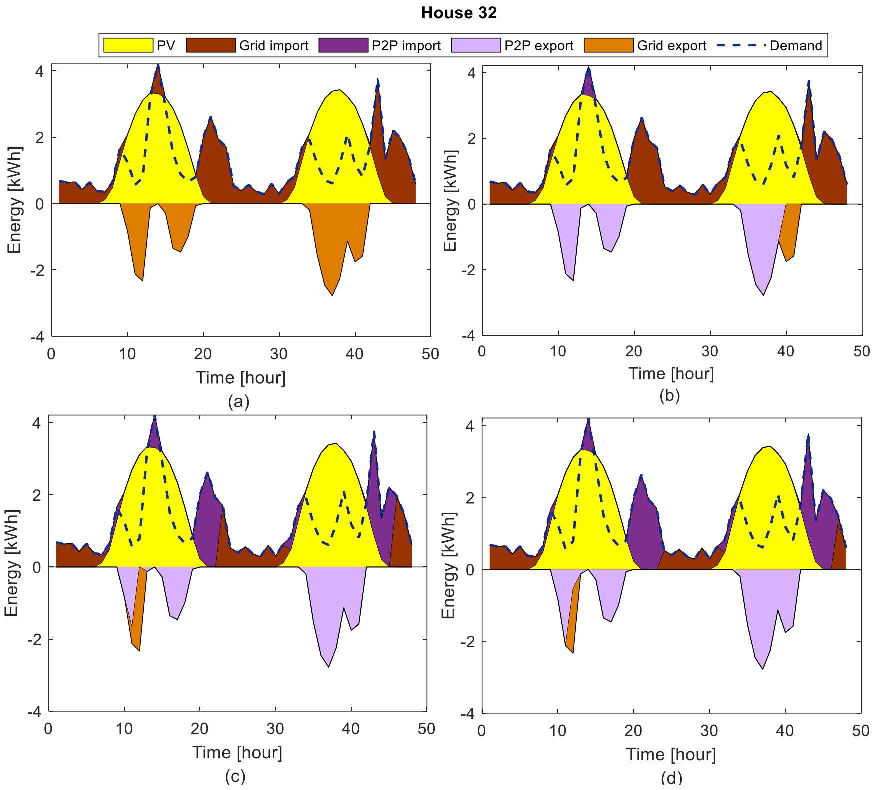

Figure 3.8. Operation of house 32. (a) no LET scenarios, (b) LET(PV) scenario, (c) LET(PV, BES) scenario, (d) LET(PV, BES, EV) scenario.

all of its demand with PV production during the day and BES discharge during the night, as illustrated in Figures 3.9(b) and (c). In LET scenarios, however, house 15 encourages selling PV production or BES discharge to other houses in the EC rather than selling to the retailer. As a result, little energy is sold to the retailer. House 15's BES engages in energy arbitrage by charging from the grid during low-price hours and discharging during high-price hours to cover home demand or sell energy to peers.

As shown in Figure 3.10, under both HEMS (PV, BES, EV) and LET (PV, BES, EV) scenarios, house 53 covers a large percentage of its demand through PV production during the day hours and BES/EV discharge during low PV production and night hours. House 53 prefers to sell PV production, BES discharge, or EV discharge to EC peers rather than the retailer. In the LET(PV, BES,

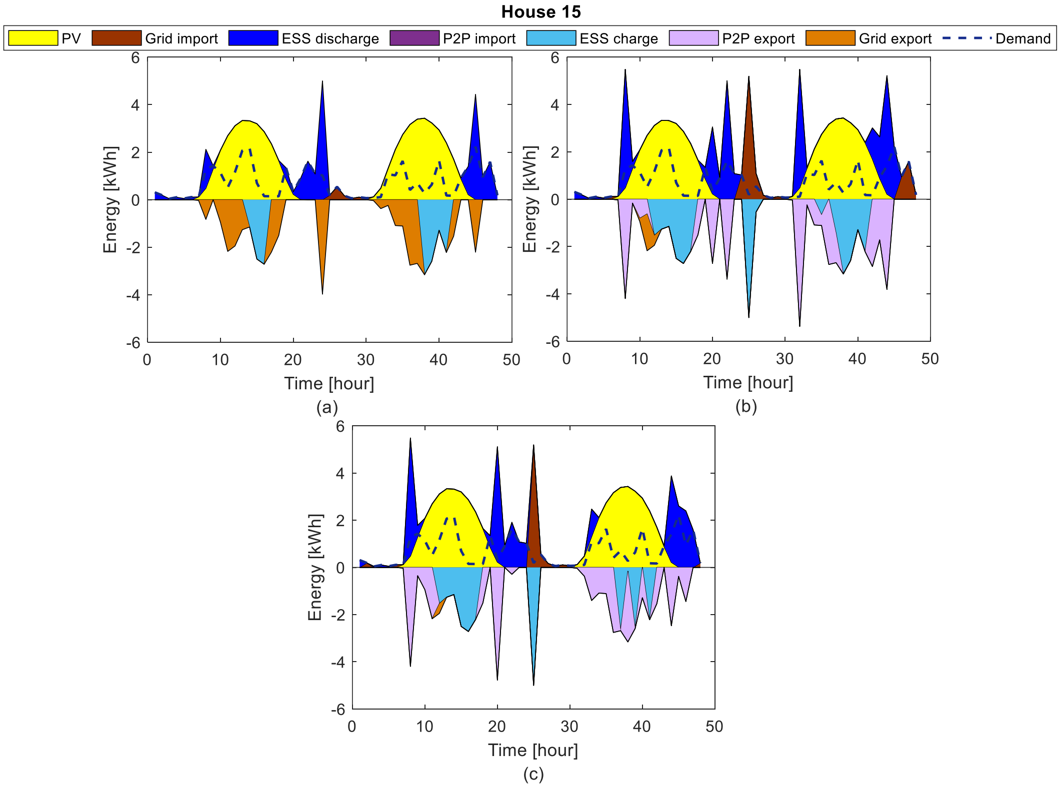

Figure 3.9. Operation of house 15. (a) no LET scenarios (b) LET(PV, BES) scenario, (c) LET(PV, BES, EV) scenario.

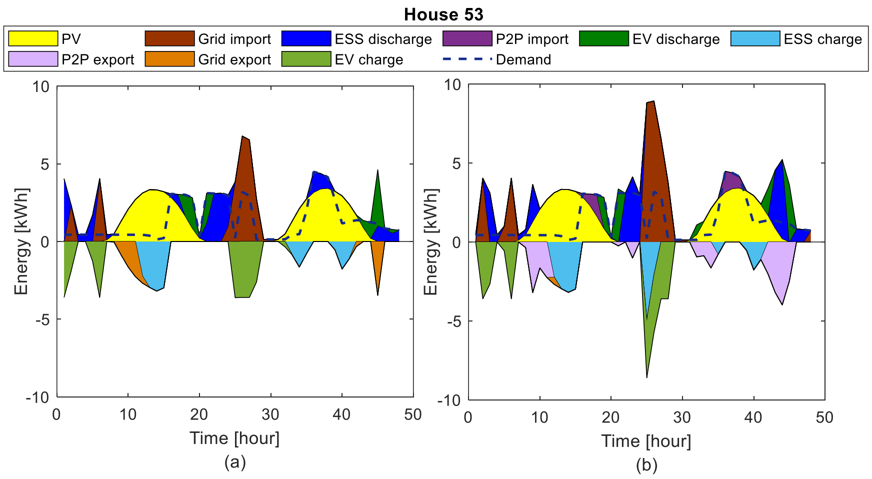

Figure 3.10. Operation of house 53. (a) HEMS (PV, BES, EV) scenario, (b) LET(PV, BES, EV) scenario.

EV) scenario, the BES and EV of house 53 engage in energy arbitrage by charging from the grid at lower prices and discharging at higher prices to fulfill the house demand or selling energy to peers.

3.4.3 Impacts of local energy trading on LVDN

The transportation electrification and massive deployment of DERs may result in network limits being violated. This subsection assesses the effects of the investigated scenarios on transformer loading, line loading, voltage deviations, and LVDN voltage unbalance. Table 3.6 presents the maximum transformer loading, maximum line loading, lowest and highest voltage values at the three phases, and maximum voltage unbalance factor ($VUF\%$) for all scenarios evaluated throughout the simulation period (i.e., one month). Because they have an identical physical flow of energy, PV and LET(PV) scenarios have identical impacts on the LVDN, as explained in subsection 3.4.1.

Table 3.6. Summary of impacts of LET on LVDN.

	No DERs	**PV**		**PV+BES**		**PV+BES+EV**	
	Reference	**PV**	**LET**	**HEMS**	**LET**	**HEMS**	**LET**
Maximum transformer loading [%]	14.99	13.65	13.65	17.68	25.56	24.70	35.69
Maximum line loading [%]	46	41.23	41.23	52.80	74.96	73.53	102.68
Lowest value of Va [pu]	1.007	1.007	1.007	1.009	0.985	0.970	0.946
Highest value of Va [pu]	1.053	1.091	1.091	1.088	1.093	1.111	1.107
Lowest value of Vb [pu]	0.983	0.998	0.998	0.968	0.934	0.932	0.891
Highest value of Vb [pu]	1.033	1.070	1.070	1.078	1.082	1.117	1.088
Lowest value of Vc [pu]	1.013	1.023	1.023	1.019	1.021	1.016	1.014
Highest value of Vc [pu]	1.051	1.073	1.073	1.073	1.073	1.073	1.073
Maximum VUF [%]	0.901	0.690	0.690	1.286	1.837	1.791	2.758

3.4.3.1 Impacts on the transformer and lines loading

The effects of LET on transformer and line loading are evaluated in this subsection. Figure 3.11(a) depicts the transformer loading for the seven scenarios over one month. Figure 3.11(b) shows the first three days of the month for greater visibility. Transformer loading is low in all scenarios, with the greatest loadings of 35.69% and 25.56% in the LET(PV, BES, EV) and LET(PV, BES) scenarios, respectively. The corresponding HEMS scenarios have lower transformer loading than LET scenarios.

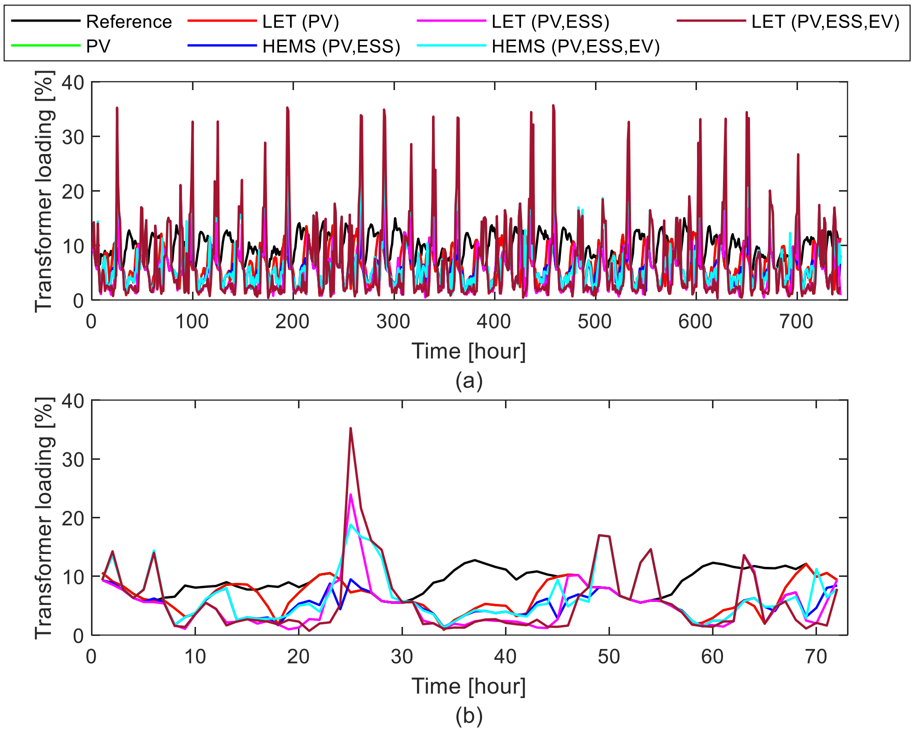

Figure 3.11. Transformer loading. (a) 1 month, (b) 3 days.

Figure 3.12(a) depicts the loading of the line linked to the transformer LV side during one month for the seven scenarios. Figure 3.12(b) depicts the first three days of the month for greater visibility. The examined network's lines have identical current capacity. As a result, several lines' loading constraints are violated for the LET(PV, BES, EV) scenario since all of the houses' energy flows through these lines. This high loading happens when BESs and EVs charge at the same time when electricity prices are low. For all of the scenarios investigated, the majority of the LVDN lines are minimally loaded. Line loading was lower in HEMS scenarios than in LET scenarios.

3.4.3.2 Impacts on voltage deviations

Because of their radial structure and absence of voltage control devices, LVDNs experience more significant voltage variations than other parts of the power system. As a result, many studies focused on the effect of large DER penetration on voltage variations at LVDNs. End nodes of lines generally have more voltage variation than other nodes near the transformer, particularly in rural locations with long lines. When the local demand is high, the LVDNs may experience a significant voltage drop, and when the local production is high, the voltage may rise. According to EN 50160, the LVDN voltage has to be between 0.90 and 1.10 pu.

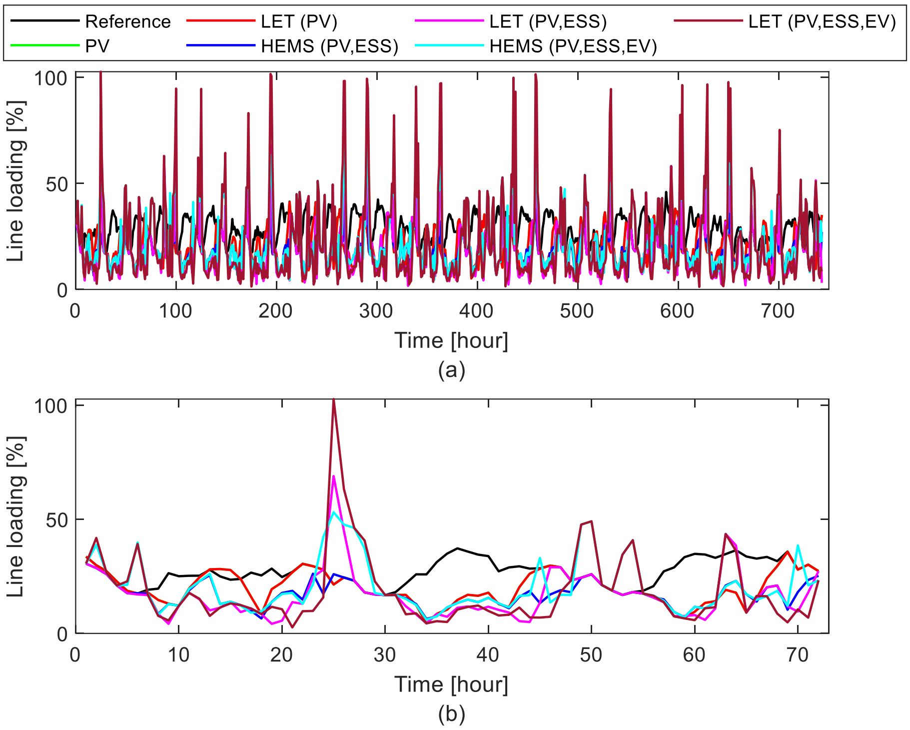

Figure 3.12. Line loading. (a) 1 month, (b) 3 days.

The influence of LET on voltage deviations at LVDN end nodes is studied and compared in this subsection to scenarios without LET. Because the examined LVDN is unbalanced and each phase contains different houses with distinct characteristics, the voltage of each phase is reported individually. The voltage shown here was measured at the connecting point of load 53, which is positioned at the line end, and notable voltage variances are to be expected at this node. Table 3.6 and Figures 3.13–3.15 demonstrate that the LET scenarios resulted in larger voltage dips than the HEMS scenarios. For the LET(PV, BES, EV) scenario, the voltage of phase b exceeded the voltage lower limit and recorded 0.891 pu. This high voltage variation occurs when high energy is purchased from the retailer to charge BES and EVs during low-price hours or to fulfill the mobility demands of EVs.

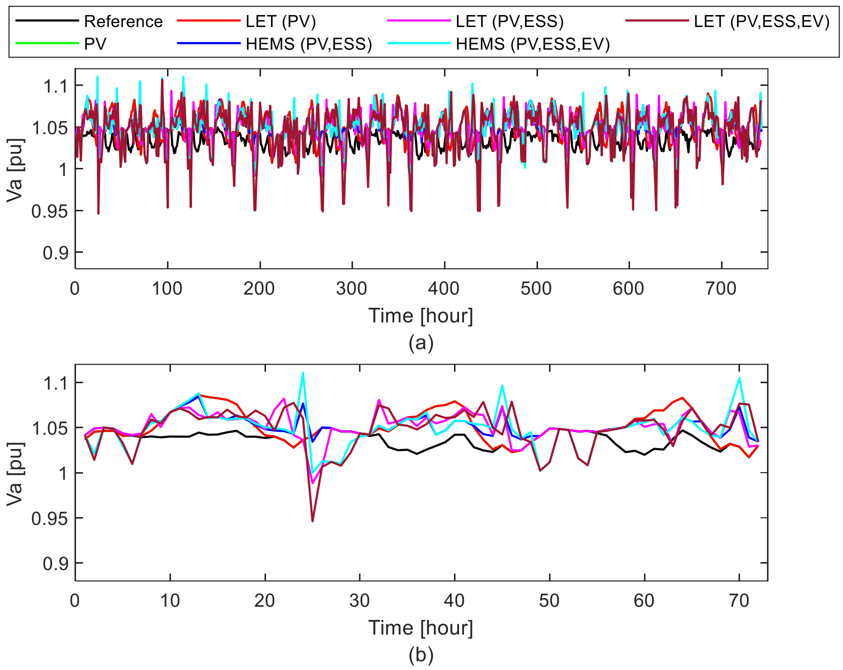

Figure 3.13. Phase a voltage (Va). (a) 1 month, (b) 3 days.

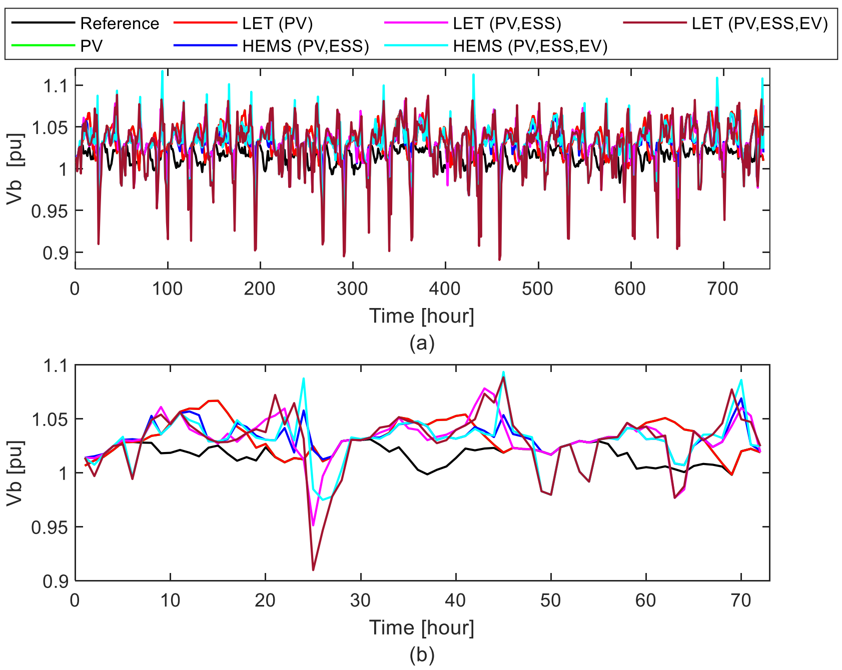

Figure 3.14. Phase b voltage (Vb). (a) 1 month, (b) 3 days.

The increased energy flow causes a larger voltage drop on the line impedances. The voltage of phase a exceeded the voltage upper limit, measuring 1.111 pu in the HEMS (PV, BES, EV) scenario and 1.107 pu in the LET (PV, BES, EV) scenario. For the HEMS (PV, BES, EV) scenario, the voltage of phase b exceeded the voltage upper limit and recorded 1.11 pu. The synchronous discharge of BES and EVs causes this voltage increase.

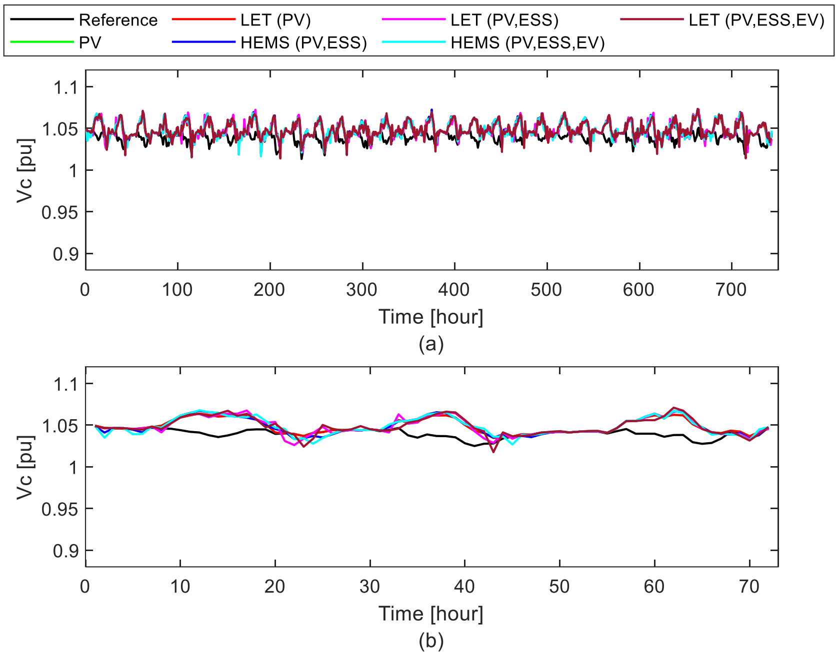

Figure 3.15. Phase c voltage (Vc). (a) 1 month, (b) 3 days.

3.4.3.3 Impacts on voltage unbalance

The VUF% for each of the seven situations is estimated in this subsection. The VUF% values for the investigated scenarios are shown in Table 3.6 and Figure 3.16. The VUF% assessments shown are recorded at the load 53 connection point, which is positioned at the end of the line, therefore, notable voltage changes are predicted at this node. VUF% stayed below 1% in scenarios without BES or EV installation. VUF% increases for scenarios with BES or EV installation, particularly LET(PV, BES, EV) and LET(PV, BES) scenarios. The VUF% for LET (PV, BES, EV) was 2.758%, which surpassed the allowed limit. This is primarily due to charging BESs and EVs at the same time when electricity prices are cheap or to fulfill the mobility demands of EVs. The VUF% for LET(PV, BES) is a bit lower than the permitted level, with a maximum value of 1.837% reached. HEMS (PV, BES, EV) has a VUF% of 1.791. Generally speaking. When compared to equivalent HEMS scenarios, LET scenarios exhibited higher VUF% values.

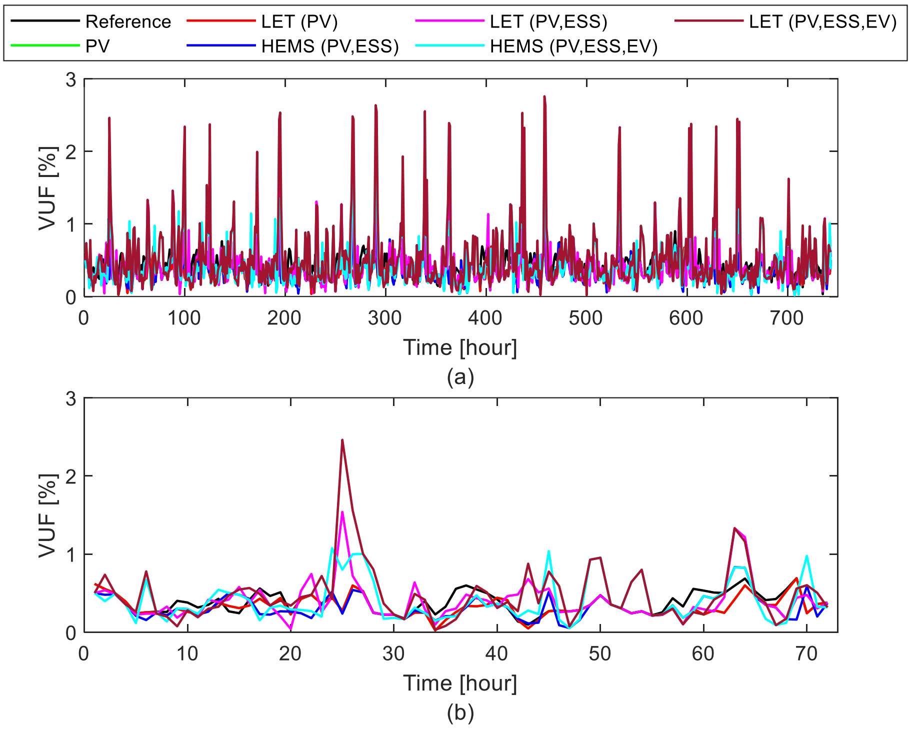

Figure 3.16. Voltage unbalance factor (VUF%) (a) 1 month, (b) 3 days.

3.4.3.4 Comparison of the impacts on LVDN of different scenarios

The preceding subsections thoroughly examined the effects of seven operating scenarios on LVDN. As illustrated in Figure 3.17, this part presents a statistical evaluation of the transformer loading, lines loading, voltage variations, and voltage unbalance over the simulation period (i.e., one month). The transformer loading is below 20% for most of the hours throughout the month for the LET (PV, BES, EV) scenario, which has the greatest impact on the LVDN and outliers with a maximum of 35.69. Similarly, for the majority of the month's hours, the line loading is below 57%, with outliers reaching 102.68. Throughout the entire month, the maximum line loading (i.e., 100%) is only exceeded for 4 hours.

The VUF% is below 1.15% for the majority of the hours over the month, with outliers reaching 2.758. During the entire month, the VUF% surpassed the maximum limit (i.e., 2%) for 23 hours. As demonstrated in Figures 3.13-3.15, the voltage at each phase is within permissible limits for almost all of the simulation time, with the exception of phases a and b, which exceeded the permitted limits for only a few hours. For the LET (PV, BES, EV) scenario, the voltage of phase a surpassed the higher limit for 1 hour, while for the HEMS (PV, BES, EV) scenario, it crossed the maximum voltage limit for 6 hours. For the LET (PV, BES, EV) scenario, the voltage of phase b crossed the minimum voltage limit for 3 hours and the maximum voltage limit for 5 hours for the HEMS (PV, BES, EV) scenario.

As a result, when evaluating the HEMS and LET scenarios using the same assets, Figure 3.17 indicates that the LET generates a higher loading level for transformers and lines, resulting in more frequent and severe voltage violations. As a result, in the provided situation, the LET approach is more likely to establish network limits violations due to the increased quantity of power flows inside the network.

The analysis in this chapter represents a very common situation where there is no incentive to limit the peak demand, as in energy-based network tariff that charges the customer based on energy use and not the rate of energy use. It can be seen that LET does not inherently reduce impacts on the LVDN and may even increase it due to enhanced charging/discharging of flexible devices and energy trading activities. To address this, an innovative approach involves incentivizing LET participants to manage LVDN through price signals or incentive structures.

The findings of this chapter may be applicable to other scenarios with comparable demand patterns, DER features, and distribution networks. In other cases, LET might achieve lower EC operating expenses than HEMS. However, the cost savings will be determined by the characteristics of the loads, the installed DERs, and the pricing structure.

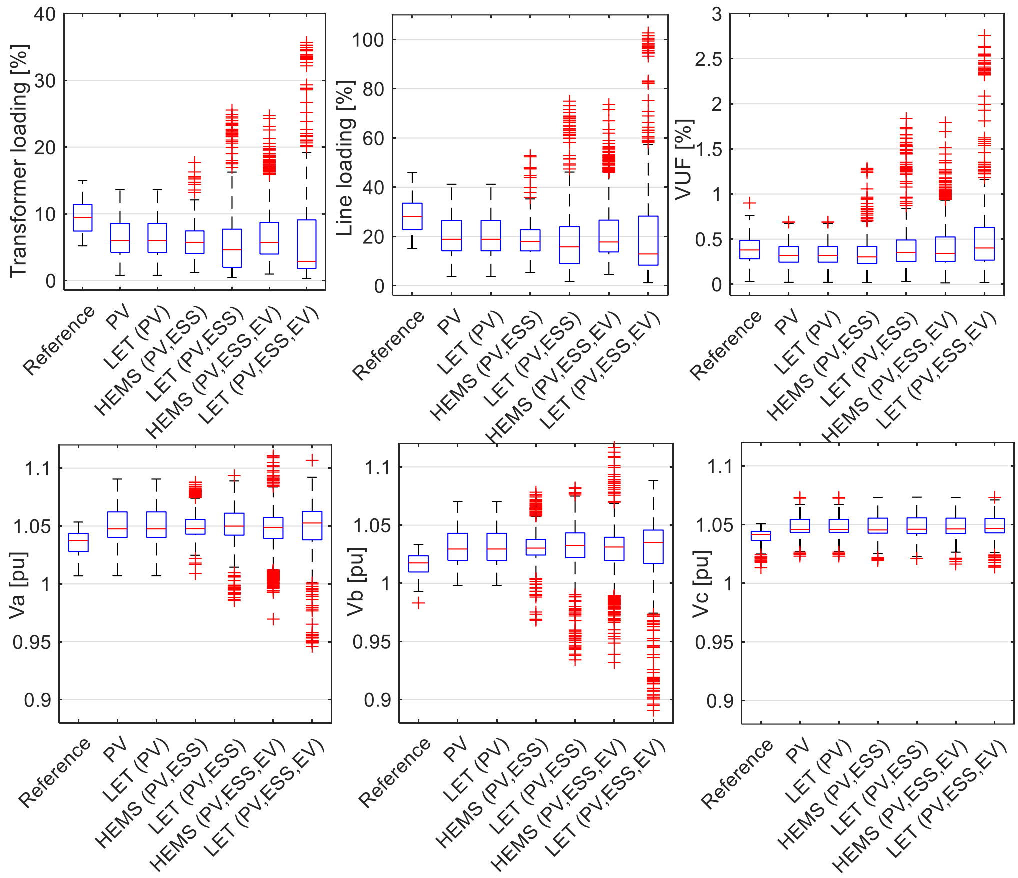

Figure 3.17. Comparison of the impacts of different scenarios using boxplot representation.

This chapter is important for the distribution network planning phase to analyze the strengths and weaknesses of the examined DERs management approaches (i.e., LET and HEMS). Based on the findings, policymakers can determine if the proposed technique's benefits exceed the challenges. Furthermore, the system operator can determine the potential effects on distribution networks and if infrastructure changes are required. Furthermore, it might be advantageous during the operation phase to assess the benefits and challenges of various DERs management systems while taking into account varied operating situations, installed DERs, variations due to the seasons, and daily variations. Network tariffs should account for the effects of DERs and set cost-reflective charges, so the different operation modes could internalize such costs.

3.5 Conclusion

This chapter investigates seven operating scenarios that take into account the existence of various types of DERs as well as two DER management methodologies (i.e., LET and HEMS), adopting a Spanish case study. Furthermore, it discusses the effect of seasonal variations on LET performance compared to HEMS. Moreover, it develops a joint optimization and network model for assessing the impacts of LET and HEMS on unbalanced LVDN.

The results demonstrated that LET outperformed HEMS in terms of lowering the EC's energy costs (i.e., economic performance), lowering energy purchased from the retailer, and enhancing self-generation. In LET scenarios, however, peak demand for EC energy imports from the retailer is higher than in HEMS. Furthermore, the effects of LET on the unbalanced LVDN are compared to HEMS, assuming the same DERs are deployed. According to the analysis, the loading of the transformer and lines increases for LET scenarios. Because of its high power rating in comparison to the aggregated demand, the transformer loading was below the maximum limit. However, several lines surpassed their maximum loading limit. LET also influences the rise in voltage drop at all phases as well as the voltage phase unbalance. The findings revealed that the cause for these LET impacts is the simultaneous charging of EC BES and EVs when energy costs are low or to fulfill the mobility demands of EVs. The case study demonstrates that the energy trading method studied significantly impacts the physical quantities transferred by network users. As a result, given similar resource circumstances, network limits are more likely to be surpassed based on the technique utilized. As explored in the next chapter, cost-reflective network tariffs could alleviate such impacts.

Chapter 4
Mitigating the Impacts of Local Energy Trading on Low Voltage Distribution Networks by Considering Contracted Power Cost

The previous chapter showed that local energy trading (LET) with flexible distributed energy resources could result in violations of the low voltage distribution network (LVDN) limits if the grid constraints are not considered in the LET optimization model. These violations mainly happen due to the synchronized charging of electric vehicles and battery energy storage (i.e., flexible devices) connected to the LVDNs, which could require an infrastructure upgrade at LVDN. This chapter proposes including contracted power cost in the LET optimization model to mitigate the impacts on unbalanced LVDN. The proposed approach does not require the consideration of grid constraints in the LET model or interaction with the distribution system operator. The results showed that the proposed approach reduced the peak demand of the energy community (EC) by 34.3% without affecting its economic performance. Moreover, the proposed approach prevents violations of LVDN limits in line loading, voltage unbalance, and voltage magnitude that occur in the LET scenario that does not consider contracted power cost.

Nomenclature

Positive variables	**Description**
$G_{t,h}$	Energy purchased from the retailer at instant t for house h
$F_{t,h}$	Energy sold to the retailer at instant t from house h
CP_{per}	Contracted power at period per
Parameters and scalars	**Description**
p_t^b	Purchase price at instant t
p_t^s	Selling price at instant t
p_{per}^{cp}	Contracted power cost for period per

$P_{t,h}^{d}$	Net power demand at time t and house h
p_{per}^{cp}	Contracted power price for period per
Sets	**Description**
$t \in T$	Time instant t in time horizon T
$per \in P$	Period per in a set of periods P for contracted power
$h, p \in H$	House h and peers p in an EC of H Houses

4.1 Introduction

Several approaches were investigated in existing literature to avoid violations of grid limits in LET. Previous studies used sensitivity coefficients [112], DC load flow equations [113], [114], or AC load flow equations [115] for network limits consideration in the model. By doing so, the operation of LVDN within limits is usually guaranteed. All of these techniques, however, have inherent drawbacks [72]. The sensitivity coefficients, for example, approximate the actual grid. DC load flow is better suited for transmission networks but inaccurate at the distribution networks [116]. Due to the non-linear nature of load flow equations, AC load flow requires a higher computation power than the other approaches, and the optimal solution cannot be ensured due to the non-convexity of the optimization problem. Previous research also proposed signals of network charges, dynamic pricing, and power losses to reflect grid limits. [69]. Nevertheless, according to [21], only 20% of the examined articles adequately represented grid limits in the market models of LET. So, further study is required to create effective approaches with low computational complexity that mitigate the impacts of LET on LVDNs.

The grid tariffs are energy-based in most countries and not power-based [132]. Energy-based grid tariffs do not incentivize end users to decrease their peak demand because they are charged on the used energy, not the rate of energy use. However, grid investments are mainly associated with power, not energy [133]. Several countries introduced power-based grid tariffs to recover grid costs. Therefore, efficient energy and grid tariff design could be a simple but feasible approach for decreasing the impacts of LET on distribution networks and postponing infrastructure upgrades. Few studies investigated the effectiveness of considering peak demand or its cost (i.e., contracted power costs or demand charges) in the LET model. Contracted power costs are common for industrial and commercial consumers in many countries, such as Norway, which has charges based on the peak demand during the month [16]. However, it is rarely applied to residential consumers [132].

LET between five industrial buildings in Norway was evaluated in [16]. The study considered the costs of energy and contracted power. The community contains combined heat and power (CHP), PV, shared BES, EVs, and controllable loads. The findings showed the effectiveness of synergies between LET and contracted power costs in decreasing the costs of industrial EC compared to individual scheduling of buildings. Another study compared the effect of energy-based and power-based grid tariffs on the peak demand of EC in Norway, containing pre-school, grocery store, and 28 houses [134]. The EC houses have PV, BES, unidirectional EVs, and controllable water heaters, enabling LET between EC participants. Each house has a different DERs, but all of them have water heaters. The findings showed the effectiveness of power-based grid tariffs in decreasing the peak demand of EC at critical hours over energy-based grid tariffs. All these studies did not assess the impacts of LET on distribution networks considering power-based grid tariffs.

Ref. [133] conducted a similar study for one week for a smaller EC in Norway. However, the local market enables trading of the contracted power capacity between EC participants, in addition to energy trading. The results proved the effectiveness of the local market and contracted power capacity in decreasing the EC peak demand in addition to decreasing the cost of EC and individual participants. The authors of [135] studied the effect of grid tariff design on the peak demand of a local electricity market for residential and commercial buildings in Germany, considering current and future scenarios of networks, loads, and installed DERs. The buildings contain PV, BES, HP, or EVs. The results showed that a power-based grid tariff is more effective than energy-based grid tariffs in decreasing peak demand and changing the behavior of flexible devices to shift their demand to hours with low demand.

The authors of [136] studied the effect of grid tariffs on the operation of LET for case studies in Ireland, Norway, and Austria. In Ireland, the electricity prices have an energy-based grid tariff component in a static time of use tariff. The study showed the viability of LET in decreasing energy imports and exports from/to the retailer. The Norwegian case study analyzed the effect of grid tariff component in retailer price on the operation of a community of industrial buildings similar to what is studied in [16]. The findings showed that grid tariff is more effective in decreasing the costs of peak demand and energy in LET than without adopting LET. The Austrian case study analyzed the effect of grid tariff applied for local trade within EC. The results showed that a grid tariff design that favors trading between customers connected to the same feeder could maximize the trade between nearby customers. Another study found that using a discriminatory grid tariff based on zones or distance between peers in LET could decrease the stress in the grid [60]. Table 4.1 compares this chapter with relevant studies.

These studies did not assess the impacts on distribution networks when LET and contracted power are considered. Moreover, the studies focused on the Norwegian context. Therefore, the impacts of LET and contracted power costs on distribution networks should be studied, considering the pricing schemes of other countries and the unbalanced nature of LVDNs.

To the best of our knowledge, this is the first study that proposes including contracted power costs in the LET objective function besides the energy cost to mitigate the impacts of LET on unbalanced LVDN besides a techno-economic analysis considering a Spanish case study with real demand measurements and electricity prices (i.e., energy and contracted power). The study analyzes EC behavior, considering efficient tariff designs rather than considering distribution network constraints. The proposed approach does not require the consideration of grid constraints in the LET model. Therefore, it has low computational costs. Moreover, it does not require any interactions with DSO while preserving LET economic performance. The contributions of this study are:

- Add the contracted power cost besides energy cost in the LET objective function based on the current charges for residential consumers in Spain. Then, compare its performance with the LET model that considers energy cost only in the objective function.
- The first study to analyze how considering the contracted power cost could mitigate the impacts of LET on unbalanced LVDN.

Table 4.1. Comparison of related studies that considered power-based grid tariffs in LET.

Ref.	Data	Study period	Evaluated impacts	voltage unbalance	DERs	G2V	V2G	Contracted power	Impacts mitigation
[46]	England	1 day	Voltage, losses, peak demand	✓	PV, EV	✓	X	X	X
[47]	Ireland	January, June	Voltage	X	PV, BES	X	X	X	X
[72]	Ireland	January, June	Voltage, Losses	X	PV, BES	X	X	X	X
[71]	Australia	1 day	Voltage, Losses	X	PV, BES, controllable loads	X	X	X	X
[121]	Norway	21 days (summer)	Voltage, losses, peak demand,	X	PV, BES/EV	✓	X	X	X
[122]	England	1 month	Voltage	X	PV, WG, BES, EV	✓	✓	X	X
[137]	Ireland	January, June	Losses, voltage	✓	PV, BES	X	X	X	X
[16]	Norway	1 year	X	X	CHP, PV, BES, EVs, controllable loads	✓	✓	✓	X
[134]	Norway	1 year	X	X	PV, BES, EV, water heater	✓	X	✓	X
[133]	Norway	1 week	X	X	PV, BES	X	X	✓	X
[135]	Germany	1 year	X	X	PV, BES, HP, EV	✓	X	✓	X
Chapter 3 [19]	Spain	1 month July	Peak demand, components loading, voltage	✓	PV, BES, EV	✓	✓	X	X
Chapter 4 [138]	Spain	1 month July	Peak demand, components loading, voltage	✓	PV, BES, EV	✓	✓	✓	✓

This chapter is organized as follows. Section 4.2 presents the EC optimization model, modeling of LVDN, DERs characteristics, energy prices, and contracted power prices. Section 4.3 presents the results of the techno-economic comparison of studied scenarios. Section 4.4 presents the impacts of LET on LVDN. The conclusion is provided in section 4.5.

4.2 Problem Formulation

This section presents EC modeling. Moreover, it introduces grid characteristics, deployed DER specifications, electricity prices, and contracted power costs. Furthermore, it describes the studied scenarios.

This study is divided into two cascaded phases. The first phase executes a LET optimization of the studied EC, resulting in the energy dispatch of houses for the study period T (i.e., one month). Every 1 hour interval t, participants' decisions are optimized. The LET model is created using MATLAB. The second phase involves performing a load flow to assess the effects on the unbalanced LVDN based on the first phase outcomes. Pandapower software is used for executing load flow [123], [124]. Figure 4.1 depicts a schematic layout of the assessment procedure of LET impacts on LVDN. As inputs, the MATLAB LET model (first phase) gets DERs characteristics, electricity prices, contracted power prices, PV profiles, and load profiles. The first phase output is the net demand for each house that is required for load flow. LVDN data and houses net demand are inputs to Pandapower (second phase), which performs 3-phase load flow.

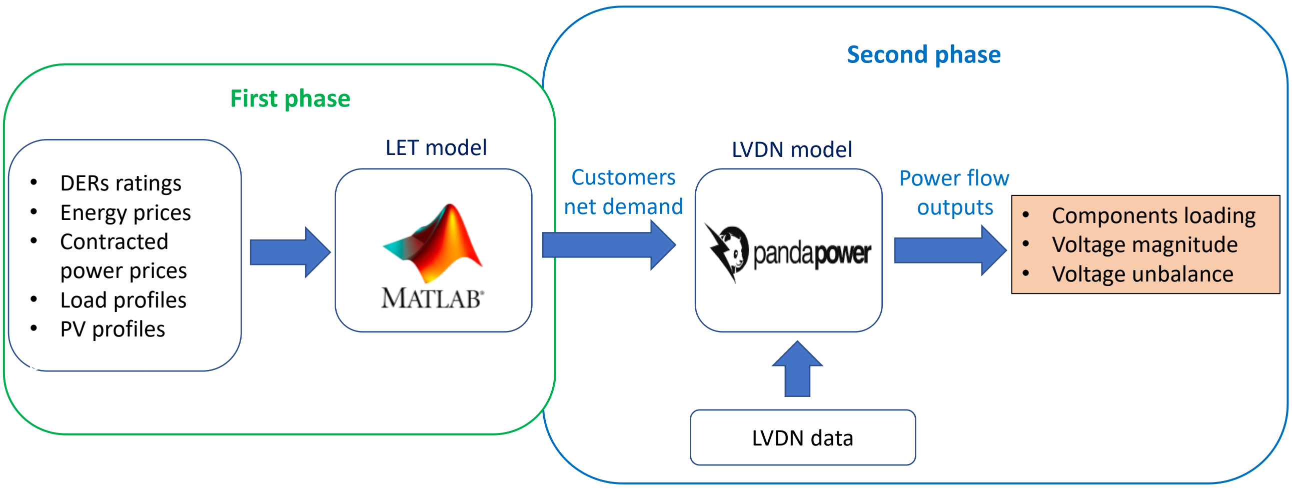

Figure 4.1. Schematic layout of the assessment procedure of LET impacts on LVDN.

4.2.1 Local energy trading model

In chapter 3, the results showed that LET within EC containing high PV, BES, and EV penetration (i.e., scenario 7) caused violations in the unbalanced LVDN under study in lines loading, voltage deviations, and voltage unbalance. These violations mainly happen due to the synchronized charging of EVs and BES (i.e., flexible devices) to take advantage of the retailer low energy prices. Similarly, the violations could happen due to the synchronized discharging of EVs and BES (i.e., flexible devices) to fulfill the EC demand at hours with high retailer energy prices.

This chapter proposes including contracted power cost in the EC objective function besides the energy cost to mitigate the impacts on LVDN. This proposal aims to decrease the impacts on LVDN without considering the grid constraints in the optimization model. This results in a lower computational power requirement and no interaction with DSO.

This chapter compares three scenarios while the detailed operation is given to scenarios one and two. In scenario one, which represents LET without contracted power, the objective of EC is minimizing the expenses of EC energy purchased from the retailer while maximizing the revenue generated from selling the EC energy excess to the retailer, as stated in (4.1). This is the same objective function used in chapter 3 [19]. In scenarios two and three, which represent LET with contracted power, the objective of EC is minimizing contracted power cost and the expenses of EC energy purchased from the retailer while maximizing the revenue generated from selling the EC energy excess to the retailer, as stated in (4.2). Where p_{per}^{cp} is the contracted power price for period per and CP_{per} is the contracted power at period per.The contracted power for the whole EC is optimized since the objective is to minimize the cost for all the EC and not each house individually (the contracted power could be modeled in this equation as a sum of the houses' contracted powers). By optimizing the contracted power for the whole EC, it could be considered an indirect subsidy to the EC. Appendix A compares the two possible ways to model the contracted power costs in the EC model. To have a fair comparison, the cost of contracted power per day in scenario two is represented as energy cost in €/kWh and added to the energy import price used in scenario one.

$$min \sum_{t} \sum_{h} (p_t^b \times G_{t,h} - p_t^s \times F_{t,h})) \tag{4.1}$$

$$min \ (\sum_{per \in P} p_{per}^{cp} \times CP_{per} + \sum_{t} \sum_{h} (p_t^b \times G_{t,h} - p_t^s \times F_{t,h})) \tag{4.2}$$

The LET model used in this chapter is similar to the model used in chapter 3. Therefore, only new equations will be discussed here. The objective function is bound by power balance limits (3.2), DERs operating limits (3.3)-(3.15), EC local trading (i.e., LET) limits (3.16)-(3.19), and contracted power limits (4.3)-(4.4). The energy purchased from the retailer by all houses in the EC must be less than or equal to the contracted power at any hour of the day, as stated in (4.3). Similarly, the energy sold to the retailer by all houses in the EC must be less than or equal to the contracted power at any hour of the day, as stated in (4.4).

$$\sum_{h \in H} G_{t,h} \leq CP_{per} \qquad \forall per \in P, \forall t \in T \tag{4.3}$$

$$\sum_{h \in H} F_{t,h} \leq CP_{per} \qquad \forall per \in P, \forall t \in T \tag{4.4}$$

4.2.2 Modeling of LVDN, DERs, energy prices, and contracted power prices

This study uses the same characteristics of LVDN, demand profiles, DERs, and energy prices used in chapter 3 [19]. However, a 5 % tax is added to the import prices based on what is currently applied in Spain (this tax was not considered in chapter 3 analysis).

The contracted power cost for the considered customers is divided into two periods. Period 1: from 8 a.m. to midnight, which has a high price for contracted power (i.e., peak hours). Period 2: from midnight to 8 a.m., which has a low price for contracted power (i.e., off-peak hours). This applies to weekdays. However, the contracted power prices for weekends are period 2 prices for all day hours. In scenario two, we considered that the contracted power for period 1 must be greater than or equal to the contracted power for period 2, as stated in (4.5), and how this constraint affects the EC peak demand and impacts on LVDN. As the EC has significant flexibility, this scenario aims to avoid peak shifting to off-peak hours.

Scenario three is similar to scenario two but does not consider constraint (4.5), which corresponds to the tariff available in Spain for residential customers with contracted power lower than 15kW, enabling customers to have a higher contracted power in period 2 than in period 1 if they want. Table 4.2 presents the contracted power cost and its components in Madrid, Spain. Policy costs represent part of the Spanish islands' extra costs regarding the cost of mainland, RES support, among others. A 5 % tax is added to the contracted power costs (the tax value was in place when doing the analysis). In practice, the houses can surpass the contracted power and pay a penalty. It is assumed for simplicity that the contracted power cannot be exceeded.

$$CP_1 \geq CP_2 \tag{4.5}$$

Table 4.2. Contracted power costs in Madrid, Spain.

Contracted power costs	Period 1 (Peak)	Period 2 (Off-peak)
Transmission and distribution costs (€/kW/year)	23.469833	0.961130
Policy costs (€/kW/year)	4.970533	0.319666
Total costs with a 5% tax (€/kW/year)	**29.8623843**	**1.3448358**

4.3 Techno-economic evaluation of the two studied scenarios

This section presents a techno-economic evaluation and comparison of the studied scenarios. Table 4.3 compares scenario one for LET without contracted power, scenario two for LET with contracted power while considering constraint (4.5), and scenario three for LET with contracted power without constraint (4.5). It can be noted that interaction with the retailer regarding energy purchased by EC and energy sold by EC from/to the retailer is approximately identical for the three scenarios. Moreover, scenario one has a slightly higher energy traded within the EC than scenario two. Furthermore, the percentage of demand covered by the retailer and EC DERs is roughly the same in the three scenarios. Similarly, the EC net operation cost, energy purchased from retailer cost, and energy sold to retailer revenues are approximately identical, while scenario three has the lowest cost. The results show a very similar performance of the studied scenarios. However, the table indicates that scenario two reduced the EC peak demand by 34.3% compared to scenario one. Moreover, scenario three reduced the EC peak demand by only 5.7% compared to scenario one.

Table 4.3. Techno-economic comparison of the studied scenarios.

	LET without CP (scenario one)	LET with CP (scenario two)	LET with CP (scenario three)
Imports from retailer (kWh)	26485.69	26449.65	26492.77
Exports to retailer (kWh)	758.64	776.26	776.26
Total LET (kWh)	17329.93	16881.14	16971.25
Demand by retailer (%)	56.08	56	56.09
Demand by DERs (%)	43.92	44	43.91
Peak of grid consumption (kW)	234.32	153.96	221.06
Total operation Costs (€)	3485.35	3513.81	3389.57
Costs of imports from retailer (€)	3541.81	3572.04	3447.80
Revenue of exports to retailer (€)	56.46	58.23	58.23

Figure 4.2 displays the interaction with the retailer regarding the sum of energy purchased by EC houses from the retailer, the sum of energy sold by EC houses to the retailer, and the sum of energy traded between houses within the EC for four days. Figure 4.2(a) demonstrates that scenario one has a larger peak in the energy purchased from the retailer than scenarios two and three, when the EC objective function considers the contracted power cost. Moreover, there are many hours with no energy purchase from the retailer in both scenarios. During these hours, the EC houses cover their demand with their DERs or other houses in EC that have surplus energy and exchange it locally within the EC. This shows that LET increases the independence of EC from the retailer for all scenarios. Notice that scenario three has a higher peak demand than scenario two. In scenario three, the EC optimization chooses a higher contracted power at period 2 than period 1 due to the lower costs. The EC imports high energy from the retailer in period 2, resulting in high peak demand. To manage such effect, ex-post network tariffs can become a tool together with local flexibility markets [139].

Figure 4.2(b) demonstrates an identical behavior of the three studied scenarios, where the EC houses sell a tiny quantity of energy to the retailer in a few hours of the displayed days. Furthermore, for most hours, no energy is sold to the retailer. This shows that LET and flexible devices (i.e., BES and EVs) increase self-generation by consuming the generation of EC RESs locally within the EC. Similarly, Figure 4.2(c) demonstrates an identical amount of energy traded locally within the EC for the three scenarios. The local trade of energy occurs mostly at hours with high PV generation (i.e., daytime hours) and night hours using the energy stored in flexible devices (i.e., BES and EV) deployed in the EC. Since scenario two resulted in a large reduction of EC peak demand compared to scenario one. The following analysis will focus on these two scenarios.

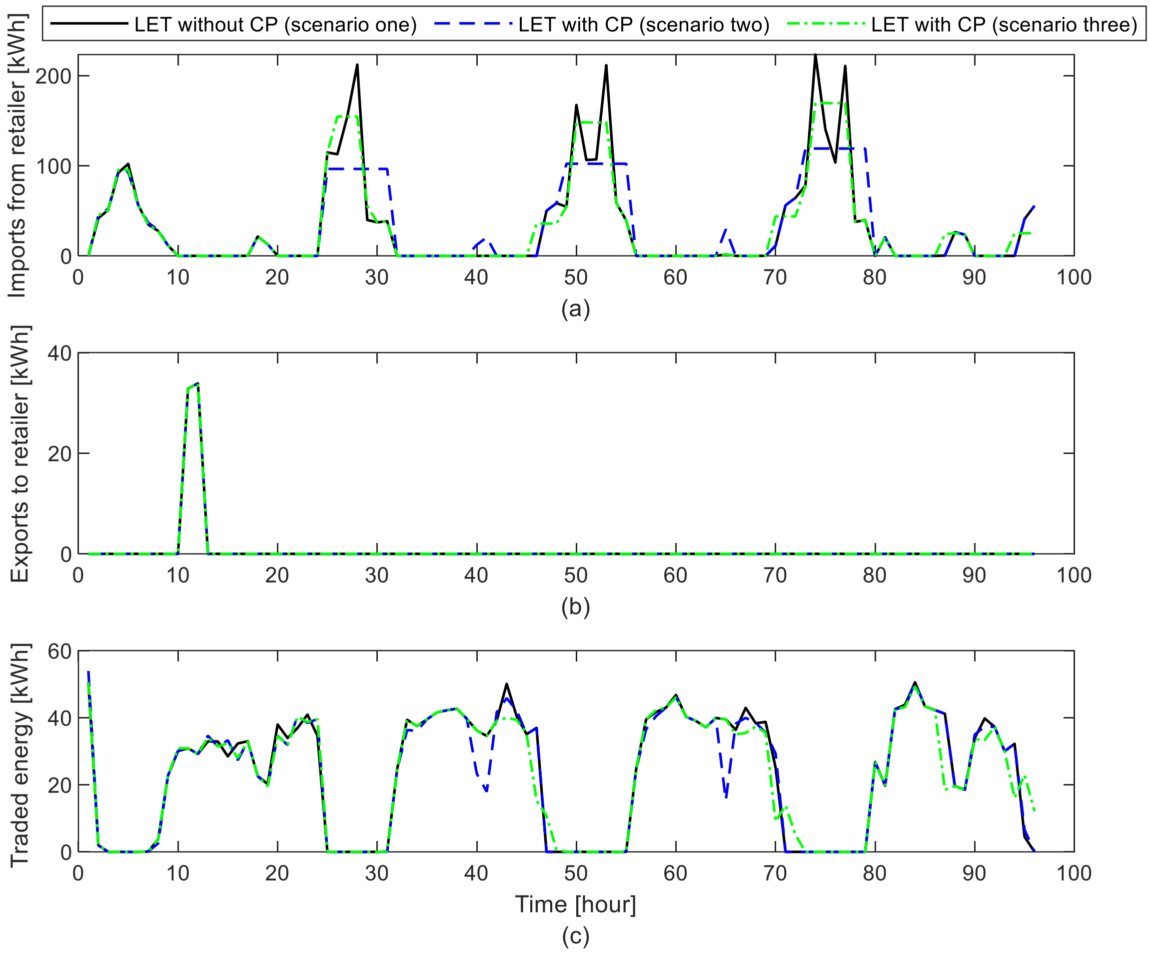

Figure 4.2. Interaction with the retailer and traded energy within EC for four days.

The aggregated charging powers of BES and EVs are presented in Figure 4.3 to analyze the reason for the higher peak demand in scenario one compared to scenario two. In scenario one, there is no limit on the peak of energy purchased/sold from/to the retailer. Therefore, there are hours with very high charging power due to the synchronized charging of most BES or EVs deployed in the EC to benefit from the low retailer prices at certain day hours or fulfill EVs' mobility needs. However, in scenario two, the sum of charging powers is limited because the contracted power of the EC limits the peak of energy purchased from the retailer or sold to the retailer at any hour of the day. The figure shows that in the early hours of the day, there are hours with very high BES and EVs charging powers in scenario one. However, at the same hours, scenario two resulted in lower charging powers of BES and EVs. It can be noticed that this behavior happens on many days. BES and EVs charge in more hours in scenario two than in scenario one since they do not charge at the maximum charging power to respect the contracted power constraint.

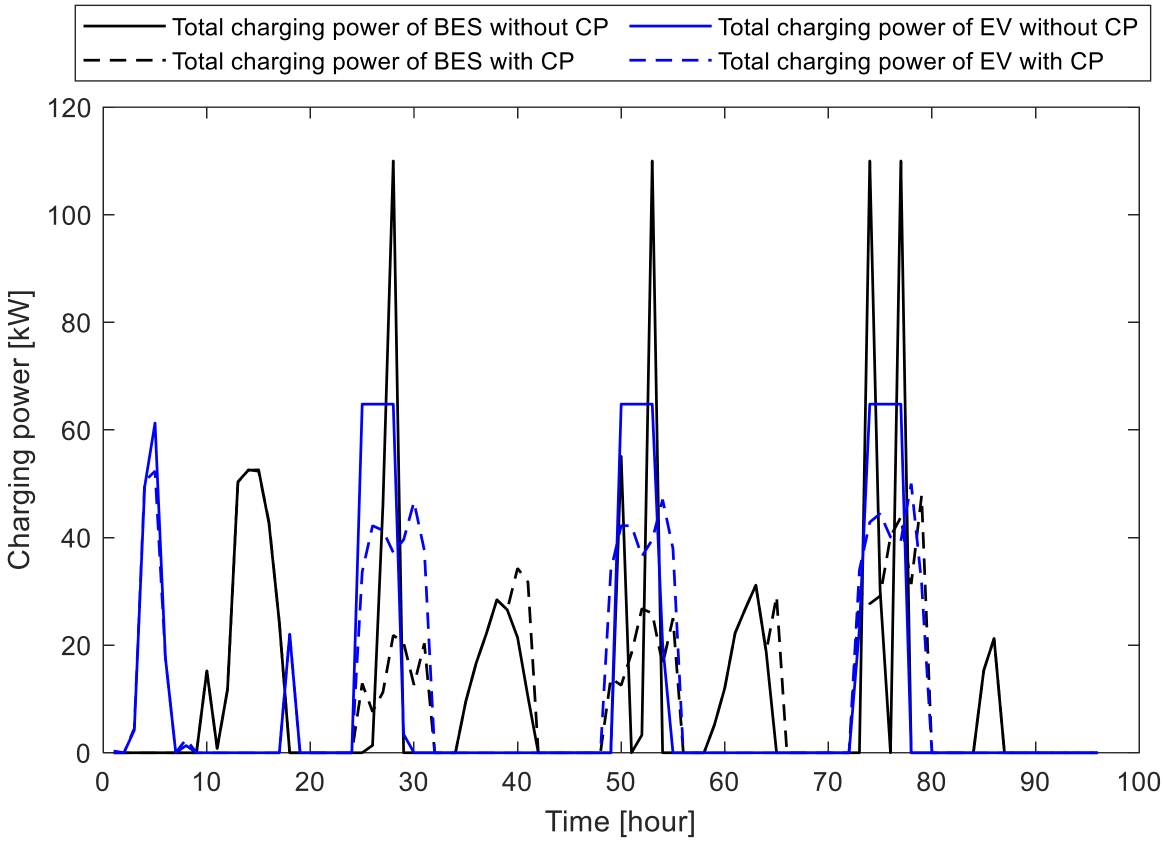

Figure 4.3. The aggregated charging powers of BES and EVs for four days.

4.4 Impacts of studied scenarios on low voltage distribution network

Similar to chapter 3, the net power demand of each house in the EC is determined from the first phase of the study (i.e., LET optimization) $P_{t,h}^{d}$ as given in (3.22) and is used as input to Pandapower software to run 3-phase load flow [124], [140]. The impacts of LET on LVDN transformer loading, lines loading, voltage unbalance, and voltage magnitude at all phases are evaluated for two scenarios.

Table 4.4 summarizes the impacts of LET scenario one (i.e., LET without CP) and scenario two (i.e., LET with CP) on LVDN. It demonstrates the maximum loading of the transformer, maximum loading of the line, maximum/minimum values of phase voltage, and maximum VUF.

Table 4.4. An overview of the impacts of LET on the studied distribution network.

	LET without CP (scenario one)	**LET with CP (scenario two)**
Max. loading of transformer [%]	37.02	24.56
Max. loading of line [%]	106.76	74.15
Max. value of Va [pu]	1.095	1.091
Min. value of Va [pu]	0.944	0.960
Max. value of Vb [pu]	1.081	1.093
Min. value of Vb [pu]	0.893	0.934
Max. value of Vc [pu]	1.078	1.078
Min. value of Vc [pu]	1.016	1.013
Max. VUF [%]	2.84	1.93

4.4.1 Impacts on the transformer and lines loading

Figure 4.4(a) displays the loading of the transformer for the studied scenarios in one month. For better clarity, Figure 4.4(b) depicts the first four days of the month. The loading of the transformer is low for both scenarios. However, Scenario one resulted in a higher loading (i.e., 37.02%) than scenario two (i.e., 24.56%), as shown in Table 4.4. The proposed approach decreased the transformer loading by 33.66%. The loading of the transformer reached the highest values on weekdays and recorded lower loading on weekends, similar to the line loading. Due to the consideration of contracted power cost in the EC objective function in scenario two, the transformer loading dropped.

The reason is that the energy exchanged with the retailer for the EC cannot go beyond the contracted power for that day. This proves the effectiveness of the proposed approach in minimizing the impacts of LET on transformer loading.

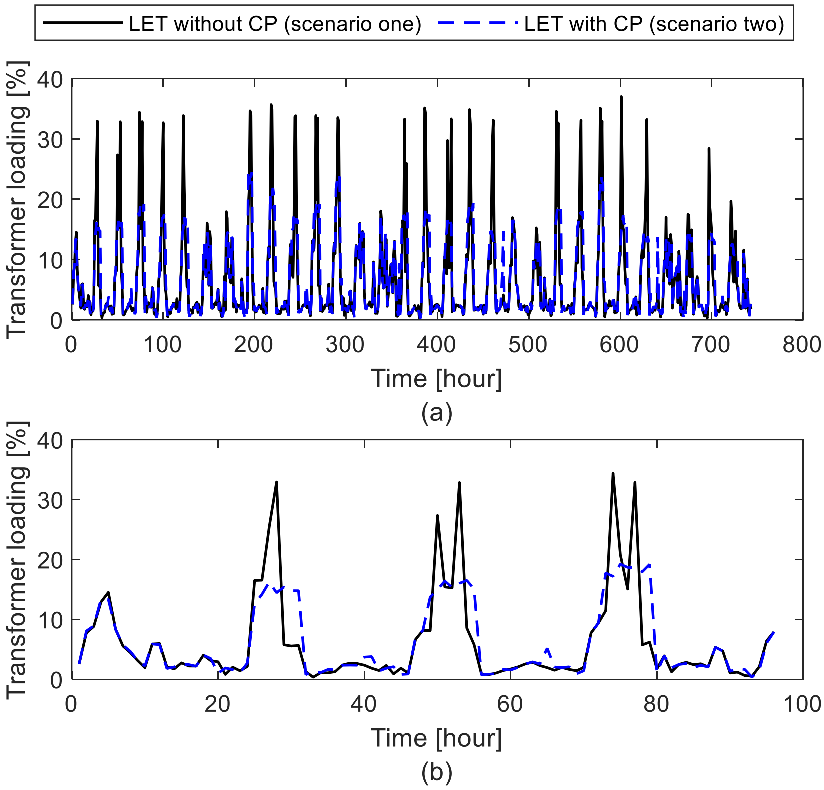

Figure 4.4. Loading of the transformer. (a) one month, (b) four days.

The lines of the studied LVDN have the same capacity. Therefore, the lines supplying a few houses are lightly loaded. However, the lines next to the LV side of the transformer have a higher loading because all of the EC houses' demand flows through them before they are divided at different feeders to supply a portion of EC houses. Figure 4.5(a) displays the line loading of a line located at the beginning of the LVDN for the studied scenarios in one month. For better clarity, Figure 4.5(b) depicts the first four days of the month. Scenario one resulted in a significantly higher line loading than scenario two. The line loading reached high values on weekdays and recorded lower loading on weekends. The reason is that the EC inflexible demand is lower on weekends than weekdays.

Moreover, the retailer energy prices have small variations throughout the day hours on weekends compared to weekdays, which have large variations in retail prices throughout the day. Therefore, on weekends, there are no hours with simultaneous charging of almost all EC BES and EV, which happens on weekdays and causes the high peak demand. The line loading of scenario one surpassed the maximum loading limit and reached 106.76%, while scenario two recorded 74.15% maximum line loading, as given in Table 4.4. The proposed approach decreased the line loading by 30.55%. In scenario two, line loading decreased because of considering the contracted power cost in the EC objective function. The imports or exports from the retailer to the EC can not exceed the contracted power on that day. This demonstrates the ability of the proposed approach to reduce the impacts of LET on line loading.

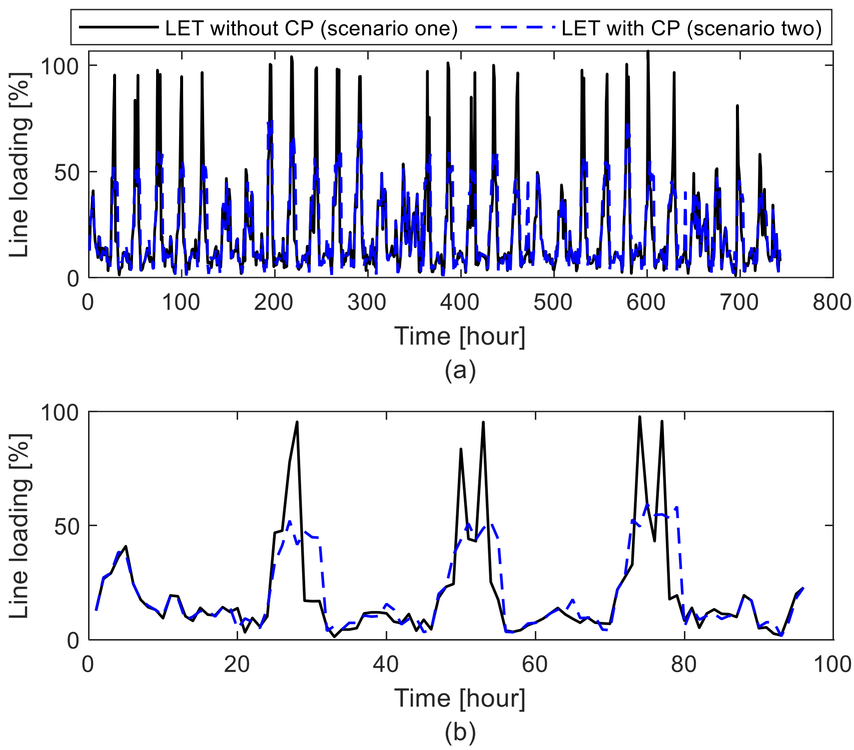

Figure 4.5. Loading of line. (a) one month, (b) four days.

4.4.2 Impacts on voltage deviations

Table 4.4 and Figure 4.6-Figure 4.8 illustrate that the voltage magnitude of different phases is within acceptable limits (i.e., 1.1 pu and 0.9 pu) for both scenarios, except for phase b, which surpassed the lower limit and reached 0.893 pu in scenario one. The voltage variation of phase a and phase b is higher on weekdays than on weekends, similar to the transformer loading and line loading. Moreover, scenario one shows more frequent large voltage deviations than scenario two, as shown in Figures 4.6(b) and 4.7(b).

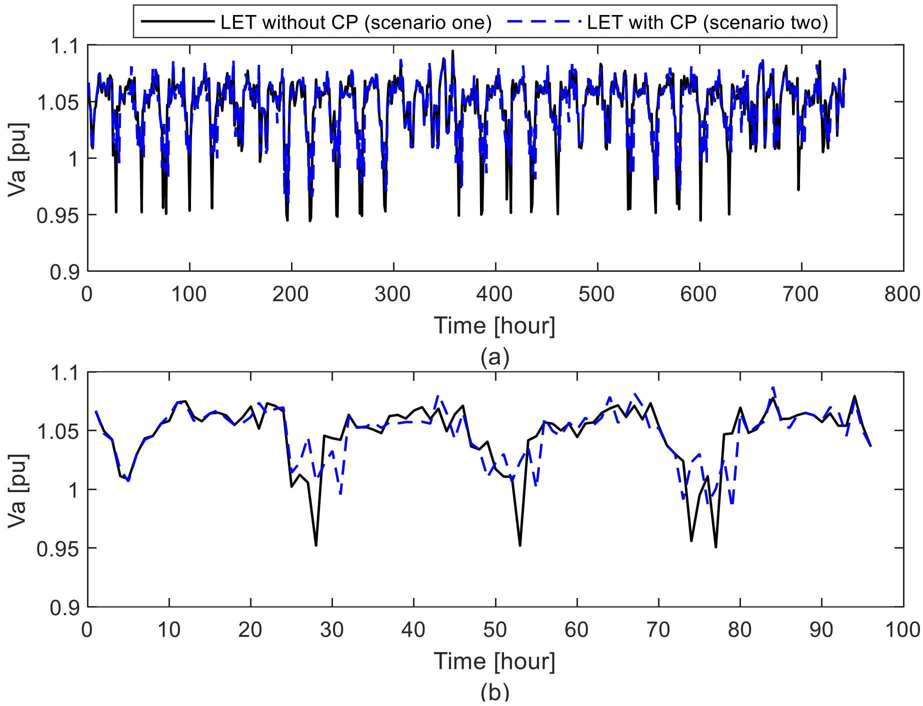

Figure 4.6. Voltage magnitude at phase a. (a) one month, (b) four days.

4.4.3 Impacts on voltage unbalance

The voltage unbalance must be maintained within acceptable limits at distribution networks. The VUF% readings shown in Figure 4.9 have been collected at the node of house 53, which is positioned at the end of a long feeder, at which substantial voltage variations are predicted. As illustrated in Table 4.4 and Figure 4.9, scenario one resulted in a higher VUF than scenario two. The

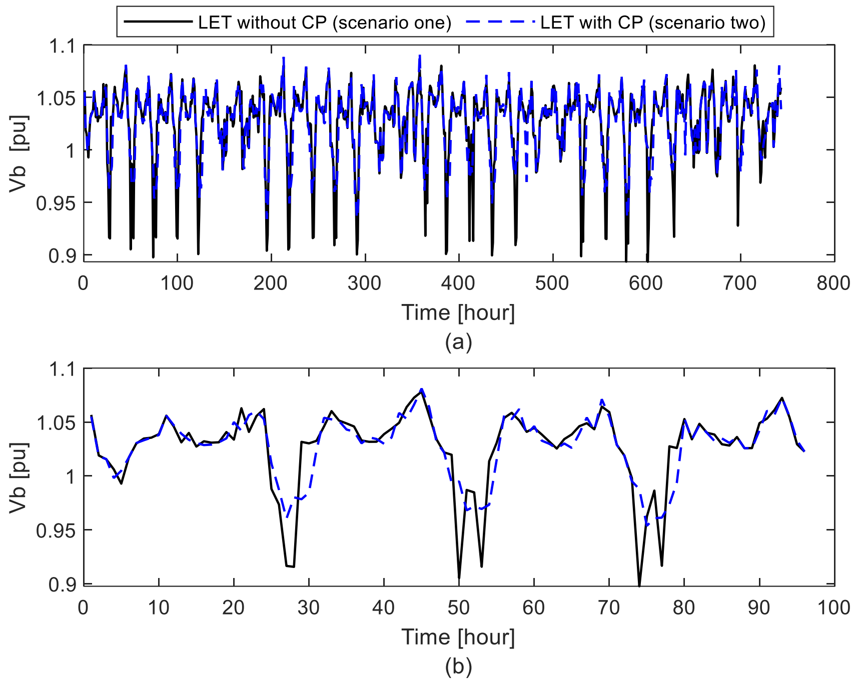

Figure 4.7. Voltage magnitude at phase b. (a) one month, (b) four days.

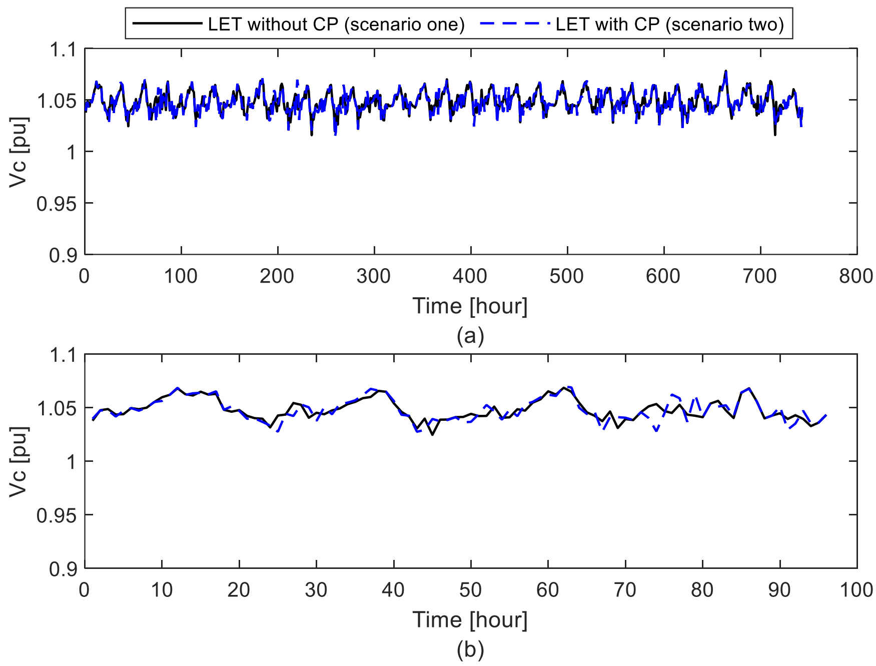

Figure 4.8. Voltage magnitude at phase c. (a) one month, (b) four days.

VUF of scenario one exceeded the acceptable limits (i.e., 2%) and reached 2.84%, while scenario two recorded 1.93%, which is within acceptable limits. The proposed approach decreased the VUF by 32%. The VUF reached the highest values on weekdays and recorded lower values on weekends, similar to the line loading and transformer loading. This proves the effectiveness of the proposed approach in minimizing the impacts of LET on voltage unbalance of LVDN.

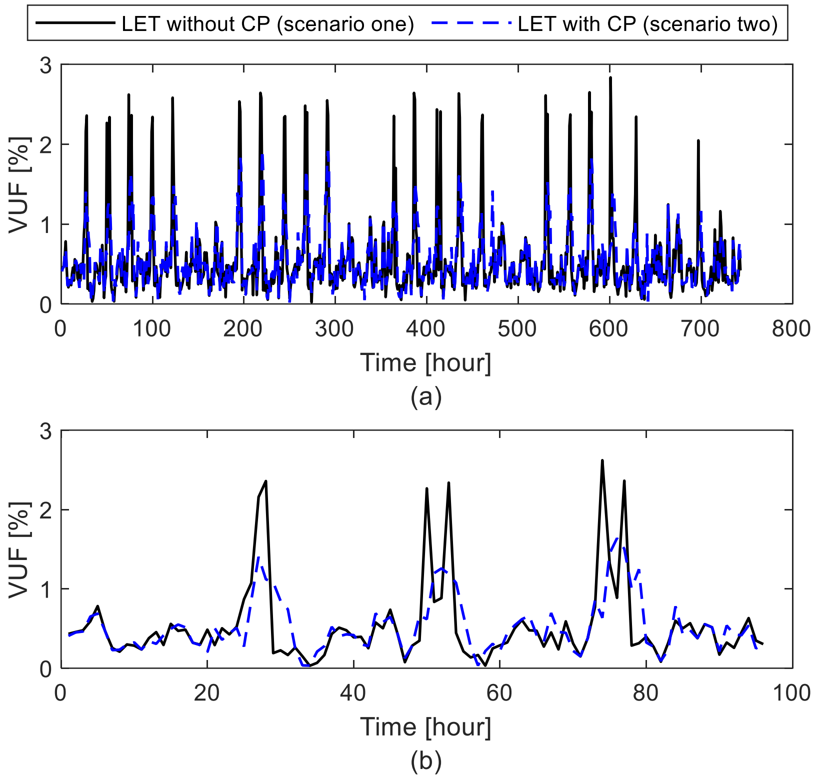

Figure 4.9. VUF(%). (a) one month, (b) four days.

4.4.4 Summary of impacts of local energy trading on LVDN considering contracted power costs

The preceding subsections offered a thorough examination of the impacts of LET on LVDN for two scenarios. This subsection presents a statistical evaluation of the line loading, transformer loading, voltage unbalance, and voltage variations over one month. The discussed findings showed that scenario one caused violations in line loading, VUF, and voltage magnitude deviations, as well as higher transformer loading than scenario two. Moreover, the proposed approach in scenario two effectively eliminated these violations and decreased the maximum transformer loading recorded during the month. Figure 4.10 depicts a boxplot representation of LET impacts on the studied distribution network for scenarios one and two.

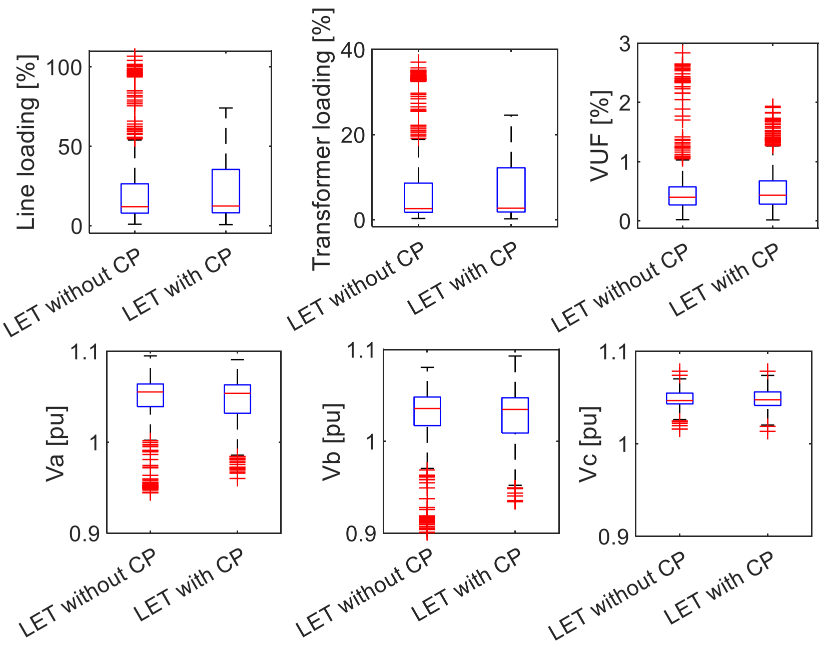

Figure 4.10. Boxplot representation of LET impacts on the studied distribution network.

The line loading of scenario one is usually below 60%, with outliers reaching 106.76%. The line loading of scenario two did not surpass 74.15%, with no outliers. The transformer loading of scenario one is usually below 20%, with outliers reaching 37.02%. The transformer loading of scenario two did not surpass 24.56%, with no outliers. The VUF of scenario one is usually below 1%, with outliers reaching 2.84%. The VUF of scenario two is usually below 1.3%, with outliers reaching 1.93%. The voltage magnitude of all phases is similar for both scenarios. However, in scenario one, phase a and phase b outliers reach lower values than in scenario two.

4.5 Conclusion

Chapter 3 has shown that when the low voltage distribution network (LVDN) limits are not considered, local energy trading (LET) can violate LVDN limits. This chapter suggests integrating contracted power cost in the LET objective function in addition to energy cost to minimize the impacts of LET on LVDN. The suggested approach does not necessitate the inclusion of LVDN limits in the LET model, which reduces the computation complexity and avoids interactions with the distribution system operator. The results demonstrated that when contracted power is included, the energy community's (EC) peak demand decreased by 34.3% for scenario two and decreased by 5.7% for scenario three compared to scenario one without impacting EC economic performance, energy exchange with the retailer, and the quantity of traded energy locally. Consequently, the suggested approach prevents LVDN limit violations in line loading, voltage unbalance, and voltage magnitude that occur in the LET scenario (i.e., scenario one) that does not take contracted power cost into account. The contracted power with limitations on peak vs. off-peak periods (scenario two) decreased the line loading by 30.55%, the transformer loading by 33.66%, and the VUF by 32%. These factors are crucial for incentivizing the development of cost-reflective network tariffs, as tariff design can effectively address significant technical challenges in distribution networks.

Chapter 5

Optimal Planning and Operation of Energy Community DERs Considering Local Energy Trading and Uncertainties

Local energy trading (LET) between customers in energy communities (ECs) received significant interest from academia and industry as a promising approach for managing a large number of distributed energy resources (DERs) and empowering end users to take an active role in energy systems. Most of the existing literature focuses on the operation of ECs, often with an implicit assumption about the ratings of the DERs, as in chapters 3 and 4. However, there is a noticeable lack of emphasis on optimizing the planning and integration of DERs within these ECs, enabling LET. Considering the high cost of DERs, there is a need to optimally size DERs of ECs' participants to maximize the benefits, minimize the expenses of DER owners, and reduce the payback period. In this chapter, a linear programming model is proposed for the optimal planning and operation of DERs installed in a residential EC in Spain, which includes photovoltaic (PV), battery energy storage (BES), and electric vehicles (EV). The objective is to minimize the EC's total annual costs, including investment, maintenance and operation (O&M), and operation costs (i.e., energy and contracted power costs). Furthermore, the proposed approach considers load demand, PV generation, electricity prices, and EVs uncertainties. The simulation results demonstrate that optimal planning reduces the annual costs by 10.95% compared to the scenario without optimal planning of PV and BES. Sensitivity analysis shows that, by decreasing the investment costs of BES, increasing the electricity prices, or decreasing the electricity selling price, it could be feasible to install BES at some of the EC houses. There are no violations of the distribution network limits in all studied scenarios.

Nomenclature

Positive variables	**Description**
$C^{\mathrm{PV,INV}}$	PV investment cost

$C^{\mathrm{PV,O\&M}}$	PV O&M cost
$C^{\mathrm{BES,INV}}$	BES investment cost
$C^{\mathrm{BES,O\&M}}$	BES O&M cost
C^{Retailer}	Retailer operation cost
$P_h^{PV,r}$	PV optimal size for house h
$E_h^{BES,r}$	Optimal energy capacity of BES for house h
$G_{t,h,s}$	Energy purchased from the retailer at instant t and state s for house h
$I_{t,h,s}$	Imports (purchase) from other houses (i.e., peers) to house h at instant t and state s
$X_{t,h,s}$	Exports (selling) to other houses (i.e., peers) from house h at instant t and state s
$F_{t,h,s}$	Energy sold to the retailer at instant t and state s from house h
$CP_{per,s}$	Contracted power at period per and state s
Parameters and scalars	**Description**
Co^{PV}	PV investment cost/kWp
$Co_{O\&M}^{PV}$	O&M cost/kWh generated from PV
$Co^{BES,C}$	BES energy capacity cost/kWh
CRF^{PV}	PV capital recovery factor
CRF^{BES}	BES capital recovery factors
$dem_{t,h,s}$	Demand at time t, house h, and state s
$P_{t,h,s}^{PV}$	PV production at time t, house h, and state s
$p_{t,s}^{b}$	Purchase price at instant t and state s
$p_{t,s}^{s}$	Selling price at instant t and state s
p_{per}^{cp}	Contracted power cost for period per
$P_{t,h,s}^{d}$	Net power demand at time t, house h, and state s
I_{MPP}	Current at the maximum power point
V_{MPP}	Voltage at the maximum power point
I_{SC}	Short circuit current
V_{OC}	Open circuit voltage
N	Number of PV modules
$I_{cell_{t,x}}$	Cell current at instant t and state x
$V_{cell_{t,x}}$	Cell voltage at instant t and state x
$T_{cell_{t,x}}$	Cell temperature at instant t and state x
T_A	Ambient temperature
R_{avs}	Average solar irradiance
N_{OT}	Nominal operating temperature
K_v	Voltage temperature coefficient
K_i	Current temperature coefficient
Sets	**Description**
$t \in T$	Time instant t in time horizon T
$h, p \in H$	House h and peers p in a community of H Houses
$s \in$ Ŋ	Ŋ is set of states for every time instant

5.1 Introduction

Electric power systems operated in a centralized manner for decades, where a large central generation connected to transmission networks supplied electricity to consumers connected to distribution networks (DNs). The money flow was unidirectional from consumers to generation plants. Currently, the structure of the power system and business model is undergoing massive changes due to the increasing deployment of distributed energy resources (DERs) such as small distributed generation, battery energy storage (BES), and potentially flexible devices such as electric vehicles (EV) and other flexible loads at the distribution level [3]–[5]. This increase in DER deployment is driven by the willingness to reduce electricity bills, environmental awareness, and the fast and continuous decay of DER costs due to technological developments, mass production, and governmental subsidies. In this new structure, consumers will take an active role in the power system, generating and storing electricity and actively participating in electricity markets. This will result in a more complex operation and control of power systems where a massive number of active participants should be coordinated for economical and reliable power system operation. Furthermore, the electricity and money flow are bidirectional in this new structure [7], [8].

Therefore, the optimal coordination of DERs received massive interest from research studies and pilot projects to enable the integration of a large number of DERs to maximize DERs owners' economic returns and comfort without compromising power system reliability and quality of supply [9]. One new approach to coordinate DERs is peer-to-peer energy trading (P2P-ET) or local energy trading (LET) [19]. LET tries to adapt the concepts of liberal wholesale electricity markets to the end consumer level [13]. The LET gives the customers an active role, where they can sell surplus energy to their neighbors (i.e., peers) in the energy community (EC) or sell it to the retailers if no neighbor is willing to buy. Consumers can also purchase energy from peers at a lower price than retailer price. By increasing the generation of renewable energy sources (RESs) besides consumption in the LET scheme, energy supplied by central conventional generation could be reduced, and local supply-demand balance could be achieved. This decentralization of the power system may provide novel means to lower the congestion of power system components and energy losses, which could postpone or eliminate the need for reinforcement at generation, transmission, and distribution levels. Moreover, LET could reduce electricity costs, increase self-generation, and increase the self-sufficiency of the ECs [15], [73].

On the other hand, the LET is associated with several challenges and barriers [4], such as the infrastructure upgrades at the distribution level like advanced smart metering, information and communication technology, participants' privacy concerns, lack of knowledge of end users about these new business models, etc. [8] Moreover, new regulations, pricing schemes, and business models should be developed to enable large scale adoption of LET. Furthermore, LET could impact the physical grid, especially the DNs, due to the power flow change and end users' energy utilization patterns [19], [69], [122]. All these challenges should be handled before LET becomes a reality and achieves a considerable adoption rate.

Photovoltaic (PV) generation is the most common renewable generation on a small scale due to its low cost and easy installation, which can fit any house or building. However, the PV peak generation is usually different from the local load peak, and the surplus energy could be fed back to the grid at low prices or curtailed to avoid grid issues. Moreover, the high penetration of PV generation could negatively impact the DNs [141]. Energy storage systems like BES are proposed as an effective technology to maximize the local consumption of PV generation, avoid curtailment, and minimize the energy fed to the grid [142]. Many countries promote self-generation by reducing incentives on electricity selling prices to retailers [143], [144]. Many studies proved the feasibility of BES for all stakeholders at the distribution level. In [20], the role of centralized and decentralized BES in an EC enabling LET was studied comprehensively, showing that the flexibility of BES resulted in a high-cost reduction to end users and the whole EC. Many other studies prove these findings [19]. However, these studies assume the capacities of the installed DERs in the EC.

The optimal planning of DERs received significant interest in existing literature considering different management approaches [145]–[148]. The optimal sizing of PV and BES for a house operating by a home energy management system is studied in [149] considering several electricity tariffs. The objective of the study is to minimize the energy cost of the house, and particle swarm optimization is used to find the optimal solution. Ref. [150] studies the optimal sizing of BES in microgrids considering several regulatory frameworks. Artificial bee colony optimization is used to find the optimal BES size to minimize the microgrid's total cost. Another study proposes a bi-level optimization model to find the optimal location and size of BES in a virtual power plant [151]. The results show a significant reduction of the installed BES costs obtained by optimal planning. Another study developed a model for optimal planning and operation of aggregated DERs to maximize the economic benefits of participating in electricity markets [148]. Other articles study the optimal sizing of isolated microgrids with various objectives [11], [152]. Besides academic studies, many tools have been developed to optimize the planning of DERs. Hybrid Optimization of Multiple Energy Resources (HOMER) is a software tool designed for modeling and optimizing microgrids and distributed energy systems. The software is widely used to design systems incorporating renewable energy sources, storage, and conventional power generation [153]. Another tool, the Distributed Energy Resource Customer Adoption Model (DER-CAM), is used to optimize the DER investments in buildings or microgrids [154].

The adopted DERs management approach affects the revenue streams of end customers. Therefore, there is a need to assess investment options considering different management approaches. The LET studies focused on the EC's operation costs (i.e., energy costs), and limited interest was given to the investment costs. For instance, there is a concern about BES' economic feasibility due to its high investment cost and low lifetime. Few articles studied the optimal planning of the DERs while considering LET. The energy trading participants could be microgrids, different types of buildings, houses, etc. In [155], particle swarm optimization (PSO) and game theory (GT) are used to find the optimal size of the DERs of clustered microgrids. These microgrids can trade energy between each other and with the main supply. The objectives are to minimize the probability of supply loss and maximize annual profit. The same authors conducted more studies about the optimal sizing of DERs in clustered microgrids [156], [157].

Furthermore, the authors in [158] proposed reinforcement learning (RL) for optimal long-term planning and short-term operation of shared community BES for a South Korean case study. The EC contains educational, residential, and commercial buildings. The objectives are minimizing peak demand, and maximizing self-sufficiency and annual profit. The study compared the economic feasibility of new BES and reused BES for this application. A bi-level optimization is developed in

[159] to minimize the cost of BES while maximizing the self-sufficiency of the EC that contains residential and commercial buildings. The study analyzed different operation conditions with different load demands, seasons of the year, and customers willing to install BES. Genetic algorithm (GA) is used to solve this problem. It was found that by increasing the installed BES capacity, the energy imported from the grid decreases until a threshold is reached. After this threshold, with the increase of BES capacity, the decrease in energy imports from the grid is negligible.

In [160], the authors used GA to find the optimal number and rating of BES installed in an energy community of commercial buildings using historical data from Japan. The study's objectives are maximizing BES profit, maximizing self-generation, and minimizing energy losses. The study compared the performance of having a centralized community BES and a decentralized private BES owned by individual community members. Ref. [161] used GA for optimal planning and operation of BES in university buildings in the USA. The buildings have PV installations and can trade energy locally. The objectives are maximizing BES's net present value (NPV) and minimizing EC energy costs.

Mixed integer linear programming (MILP) is used for optimal planning of PV and BES in an EC in Turkey, enabling LET between houses [162]. The objective of the study is to maximize the profit of the community. In [163], GT is used for optimal planning of DERs of an EC in Italy containing residential and commercial consumers. Due to the lack of demand profile data, the authors used data from Portugal. The study compared the performance of aggregated non-cooperative, non-cooperative, and cooperative games. Many objective functions were considered, such as maximizing NPV. Another study used GA for the optimal planning of PV installations in an EC of residential consumers in Spain and the optimal operation of the EC [164]. The objectives are maximizing profit and self-generation of locally generated energy from PV.

Table 5.1 compares the existing studies addressing the optimal planning of DERs in ECs considering LET. Obviously, most of the studies focused on ECs with buildings and did not consider RESs, electricity prices, and demand uncertainties. Moreover, most reviewed studies did not assess the effect of variations in BES and electricity prices on the optimal sizing of DERs. Furthermore, they focused on the optimal planning of DERs in EC and did not assess the impacts on DNs. In addition, the unbalanced nature of LVDN is not considered in any study of the reviewed literature focusing on optimal planning of ECs. The reviewed papers highlighted the research gap in optimal planning of ECs enabling LET that considered uncertainties, impacts on DNs, and the unbalanced nature of DN. Therefore, this chapter proposes a linear model for the optimal planning and operation of residential EC in Spain containing PV, BES, and EV while considering the uncertainties of solar irradiance, load demand, and electricity prices. Moreover, the impacts on unbalanced LVDN are assessed.

The contributions of this chapter can be summarized as follows:

- The first study of optimal planning of ECs enabling LET that considers PV, EV, electricity prices, and house demand uncertainties and the associated impacts on unbalanced LVDN.
- Sensitivity analysis of PV and BES optimal planning to cost of BES investments, electricity prices, and electricity selling prices.

The rest of this chapter is organized as follows. Section 5.2 introduces the planning and operation optimization model, and LVDN impacts assessment. Section 5.3 presents the case study details (i.e., buying and selling prices, contracted power prices, DERs characteristics, load profiles, studied LVDN, and uncertainties modeling). Section 5.4 discusses the findings of optimal planning and operation and evaluates the impacts on the unbalanced LVDN. Section 5.5 presents the conclusion.

5.2 Problem formulation

This section introduces the planning and operation optimization model and evaluation of LET impacts on LVDN.

5.2.1 Objective function

The objective of this study is to minimize the total annual costs of the studied EC, as stated in (5.1). The control variables of this objective function are the size of PV generation, the power rate of BES chargers, the energy capacity of BES, and many operation variables. In this study, objective function expected values f_{exp} are used to address the uncertainties of PV, house demands, and electricity buying and selling prices, as stated in (5.2). In this approach, every objective function is weighted according to every state probability of occurrence for all the considered planning period [165], [166].

Table 5.1. Comparison of existing studies addressing optimal planning of DERs installed in ECs considering LET.

Ref.	**Data**	**DERs**	**Participants**	**Algor-ithm**	**Objective**	**Grid impacts**	**Uncert-ainties**	**Unbalan-ced DN**
[155]	Australia	PV, WG, BES	Microgrids	PSO, GT	Min. loss of supply, max. annual profit	X	X	X
[158]	South Korea	PV, BES	Buildings	RL	Min. peak demand, max. self-sufficiency, annual profit	X	X	X
[159]	Synthetic	PV, HP, BES	Buildings	GA	Max. self-sufficiency, min. BES cost	✓	X	X
[160]	Japan	PV, BES	Buildings	GA	Max. BES profit, max. self-generation, min. losses	X	X	X
[161]	USA	PV, BES	Buildings	GA	Max. BES NPV, min. energy costs	X	X	X
[162]	Turkey	PV, BES	Houses	MILP	Max. profit	X	X	X
[163]	Italy, Portugal	PV, WG, BES	Residential, commercial	GT	Max. NPV	X	X	X
[164]	Spain	PV	Houses	GA	Max. profit, max. self-generation	X	X	X
Chapter 5	Spain	PV, BES, EV	Houses	LP	Min. annual costs	✓	✓	✓

$$min\, f \tag{5.1}$$

$$f_{exp} = \sum_{t\in T}\sum_{s\in Ŋ} f(t,s) \times \mathbb{C}(t,s) \tag{5.2}$$

where T is a set of time instants, $T = \{1, 2, 3, .., N_t\}$ and N_t represents the number of time instants. Ŋ is a set of states for every time instant t, $Ŋ = \{1, 2, 3, .., N_s\}$ and N_s represents the total number of the states every time instant. The combined probability of PV, house demand, and electricity prices is represented by $\mathbb{C}(t,s)$.

The total annual cost f calculated by (5.3) includes PV investment cost $C^{\mathrm{PV,INV}}$ (5.4), PV O&M cost $C^{\mathrm{PV,O\&M}}$ (5.5), BES investment cost $C^{\mathrm{BES,INV}}$ (5.6), BES O&M cost $C^{\mathrm{BES,O\&M}}$ (5.7), and retailer operation cost C^{Retailer} (5.8), which represents the energy cost and contracted power cost. CRF^{PV} and CRF^{BES} are capital recovery factors for PV and BES, respectively, and they are calculated by (5.9) and (5.10), respectively.

$$f = C^{\mathrm{PV,INV}} + C^{\mathrm{PV,O\&M}} + C^{\mathrm{BES,INV}} + C^{\mathrm{BES,O\&M}} + C^{\mathrm{Retailer}} \tag{5.3}$$

$$C^{\mathrm{PV,INV}} = CRF^{PV} \times \sum_{h\in H} P_h^{PV,r} \times Co^{PV} \tag{5.4}$$

$$C^{\mathrm{PV,O\&M}} = N_{days} \times \sum_{t\in T} \sum_{h\in H} \sum_{s\in \mathbb{S}} Co_{O\&M}^{PV} \times P_{t,h,s}^{PV} \times \mathbb{C}(t,s) \tag{5.5}$$

$$C^{\mathrm{BES,INV}} = CRF^{BES} \times \sum_{h\in H} E_h^{BES,r} \times Co^{BES,C} \tag{5.6}$$

$$C^{\mathrm{BES,O\&M}} = 0.02 \times C^{\mathrm{BES,INV}} \tag{5.7}$$

$$\begin{aligned} C^{\mathrm{Retailer}} = N_{days} \times \Big(&\sum_{per\in P} \sum_{s\in \mathbb{S}} p_{per}^{cp} \times CP_{per,s} \times \mathbb{C}(per,s) \\ &+ \sum_{t\in T} \sum_{h\in H} \sum_{s\in \mathbb{S}} \left(p_{t,s}^{b} \times G_{t,h,s} - p_{t,s}^{s} \times F_{t,h,s} \right) \times \mathbb{C}(t,s) \Big) \end{aligned} \tag{5.8}$$

$$CRF^{PV} = \frac{r(r+1)^{N^{PV}}}{(r+1)^{N^{PV}} - 1} \tag{5.9}$$

$$CRF^{BES} = \frac{r(r+1)^{N^{BES}}}{(r+1)^{N^{BES}} - 1} \tag{5.10}$$

where H is a set of houses, $H = \{1, 2, 3, .., N_h\}$ and N_h represents the number of houses in the EC. $P_h^{PV,r}$ is PV size for house h, and Co^{PV} is PV investment cost/kWp. N_{days} is equal to 365 (i.e., number of days/year), $Co_{O\&M}^{PV}$ is O&M cost/kWh generated from PV and is equal to 1 Cent/kWh of PV generation, $P_{t,h,s}^{PV}$ is generated power from PV at time instant t, house h, and state s. $E_h^{BES,r}$ is energy capacity of BES for house h, $Co^{BES,C}$ is BES energy capacity cost/kWh. BES O&M cost is equal to 2% of BES investment cost. p_{per}^{cp} is contracted power cost for period per, $CP_{per,s}$ is contracted power at period per and state s, $p_{t,s}^{b}$ is energy purchase price at time t and state s, $G_{t,h,s}$ is energy purchased from the retailer at time t and state s for house h. $p_{t,s}^{s}$ is the energy selling price at time t and state s, $F_{t,h,s}$ is energy sold to the retailer at time t and state s from house h. $r = 6\%$ for PV and BES, and it represents the interest rate. $N^{PV} = 20$ and $N^{BES} = 10$, and they define loan term [165].

5.2.2 Local energy trading operation constraints

This section presents a linear model for LET operation constraints. Recent research studies have presented a similar concept in detail for centralized LET [47], [55], [121]. The community aims to reduce contracted power costs and the expenses of energy purchases from the retailer while increasing the earnings of selling the EC's energy excess to the retailer, as given in (5.8). For the considered houses, the contracted power cost has two values for different hours of the day (i.e., peak and off-peak hours). Several constraints, such as the ones related to power balance at each house node (3.2), DER limits (3.3)-(3.15), LET in the EC (3.16)-(3.19), and contracted power limits (4.3) and (4.4), bound the operation cost function of EC. The equations are used in problem formulation in chapters 3 and 4, but in this chapter, the states $s \in \mathrm{Ŋ}$ are considered at each time instant.

5.2.3 Impacts of local energy trading on LVDN

Equation (5.11) is used to calculate each house's net power demand $P_{t,h,s}^{d}$ at time t and state s. $P_{t,h,s}^{d}$ is the input to Pandapower to run the three-phase load flow since the studied LVDN is unbalanced with different numbers of houses connected to each phase.

$$P_{t,h,s}^{d} = G_{t,h,s} + I_{t,h,s} - F_{t,h,s} - X_{t,h,s} \tag{5.11}$$

5.3 Low voltage distribution network and DER characteristics

The details about the LVDN utilized as a case study are presented in this section. Furthermore, the properties of the loads and DERs are described. Moreover, it presents the modeling of PV, demand, and electricity price uncertainties.

5.3.1 Low voltage distribution network and DERs characteristics

This chapter uses the unbalanced IEEE European test system that is used as a case study in chapters 3 and 4 [127]. The test network in this study contains flexible devices such as EV and BES, and RES such as PV. Any house may possess any or a mix of these DERs, while some houses do not have DERs connected. The PV penetration level is 60% of the EC houses (i.e., 33 PV). The BES penetration level is 40% (i.e., 22 BES). These penetration levels represent the houses willing to install PV and BES. The EV penetration level is 33% (i.e., 18 EVs). The DERs' characteristics are the same characteristics described in chapter 3.

In the studied EC, 33 houses are willing to install PV generation. A portion of the 33 houses that want to install PV generation (i.e., 22 houses) are also willing to install BES. The characteristics of PV [165] and BES [142] used in this study are given in Table 5.2. The optimizer finds the optimal size of PV and BES under their current investment costs and electricity prices in Madrid, Spain. The lower and upper limits of the PV size are zero and 5 kWp, respectively. The assumed upper limit of PV is based on the limited area available in houses and could be used to install a PV. The houses usually have limited space on the rooftop or in the yard to be used for PV installation. The lower and upper limits of the BES energy capacity are zero and 13.5 kWh, respectively. The lower and upper limits of the BES power capacity are zero and 5.4 kW, respectively.

Table 5.2. Characteristics of PV and BES used in optimization.

Index	PV	BES
Investment cost	550 (€/kW)	400 (€/kWh)
O&M cost	0.01 (€/kWh)	0.02 * all investment cost (€)
Lifetime (years)	20	10
Energy to power ratio	-	2.5

EVs departure is represented by a normal probability distribution function (pdf) with mean = 9 and standard deviation = 2. The number of EVs leaves at each hour is shown in Figure 5.1 in green. EVs arrival is represented by a normal pdf with mean = 18 and standard deviation = 2. The number of EVs that arrive at each hour is shown in Figure 5.1 in blue. At departure, the EV SoC must be ≥

75%, and when connected to the charger, it must be between 100% and 20%. The SoC of BES or EV at the last hour of the representative day must equal their initial SoC.

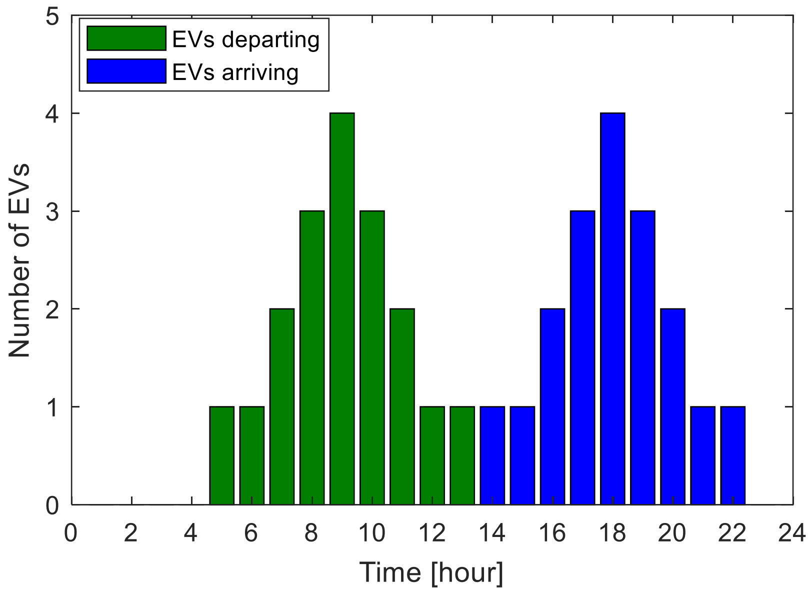

Figure 5.1. Number of electric vehicles departing or arriving at each hour of the day.

5.3.2 Modelling of PV generation, demand, and electricity prices uncertainties

The uncertainties of PV generation, house demand, and electricity prices are described in this section. Beta probability distribution function (pdf) is utilized to simulate hourly PV generation, while normal pdf is utilized to simulate hourly house demand and electricity prices [167].

5.3.2.1 PV generation modeling

The PV generation is highly uncertain because it depends on solar irradiance, which is difficult to forecast accurately. Therefore, a pdf is used to model this uncertainty. In this study, a Beta pdf is used to model the solar irradiance in the EC in every time instant t as given in (5.12). The data for PV generation for Madrid was acquired from Renewables Ninja over one year [130]. Figure 5.2 depicts a single house's normalized PV production profile for one representative day. The PV generation profile is the same for all houses in the EC.

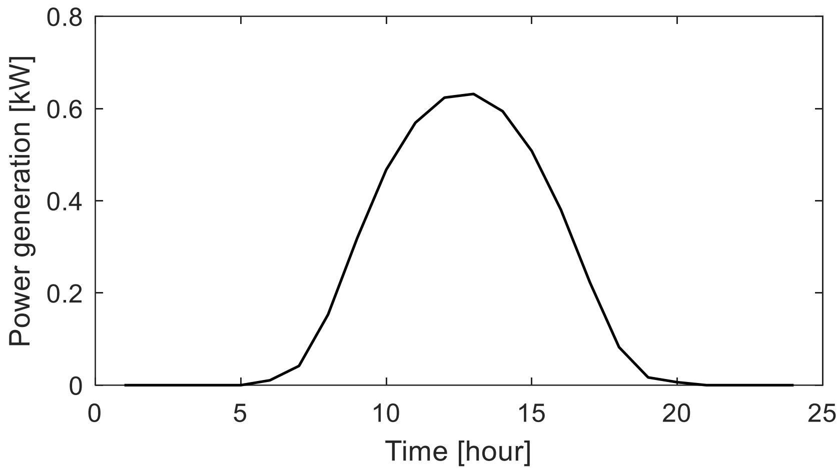

Figure 5.2. PV production of a single house for representative day.

$$f_b(R^t) = \begin{cases} \dfrac{\Gamma(\alpha^t + \beta^t)}{\Gamma(\alpha^t)\Gamma(\beta^t)} \times (R^t)^{(\alpha^t - 1)} \times (1 - R^t)^{(\beta^t - 1)}, & 0 \le R^t \le 1, \alpha^t, \beta^t \ge 0 \\ 0, & otherwise \end{cases} \tag{5.12}$$

where α^t and β^t could be calculated using μ^t (i.e., mean) and σ^t (i.e., standard deviation) of the solar irradiance R in every time instant t as given in (5.13) and (5.14).

$$\beta^t = (1 - \mu^t) \times \left(\frac{\mu^t \times (1 + \mu^t)}{(\sigma^t)^2} - 1\right) \tag{5.13}$$

$$\alpha^t = \frac{\mu^t \times \beta^t}{1 - \mu^t} \tag{5.14}$$

The probability of solar irradiance ($prob_R^t(G_x)$) for time instant t, and every state x could be determined by (5.15).

$$prob_R^t\{G_x\} = \int_{R_{x1}}^{R_{x2}} f_b\,(R^t).\,dR \tag{5.15}$$

PV generation of any house h in the EC for time instant t, and every state x could be calculated using (5.16)-(5.19).

$$P_{t,x}^{PV} = N \times \frac{V_{MPP} \times I_{MPP}}{V_{OC} \times I_{SC}} \times V_{cell_{t,x}} \times I_{cell_{t,x}} \tag{5.16}$$

Where

$$T_{cell_{t,x}} = T_A + R_{avs}\left(\frac{N_{OT} - 20}{0.8}\right) \tag{5.17}$$

$$I_{cell_{t,x}} = R_{avs}\left(I_{SC} + K_i\left(T_{cell_{t,x}} - 25\right)\right) \tag{5.18}$$

$$V_{cell_{t,x}} = V_{OC} - K_v \times T_{cell_{t,x}} \tag{5.19}$$

5.3.2.2 House demand modeling

The electricity demand of residential consumers varies from hour to hour and day to day and is highly uncertain. Therefore, pdf is used to model this uncertainty. This study uses a normal pdf to model the demand for EC houses, as given in (5.20). The houses demand profiles are anonymized real measurements with one-hour resolution from Madrid for one year, and they are given by i-DE, a Spanish DSO that belongs to Iberdrola Group. Figure 5.3 depicts the aggregated demand of all houses for one representative day. Each color represents one house.

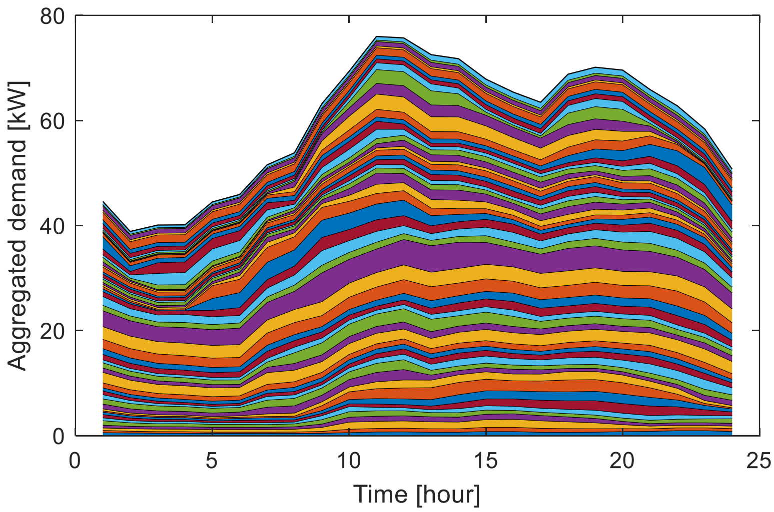

Figure 5.3. Aggregated demand of all houses for representative day.

$$f_n(l^t) = \frac{exp\left[-\frac{(l-\mu_l^t)^2}{2(\sigma_l^t)^2}\right]}{\sigma_l^t\sqrt{2\pi}} \tag{5.20}$$

The probability of load (i.e., demand) ($prob_l^t(G_u)$) for a time instant t and every state u could be determined by (5.21).

$$prob_l^t\{G_u\} = \int_{l_{u1}}^{l_{u2}} f_n(l^t).dl \tag{5.21}$$

5.3.2.3 Electricity price modeling

Normal pdf is used to model the uncertainty of energy buying price in Madrid as given in (5.22). The probability of electricity prices ($prob_b^t(G_y)$) for time instant t, and every state y could be determined by (5.23). Similarly, a normal pdf is used to model the uncertainty of energy export (i.e., selling) price in Madrid as given in (5.24). The probability of electricity prices ($prob_e^t(G_z)$) for time instant t, and every state e could be determined by (5.25). The Spanish pricing for selling or purchasing electricity to/from retailers is utilized in this study. The customers sell based on self-generation surplus energy price for the simplified compensation mechanism (PVPC) and purchase according to retailer tariff. The selling and purchasing prices were collected from Red Eléctrica (i.e., Spanish TSO) [131]. The retailer prices for one representative day corresponding to one year (i.e., 2022) are depicted in Figure 5.4. A 5% tax is considered for energy buying price [168]. Besides the energy cost, the electricity charges have a cost for the contracted power. For the considered houses, the contracted power costs have two values for different hours of the day (i.e., peak and off-peak hours). Table 4.2 in chapter 4 [168], [169] presents the contracted power costs. In reality, the houses can exceed the contracted power and pay a penalty. For simplicity, it is assumed that the contracted power is not exceeded.

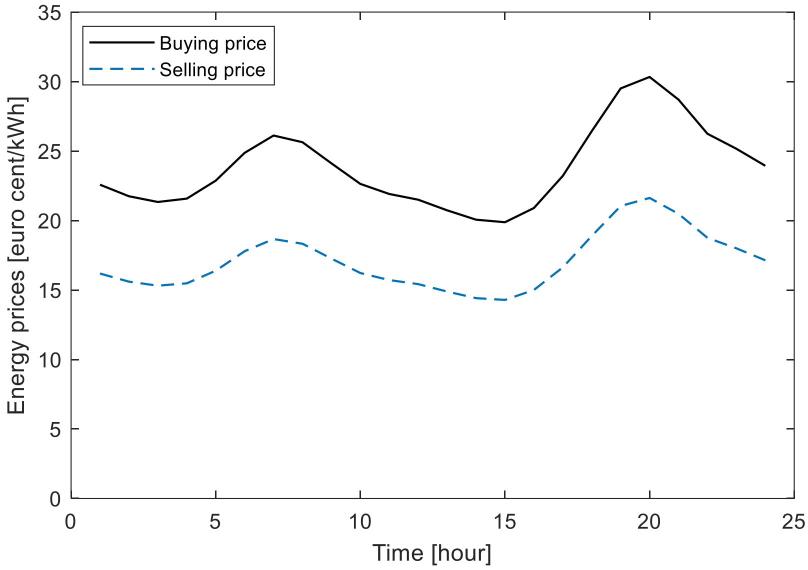

Figure 5.4. Houses purchase/sell prices from/to the retailer for representative day.

$$f_n(b^t) = \frac{exp\left[-\frac{(l-\mu_b^t)^2}{2(\sigma_b^t)^2}\right]}{(\sigma_b^t\sqrt{2\pi}} \tag{5.22}$$

$$prob_b^t\{G_y\} = \int_{b_{y1}}^{b_{y2}} f_n(b^t).db \tag{5.23}$$

$$f_n(e^t) = \frac{exp\left[-\frac{(l-\mu_e^t)^2}{2(\sigma_e^t)^2}\right]}{(\sigma_e^t\sqrt{2\pi}} \tag{5.24}$$

$$prob_e^t\{G_z\} = \int_{e_{z1}}^{e_{z2}} f_n(e^t).de \tag{5.25}$$

5.3.2.4 Combined model of PV generation, demand, and electricity prices

The combined model could be formulated as in (5.26), and it consists of a conjoined set of $prob_R^t(G_x), prob_l^t(G_u), prob_b^t(G_y)$, and $prob_e^t(G_z)$. It is obtained by taking into account all potential PV generation, demand, and electricity price combinations. Equation (5.27) represents the combined probability complete model (*ψ*). $\mathbb{C}(t,s)$ includes the elements of the combined model derived from the matrix λ.

$$\mathbb{C}(t,s) = prob_R^t\{G_x\} \times prob_l^t\{G_u\} \times prob_b^t\{G_y\} \times prob_e^t(G_z) \tag{5.26}$$

$$\psi = [\{\lambda_s, \mathbb{C}(t)\{\lambda_s\}\} : s = 1 : n_S] \tag{5.27}$$

5.4 Results and discussions

This section presents the results of optimal planning of PV and BES installed in the EC houses based on one representative day derived from one year of historical data of demand, PV generation, and electricity prices. Next, it presents a sensitivity analysis of the size of PV and BES with variations in BES price, electricity buying/selling prices, and electricity selling price. Then, the techno-economic performance of three scenarios is discussed. Finally, the assessment of the impacts of three scenarios on unbalanced LVDN is presented.

5.4.1 Optimal size and operation of PV and BES in the energy community

The optimal size for PV is 5 kW for all houses willing to install PV generation (i.e., 33 houses). However, the optimal sizes of BES kWh energy capacity and charger kW capacity are zero for all 22 houses willing to install BES under the current electricity prices and BES prices. The findings show the economic feasibility of installing PV in the studied EC. On the other hand, it shows the lack of economic feasibility of installing BES in the studied EC.

5.4.2 Sensitivity analysis

The obtained optimal sizes of PV and BES could change with the variation of several parameters, such as BES investment costs, electricity buying/selling price, and electricity selling price. BES costs are decreasing continuously due to technological developments and mass production. Moreover, many countries provide subsidies and incentives for BES to increase their adoption and increase BES's economic viability for end users [142]. Moreover, many countries' electricity buying/selling prices vary significantly for various reasons, such as political conflicts, changes in taxes, etc. Furthermore, many countries decreased the energy selling price to retailers by reducing support schemes. Therefore, this section provides a sensitivity analysis of the optimal size of PV and BES with the decrease in BES price, increase in electricity buying and selling prices, and decrease in selling price only.

5.4.2.1 Sensitivity analysis with the decrease of BES investment costs

Figure 5.5 shows the optimal energy capacities of BES in kWh for 22 houses with the decrease of BES investment costs from the current price (i.e., 1 pu) to 10% of the current price (i.e., 0.1 pu). Moreover, The optimal power capacities of the installed BES charger in kW for 22 houses with the decrease of BES investment costs from the current price can be calculated by multiplying the BES energy capacity by 0.4 (since the BES has a 2.5 energy to power ratio) as illustrated in Table 5.2.

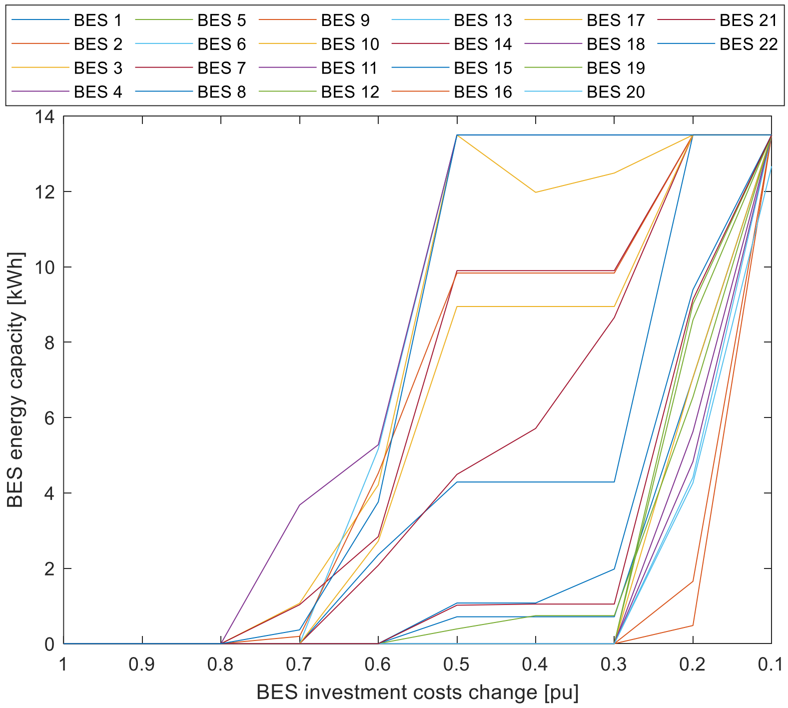

Figure 5.5. Sensitivity analysis of the optimal size of BES to decrease of BES investment costs.

The figure shows that it is economically viable for some houses to install BES when the BES price reaches 0.7 pu of its current price. In addition, the optimal values of the energy capacity of BES increase with the decrease in BES investment prices. The optimal BES energy capacities for all the houses reach the maximum limit (i.e., 13.5 kWh) when the investment costs reach 0.1 pu of the current price.

5.4.2.2 Sensitivity analysis with the increase in electricity buying and selling prices

The optimal energy capacities of BES in kWh with the increase of electricity prices from the current prices (i.e., 1 pu) to 2 pu of the current price are shown in Figure 5.6. The figure shows that it is economically viable for some houses to install BES when electricity prices reach 1.4 pu of the current prices. In addition, the optimal values of BES's energy capacity increase with the increase in electricity prices. The optimal BES energy capacities do not reach the maximum limit for all the houses except three houses. It is not economically viable for a few houses to install BES, even with a 200% increase in electricity prices. These houses have low demand at hours with no PV generation, which makes it more economical to cover their demand at this period from other houses in the EC or retailer compared to installing BES.

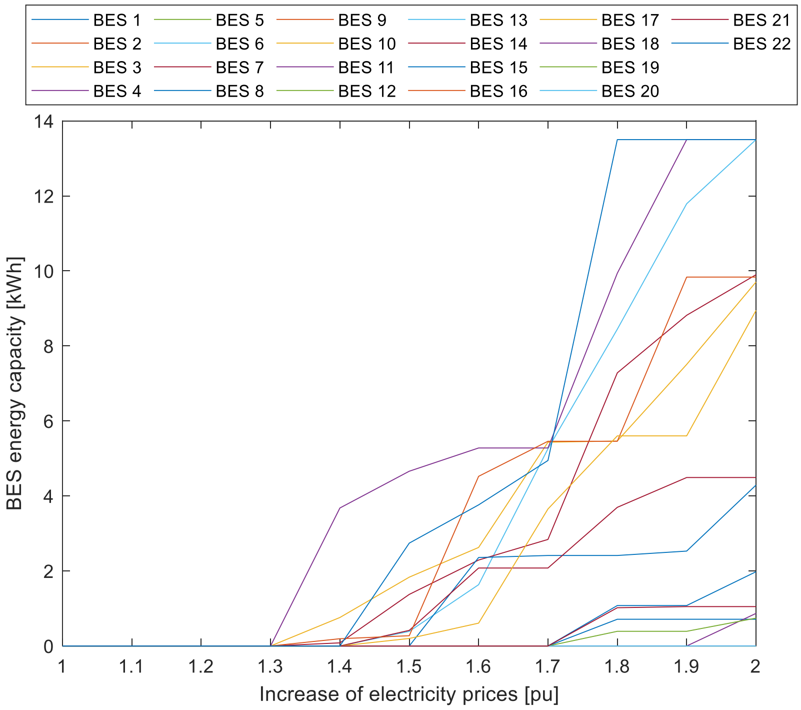

Figure 5.6. Sensitivity analysis of the optimal size of BES to increase of electricity buying and selling prices.

5.4.2.3 Sensitivity analysis with the decrease in electricity selling price

The optimal energy capacities of BES in kWh with the decrease of electricity selling price from the current price (i.e., 1 pu) to zero electricity selling price are shown in Figure 5.7. The figure shows that it is economically viable for some houses to install BES when the electricity selling price reaches 0.6 pu of the current price. In addition, the optimal values of BES's energy capacity increase with the decrease in electricity selling price since it becomes more economical to install BES to maximize the house self-generation and trade energy locally instead of selling it to retailers at low prices.

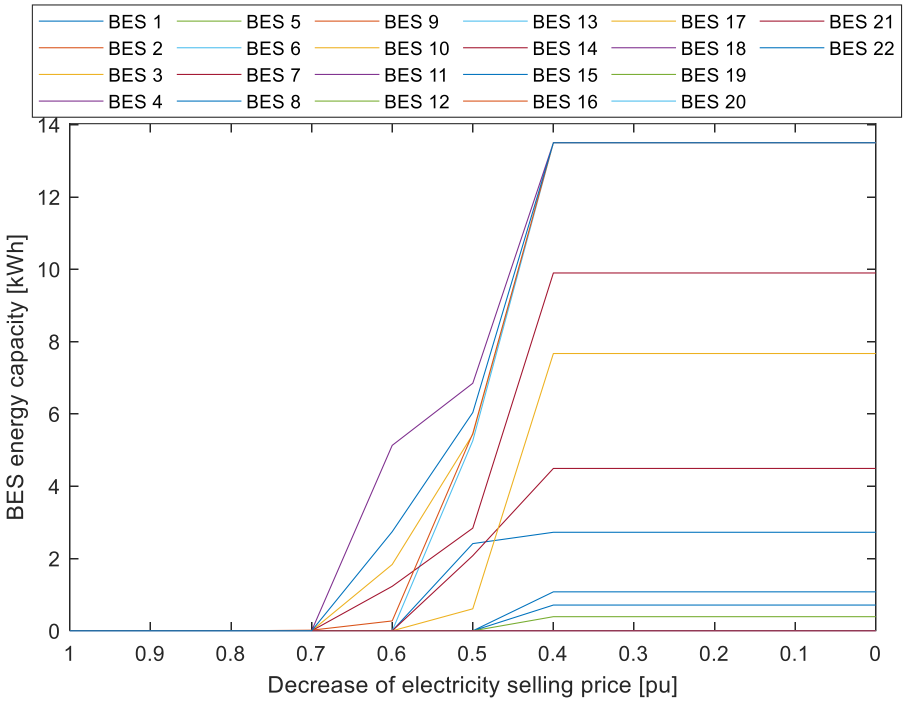

Figure 5.7. Sensitivity analysis of the optimal size of BES to decrease of the electricity selling price.

The capacities of installed BES in the EC do not change with the decrease of price beyond 0.4 pu. The optimal BES energy capacities reach the maximum limits for a few houses and do not reach the maximum limits for most houses. Moreover, it is not economically viable for a few houses to install BES even with zero electricity selling price. These houses have low demand at hours with no PV generation, which makes it more economical to cover their demand at this period from other houses in the EC or retailer compared to installing BES.

For PV generation, the optimal size is always 5 kW for the 33 houses willing to install PV generation, considering the changes in BES prices, electricity buying/selling prices, and electricity selling price. This shows the economic viability of installing PV generation in the studied EC under different variations in operating conditions.

5.4.3 Techno-economic comparison of studied scenarios

This subsection offers insights into the economic feasibility of optimizing energy systems and the potential impact of cost reductions in enhancing the adoption of energy technologies. Based on the sensitivity analysis in section 5.4.2, three scenarios are defined to analyze the techno-economic performance of residential ECs under different conditions: no optimization of DERs size, optimization of DERs size, and optimization of DERs size with a significant reduction in BES costs.

Scenario 1: No optimal planning. In this scenario, the PV size is 5 kWp, the BES energy capacity is 13.5 kWh, and the power capacity of the BES charger is 5.4 kW. The installed DERs in each house are given in Table 3.2 in chapter 3. LP is used for the optimal operation of EC, considering operational limits (3.2)-(3.19). The objective is to minimize the costs of contracted power and energy purchase while maximizing energy sales revenues (i.e., retailer operation costs) as given in (5.8).

Scenario 2: Optimal planning. In scenario two, LP is used to find the optimal size of PV and BES to minimize the total annual cost of EC, as represented by (5.3), considering EC operational limits (3.2)-(3.19). The total annual costs include investment costs, O&M costs, and retailer operation costs. This scenario represents the current electricity prices and investment costs of PV and BES.

Scenario 3: Optimal planning with 0.5 pu BES cost. In scenario two, LP is used to find the optimal size of PV and BES to minimize the total annual cost of EC, as represented by (5.3), considering EC operational limits (3.2)-(3.19). This scenario represents the current electricity prices and investment costs of PV. However, it considers a 50% reduction of BES investment costs. This cost reduction could be achieved through government subsidies or BES technological developments. The optimal values of PV and BES for this scenario are given in Table 5.3. These optimal values are used in the simulation. However, practically, the house owner could install a BES available on the market with capacities near the optimal values obtained. The table shows that installing PV generation at all houses willing to install PV is economically viable. Moreover, it is economically viable for some houses to install BES when the BES investment cost reaches 0.5 pu of its current cost.

Table 5.4 shows a comparison of the three scenarios in terms of energy exchanges with the retailer, energy traded locally between EC houses, the percentage of demand covered by the retailer or EC DERs, and EC costs and revenues. Scenario 3 has the lowest imports from the retailer, followed by Scenario 1, and Scenario 2 has the largest imports from the retailer. The presence of BES enables effective usage of PV generation and decreases the imports from the retailer. Scenarios 1 and 3 do not sell any energy to the retailer since each house uses its generation locally or sells to other houses within the EC by taking advantage of BES and EV flexibility. Scenario 1 has the lowest amount of energy traded locally since the large BES enables houses to store large amounts of PV generation to cover their own demand or sell it within EC at different hours of the day. Scenario 2 has a slightly higher amount of energy traded locally than scenario 1 because there are no BES installed and the surplus PV generation can be stored in EVs if they are connected or sold to other houses or sold to the retailer. The highest amount of energy traded locally is achieved in scenario 3. Scenario 1 and Scenario 3 cover a larger percentage of demand by EC DERs than Scenario 2 by taking advantage of BES flexibility to store the PV generation and use it for the house's own demand or local trade of energy.

The proposed approach in Scenario 2 reduced the total costs (i.e., costs of investments, O&M, and retailer) by 10.95% compared to Scenario 1. For fairness, the total costs of scenario 3 are not compared with other scenarios because it represents a 50% reduction in BES price, which will result in lower total costs. Scenario 1 has the lowest operation costs (i.e., retailer costs) of EC since the houses use their large BES to cover their demand and sell their surplus energy to other houses in the EC. Moreover, the large BES enables buying a large amount of energy from the retailer at hours with low prices and using the stored energy to cover the house demand or sell it within EC. Scenario 3 has a lower operation cost (because some houses have BES) than Scenario 2 at which no BES are installed in the EC. Scenario 2 has gained revenues from selling surplus energy to retailers. However, Scenario 1 and Scenario 3 have no revenues from selling energy to the retailer because no energy is sold to the retailer for these scenarios because the installed BES enables better utilization of PV generation.

Table 5.3. Optimal PV and BES capacities for scenario 3 (i.e., optimal planning with 0.5 pu BES cost).

Optimal capacity of PV generation (kW)										
H1	**H2**	**H3**	**H5**	**H7**	**H8**	**H9**	**H12**	**H15**	**H16**	**H18**
5	5	5	5	5	5	5	5	5	5	5
H20	**H23**	**H24**	**H25**	**H27**	**H30**	**H32**	**H33**	**H34**	**H37**	**H39**
5	5	5	5	5	5	5	5	5	5	5
H40	**H41**	**H43**	**H45**	**H48**	**H49**	**H50**	**H52**	**H53**	**H54**	**H55**
5	5	5	5	5	5	5	5	5	5	5
Optimal energy capacity of BES (kWh)										
H1	**H2**	**H3**	**H5**	**H9**	**H12**	**H15**	**H18**	**H20**	**H23**	**H27**
0.71	0	13.5	0	0	13.5	9.9	4.29	0	0	13.5
H30	**H33**	**H37**	**H40**	**H45**	**H48**	**H50**	**H52**	**H53**	**H54**	**H55**
0	0	4.5	1.08	9.84	8.95	0	0.39	0	1.02	13.5
Optimal power capacity of BES charger (kW)										
H1	**H2**	**H3**	**H5**	**H9**	**H12**	**H15**	**H18**	**H20**	**H23**	**H27**
0.29	0	5.4	0	0	5.4	3.96	1.72	0	0	5.4
H30	**H33**	**H37**	**H40**	**H45**	**H48**	**H50**	**H52**	**H53**	**H54**	**H55**
0	0	1.8	0.43	3.93	3.58	0	0.16	0	0.41	5.4

Table 5.4. Comparison of the three studied scenarios.

	LET without optimal planning (Scenario 1)	**LET with optimal planning (Scenario 2)**	**LET with optimal planning with 0.5 pu BES cost (Scenario 3)**
Imports from retailer (kWh)	313689.11	336807.37	311392.96
Exports to retailer (kWh)	0	29645.68	0
Total LET (kWh)	128870.46	129666.53	152849.61
Demand by retailer (%)	60.07	64.49	59.63
Demand by DERs (%)	39.93	35.51	40.37
Total costs (€)	101441.34	90328.65	-
Optimal planning cost reduction (%)	-	10.95	-
Total operation Costs (€)	74507.09	79858.34	76773.69
Costs of imports from retailer (€)	74507.09	84246.26	76773.69
Revenue of exports to retailer (€)	0	4387.92	0

Figure 5.8(a) shows that EC energy imports from the retailer are very similar in the first hours of the day for scenarios 2 and 3, and scenario 1 has lower imports. All scenarios take advantage of the low energy prices during early days hours and the low cost of contracted power during off-peak period. The energy imports are used to cover EC inflexible demand and to charge flexible devices, mainly EVs that must have more than 75% SoC when they leave houses for mobility. Scenarios 2

and 3 have higher imports from the retailer at the first 5 hours than scenario 1 because they have a higher charging power of EVs as illustrated in Figure 5.9. EVs use this energy to satisfy mobility needs at departure time and avoid buying energy at high prices from the retailer or selling it to other houses in the EC. Starting from hour 5, the EC energy imports are reduced for all scenarios by using PV generation and energy stored in flexible devices to avoid buying from the retailer at high prices. In scenario 1, EC imports a large amount of energy from the retailer after mid-day to charge BES at hours with low energy prices. In late afternoon hours and night hours, the imports increase again for all scenarios because the PV generation decreases, and EVs arrive at houses and are connected to the

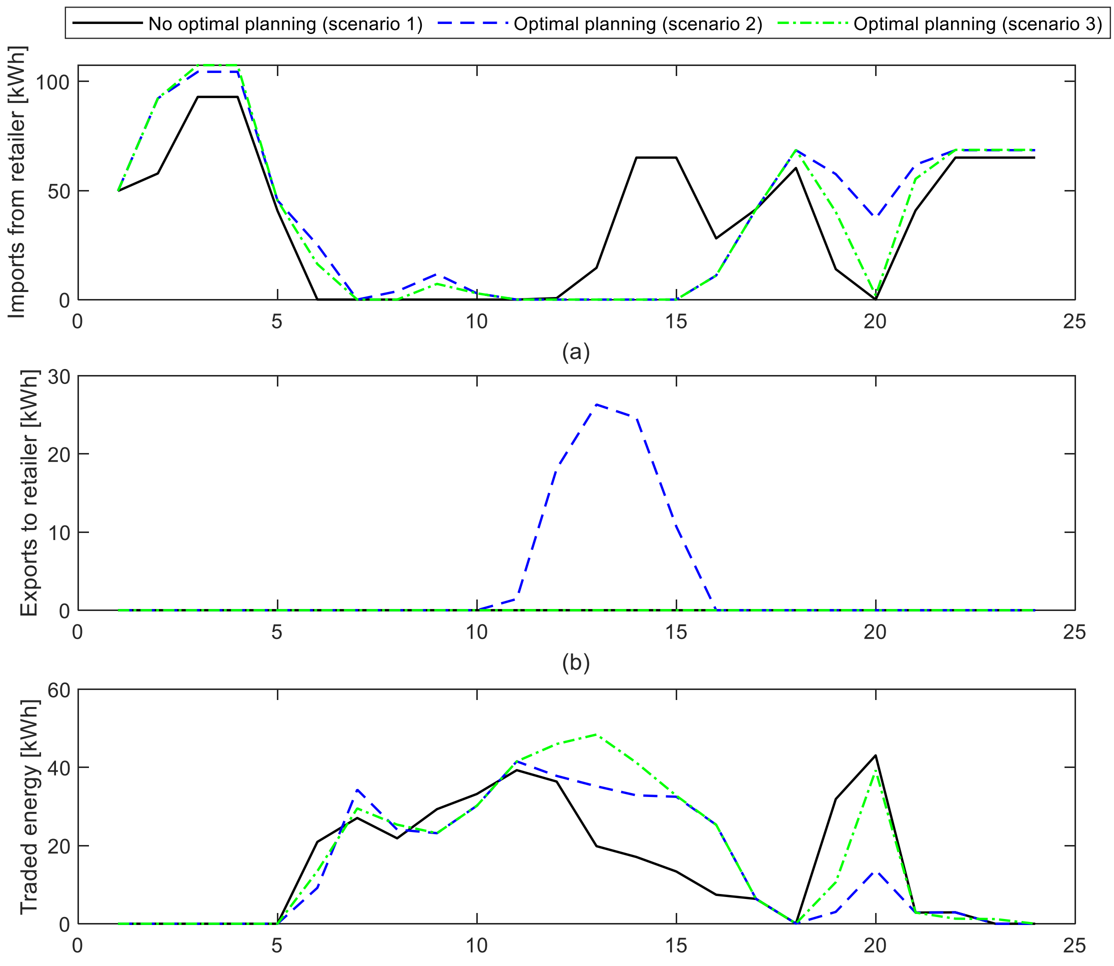

Figure 5.8. Comparison of the three scenarios in terms of energy exchange with retailer and locally traded energy.

grid for charging. The energy imports decreased around hour 20 because of the high electricity price. The EC houses take advantage of flexible devices to decrease or avoid buying energy from the retailer. The flexible devices discharge at these hours, as shown in Figure 5.9.

Figure 5.8(b) shows that in scenario 2 the EC sells surplus PV generation to the retailer because there are no BES installed, and EVs are used for mobility for most of the hours with high PV

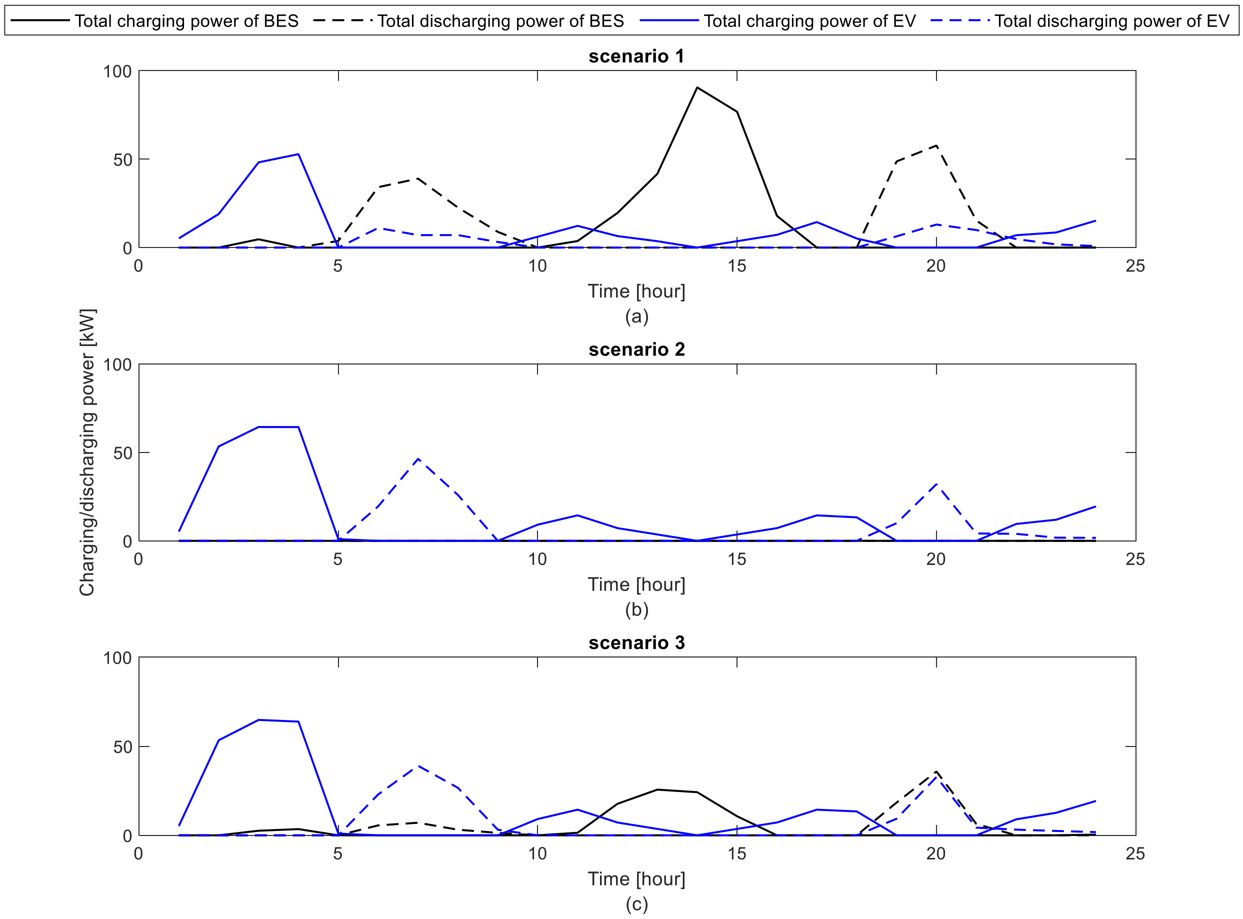

Figure 5.9. Total charging/discharging power of BES and EVs for the three scenarios.

generation. On the other hand, the presence of BES in scenarios 1 and 3 enables the use of PV generation within EC, and no energy is sold to the retailer, as shown in Figure 5.9. Figure 5.8(c) shows that for Scenarios 2 and 3 most of the local energy trade occurs at hours with high PV generation, and some energy is traded at night hours by energy stored in flexible devices. Scenario 1 has similar behavior to other scenarios, but the local energy traded in early morning hours (with low PV generation) PV generation hours are lower than other scenarios and night hours are larger than other scenarios due to the large capacities of installed BES that enable storing larger amounts of energy compared to other scenarios to cover the house demand at other hours or selling it locally to achieve the highest economic benefits.

5.4.4. Impacts on low voltage distribution network

The widespread deployment of DERs and transportation electrification might lead to exceeding grid limits. This subsection evaluates the effects of the three investigated scenarios on the LVDN's transformer loading, line loading, voltage unbalance, and variation of phases' voltage magnitude for the representative day. Pandapower is used to run a 3-phase load flow due to the unbalanced nature of the LVDN under study.

5.4.4.1 Impacts on transformer loading, line loading, and voltage unbalance

Table 5.5 and Figure 5.10(a) show that the MV/LV transformer supplying the EC has a very low loading in the three scenarios. Scenario 3 recorded a slightly higher transformer loading than the other two scenarios. The highest loading is recorded at the first hours of the day due to the simultaneous charging of EVs in the EC. The loading of a line connected directly to the LV side of the transformer is evaluated because all of the EC energy imported from the retailer flows through this line. The line is lightly loaded, and scenario 3 recorded a higher line loading than the other two scenarios, as shown in Table 5.5 and Figure 5.10(b). Most of the lines in LVDN have lower loading than the values presented because they supply a percentage of EC houses, and all lines of the studied LVDN have the same current rating.

VUF is used to evaluate the unbalance between phases of LVDN. VUF is within limits (i.e., less than 2%) for the three scenarios. However, the VUF value in scenario 1 is higher than the other two scenarios, as shown in Table 5.5 and Figure 5.10(c). The VUF in scenario 1 has high values at hours when there are simultaneous charging or discharging of EC flexible devices. In scenario 2,

Table 5.5. Summary of impacts on LVDN.

	LET without optimal planning (Scenario 1)	LET with optimal planning (Scenario 2)	LET with optimal planning with 0.5 pu BES cost (Scenario 3)
Maximum transformer loading [%]	12.93	14.88	15.19
Maximum line loading [%]	36.48	42.50	43.13
Maximum VUF [%]	0.89	0.65	0.60
Lowest value of Va [pu]	1.010	1.003	1.002
Highest value of Va [pu]	1.061	1.066	1.067
Lowest value of Vb [pu]	0.999	0.998	0.999
Highest value of Vb [pu]	1.087	1.072	1.074
Lowest value of Vc [pu]	1.018	1.023	1.021
Highest value of Vc [pu]	1.061	1.056	1.059

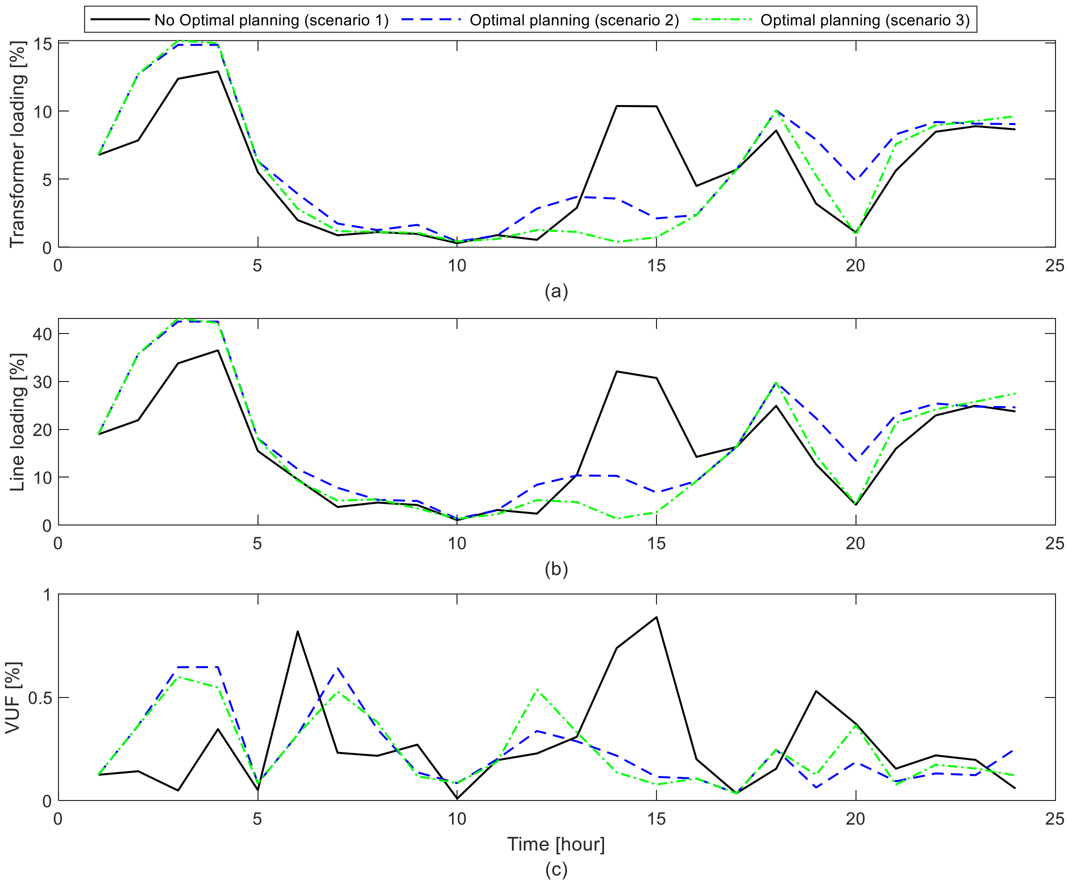

Figure 5.10. impacts on LVDN. (a) transformer loading, (b) line loading, (c) voltage unbalance factor.

there is no BES installed, and in scenario 3 there is less BES installed and with lower capacities compared to scenario 1, which prevents or reduces the effect of simultaneous charging or discharging. However, in scenario 1, the customers simultaneously exploit the larger BES energy and power capacities installed.

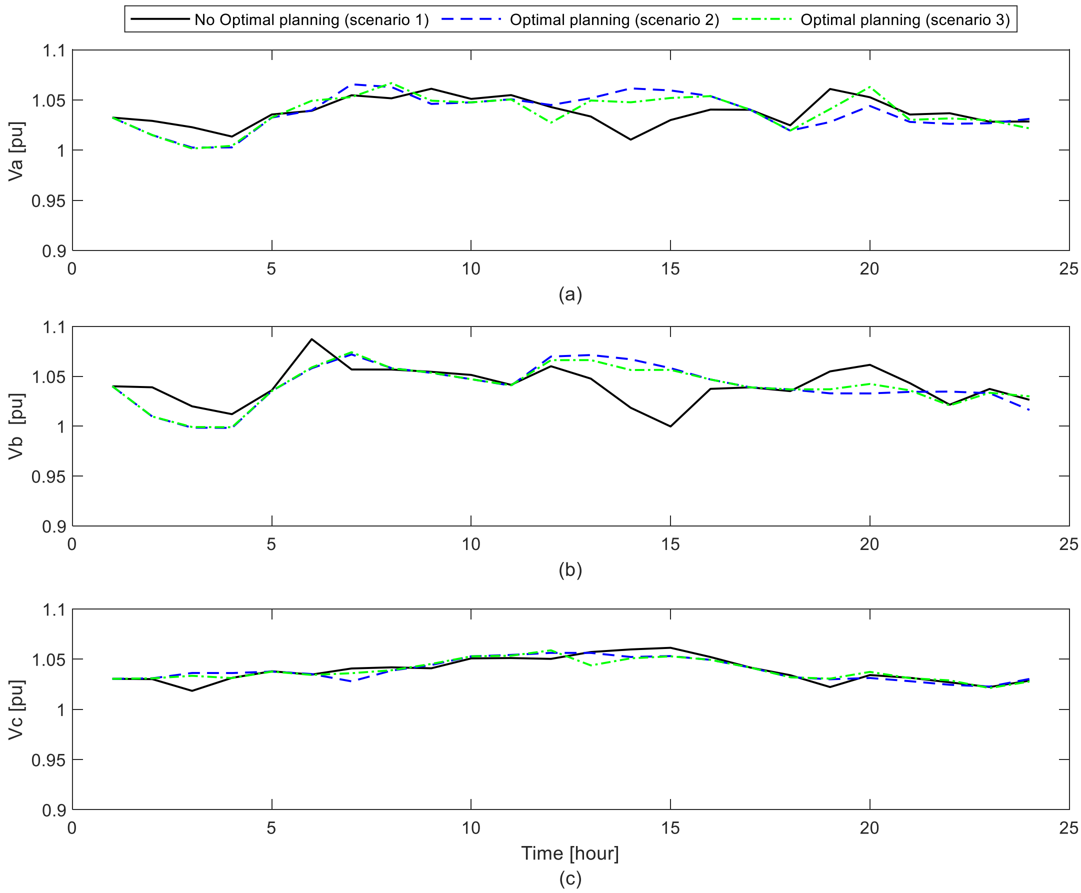

Figure 5.11. Variations of phases voltage magnitude. (a) phase a, (b) phase b, (c) phase c.

5.4.4.2 Impacts on voltage deviations

The effect of three studied scenarios on the variation of voltage magnitudes at the LVDN end node is evaluated in this subsection. The given voltage was measured at the house 53 node, which is at the line end and is likely to experience substantial voltage variations. Due to the unbalanced nature of the network under study, the variation of voltage magnitude for every phase is given individually.

Table 5.5 and Figure 5.11 show that the voltage magnitudes of all phases are within limits for all scenarios. The highest voltage magnitude deviations at all phases are similar for the three scenarios. In all scenarios, the highest variations occur due to the simultaneous charging or discharging of flexible devices to take advantage of changes in energy price. Phase c has the lowest variation in voltage magnitude during the day, as depicted in Figure 5.11(c).

5.5 Conclusion

Local energy trading (LET) is an emerging approach for distributed energy resources (DERs) management that has received a large interest in existing studies. However, these studies focused on LET operation assuming the capacities of installed DERs. Existing studies did not address the optimal planning of energy communities (ECs) enabling LET, which considered uncertainties, impacts on distribution networks, and the unbalanced nature of distribution networks. Therefore, This chapter introduced a methodology for the optimal planning of the DERs within ECs, which can guide investment decisions towards more cost-effective solutions. Linear programming is used for optimal planning and operation of EC in Madrid, Spain, aiming to minimize the total annual costs. The optimal planning reduced the annual costs by 10.95% compared to the scenario without optimal planning of photovoltaic generation and battery energy storage (BES). Under the current operating conditions in Madrid, Spain, it is not economically feasible to install private BES in ECs. Sensitivity analysis shows that, by decreasing BES investment costs, increasing electricity prices, or decreasing electricity selling price, it could be feasible to install BES at part of the EC houses. The sensitivity analysis clarified how changes in external economic conditions affect the economic performances of ECs and the economic feasibility of DER deployment. There are no violations of the distribution network limits in all studied scenarios.

Chapter 6

Techno-economic Assessment of Local Energy Trading Market Models Deployed Using Blockchain-Based Platforms

Distributed energy resources have transformed system operations, necessitating a shift from the centralized to a decentralized approach enabling local energy trading (LET), facilitated by distributed ledger technology and blockchain. Literature shows that peer-to-peer energy trading are appropriate for power systems under certain conditions. This chapter compares several market models for peer-to-peer transactions developed on various technologies, such as a centralized server and a distributed ledger. The output-based quantitative comparison highlights the limitations and advantages of different market models and implementations. Technical constraints on the power system through a congestion market are also analyzed. Simulation results show that there is no single best solution for general validity. A centralized double auction market is faster, while a distributed continuous double auction market guarantees larger energy traded. Moreover, the results show that public blockchain still has several limitations for the tested application and assumed conditions that do not allow its efficient applicability to LET.

Nomenclature

Positive variables	**Description**
P_i^{up}	Cleared upward flexibility bid from FSP i^{th}
P_j^{down}	Cleared downward flexibility bid from FSP j^{th}
s_r^{up}	Upward flexibility slack variable and DSO requested r
s_r^{down}	Downward flexibility slack variable and DSO requested r
Parameters and scalars	**Description**
c_i^{up}	Upward flexibility cost for every FSP bid
c_j^{down}	Downward flexibility cost for every FSP bid
c^{slack}	Cost of not provided flexibility request (value of slack variables)
$PTDF$	Sensitivity factor between the location (node) of FSP and the location of the DSO request

$P_i^{up_{min}}$	Lower limit of the FSP upward flexibility bid
$P_i^{up_{max}}$	Upper limit of the FSP upward flexibility bid
$P_j^{down_{min}}$	Lower limit of the FSP downward flexibility bid
$P_j^{down_{max}}$	Upper limit of the FSP downward flexibility bid
Sets	**Description**
$i \in FSP_{up}$	FSP that offers upward flexibility
$j \in FSP_{down}$	FSP that offers downward flexibility
$r \in R^{up}$	Upward flexibility requested by DSO
$r \in R^{down}$	Downward flexibility requested by DSO

6.1 Introduction

Many management approaches (e.g., microgrids and virtual power plants - VPPs) have been proposed to efficiently integrate distributed energy resources (DERs) and provide ancillary services [9]. One recent promising approach to integrate DERs is the local electricity markets (LEMs) [21]. The LEM in the form of peer to peer energy trading (P2P-ET) or local energy trading (LET) allows active customers to trade energy surpluses with their neighbors, like an energy community. LET objectives include increasing local self-generation, achieving supply-demand balance at the local level, postponing grid investments, and maximizing economic benefits for LET participants [13], [169]. Finally, a further objective concerns congestion management at the distribution level and through ad-hoc TSO-DSO coordination also at the transmission level [13], [170], [171].

The LET could be managed by a central entity such as a distribution system operator (DSO), retailer, market operator, aggregator, etc. [62]. For instance, Ref. [55] studied a centralized LET between customers in a small community in England, UK. The study considered the presence of photovoltaic (PV), wind generation (WG), and energy storage. The market is modeled as an optimization problem to reduce the energy consumption cost from the grid. The results showed that customers owning energy storage and participating in LET could reduce energy consumption from the grid and energy costs by 31%. The LET could be designed as an auction. Ref. [172] proposed many auction mechanisms for LETs to consider the participants' preferences in the market model. In [16], a LET between buildings in an industrial site proved that LET could reduce energy cost, peak demand cost, and increase self-sufficiency. Despite the simplicity of the central approach to managing

LET, it has some drawbacks, such as a single point of failure, privacy concerns for LET participants' data, and scalability issues. Therefore, other approaches were proposed to manage the LET [8].

LET could be managed in a distributed manner, and no central entity is needed to manage the market [62]. This is driven by the development of digitalization tools such as blockchain or distributed ledger technologies (DLTs) [173]. Many studies proposed the use of blockchain technology to manage LET due to its decentralized nature [174], [175]. Blockchain technology could solve some challenges in central LET, such as single point of failure, privacy concerns, and scalability issues. In [176], a blockchain-based LET is developed for a residential community in Amsterdam, the Netherlands. The community contains PV, energy storage, and EVs operating in charging mode. The study found that LET reduced the interaction with the grid for all LET participants and reduced their energy costs. In [177], a blockchain-based LET between EVs is proposed. In this study, EVs with surplus energy are incentivized by a financial return to discharge part of this energy to other EVs with an energy deficit. The study used an iterative double auction to clear the market. The security analysis showed that the proposed blockchain-based LET improved the protection of EVs data privacy and transactions security.

Besides academic studies, many pilot projects and startups developed blockchain-based LETs. For instance, the Brooklyn microgrid project developed by LO3 energy company was the first to implement a blockchain-based LET between a community neighbor in New York, USA. After that, many other projects were implemented in different countries. In the Quartierstrom project in Switzerland [18], a private blockchain-based LET was implemented in an energy community containing 37 houses. The houses have many DERs, such as PV, ESS, and EVs. The project aims to test the blockchain-based LET technically and check the market participants' behavior [84]. The proposed LET doubled the self-generation of the community. However, they faced many hardware issues and scalability issues regarding the number of market participants in the LET [178]. Many startups developed blockchain-based platforms for LET. For instance, the Australian startup PowerLedger partnered in many pilot projects of LET in different countries such as Malaysia, Japan, Australia, and India [111].

Most of the LET studies in the literature focus their contribution on the market design and do not consider the physical grid constraints in the market model. However, the LET between customers could result in violations of grid constraints [69]. To handle this concern, recent studies have proposed different methods to consider the physical grid constraints in the LET. Some studies used the DC power flow equations in the market model [113], [114]. Other studies used AC power flow equations in the market model [115]. Few studies used voltage sensitivity coefficients, power transfer distribution factors, and loss sensitivity factors to represent the physical grid in the market model [112]. Few studies run a power flow after the market clearing to evaluate if the trading between specific peers could violate physical grid constraints [71], [72].

The focus of the previous studies proposing blockchain for LET was on proving the applicability of blockchain for LET and improving the performance of blockchain in this application. However, little attention was given to comparing the blockchain-based and centralized approaches [8]. For instance, [179] compared the blockchain-based LET with centralized LET regarding computation time. The study found that blockchain-based LET requires a much larger computation time than central LET. However, they did not consider additional indicators that could give a more quantitative assessment of the problem. Still, the authors report a qualitative analysis of a blockchain-based LET. The work highlights how a central system is more easily scalable and less costly for local market actors under certain conditions. Therefore, there is still a need for a detailed comparison between blockchain-based and centralized LET to consider factors other than computation time. This chapter focused on blockchain and not other DLTs because blockchain is more mature than other DLTs that are in an early stage of development. Considering the limited research comparing blockchain-based LET with centralized LET, this study proposes a techno-economic comparison of two market models for blockchain-based LET and one market model for centralized LET. The contributions of this chapter are as follows:

- Development of a distributed blockchain-based LET in a realistic representation of a distribution network in Italy considering several market designs (i.e., double auction (DA), continuous double auction (CDA), and pseudo-continuous double auction (PCDA).

- Comparison of two blockchain-based LET with a centralized LET, proposing several key performance indicators (KPIs).
- Eliminate any congestion in LVDN through the congestion management market.

The chapter is organized as follows. Section 6.2 presents the proposed market models. Section 6.3 describes blockchain technology and blockchain-based market implementation. In addition, it contains the market's agent behaviors and reports the KPIs to evaluate the market models. Finally, Section 6.4 presents the case study for LET evaluation and the results with discussions. Section 6.5 presents the conclusion.

6.2 Market models

In this section, three LET market models are explained: the double auction (DA) implemented as a centralized market [180], the pseudo-continuous double auction (PCDA) implemented as a distributed market, and the continuous double auction (CDA) implemented as distributed market [181], [182].

In the centralized LET, a central entity (i.e., third party) is responsible for market operation. The central entity collects selling and buying bids from market participants, matches the bids based on the adopted matching algorithm, and distributes the revenues and expenses to market participants. The centralized LET is modeled as a double-sided auction (DA) market with uniform pricing.

In contrast, no central entity is needed in distributed LET models (i.e., CDA and a modified version called PCDA), and a blockchain-based distributed platform is used instead. In the distributed market, the system is managed by an inherently distributed platform. In this case, the smart contracts deployed in the blockchain allow participants to submit bids, match the bids, and perform settlement. In the CDA, there is a fixed duration for participants to submit bids and they are matched continuously in a distributed manner without the need for a central entity.

The three LET models may be broken down into three major processes:

1. *Energy trading process*: It specifies the rules for submitting bids by sellers and buyers and the rules for matching the bids.
2. *Congestion check process*: it checks the LVDN limits buy running a power flow.
3. *Congestion management process*: If any congestion in LVDN is observed in the previous process, the DSO operates a congestion management market to relieve them.

Figure 6.1 illustrates the main steps of the studied three models and the timeframes. In this study, every bid is an elastic limit order. This means that the price indicates the request to sell/buy energy at a price not lower/more than that submitted in the bid. Moreover, the prices for exchanging energy locally are set to be advantageous for both sellers and buyers in LET than exchanging energy with the retailer. Sellers and buyers can exchange energy with the retailer if their bids are not matched in LET.

6.2.1 Energy trading period

This subsection describes the energy trading period characterized by the rules that govern the energy trading between sellers and buyers in LET. The energy trading period is divided into *i*) the bid presentation stage and *ii*) the market clearing stage. The first stage is the same for all market models, whether centralized or distributed. However, the second stage is different depending on the type of market.

6.2.1.1 Bid presentation stage.

In the market models considered, multiple buyers and sellers compete by submitting two types of bids: *i*) bid to buy energy and *ii*) bid to sell energy. The bids consist of the identifier of the participant node of connection, identification number, price of the energy, and energy quantity. Both types of bids are considered elastic limit orders (i.e., orders to buy or sell with a price constraint). Information about the state of the market is made public to all market participants through the order books, where bids to buy and to sell are sorted according to the price in descending order and ascending order, respectively. By publishing the order book, users can adjust their positions in the market based on the positions of their competitors.

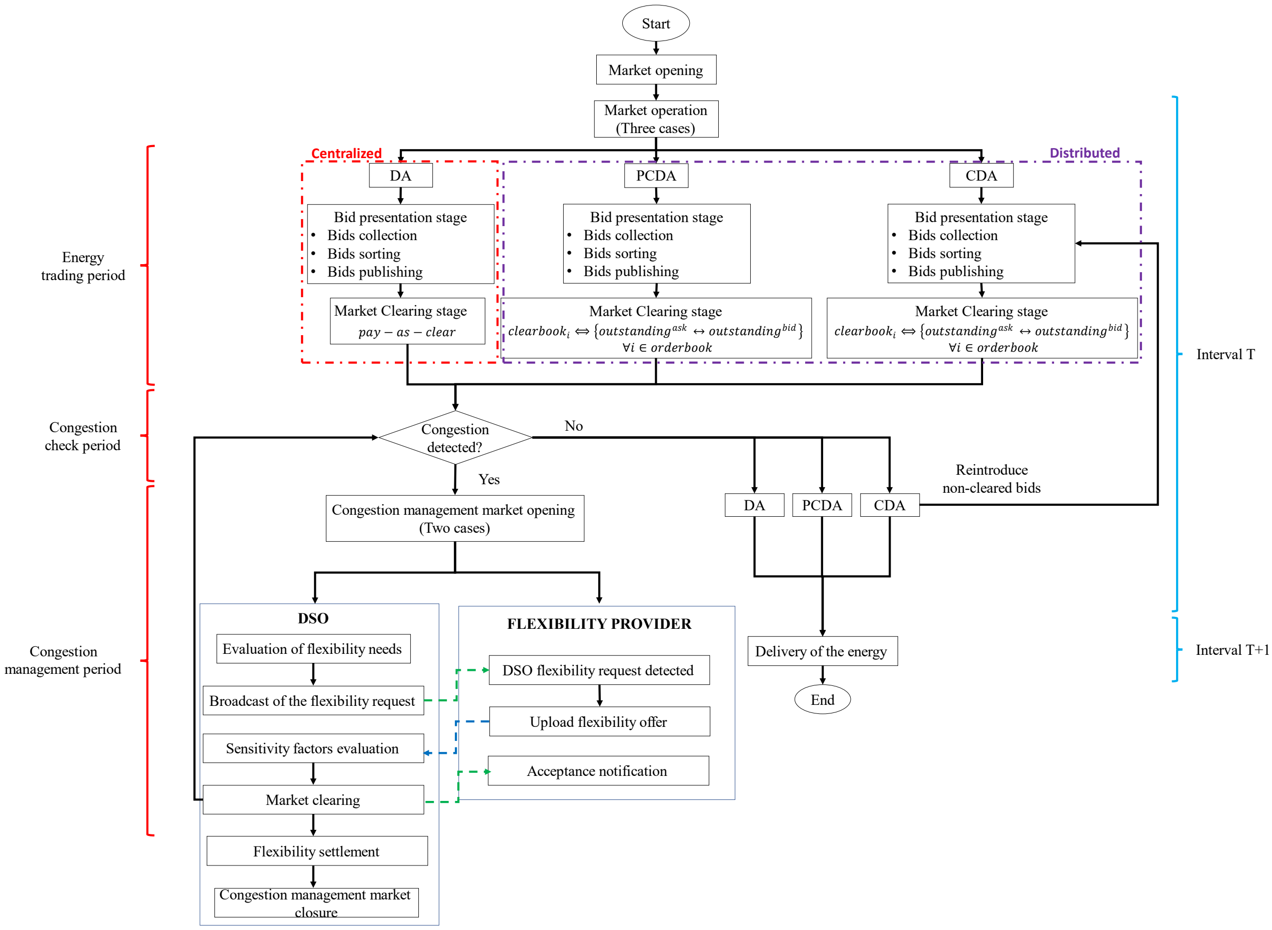

Figure 6.1. The flowchart of the studied local market models: DA, PCDA, and CDA.

6.2.1.2 Market clearing stage.

This section describes the bids matching mechanism. However, since this process is different depending on whether the market is centralized or distributed, the two matching mechanisms are described in two separate sections below for ease of reading.

6.2.1.2.1 Centralized market.

Clearing the centralized market requires an entity to collect and sort all bids placed during the bid presentation stage. Once the bids are collected and sorted, two curves can be defined: *i*) the demand curve and *ii*) the supply curve. Their intersection determines the accepted bids, quantity, market price, and schedules for energy withdrawal and injection, as defined in [180]. The equilibrium price is unique and equal to the Market Clearing Price (MCP). In addition, the accepted bids are those with a selling price not higher than the MCP and a purchasing price not lower than the MCP. Any bids left in the market that have higher prices (in the case of selling bids) or lower prices (in the case of purchasing bids) are matched with the energy retailer. The Centralized market matching process is illustrated in Algorithm 1.

Algorithm 1 Centralized clearing process

Input $supply^{p,q}$, $demand^{p,q}$
Output p, q
$p, q, i, j = 0$
while $min\left\{\sum_i demand_i^q, \sum_j supply_j^q\right\} > 0$
    if $demand_i^p \geq supply_j^p$ **do**
        $p = min\left\{demand_i^p, supply_j^p\right\}$
        if $demand_i^q > supply_j^q$ **do**
            $q += supply_j^q$
            $demand_i^q -= supply_j^q$
            $supply_j^q = 0$
            $j += 1$
        else if $demand_i^q < supply_j^q$ **do**
            $q += demand_i^q$
            $supply_j^q -= demand_i^q$
            $demand_i^q = 0$
            $i += 1$
        else do
            $q += demand_i^q$
            $demand_i^q = 0$
            $supply_j^q = 0$
            $j += 1$
            $i += 1$
        end if
    else do
        break
    end if
end while

6.2.1.2.2 Distributed market.

In this chapter, the CDA and the PCDA represent the distributed market models. The PCDA and CDA markets resemble. However, for PCDA, the arrival time of the bids is not considered during the matching mechanism. Unlike the CDA, in which there is a continuous clearing of the market, in the PCDA market, the clearing process is performed only once. Due to this distinctive feature, this market mechanism can be considered intermediate between the centralized DA and the distributed

CDA mechanism. As for the centralized model, the purchasing price refers to the maximum value acceptable, while the selling price identifies the minimum price acceptable. Since there is no central entity in the distributed market, the bids' collection process is entrusted to a non-physical entity called "smart contract", which intervenes when the bid presentation stage closes and the market clearing stage begins.

Once the bid presentation stage is completed, the distributed non-physical entity will sort the bids by creating the order books for purchasing and selling bids. As for the centralized market, the order books are sorted according to the "price" field. In the CDA market, the order books are cleared continuously, while in the PCDA market, the order books are cleared only once, such as in the centralized market. The outstanding bid (i.e., the highest price of buyers) is matched with the outstanding ask (i.e., the lowest price of sellers) [183]. The matching happens when the outstanding bid is greater than or equal to the outstanding ask. The transaction price is the average of the matched offers.

To clarify the concept, an example of the distributed matching process after sorting is presented in Figure 6.2. The figure shows 5 users divided into 3 buyers and 2 sellers. The matching process involves matching the purchasing offer with the highest price and the selling offer with the lowest price first. In the example, matching the outstanding ask and the outstanding bid allows buyer 1 to buy all the energy demanded while allowing seller 1 to sell some of the energy produced. The trading price will equal half the prices offered for purchase and sale. Following this procedure, the matching process continues, with buyer 2 being able to match seller 1 with the remaining amount of energy provided for sale. The process continues until only buyer 3 and seller 2 remain, who, based on the prices offered, are not compatible for matching.

To clarify the matching process of the distributed markets, algorithm 2 presents the steps of the method. The $match_{Energy\ Retailer}$ function in algorithm 2 illustrates the way of coupling unmatched bids in the local market with the prices offered by the energy retailer. Algorithm 3 describes the function $match_{Energy\ Retailer}$. It's vital to note that how often this function is called is defined by the type of market model (i.e., CDA or PCDA). For the CDA market, this function is only called when the delivery stage is approaching. Nonetheless, for the PCDA market, this function is run each time the clearing takes place. Moreover, the $match_{Energy\ Retailer}$ is called just one time throughout the market clearing procedure.

Orderbook before clearing					
Buy orders			Sell orders		
#	Price [EUR/kWh]	Quantity [kWh]	#	Price [EUR/kWh]	Quantity [kWh]
b1	14	5	*s1*	10	60
b2	13	50	*s2*	12	35
b3	11	25			

Orderbook after clearing					
Buy orders			Sell orders		
#	Price [EUR/kWh]	Quantity [kWh]	#	Price [EUR/kWh]	Quantity [kWh]
b3	11	20	*s2*	12	35

Figure 6.2. The distributed market orderbook before and after the market clearing.

Algorithm 2 Distributed clearing process

Input $obook_{buy}^{p,q}$, $obook_{sell}^{p,q}$

Output $cbook^{p,q}$

for $\_k : min\{length(obook_{buy}), length(obook_{sell})\}$

  if $obook_{buy,\ \_k}^{p} \geq obook_{sell,\ \_k}^{p}$ **do**

    $pr\_c = mean(obook_{buy,\ \_k}^{p,q}; obook_{sell,\ \_k}^{p,q})$

    if $obook_{sell,\ \_k}^{q} \geq obook_{buy,\ \_k}^{q}$ **do**

      $cbook_{\_k}^{p,q} \leftarrow match(pr_c;\ obook_{buy,\ \_k}^{p,q})$

    else do

      $cbook_{\_k}^{p,q} \leftarrow match(pr_c;\ obook_{sell,\ \_k}^{p,q})$

    end if

  else do

    $break$

  end if

end for

call function $match_{Energy\ \ Retailer}^{p,q}\ (obook_{buy}^{p,q}\ ;\ obook_{sell}^{p,q})$

Algorithm 3 Matching process with energy retailer

Input $obook_{buy}^{p,q}$, $obook_{sell}^{p,q}$

Output $cbook^{p,q}$

for $\_bid : obook_{buy}$ **and** $\_ask : obook_{sell}$ **do**

$$cbook^{p,q} \leftarrow \begin{cases} match(ER_{sell}^{price}\ ,\_bid^{q}) \\ match(ER_{buy}^{price}\ ,\_ask^{q}) \end{cases}$$

end for

6.2.2 Congestion check period

Grid congestion happens whenever high current flows in an element (e.g., line, transformer), resulting in overloading. Therefore, it is essential to confirm that each exchange defined in the market is sustainable by the network. Given the current state of the network where some exchanges occurred, we calculate the load in each line using the power flow model [124]. For all the market models, the power flow operation is centralized and performed by the DSO.

In the centralized market model, in the case of a network with a low probability of network constraint violation, the DSO assumes the operational risk of not performing the verification. Contrarily, in the case of a network with a high probability of network constraint violation, the DSO performs the verification.

6.2.3 Congestion management period

At the end of the congestion check period, no more transactions are allowed, with the cleared book showing how the purchasing and selling bids are matched. If network constraints are violated, users' power injection and consumption must be reshaped to solve the network constraints violations. The congestion management market accomplishes this task by providing the necessary flexibility from the market actors to cover DSO's flexibility requirements. Since the congestion management market has to be implemented in centralized and distributed manner, its description is divided between actions that the DSO takes in the market and steps that flexibility providers take. This subdivision is essential because the DSO executes its actions centrally, as opposed to the flexibility providers who, depending on the market, perform different actions through a centralized or distributed platform.

It is essential to report that the congestion market occurs only once for the DA and PCDA markets, while it may occur more than once for the CDA market. This is because the congestion market occurs whenever there is congestion in the network after the clearing process of the energy trading period. Still, in the CDA market, the clearing process is performed more than once due to the market characteristic of being cleared continuously.

6.2.3.1 Distribution System Operator operations.

This process 7 steps described below from a. to g.

a. *Congestion detected from local energy market results*. The power flow results reveal a system congestion. DSO commences congestion resolution procedure through the congestion management market.

b. *DSO evaluates the flexibility needs*. The DSO calculates its flexibility needs according to the results obtained from the power flow. These needs are useful for clearing the congestion management market, where the DSO submits a request for active power in either an upward or downward direction. In the congestion management market model, the concept of flexibility is the amount of energy that the market participant can vary with respect to its consumption and/or injection plans. In particular, upward flexibility is defined as the energy a generator can inject more and the energy that a controllable load can consume less than their schedule. On the contrary, downward flexibility is the energy a generator can cut off and the energy that a controllable load can consume more with respect to their plans.

c. *Broadcast flexibility request*. The DSO transmits the flexibility request to flexibility providers via the platform adopted. Specifically, the request is uploaded on the market platform in both centralized and distributed cases. All market participants are aware that they can offer their flexibility [184].

d. *Sensitivity factor evaluation*. The market model considers the grid information in the market clearing using linear network representation by adopting sensitivity factors. Thus, the DSO determines the flexibility provider's sensitivity factor depending on the location of the provider resource [124]. In this chapter, sensitivity is based on the direct current (DC) power transfer distribution factor (PTDF) [124], where the variation in the energy flow of line *ij* in the LVDN is linked to a power injection at node *k* and equivalent withdrawal at node *m* as expressed in (6.1). The calculation of total energy flow in a line is done by (6.2)

$$\Delta P_{ij} = PTDF_{ij,km} \cdot \Delta P_{km} \tag{6.1}$$

$$P_{ij} = \sum_{m} PTDF_{ij,km} \cdot P_m \tag{6.2}$$

Where node *k* represents the slack bus, and the calculation of all PTDFs is with respect to node *k*. The value of the elements of the PTDF matrix can vary in the range [-1; 1]; however, it should be remembered that since the matrix is extracted from a DC power flow, it neglects losses and reactive power, so intermediate values are not available. Although with alternate current (AC) PTDFs, it is possible to discriminate between flexibility providers downstream of congestion, with DC PTDFs it is still possible to understand which user is useful and which is not as well as to understand which bid to use upward or downward. To avoid influencing the price-based order book, it was decided to use DC PTDFs to identify providers of interest and leave them free to compete based on prices.

Assuming a positive flow, if the sensitivity of the congested component with respect to a flexibility provider is negative, it means that the provider has a positive effect on the congested element, and each increment leads proportionally to a reduction in the flow of that specific congested element. On the other hand, if the sensitivity value is positive, increments have adverse effects on the congested element. In this sense, reducing the provider's output reduces the flow of the congested line. Furthermore, considering a radial network, as in the case study, the sensitivity of the congested line to the provider located in the same network is -1, which means that a 1 kWh increase in flexibility can mitigate the flow of the congested element by 1 kWh.

e. *Market-clearing*. In the market clearing process, the most effective bids from the flexibility providers are selected to relieve the congestion at the minimum cost. The DSO gathers all the flexibility provider bids to perform the market clearing. Afterward, the DSO solves the linear programming market-clearing problem defined by (6.3) to (6.8) [185].

The objective function of this congestion management market [185] is given in (6.3). The cost of upward and downward flexibility activation is represented by the first and the second terms, respectively, whilst the cost of slack variables is represented by the last term that is useful to always obtain a solution for the problem. The constraints in (6.4) and (6.5) match flexibility offers from FSPs with flexibility requests from the DSO for upward and downward bids, respectively. Every bid of FSP is multiplied by its respective PTDF (i.e., sensitivity factor). This affects the merit order on the market. The limits of the FSPs bids are represented by (6.6) and (6.7), and the constraint in (6.8) guarantees that the variable representing the slack and the cleared upward and downward flexibility are positive.

$$\min_{P_i^{up}, P_j^{down}, s_r^{up}, s_r^{down}} \left\{ \sum_{i \in FSP_{up}} c_i^{up} \cdot P_i^{up} + \sum_{j \in FSP_{down}} c_j^{down} \cdot P_j^{down} + \sum_{r \in R} c^{slack} \cdot \left(s_r^{up} + s_r^{down} \right) \right\} \tag{6.3}$$

s.t.

$$P_r^{DSO_{up}} - \sum_{i \in FSP_{up}} PTDF_{i,r} \cdot P_i^{up} - s_r^{up} \leq 0 \qquad \forall r \in R^{up} \tag{6.4}$$

$$P_r^{SO_{down}} - \sum_{j \in FSP_{down}} PTDF_{j,r} \cdot P_j^{down} - s_r^{down} \leq 0 \qquad \forall r \in R^{down} \tag{6.5}$$

$$P_i^{up_{min}} \leq P_i^{up} \leq P_i^{up_{max}} \qquad \forall i \in FSP_{up} \tag{6.6}$$

$$P_j^{down_{min}} \leq P_j^{down} \leq P_j^{down_{max}} \qquad \forall j \in FSP_{down} \tag{6.7}$$

$$s_r^{up}, s_r^{down}, P_i^{up}, P_j^{down} \geq 0 \tag{6.8}$$

f. *Post-evaluation*. Finally, the DSO performs a new power flow considering the new generation and load profiles obtained after clearing the market to check network constraints violations.

g. *Flexibility settlement*. The flexibility payment is made through a redistribution of costs to users. Hence, the cost of managing the grid through flexibility requests is proportional to the amount of energy each user trades in the energy market. This cost redistribution implies that if a user does not buy (or sell) energy from (to) the grid (i.e., hypothetically has a self-consumption of 1, and has yet to enter the energy market), then the user would have no additional cost to pay for the flexibility request, as the energy exchanged in the energy market would be zero. To better explain the flexibility cost redistribution process, (6.9) reports the equation that distributes the flexibility cost according to the quantity traded in the energy market.

$$c_h^{CMM} = \frac{c_{CMM} \cdot kWh_h}{\sum_{i=1}^{N_{user}} kWh_i} \qquad \forall h \in N_{user} \tag{6.9}$$

Where c_h^{CMM} represents user h flexibility cost, c_{CMM} represents all flexibility costs, and kWh_hrepresents user h exchanged energy in the energy market.

6.2.3.2 Flexibility providers operations.

This process 3 steps described below from a. to c.

a. *Flag DSO request detected*. When the DSO uploads the flexibility request on the market platform, the congestion management market opens, and eligible participants can submit their flexibility offers. It should be noted that the eligible users are those who, before the congestion, can buy and/or sell energy during the energy trading period. This definition is of no particular interest to the DA and PCDA markets, as the congestion market only opens once the energy market has closed for the trading period. However, this definition is relevant for the CDA market as the DSO can request flexibility from users several times during a single transaction period. In fact, the energy market is cleared several times in a single hour. Therefore, the definition of eligible users for the CDA market is crucial, as not all network users may be enabled to participate in the congestion management market during a transaction round.

b. *Upload flexibility offer*. As soon as the congestion management market opens, eligible participants can submit their flexibility offerings to the platform. These offers are provided in terms of connection node, maximum and minimum quantity, and price.

c. *Acceptance notification*. If the DSO's post-evaluation is successful - after the market clearing step - then participants selected for their flexibility are notified.

6.3 Methodology

6.3.1 Market models design implementation

A modern marketplace must be structured according to guidelines that are as technologically advanced as possible and user-friendly for the end users [186]. In the current technological era, these guidelines state that a marketplace must ensure access for any user wishing to participate in the market via an internet connection [187], [188]. The scientific literature [189]–[192] shows that an energy market should consist of four fundamental elements:

1. *Data acquisition*. It involves reading the consumption and production data of market users.
2. *Data management*. It consists of software elements that enable the processing of users' interactions with the market.
3. *Data processing*. It represents the processes of execution and validation of market actions.
4. *Data provisioning*. It explains how users can access data.

This study considered and developed these four elements following the strategies presented in [186], [188], [189]. The measured data are the basis for payments in the market application. Our study considers smart meters for data acquisition, hosting the market application, and the platform's data management and processing functionalities. The agent software module handles the management of actions, such as sending buy or sell orders based on acquired data. This module contains two fundamental functions for the market. The first function is the user's ability to register with the market to allow market access. The second function allows the member to place buy or sell orders based on current consumption and production, which are the inputs to the market mechanism. Once the energy trading period ends, the market is ready to execute the clearing process. This process can be executed through a dedicated module. This same module will access users' portfolios, thus ensuring that money can be exchanged within the market. At the end of the clearing process, the data is made available to the users registered in the market. A picture representing the technical architecture of the market is depicted in Figure 6.3.

These four elements can be summarized in four market functions: "*Register participant*", "*Place bid*", "*Clearing market*" and "*Transfer money*". These functions represent the core of the markets and are the basis on which the markets developed in this study are based.

The process of deploying a smart contract on the adopted blockchain involves several key steps. First, the smart contract, already written, is compiled into bytecode and an Application Binary Interface (ABI) using the Remix compiler, which transforms the smart contract code into a format that can be understood by the Ethereum Virtual Machine (EVM). Next, a transaction that includes the contract's bytecode is created and sent to the blockchain network from a wallet that holds sufficient Ether to cover the gas fees. Once the transaction is mined and included in a block, the contract is deployed and assigned a unique address on the blockchain. It must be pointed out that a blockchain test network has been adopted for this study. This allows us to neglect the gas fees and the mining time required to include the contract in the blockchain network. The address linked to the smart contract can then interact with the contract, invoking the functions shown in Figure 6.3.

6.3.2 Blockchain description

This section briefly describes the blockchain platform for LET that was developed during the study. Although blockchain technology is becoming known in the scientific research community, the blockchain platform used in the study, with its features [193], is critical to the final evaluations of the study. In our study, the relevant features of a market platform are:

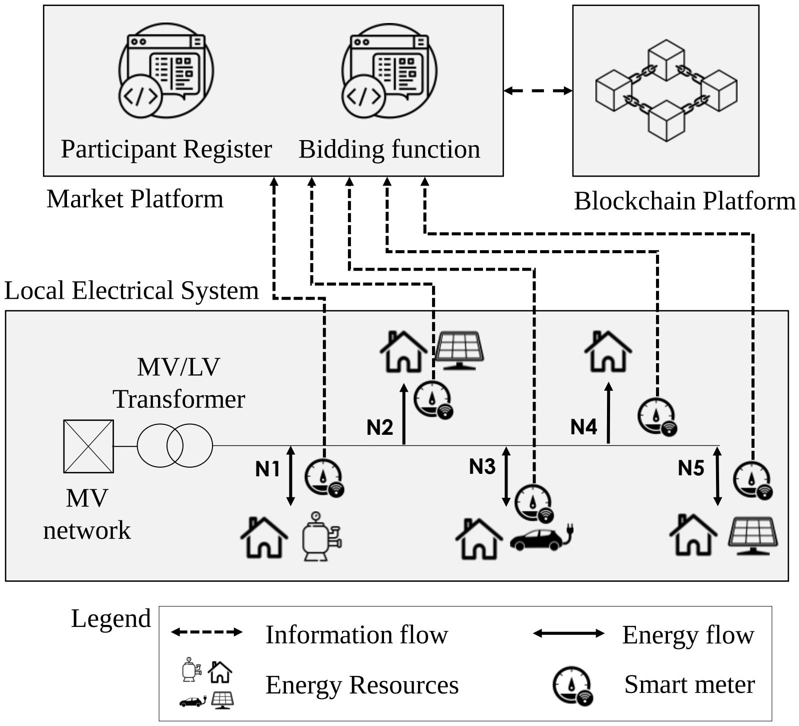

Figure 6.3. Technical architecture representation of the market.

1. Security (i.e., the ability of the market platform to be resistant to cyber-attacks);
2. Programmability/Automation (i.e., the ability to change/accept a new set of instructions that alter its behavior); and finally
3. Decentralization (i.e., the ability to transfer the management of certain operations to several entities rather than to a single actor).

These features are all included in distributed ledgers, particularly in the blockchain adopted in this study. The blockchain network technology adopted in the study is Ethereum [194]. This technology is widely used in several studies in the field. In this section, some elements relevant to the study addressed are described.

Ethereum is categorized as a transaction-based state machine. Unlike other blockchain platforms, the Ethereum platform began as a distributed computer rather than a cryptocurrency exchange platform. Ethereum adopts a commonly accepted method of transferring values to encourage computation within the network. This method is enabled through Ethereum's intrinsic currency called Ether. Given the possible growth of cryptocurrencies, such as Bitcoin, Ethereum's developers decided to break Ether down into smaller units. The smallest part of Ether is called Wei and corresponds to 10^{-18} Ether. Ethereum's distributed computer runs via a virtual state machine model known as the Ethereum Virtual Machine (EVM). Ethereum uses a unit called gas, which measures the computational effort required to perform operations on the Ethereum network. The blockchain user must spend gas to perform mathematical operations, transactions, call functions, and execute smart contracts [194]. The EVM is a stack-based machine whose primary computation mechanism is a stack. A stack is a data structure where elements are added (pushed) and removed (popped) in a last-in-first-out manner.

In Ethereum, with each action, instructions can be added to or removed from the stack. The parameters δ and α represent the number of instructions added and removed, respectively. The δ parameter increases with each added instruction, and the α parameter increases with each removed instruction. A cost function calculates the total gas required for executing each instruction as elements are added or removed from the stack. After determining the gas cost of a transaction, the user must submit it to the blockchain network, which traditionally involves the proof-of-work algorithm. Additionally, users must pay a fee to miners to process the transaction, with higher fees leading to faster validation and inclusion in the blockchain. [195]. The final cost function in euros of a blockchain transaction is represented by (6.10).

$$€ = G \cdot F \cdot H_{€} \tag{6.10}$$

Where €, represents the final cost in euros for the transaction, G represents the cost in gas of the transaction evaluated by the cost function that considers the stack parameters δ and α. Finally, F represents the fee to the miners, expressed by GWei/Gas, and $H_{€}$ represents the conversion factor from Ether to Dollars, considering the fact that one Ether is equivalent to 10^{18} Wei. This factor enormously influences the cryptocurrency market [196]. The same F parameters are highly volatile, but conversely, this depends on the miners and network actors, which are influenced by actions outside the blockchain.

Ethereum blockchain adopts decentralized finance, eliminating the need for third-party intermediaries and making it independent of central bank policies. Its price is influenced by traders' actions and technological advancements. In 2018, its price peaked due to an increase in investors, and in 2021, the release of Ethereum 2.0 led to rapid growth [196]. The technology has a volatile cost, and its application to local energy markets may require high costs due to strong variations in Ether value. The study focuses on the Ethereum distributed database structure, automation of processes through smart contracts, quantitative assessment of process complexity using delta and alpha parameters, and associated costs.

6.3.3 Market's agent behavior

In the implemented market models described in section 6.2, buyers and sellers must prepare bids to buy and sell. In a real market, the entities should also consider the offers from other participants to gain a place in the market and thus increase their profits. Therefore, choosing a trading strategy is very complicated. In addition, the different developed markets have distinct dynamic characteristics, as bids can be placed and changed at varying intervals. Since the purpose of the study is not to prove a market strategy suitable for every market model, it is chosen to adopt a behavior of market players that is easy to implement but ensures minimum behavior that is useful for the user's profit. The strategy market participants adopt is called zero intelligence (ZI) [197]. ZI behavior involves random quotes in each range of Gaussian distribution without considering market transactions. The Gaussian distribution is truncated at a maximum and minimum value. The maximum and minimum values are the energy retailer's selling and buying prices of energy.

The distribution has a mean value (μ) equal to the average interval between retail and export prices. Instead, the standard deviation (σ) is equal to 1/3 of the gap between the retail price and the μ price. Although this strategy has already shown that market participants do not achieve personal or collective benefits [198], [199], this approach nevertheless succeeds in maintaining market allocative efficiency close to the maximum value [199].

Finally, it is essential to mention that this ZI approach is applied not only to the energy market but also to the congestion market. This means that users extract flexibility offers from a Gaussian distribution. The energy retailer's market prices and maximum and minimum prices for flexibility market offers are presented in Table 6.3.

6.3.4 Key performance indicators

In the present study, the three market models described in section 6.2, are evaluated considering their effectiveness. To accomplish the evaluation, we design the corresponding performance metrics: *i*) The local welfare and the cleared quantity ratio of the market scheme. *ii*) The complexity and the cost that the market implemented at the blockchain level reflects. *iii*) the bids' waiting time before they are cleared. *iv)* The flexibility costs, and finally, *v)* the flexibility volume. However, it should be noted that the last two indicators will only be evaluated for the scenario in which network congestions are detected (i.e., scenario B).

i. *Evaluation of the market model*. We define two metrics to evaluate the market model performances: the local welfare and the clear quantity ratio (CQR). Local welfare is defined as the sum of consumer surplus and producer surplus for the energy traded locally. Local welfare is a crucial performance indicator for evaluating the models' performance from an economic perspective. In the local welfare calculation, we only consider the resources that are within the local market and discard the suppliers that are not. The definition resembles social welfare [180], but with such a feature, the label changes to "Local Welfare", as if to indicate the welfare of energy exchange locally. The higher the value of the local welfare metric, the better the social welfare of local network users.

   The cleared quantity ratio is defined as the ratio of the quantity cleared to the quantity offered in the market. This indicator has no dimensional value but expresses how much energy can be traded through the selected model as a percentage of the total quantity offered for both selling and buying. The higher the cleared quantity ratio, the higher the trading volumes and, thus, the greater market liquidity. The cleared quantity ratio metric is defined by (6.11).

$$CQR = \frac{tot\ quantity\ cleared\ [kWh]}{tot\ quantity\ bid\ [kWh]} \tag{6.11}$$

ii. *Complexity and cost of the blockchain-based model.* Blockchain-based complexity is measured for the three market models considering the complexity and associated cost of blockchain execution of smart contracts. The concept of complexity can be defined as the condition in which several components are intricately linked or interrelated. In the electricity market, this concept can be observed from various points of view. One example is the market players' point of view, who can assess the complexity from their interactions with the market platform. Another one is from the platform perspective: how many steps are required for a user request to be completed? These steps are evaluated in terms of machine language. In computer science, complexity is defined as "*the degree to which a system's design or code is difficult to understand because of numerous components or relationships among components*". In the present study, the concept of complexity is linked to the blockchain platform, so the definition of market complexity is the complexity determined by the number of operations required to execute a process in the blockchain platform. Hence, this metric is evaluated as the sum of items that are added (α) and removed (δ) from the "*stack*". As explained in section 6.3.2, these two parameters reflect the number of operations required to perform a specific process inside the platform. The higher the number, the higher the number of added and removed items, thus the greater complexity. Based on the number of operations performed and their type, it is possible to calculate the total implementation cost of each market model implemented via the blockchain platform. The cost associated with each share is expressed in two different ways: exploiting the blockchain platform cryptocurrency and in euros. We consider a fee per transaction per interval represented in Wei [187]. Moreover, the evaluation is assessed by transforming the cost in Wei to cost in euros. As shown in section 6.3.2, this conversion factor is strongly influenced by the market, which is affected by drivers outside the local market itself.

iii. *Bid's waiting time.* The waiting time metric assesses how long it takes for an offer to be cleared by the market. This metric is calculated as the difference between when the bid arrives and when the bids are cleared. The evaluation is not based on an average time based on a single simulation but is based on an analysis of the time distribution performed on repeated simulations. The parameters adopted for calculating the waiting time are the first quartile, the median, the third quartile, the minimum, the maximum value, and finally, the errors from the median value.

iv. *Flexibility costs*. This indicator assesses the final cost of the flexibility provided to the DSO, which will then be redistributed by the DSO to market participants according to (6.3)

v. *Flexibility volume*. This indicator defines the amount of flexibility provided by flexibility service providers to the DSO.

6.4 Case study, results, and discussion

6.4.1 Case study

The case study considers a real LVDN by using a part of a grid from the ATLANTIDE database [200]. The LVDN has a 250 kVA transformer transforming the voltage from 20 kV to 0.4 kV. The LVDN is rural and radially operated. The LVDN under study is shown in Figure 6.4. It has 16 nodes, with 6 electric vehicles (EVs), 5 battery energy storages, and 5 distributed generators (i.e., photovoltaic (PV) and combined heat and power (CHP)).

Table 6.1 presents data of generators, EV chargers, energy storage, and loads. Table 6.2 presents the LVDN branches' data in terms of length and electrical parameters. The input data for the connected EVs are the charging station (CS) power rating and charging profile. Since there is a large number of EVs in the market with different characteristics, in this study, the EVs energy ratings in kWh are determined based on a Gaussian distribution. The mean and standard deviation of the Gaussian distribution are 57 kWh and 15 kWh, respectively. EVs are assumed to have a unidirectional charger and operate only in the charging mode. The EVs are connected to the charger from 18 to 7 and used for mobility in the day's remaining hours. The LVDN under study supplies four types of customers, and their demand profiles are obtained from the ATLANTIDE project, as displayed in Figure 6.5 [200].

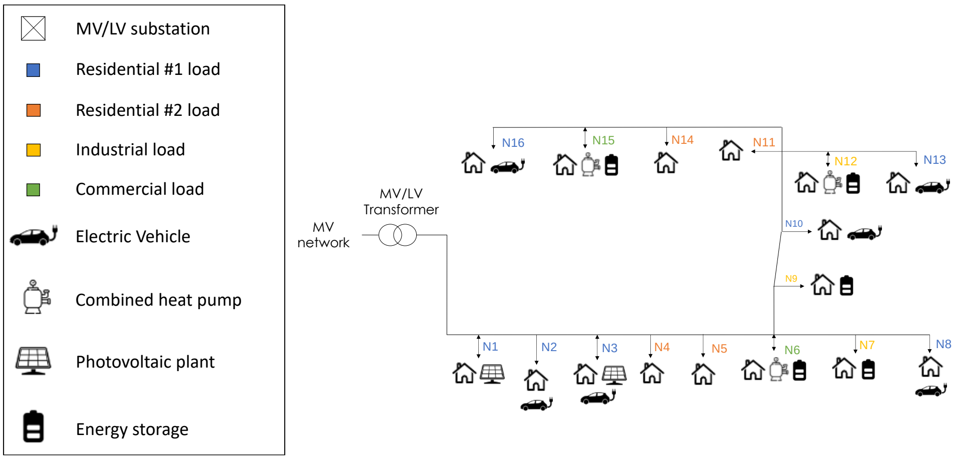

Figure 6.4. Schematic diagram of the studied LVDN indicating the type of customer and installed DERs.

Table 6.1. Data of loads, generators, energy storage, and electric vehicles.

Node	**Generator**	**EV charger**	**BES**		**Load**	
	P [kW]	P [kW]	P [kW]	E [kWh]	P [kW]	Q [kVar]
1	10	-	-	-	3	1.45
2	-	3	-	-	4.5	2.18
3	6	3	-	-	3	1.45
4	-	-	-	-	4.5	2.18
5	-	-	-	-	3	1.45
6	15	-	5	10	4.5	2.18
7	-	-	5	10	6	2.91
8	-	3	-	-	3	1.45
9	-	-	5	10	4.5	2.18
10	-	3	-	-	3	1.45
11	-	-	-	-	3	1.45
12	30	-	5	10	4.5	2.18
13	-	3	-	-	3	1.45
14	-	-	-	-	3	1.45
15	10	-	10	20	4.5	2.18
16	-	3	-	-	4.5	2.18

Table 6.2. Characteristics of the low voltage distribution network branches.

Branch	**L** [m]	**r** [Ohm/km]	**x** [Ohm/km]	**c** [nF/km]	**Ampacity** [A]
1 – 2	30	0.190	0.082	720	185
2 – 3	10	0.190	0.082	720	185
3 – 4	30	0.190	0.082	720	185
4 – 5	10	0.190	0.082	720	185
5 – 6	10	0.190	0.082	720	185
6 – 7	30	0.250	0.085	640	161
7 – 8	10	0.250	0.085	640	161
6 – 9	10	0.190	0.082	720	185
9 – 10	10	0.190	0.082	720	185
10 – 11	10	0.190	0.082	720	185
11 – 12	20	0.330	0.085	620	137
12 – 13	20	0.330	0.085	620	137
11 – 14	20	0.250	0.085	640	161
14 – 15	30	0.250	0.085	640	161
15 – 16	20	0.250	0.085	640	161

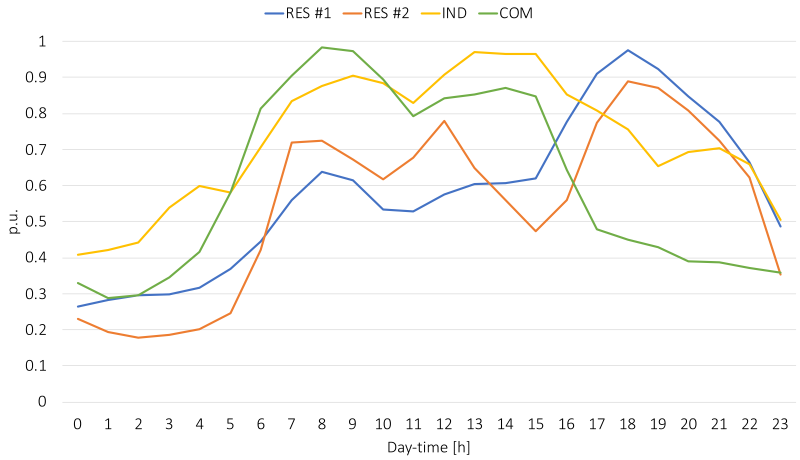

Figure 6.5. Demand profiles of different customers in the studied LVDN in pu.

In the studied LVDN, 2 PV and 3 CHP generators are installed. The profile of CHP considers the customer's thermal production. In fact, the CHP generators are intended for heating purposes rather than electricity production. Figure 6.6 displays the sum of customers' consumption and generation. The generation profiles of PV and CHP are depicted in Figure 6.7.

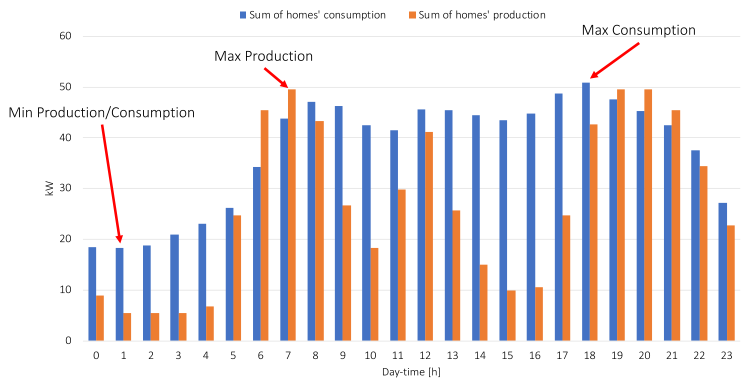

Figure 6.6. Aggregated profiles for generators and loads of the studied LVDN.

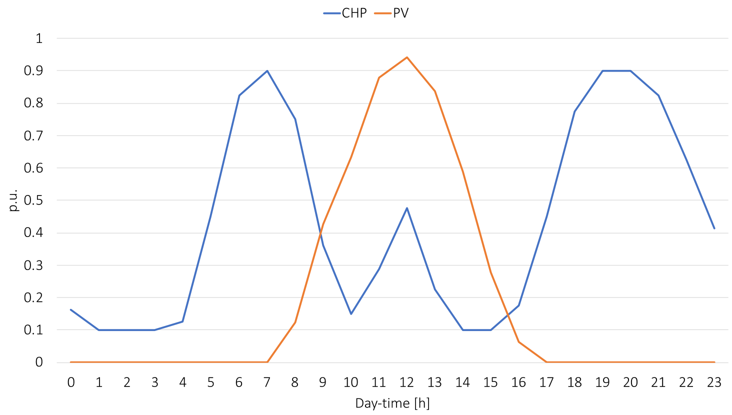

Figure 6.7. Generation profiles of different generators in pu.

Table 6.3 specifies the highest and lowest values within which the two markets' prices should be contained. For the energy market (i.e., LET), energy prices are primarily determined by energy retailers' purchasing and selling prices. On the other hand, the congestion management market prices are taken from PicloFlex for a winter day in 2023/2024 [201].

6.4.2 Scenario description

The comparative analysis is performed by considering two operation scenarios. Scenario A represents the LVDN without congestion during the study duration. On the other hand, scenario B considers LVDN congestion that happens at specific time instants. In order to create scenario B, the branches “11-12” and “12-13” have an ampacity reduced by 47% compared to scenario A. The choice of this reduction, and therefore of the two specific lines in the case study, is due to the willingness to evaluate the performance of market models under variation of LVDN conditions.

Table 6.3. Maximum and minimum prices of the energy market and congestion management market.

Energy market prices	
Maximum price [€/kWh]	Minimum price [€/kWh]
0.4	0.025
Congestion management market prices	
Maximum price [€/kWh]	Minimum price [€/kWh]
0.4995	0.1662

6.4.3 Results

This section describes the results of the analysis. The contents are divided into the following points: *i*) a general description of the evaluation metrics and *ii*) an in-depth description of the results.

6.4.3.1 Techno-economic assessment

The findings represent different performance indicators based on a red-to-green scale, with the worst value represented in red, the best value represented in green, and the intermediate value represented in yellow. The comparison of the studied market models for scenarios A and B are presented in Figure 6.8 and Figure 6.9, respectively. The DA model is taken as a reference in all the following comparisons between market models.

	DA	CDA	PCDA
Local Welfare [EUR]	24.204	23.599	24.204
Clear Quantity Ratio [%]	24.933	27.452	24.933
Waiting Clearing Time [min]	30.021	28.061	30.398
Complexity [**δ**]	4167	4347	2871
Complexity [**α**]	4304	4531	2992
Gas Cost [Gas/GWei]	995585	1017130	921378
Complexity [**δ+α**]	8471	8878	5863

Figure 6.8. Comparison of studied market designs (Scenario A).

Figure 6.8 illustrates that the DA market cannot ensure the best performance for all metrics. The DA market provides the greatest local welfare. Nevertheless, the DA performance is not the best among other market models in terms of cleared quantity ratio and waiting clearing times. It can be noticed that DA and PCDA have the same local welfare and cleared quantity ratio. The reason is that the market clearing in these two market models does not consider the time of bid arrival, and it is cleared after the closure of the market gate. Since the solution is extracted continuously in the CDA market, the coupling of peers is not optimal, lowering the local welfare value.

In contrast, the CDA market has the best performance among market models in terms of cleared quantity ratio and waiting clearing time indicators. These findings show how the CDA market may increase the cleared quantities for the same amount submitted to the market while decreasing the waiting clearing time. The latter factor, allows for rapid user turnover while also adding extra complexity term.

The CDA results in the highest complexity and blockchain gas cost (i.e., the worst performance among market models). This poor performance is driven by continuous matching, which significantly raises interactions between participants and blockchain. On the other hand, the PCDA market results in the lowest complexity and blockchain gas cost. This is achieved via one-shot interaction with blockchain.

Figure 6.9 shows a comparison between the three marked models for scenario B, which considers the congestion management market. The figure shows that the performance of the market models in scenario B is similar to their performance in scenario A. This proves that the market models maintain their performance with changes in LVDN status. CDA and PCDA markets have identical amounts of accepted flexibility and the associated flexibility cost because they have the same energy matched in the energy market, leading to the same results in the congestion management market.

CDA results in a higher flexibility cost than DA and PCDA and lower flexibility volume. In the CDA market, there is a continuous clearing of the market, which decreases the number of available participants who can submit flexibility provision offers in the congestion management market.

	DA	CDA	PCDA
Local Welfare [EUR]	23.953	23.395	23.953
Clear Quantity Ratio [%]	25.621	27.906	25.621
Waiting Clearing Time [min]	30.359	27.901	30.740
Complexity [δ]	4503	4750	3274
Complexity [α]	4651	4946	3407
Gas Cost [Gas/GWei]	1271598	1293279	1197527
Complexity [δ+α]	9154	9696	6681
Flexibility Volume [kWh]	42.489	42.114	42.489
Flexibility Cost [EUR]	18.691	18.850	18.691

Figure 6.9. Comparison of studied market designs (Scenario B).

DA and PCDA have the same local welfare and cleared quantity ratio, and their values are close to those obtained in the CDA market. Nevertheless, the hourly performance of these markets clarifies the differences. Figure 6.10 presents the three market models' order book after bids sorting for the 12th hour, and Figure 6.11 presents the associated results of market clearing. Only the results of scenario A are given because of the similar performance of scenarios A and B. The matching between buyers and sellers is presented in Figure 6.11. The first column shows the contracts of each market participant. It can be seen that the participant can have more than one contract each hour. For instance, b5-2 refers to the 2nd contract of participant b5. The second column refers to the buying or selling price and the third column refers to the energy quantity. It can be noticed that the participant s4 bid is not matched in DA and PCDA since the matching occurs after receiving all bids from participants without considering the time for submitting the bids. However, the s4 bid is matched in CDA because the matching depends on the time of bid submission.

6.4.3.2 Market times assessment

This subsection presents more analysis of waiting clearing time for the studied market models. Figure 6.12 presents the minimum, median, and maximum waiting clearing time for the three market models for scenarios A and B. The performance of the three market models is compared for the same scenario, besides evaluating the performance of each market model considering scenarios A and B. The DA market shows the lowest variation of waiting clearing time among market models. However, CDA shows the most significant variation in waiting clearing time among market models. The PCDA market has a performance in between DA and CDA.

Orderbook – 12th hour					
Buy orders			Sell orders		
#	Price [EUR/kWh]	Quantity [kWh]	#	Price [EUR/kWh]	Quantity [kWh]
b1	0.391	2.337	*s1*	0.101	3.933
b2	0.283	2.337	*s2*	0.123	10.169
b3	0.273	2.337	*s3*	0.197	2.301
b4	0.259	3.506	*s4*	0.265	7.705
b5	0.233	1.725			
b6	0.225	4.082			
b7	0.223	5.442			
b8	0.221	1.725			
b9	0.179	2.588			
b10	0.145	1.725			
b11	0.115	2.588			

Figure 6.10. Orderbook of the studied markets at 12th hour after sorting - scenario A.

Clear book CDA – 12th hour		
# Contract	Price [EUR/kWh]	Quantity [kWh]
b1-1	0.294	2.301
b1-2	0.246	0.036
b2	0.203	2.337
b3	0.269	2.337
b4	0.180	3.506
b5-1	0.167	0.392
b5-2	0.178	0.665
b7	0.173	5.442
b8	0.172	1.725
s1-1	0.246	0.036
s1-2	0.180	3.506
s1-3	0.167	0.392
s2-1	0.203	2.337
s2-2	0.173	5.442
s2-3	0.172	1.725
s2-4	0.178	0.665
s3	0.294	2.301
s4	0.269	2.337

Clear book DA – 12th hour		
# Contract	Price [EUR/kWh]	Quantity [kWh]
b1	0.197	2.337
b2	0.197	2.337
b3	0.197	2.337
b4	0.197	3.506
b5	0.197	1.725
b6	0.197	4.082
b7	0.197	0.079
s1	0.197	3.933
s2	0.197	10.169
s3	0.197	2.301

Clear book PCDA – 12th hour		
# Contract	Price [EUR/kWh]	Quantity [kWh]
b1	0.246	2.337
b2-1	0.192	1.596
b2-2	0.203	0.741
b3	0.198	2.337
b4	0.191	3.506
b5	0.178	1.725
b6-1	0.174	1.860
b6-2	0.211	2.222
b7	0.210	0.079
s1-1	0.246	2.337
s1-2	0.192	1.596
s2-1	0.203	0.741
s2-2	0.198	2.337
s2-3	0.191	3.506
s2-4	0.178	1.725
s2-5	0.174	1.860
s3-1	0.211	2.222
s3-2	0.210	0.079

Figure 6.11. Market clearing results for the studied market models at the 12th hour - scenario A.

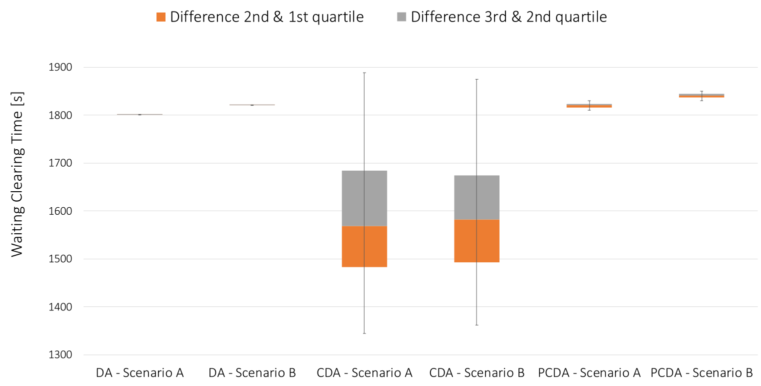

Figure 6.12. Waiting clearing time for scenarios A and B.

6.4.3.3 Blockchain-based complexity assessment

Another performance assessment metric is the market blockchain-based complexity. Tables 6.4 and 6.5 present the blockchain-based complexity in terms of δ and α for the four functions needed to operate the market. The DA, CDA, and PCDA are different in the way they clear the market. Therefore, they have different values for the complexity and associated cost of clearing the market as illustrated in Table 6.5. However, the functions for participant registration, bid submission, and money transfer are the same for the three studied markets. Therefore, the complexity and associated cost are identical for the three market models. Table 6.4 presents the complexity and associated costs for calling these functions for one bid submitted to the market. The results presented in Tables 6.4 and 6.5 are for a single call of the function in one hour.

Table 6.4. Blockchain-based cost and complexity for functions for participant registration, placing a bid, and money transfer.

	Register participant	**Place bid**	**Transfer money**
Complexity - δ	99	403	540
Complexity - α	100	415	559
Gas Cost – Gas/GWei	52690	276149	190395
EUR Cost (2020)	0.299	1.570	1.082
EUR Cost (2022)	0.742	3.890	2.682

Table 6.5. Blockchain-based cost and complexity for the function of clearing the market.

	DA	**CDA**	**PCDA**
Complexity - δ	3058	3305	1829
Complexity - α	3162	3457	1918
Gas Cost – Gas/GWei	476351	497896	402144
EUR Cost (2020)	2.708	2.832	2.287
EUR Cost (2022)	6.708	7.014	5.665

It is clear that the function of clearing the market has significantly higher complexity and cost than the other three functions. These costs are for a single call and are very high considering the amount of energy being traded between small customers participating in LET. The costs in Euros depend on the conversion rates between Ethers and Euros. The costs for the years 2020 and 2022 are presented in the tables.

6.4.3.4 Market model behaviors during congestion

This subsection analyses the congestion management market. Figure 6.13 shows the amount of flexibility provided by different participants for the three studied market models. In this analysis, there is congestion in lines 11-12 and 12-13. This means that the flexibility of customers connected to nodes 11, 12, and 13 is effective in mitigating the congestion. Nevertheless, customers 12 and 13 provide flexibility since the sensitivity of congested lines to these nodes is higher than the sensitivity to node 11.

Figure 6.14 and Figure 6.15 present the order books for the congestion management market for DA and CDA for the 7^{th} and 18^{th} hours. There are large differences in the results of DA and CDA. The figures illustrate the submitted bids to the congestion management market that contain the price and quantity of flexibility at each node. There are no prices for flexibility in the 18^{th} hour for the DA market since there is no congestion observed in this hour for the DA market while there is congestion for the CDA market.

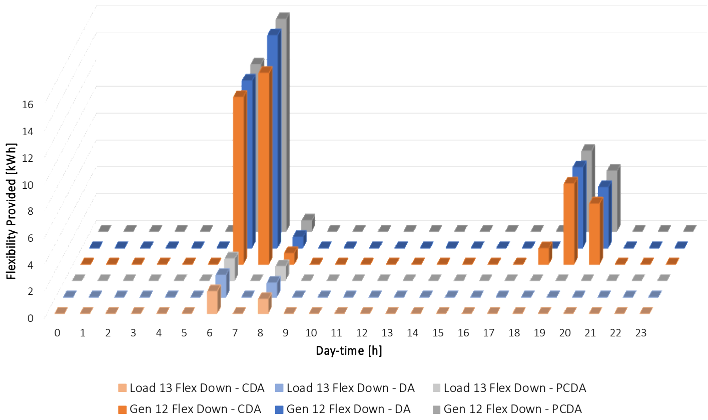

Figure 6.13. The flexibility provided in the congestion management market.

In the 7^{th} hour, the market models have different bids accepted, and therefore, the order book of the congestion management market shows a variation in generators offers number. The generators available for DA and CDA are 3 and 2, respectively. This largely decreases the available downward flexibility of generators. Although the second supplier is not chosen in the CDA market as a flexibility provider, because supplier 15 PTDFs combination with the available flexibility being insufficient to resolve the observed congestion, it is obvious that the flexibility quantity required by the DSO is different. Figure 6.16 presents the values of the PTDFs to clarify this situation.

CMM Orderbook DA – 7^{th} hour		
# Node	Price Flex [EUR/kWh]	Downward Flex. [kWh]
1	0.112	0.839
2	0.168	1.258
3	0.112	0.839
4	0.215	1.616
5	0.144	1.077
6	0.629	-9.428
7	0.309	2.320
8	0.112	0.839
9	0.250	1.877
10	0.312	2.339
11	0.144	1.077
12	1.550	-23.247
13	0.112	0.839
14	0.144	1.077
15	0.116	-1.747
16	0.168	1.258

CMM Orderbook CDA – 7^{th} hour		
# Node	Price Flex [EUR/kWh]	Downward Flex. [kWh]
1	0.151	0.839
3	0.151	0.839
9	0.338	1.877
10	0.421	2.339
11	0.194	1.077
12	0.405	-14.707
15	0.157	-1.747
16	0.069	1.258

Figure 6.14. 7th-hour order book for congestion management market.

CMM Orderbook DA– 18th hour		
# Node	Price Flex [EUR/kWh]	Downward Flex. [kWh]
1	-	1.298
2	-	3.446
3	-	2.798
4	-	1.850
5	-	1.233
6	-	-8.786
7	-	2.148
8	-	2.798
9	-	1.611
10	-	2.798
11	-	1.233
12	-	-20.028
13	-	2.798
14	-	1.233
16	-	3.446

CMM Orderbook CDA– 18th hour		
# Node	Price Flex [EUR/kWh]	Downward Flex. [kWh]
1	0.028	1.298
3	0.060	2.798
6	0.026	-2.466
12	0.074	-15.083
13	0.060	2.798
14	0.026	1.233
16	0.074	3.446

Figure 6.15. 18th-hour order book for the congestion management market.

The quantity of the needed flexibility is different for the studied market models because in CDA the congestion happens after the acceptance of user 11 demand in the energy market. After clearing the user 11 bid in the CDA market, there are users (i.e., 14, 7, and 2) that will submit bids in the market. For all market models, only the generator connected to node 12 is offering to sell energy in the market. Consequently, in the CDA market, where the LVDN congestion happens several clearing instants before the energy trading period closure, the flexibility quantity requested by the DSO from the flexibility provider in node 12 is lower because the provider in node 12 provides less flexibility compared to the plans established in the energy market. There is only one clearing instant in DA, and this situation does not occur.

Figure 6.15 illustrates that in the 18^{th} hour, the opposite occurs. At this hour, there are no congestions in LVDN for DA and PCDA. The figure presents the order book for DA at this hour for clarification but without flexibility prices. The congestion in LVDN arises after the fourth market clearing in the CDA market. In this condition, user 13, who can alleviate the congestion, has not yet participated in the market, thus preventing high energy flow in line 11-12. Consequently, the generator at node 6 can partially meet the demand of users 1 and 3, while the generator at node 12 must supply the rest of the users. Nevertheless, there is congestion in line 11-12 due to the lack of demand from the other users. This congestion is not observed in the DA and PCDA because service delivery occurs after all bids have been collected and cleared.

		Nodes															
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Branches	$0-1$	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
	$1-2$		-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
	$2-3$			-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
	$3-4$				1	1	1	1	1	1	1	1	1	1	1	1	1
	$4-5$					1	1	1	1	1	1	1	1	1	1	1	1
	$5-6$						1	1	1	1	1	1	1	1	1	1	1
	$6-7$							-1	-1								
	$7-8$								-1								
	$6-9$									1	1	1	1	1	1	1	1
	$9-10$										1	1	1	1	1	1	1
	$10-11$											1	1	1	1	1	1
	$11-12$												1	1			
	$12-13$													-1			
	$11-14$														-1	-1	-1
	$14-15$															-1	-1
	$15-16$																-1

Figure 6.16. PTDFs of congestion management market for the 7th hour.

In the analyzed scenario, the congestion market relieved the congestion that occurred due to LET. However, there could be a situation where the available flexibility from flexibility providers is not enough to deal with the congestion. In this case, the DSO may use the most effective or a combination of effective non-market-based solutions according to the regulations. Non-market-based solutions include distribution network reconfiguration, local regulation devices, grid investment, generation curtailment, or load shedding.

6.5 Conclusion

This chapter Compares three market models used for local energy trading (LET): double auction (DA) implemented as a centralized market model, continuous double auction (CDA) implemented as a distributed market model, and pseudo-continuous double auction (PCDA) implemented as a distributed market model. The distributed market models are implemented using a blockchain platform. To eliminate any congestion at the low voltage distribution network (LVDN), a congestion management market operated by the distribution system operator is used.

The three market models are compared, considering several performance metrics. The findings show that the centralized DA has 2% lower operating costs than distributed CDA but 7% higher operating costs than distributed PCDA. Moreover, the DA has a 5% lower complexity than the CDA market but a 30% higher complexity than PCDA. Furthermore, the DA has a 7% higher waiting clearing time than CDA but a 1% lower waiting clearing time than PCDA

The results show that the current public blockchain technology, like Ethereum, is only partially suitable for the LET application. Mainly, the associated gas costs for implementing LET on public blockchain platforms significantly limit the use of public blockchain in this application. Other new distributed ledger technologies, such as IOTA could surpass the public blockchain limitations.

This study is a proof of concept of public blockchain utilization for implementing several market models and evaluating their performance. It could be extended by performing a replicability analysis that considers other scenarios, different participants, and LVDNs. Moreover, there is a need for scalability analysis considering a larger number of participants.

Chapter 7
Conclusions and Future Work

7.1 Conclusions

Local energy trading (LET) is an emerging approach for successfully integrating distributed energy resources (DERs) into future power systems. It seeks to extend the concepts of deregulated wholesale electricity markets to end customers. Many studies and projects have proven the superiority and benefits of LET over many other DER management approaches. LET could reduce energy costs, maximize the self-generation of local generation in the energy community (EC), maximize EC self-sufficiency, and empower end customers to take an active role in the power system. However, many open questions need more research before adopting LET. What are the benefits of LET compared to other approaches? How are LET benefits affected by the deployed DERs? What are the impacts of LET on unbalanced low voltage distribution networks (LVDN) in the presence of different DERs? What is the effect of network tariffs on LET's impact on LVDN? What are the optimal sizes of DERs in LET that minimize the total costs considering the current conditions and future variations? What are the suitable technologies for LET?

The findings demonstrated the trade-offs between the benefits of LET and the associated impacts on unbalanced LVDN. LET outperformed the home energy management system (HEMS) by lowering the EC's energy costs, lowering energy purchased from the retailer, and enhancing self-generation in the presence of different DERs. However, in LET scenarios with flexible devices like battery energy storage (BES) and electric vehicles (EVs), the peak of EC energy imports from the retailer is higher than in HEMS. Furthermore, the impacts of LET and HEMs on LVDN are identical for scenarios with photovoltaic (PV) only (i.e., without BES and EVs) since the actual energy flow in the LVDN is the same (i.e., all generated energy from the PV is injected to the grid). Moreover, LET results in higher impacts on the unbalanced LVDN for scenarios with high penetration of BES and EVs. The findings revealed that the cause for these LET impacts is the simultaneous charging of EC BES and EVs when energy costs are low or to fulfill the mobility demands of EVs.

Next, the contracted power cost (i.e., power-based network tariff) is integrated into the LET model to address the technical challenges of LET on unbalanced LVDN without complicating the optimization process. The results demonstrated that the proposed approach lowered the EC's peak demand significantly without impacting its economic performance, energy exchange with the retailer, and the quantity of traded energy locally. Consequently, the proposed approach prevents LVDN limit violations that occur in the LET scenario that do not consider contracted power cost. These findings highlight the significance of network tariffs in guiding customers' behavior and reducing the impact on LVDN.

Existing studies focused on EC operation assuming the ratings of installed DERs. A limited number of studies proposed optimal planning of DERs installed in ECs, enabling LET. The optimal planning reduced the annual costs compared to the scenario without optimal planning of photovoltaic (PV) and BES. Under the current operating conditions in Madrid, Spain, it is not economically feasible to install private BES. Sensitivity analysis shows that, by the decrease of BES investment costs, increase of electricity prices, or decrease of electricity selling price, it could be feasible to install BES at part of the EC houses.

Finally, we conducted a comparative analysis of three different market models for LET: double auction (DA), continuous double auction (CDA), and pseudo-continuous double auction (PCDA). The DA market model is proposed as a centralized version, while the CDA and PCDA market models are realized in a distributed manner via the blockchain platform. For the analyzed case study, there is no market model that is superior in all performance indices. Moreover, public blockchain shows many limitations in its use in LET.

7.2 Implications for stakeholders and recommendations

The findings of this thesis are significant for several stakeholders as follows:

- **End customers**

The findings show that end customers can obtain substantial economic benefits and better utilization of their DERs through LET among their participants. The consumers can buy energy from other peers at lower prices than the retailer's prices, and prosumers can sell energy to other peers at higher prices than the retailer's selling prices, which is a win-win situation for both consumers and prosumers. These benefits can encourage the adoption of DERs and decrease their payback periods. Moreover, LET enables customers to gain more control over their energy sources and consumption. They can choose to buy energy from renewable energy sources (RESs) or specific peers. Furthermore, LET allows customers to become more energy-independent, reducing their reliance on retailers and energy purchased from the main grid. All these benefits are achieved only by convincing end customers of this new approach to manage their DERs. Therefore, there is a need to launch awareness and education programs to inform customers about the benefits of LET and encourage active participation and cooperation. On the other hand, the participation of end customers in some LET designs results in lower autonomy and raises privacy concerns. These challenges should be surpassed to ensure end customers' acceptance of LET.

- **Distribution system operators**

For distribution system operators (DSOs), the findings show that the high penetration of BES and EVs in LET can lead to operation limit violations in LVDN. Therefore, advanced management strategies and monitoring devices are needed to ensure the operation of LVDNs within acceptable limits while maximizing the use of DERs in LET. Moreover, LET requires advanced information and communication technologies (ICT) to enable the interaction between LET participants and LET manager.

- **Policymakers**

The benefits of LET, as clarified in the results obtained, encourage policymakers to develop regulations to enable end customers to trade energy locally. Moreover, the regulations should state the associated developments in ICT, monitoring, and regulation devices required in LVDNs to ensure normal operation of the grid. Additionally, there is a need for regulations for market-based solutions (e.g., local flexibility markets) to eliminate violations of LVDNs constraints. Additionally, the findings show that efficient network tariff design is effective in decreasing peak demand and can defer infrastructure investments at the distribution level. Therefore, policymakers should explore and implement cost-reflective network tariffs that can dynamically adapt to varying peak and off-peak periods, encouraging efficient implementation of LET and fair allocation of network usage charges while avoiding grid issues. In addition, it is essential to have synergy between different mechanisms (i.e., network tariffs and local flexibility markets) used [202]. Furthermore, the findings show that installing BES in LET is not economically feasible under the current prices. Therefore, regulations should put economic incentives in place to enable better utilization of local generation from RESs. Considering the limitations of public blockchain in LET, policymakers need to perform pilot projects to study the suitability of other distributed ledger technologies in LET.

- **Retailers**

LET could decrease the energy exchange between customers and retailers and decrease the associated costs, which may negatively impact retailers' revenue streams. Moreover, LET increases the competition between retailers and other local energy producers. Therefore, retailers should explore and develop new business models suitable for LET.

- **Technology developers**

Implementing the studied LET approaches requires developing and adopting many innovative technologies and techniques at the distribution level, such as trading platforms, ICT infrastructure, smart metering, forecasting algorithms, etc. These technologies should be reliable and scalable to enable efficient performance with the increased number of participants and be secure against any cyber-attacks. Moreover, the developed technologies should be interoperable with each other and with existing technologies in power systems. Furthermore, developers need to create easy-to-use applications for phones, PCs, etc., that enable the customers to set preferences and monitor their DERs management and exchange of energy with peers with low effort. The end customers will probably not specify their trading preferences manually and will need automation in their decisions. Therefore, developers must create efficient algorithms to automate DER management and trading decisions.

7.3 Future work

This thesis addressed many interesting research questions regarding LET and delivered important findings. However, there is still a need for more studies to address other relevant research questions. Future studies should address the following areas:

- Assess the impact of LET on different LVDNs, considering different tariff designs.
- Stochastic assessment of the impacts of LET on LVDNs with different topologies considering uncertainties.
- Consider other flexible devices in the EC, like heat pumps and different types of communities containing commercial and industrial participants.
- Evaluate the effect of the end customer power factor on LET impacts on LVDNs.
- Develop other market-based and non-market-based approaches to mitigate the impacts of LET on LVDNs.
- Assess the effect of contract power costs on LET with different types of customers (i.e., commercial and industrial).
- Assessment of the impacts of LET on generation and transmission levels.
- Optimal planning and operation of ECs DERs considering different tariff designs.
- Optimal planning and operation of ECs DERs using different optimization methods that model uncertainties.
- Consider different regulations regarding ECs and how they can affect the communities' operations, investments, and impacts on the electricity system.
- Evaluate the performance of emerging distributed ledger technologies like IOTA in LET and compare them with different blockchain technologies (i.e., public and private).
- Assess the performance of ECs using different designs of energy sharing coefficients among members of the community.

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Appendix A

This appendix compares two methods to model the contracted power costs in EC model. Equation (A.1) presents the objective function of scenario 3 in chapter 4. In this scenario, the contracted power for the whole EC is optimized. Equation (A.2) presents the objective function of scenario 4. In this scenario, the contracted power for each house is optimized. Table A.1 shows that the two scenarios have very similar performance.

$$min \ (\sum_{per\in P} p_{per}^{cp} \times CP_{per} + \sum_{t} \sum_{h} (\ p_t^b \times G_{t,h} - p_t^s \times F_{t,h})) \tag{A.1}$$

$$min \ (\sum_{per\in P} \sum_{h} p_{per}^{cp} \times CP_{per,h} + \sum_{t} \sum_{h} (\ p_t^b \times G_{t,h} - p_t^s \times F_{t,h})) \tag{A.2}$$

Table A.1. Comparison of two methods to model contracted power costs.

	Scenario 3 in chapter 4	**Scenario 4**
Imports from retailer (kWh)	26492.77	26499.84
Exports to retailer (kWh)	776.26	776.11
Total LET (kWh)	16971.25	17165.85
Demand by retailer (%)	56.09	56.11
Demand by DERs (%)	43.91	43.89
Peak of grid consumption (kW)	221.06	221.97
Total operation Costs (€)	3389.57	3392.80
Costs of imports from retailer (€)	3447.80	3450.98
Revenue of exports to retailer (€)	58.23	58.18