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Research paper

Optimal planning and operation of energy community DERs considering local energy trading and uncertainties

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ABSTRACT

Local energy trading 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 capacities (i.e., ratings) and penetration levels of the DERs. However, there is a noticeable lack of emphasis on optimizing the planning and integration of DERs within these ECs. Considering the high cost of DERs, there is a need to optimally size DERs of ECs' participants that maximize the benefits, minimize the expenses of DER owners, and reduce the payback period. In this paper, 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 arrival and departure uncertainties. The simulation results demonstrate that optimal planning reduces the annual costs by 10.95 % compared to the scenario without optimal PV and BES planning. Sensitivity analysis shows that, by decreasing the investment costs of BES by 30 %, increasing the electricity prices by 40 %, or decreasing the electricity selling price by 40 %, it could be feasible to install BES at part of the EC houses. There are no violations of the distribution network limits in all studied scenarios. © 2017 Elsevier Inc. All rights reserved.

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 mo-del 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 [1–4]. 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 [5,6].

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 [7]. One new approach to coordinate DERs is peer-to-peer energy trading (P2P-ET) or community energy trading (CET) [8,9].

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Nomenclature

Abbreviations

BES	Battery energy storage
CEC	Citizen energy communities
CET	Community energy trading
DER	Distributed energy resource
DN	Distribution network
EC	Energy community
EV	Electric vehicle
GA	Genetic algorithm
GT	Game theory
HP	Heat pump
LP	Linear programming
LVDN	Low voltage distribution network
MILP	Mixed integer linear programming
NPV	Net present value
O&M	Operation and maintenance
P2P	Peer-to-Peer
P2P-ET	Peer-to-Peer energy trading
PSO	Particle swarm optimization
pu	Per unit
PV	Photovoltaic
REC	Renewable energy communities
RES	Renewable energy source
RL	Reinforcement learning
VUF	Voltage unbalance factor
WG	Wind generation

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
$E_{t,h,s}^{\mathrm{BES}}$	BES stored energy at time t, house h, and state s
$D_{t,h,s}^{\mathrm{BES}}$	BES discharge power at time t, house h, and state s
$D_{t,h,s}^{\mathrm{EV}}$	EV discharge power at time t, house h, and state s
$X_{t,h,s}$	Exports (selling) to other houses (i.e., peers) from house h at instant t and state s
$E_{t,h,s}^{\mathrm{EV}}$	EV stored energy at time t, house h, and state s
$F_{t,h,s}$	Energy sold to the retailer at instant t and state s from house h
$C_{t,h,s}^{\mathrm{BES}}$	BES charge power at time t, house h, and state s
$C_{t,h,s}^{\mathrm{EV}}$	EV charge power at time t, house h, and state s
$I_{t,h\leftarrow p,s}^{p}$	Energy imported (i.e., purchased) to house h from its peer p at instant t and state s
$X_{t,h\rightarrow p,s}^{p}$	Energy exported (i.e., sold) from house h to its peer p at instant t and state s
$CP_{per,s}$	Contracted power at period per and state s

Parameters, scalars, and sets	Description
Co^{PV}	PV investment cost/kWp
$Co^{PV}_{O\&M}$	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
η_C^{BES}	Efficiency of BES charging
η_D^{BES}	Efficiency of BES discharging
$P_{t,h,s}^{d}$	Net power demand at time t, house h, and state s
η_C^{EV}	Efficiency of EV charging
η_D^{EV}	Efficiency of EV discharging
$\overline{C}_{BES}$ and $\overline{D}_{BES}$	Upper limits of BES charging and discharging powers
$\overline{C}_{EV}$ and $\overline{D}_{EV}$	Upper limits of EV charging and discharging powers
$\underline{E}_{BES}$ and $\overline{E}_{BES}$	BES storage level lower and upper limits
$\underline{E}_{EV}$ and $\overline{E}_{EV}$	EV storage level lower and upper limits
b_t	Binary parameter value and time t.It indicates if the EV is connected to the charger or not.
ψ^{P2P}	P2P trade loss factor
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
$t \in T$	Time instant t in time horizon T
$h,p \in H$	House h and peers p in a community of H Houses
$s \in$ Ɗ	Ɗ is a set of states for every time instant

CET tries to adapt the concepts of liberalized wholesale electricity markets to the end consumer level [10]. The CET could be managed in a centralized or decentralized manner using promising technologies like blockchain, with each approach having its strengths and weaknesses [11]. The CET gives the customers an active role, where the customers have the choice to 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 may also have the opportunity to purchase energy from peers at a lower price than the retailer's price. By increasing the renewable energy sources (RESs) generation besides consumption in the P2P trading scheme, energy supplied by central conventional generation could be reduced, and local supply-demand balance could be achieved [12]. 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, CET could reduce electricity costs, increase self-generation, and increase the self-sufficiency of the ECs [13,14].

On the other hand, the CET is associated with several challenges and barriers [2], 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. [6]. Moreover, new regulations, pricing schemes, and business models should be developed to enable large-scale adoption of CET. Furthermore, CET could impact the physical grid, especially the DNs, due to the power flow change and end users' energy utilization patterns [9,15–17]. All these challenges should be handled before CET becomes a reality and achieves a considerable adoption rate.

European Union directives have facilitated the creation of ECs across member states, aiming to foster positive social, environmental, and economic outcomes [18–20]. These directives established the concepts of renewable energy communities (RECs) and citizen energy communities (CECs), which have subsequently been incorporated into the national laws of individual countries. RECs and CECs empower members to share locally generated energy through simple approaches such as energy sharing coefficients. However, the specific regulations governing the formation of ECs vary significantly from country to country. These differences can include rules regarding the types of generation permitted, limits on installed generation capacity, ownership of local generation assets, geographical proximity requirements for EC members, methods for sharing locally produced energy, and the pricing structures for energy exchanged with traditional retailers [21,22].

Spain has made significant advancements in regulating ECs to promote collective self-consumption and the decentralized generation of renewable energy. The cornerstone of this regulatory framework is Royal Decree 244/2019, which establishes the administrative, technical, and economic conditions for self-consumption of electricity [23]. This decree enables multiple consumers within a defined proximity, such as residents of the same building or neighborhood, to collectively own and benefit from shared renewable energy installations. By facilitating the formation of ECs, the decree aims to enhance energy efficiency, reduce costs, and empower consumers to participate in the energy transition actively. Several studies assessed the performance of different energy sharing coefficient designs (static, dynamic, etc.) considering Spanish case studies with different types of EC members (i.e., residential, industrial, and commercial) [24–27]. The findings highlight the enhanced performance of EC when dynamic energy charging coefficients over static energy sharing coefficients. However, dynamic energy sharing coefficients make EC operation more complex than the use of static energy sharing coefficients.

Photovoltaic (PV) generation is the most common renewable generation at a small scale due to its low cost and easy installation that 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 [28]. 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 [29]. Many countries promote self-generation by reducing incentives on electricity selling prices to retailers [30,31]. Many studies proved the feasibility of BES for all stakeholders at the distribution level. In [32], the role of centralized and decentralized BES in an EC enabling local energy trading 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 [9]. 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 [33–35]. The optimal sizing of PV and BES for a house operating by a home energy management system is studied in [36] 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. [37] 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 [38]. 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 [35]. The authors of [39] developed a two-stage multi-objective optimization for optimal planning and management of PV, WG, BES, demand response, and network reconfiguration. The findings demonstrate significant improvements in system performance in reducing system costs, power losses, and voltage deviation. Other articles study the optimal sizing of isolated microgrids with various objectives [40,41].

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 [42]. Another tool, the Distributed Energy Resource Customer Adoption Model (DER-CAM), is used to optimize the DER investments in buildings or microgrids [43].

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. However, most CET 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 local energy trading. The energy trading participants could be microgrids, different types of buildings, houses, etc. In [44], 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 [45,46].

Furthermore, the authors in [47] 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 [48] 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 [49], 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. [50] used GA for optimal planning and operation of BES in university buildings in the USA. The buildings have PV installations and can trade energy in P2P. 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 P2P-ET between houses [51]. The objective of the study is to maximize the profit of the community. In [52], 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 [53]. The objectives are maximizing profit and self-generation of locally generated energy from PV.

Table 1 compares the existing studies addressing the optimal planning of DERs in ECs considering local energy trading. Most of the studies focused on ECs with buildings and none of the reviewed studies 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, the literature focused on the optimal planning of DERs in EC and did not assess the impacts on DNs. Only, Ref. [48] assessed the impacts of EC on DNs, but it did not consider the unbalanced nature of DN. 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 local energy trading that considered uncertainties, impacts on DNs, and the unbalanced nature of DN. Therefore, this paper addresses the research gap in the literature by proposing 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 an unbalanced low voltage distribution network (LVDN) are assessed.

The contributions of this paper can be summarized as follows:

- LP-based optimal planning and operation approach of EC's DERs in Madrid, Spain, to minimize the annual costs, including investment, operation and maintenance (O&M), and retailer operation (i.e., energy and contracted power).
- The first study of optimal planning of ECs enabling local energy trading 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.
- Assessing the impacts of the EC on transformer loading, line loading, voltage unbalance, and voltage deviations of unbalanced LVDN.

The rest of this paper is organized as follows. Section 2 introduces the planning and operation optimization model, and LVDN impacts assessment. Section 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 4 discusses the findings of optimal planning and operation and evaluates the impacts on the unbalanced LVDN. Section 5 presents the conclusion.

2. Problem formulation

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

2.1. Objective function

The objective of this study is to minimize the total annual costs of the studied EC, as stated in (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 (2). In this approach, every objective function is weighted according to every state probability of occurrence for all the considered planning period [54,55].

$$\min f, \tag{1}$$

$$f_{\exp} = \sum_{t \in T} \sum_{s \in \text{Ɒ}} f(t,s) \times \mathbb{C}(t,s), \tag{2}$$

where T is a set of time instants, $T = \{1, 2, 3, .., N_t\}$ and N_t represents the number of time instants. Ɒ is a set of states for every time instant t, $\text{Ɒ} = \{1, 2, 3, .., N_s\}$ 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 (3) includes the PV investment cost ($C^{\mathrm{PV,INV}}$) (4), PV O&M cost ($C^{\mathrm{PV,O\&M}}$) (5), BES investment cost ($C^{\mathrm{BES,INV}}$) (6), BES O&M cost ($C^{\mathrm{BES,O\&M}}$) (7), and retailer operation cost (C^{Retailer}) (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 (9) and (10), respectively.

$$f = C^{\mathrm{PV,INV}} + C^{\mathrm{PV,O\&M}} + C^{\mathrm{BES,INV}} + C^{\mathrm{BES,O\&M}} + C^{\mathrm{Retailer}}, \tag{3}$$

$$C^{\mathrm{PV,INV}} = CRF^{PV} \times \sum_{h \in H} P_h^{PV,r} \times Co^{PV}, \tag{4}$$

Table 1
Comparison of existing studies addressing optimal planning of DERs installed in ECs considering local energy trading.

Ref.	Data	DERs	Participants	Algorithm	Objective	Grid impacts	Uncertainties	Unbalanced DN
[44]	Australia	PV, WG, BES	Microgrids	PSO, GT	Min. loss of supply, max. annual profit	X	X	X
[47]	South Korea	PV, BES	Buildings	RL	Min. peak demand, max. self-sufficiency, annual profit	X	X	X
[48]	Synthetic	PV, HP, BES	Buildings	GA	Max. self-sufficiency, min. BES cost	✓	X	X
[49]	Japan	PV, BES	Buildings	GA	Max. BES profit, max. self-generation, min. losses	X	X	X
[50]	USA	PV, BES	Buildings	GA	Max. BES NPV, min. energy costs	X	X	X
[51]	Turkey	PV, BES	Houses	MILP	Max. profit	X	X	X
[52]	Italy, Portugal	PV, WG, BES	Residential, commercial	GT	Max. NPV	X	X	X
[53]	Spain	PV	Houses	GA	Max. profit, max. self-generation	X	X	X
This study	Spain	PV, BES, EV	Houses	LP	Min. annual costs	✓	✓	✓

$$C^{\mathrm{PV,O\&M}} = N_{days} \times \sum_{t\in T}\sum_{h\in H}\sum_{s\in \mathfrak{D}} Co^{PV}_{O\&M} \times P^{PV}_{t,h,s} \times \mathbb{C}(t,s), \tag{5}$$

$$C^{\mathrm{BES,INV}} = CRF^{BES} \times \sum_{h\in H} E^{BES,r}_{h} \times Co^{BES,C}, \tag{6}$$

$$C^{\mathrm{BES,O\&M}} = 0.02 \times C^{\mathrm{BES,INV}}, \tag{7}$$

$$C^{\mathrm{Retailer}} = N_{days} \times \left(\sum_{per\in P}\sum_{s\in N_J} p^{cp}_{per} \times CP_{per,s} \times \mathbb{C}(per,s) + \sum_{t\in T}\sum_{h\in H}\sum_{s\in N_J}\left(p^{b}_{t,s} \times G_{t,h,s} - p^{s}_{t,s} \times F_{t,h,s}\right) \times \mathbb{C}(t,s)\right), \tag{8}$$

$$CRF^{PV} = \frac{r(r+1)^{N^{PV}}}{(r+1)^{N^{PV}} - 1}, \tag{9}$$

$$CRF^{BES} = \frac{r(r+1)^{N^{BES}}}{(r+1)^{N^{BES}} - 1}, \tag{10}$$

where H is a set of houses, $H = \{1, 2, 3, .., N_h\}$ and N_h represents the number of houses in the EC. $P^{PV,r}_{h}$ 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), $Co^{PV}_{O\&M}$ is O&M cost/kWh generated from PV and is equal to 1 Cent/kWh of PV generation, $P^{PV}_{t,h,s}$ is generated power from PV at time instant t, house h, and state s. $E^{BES,r}_{h}$ 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^{cp}_{per} is contracted power cost for period per, $CP_{per,s}$ is contracted power at period per and state s, $p^{b}_{t,s}$ 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. $p^{s}_{t,s}$ 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 [54].

2.2. Community energy trading operation constraints

This section presents a linear model for CET operation constraints. Recent research studies have presented a similar concept in detail for centralized CET [56–58]. 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 (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 P2P energy trading in the EC, DER limits, power balance at each house node, and contracted power limits, bound the operation cost function of EC.

The power balance constraint is given in (11). It means that at each house, the sum of supply should be equal to the sum of demand at every time t and state s. Eq. (11) represents the power balance of a house equipped with EV, BES, and PV. Other houses with no DERs or different DER installations could be represented by removing some components from (11). Eq. (12) shows that the sum of energy purchased from the retailer by all houses at any time instant t and state s must be less than or equal to the contracted power at that time instant. Similarly, the sum of energy sold to the retailer by all houses at any time instant t and state s must be less than or equal to the contracted power at that time instant as given in (13).

$$G_{t,h,s} + I_{t,h,s} + P^{PV}_{t,h,s} + D^{\mathrm{BES}}_{t,h,s} + D^{\mathrm{EV}}_{t,h,s} = X_{t,h,s} + dem_{t,h,s} + F_{t,h,s} + C^{\mathrm{BES}}_{t,h,s} + C^{\mathrm{EV}}_{t,h,s} \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D}, \tag{11}$$

$$\sum_{h\in H}\sum_{s\in \mathfrak{D}} G_{t,h,s} \leq CP_{per,s}\ \forall per \in P, \forall t \in T, \tag{12}$$

$$\sum_{h\in H}\sum_{s\in \mathfrak{D}} F_{t,h,s} \leq CP_{per,s}\ \forall per \in P, \forall t \in T, \tag{13}$$

BES constraints are given in (14)-(17). Eqs. (14) and (15) represent the charging and discharging power limits, respectively, while (16) describes the BES stored energy limits. The minimum state of charge (SoC) of BES is 20 %, and the maximum SoC is 100 %. The BES stored energy at any time instant t is calculated by (17), and it is equal to the energy charged/energy discharged added to/subtracted from the stored energy at the previous time instant $t-1$.

$$0 \leqslant C^{\mathrm{BES}}_{t,h,s} \leqslant \overline{C}_{BES} \quad \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D}, \tag{14}$$

$$0 \leqslant D^{\mathrm{BES}}_{t,h,s} \leqslant \overline{D}_{BES} \quad \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D}, \tag{15}$$

$$\underline{E}_{BES} \leqslant E^{\mathrm{BES}}_{t,h,s} \leqslant \overline{E}_{BES} \quad \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D}, \tag{16}$$

$$E^{\mathrm{BES}}_{t,h,s} = E^{\mathrm{BES}}_{t-1,h,s} + \eta^{BES}_{C} \times C^{\mathrm{BES}}_{t,h,s} - \left(\frac{1}{\eta^{BES}_{D}}\right) \times D^{\mathrm{BES}}_{t,h,s} \quad \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D}. \tag{17}$$

Similarly, EV constraints are given in (18)-(22). Eqs. (18) and (19) represent the charging and discharging power limits, respectively, while (20) describes the EV stored energy limits. The minimum SoC of EV is 20 %, and the maximum SoC is 100 %. b_t is a binary parameter to indicate if the EV is connected to the charger or not at the time instant t as given in (21). The value of b_t is 0 when the EV is used for mobility and 1 when the EV is connected to the charger. The EV stored energy at any time instant t is calculated by (22), and it is equal to the energy charged/ energy

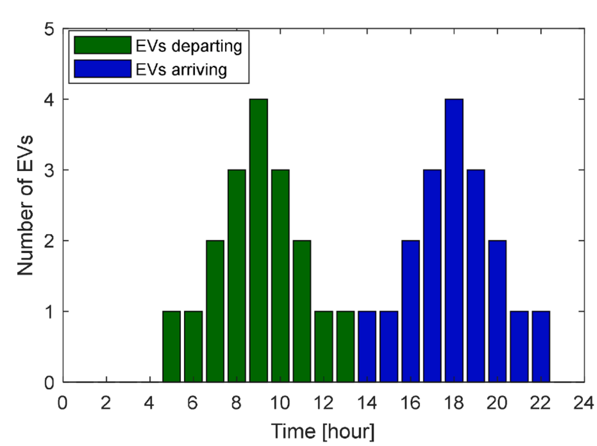

Fig. 1. The number of electric vehicles departing or arriving at each hour of the day.

discharged added to/subtracted from the stored energy at the previous time instant $t-1$ [59].

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 Fig. 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 Fig. 1 in blue. At departure, the EV SoC must be ≥ 75 %, and when they are connected to the charger, the EV SoC 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.

$$0 \leqslant C^{\mathrm{EV}}_{t,h,s} \leqslant \overline{C}_{EV} \times b_t \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D}, \tag{18}$$

$$0 \leqslant D^{\mathrm{EV}}_{t,h,s} \leqslant \overline{D}_{EV} \times b_t \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D}, \tag{19}$$

$$\underline{E}_{EV} \leqslant E^{\mathrm{EV}}_{t,h,s} \leqslant \overline{E}_{EV} \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D}, \tag{20}$$

$$b_t = \begin{cases} 1, \ \text{if EV is connected to the LVDN at time instant } t \\ 0, \ \text{otherwise} \end{cases} \forall t \in T, \tag{21}$$

$$E^{\mathrm{EV}}_{t,h,s} = E^{\mathrm{EV}}_{t-1,h,s} + \eta^{EV}_{C} \times C^{\mathrm{EV}}_{t,h,s} - \left(\frac{1}{\eta^{EV}_{D}}\right) \times D^{\mathrm{EV}}_{t,h,s} \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D}. \tag{22}$$

Eqs. (23)-(26) represent the constraints for P2P energy trading in the EC. The purchased energy by house h from peer p should be equal to the sold energy from p to h at time instant t and state s taking into account the losses at LVDN due to this P2P energy trading within the EC as given in (23). P2P energy trading losses (i.e., ψ^{P2P}) is equal to 5 %.

$$I^{p}_{t,h\leftarrow p,s} = \psi^{P2P} * X^{p}_{t,p\rightarrow h,s} \quad \forall p \rightarrow h, \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D} \tag{23}$$

Eq. (24) indicates that the sold energy at time instant t and state s by house h should equal the sum of energy sold to any other peer p within EC from house h.

$$X_{t,h,s} = \sum_{p\rightarrow h} X^{p}_{t,h\rightarrow p,s} \quad \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D}. \tag{24}$$

Similarly, (25) indicates that the purchased energy at time instant t and state s by house h should equal the sum of energy purchased from any other peer p within the EC by house h.

$$I_{t,h,s} = \sum_{p \neq h} I^{p}_{t,h\leftarrow p,s} \quad \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D}. \tag{25}$$

The sum of the EC houses P2P exports at time instant t and state s should be equal to the sum of the EC houses' P2P imports, taking into account the losses at LVDN due to P2P energy trading as indicated in (26).

$$\sum_{h} \psi^{P2P} \cdot X_{t,h,s} = \sum_{h} I_{t,h,s} \ \forall t \in T,\ \forall s \mathfrak{D}. \tag{26}$$

2.3. Impacts of CET on LVDN

Eq. (27) is used to calculate each house's net power demand $P^{d}_{t,h,s}$ at time t and state s. $P^{d}_{t,h,s}$ is the input to Pandapower in order to run the three-phase load flow since the studied LVDN is unbalanced with different numbers of houses connected to each phase.

$$P^{d}_{t,h,s} = \ G_{t,h,s} + I_{t,h,s} - F_{t,h,s} - X_{t,h,s} \ \forall t \in T,\ \forall h \in H,\ \forall s \in \mathfrak{D}. \tag{27}$$

In practice, there is usually an imbalance (i.e., unbalance) in the one-phase loads attached to different phases at the LVDNs. To ensure the proper operation of LVDNs, this imbalance must be maintained within prescribed limits. Because customers in a geographical region usually exhibit nearly identical consumption patterns, preserving the imbalance degree within allowed technical limits was simple by spreading the loads uniformly at each phase. The high deployment of one-phase DERs (e.g., EV, BES, PV, etc.) is predicted to drastically alter this scenario [60]. As a result, several research studies were conducted to examine the effects of one-phase DERs on LVDNs phase imbalance. Moreover, new DER management approaches (i.e., CET) could change the houses' supply and demand habits. As a result, it is critical to analyze the effects of CET on phase imbalance. The value of imbalance is measured by the voltage unbalance factor (*VUF*%). *VUF*% is a ratio between the negative sequence component and the positive sequence component according to IEC 62749, as indicated in (28) [61]. *VUF*% should not exceed 2 %.

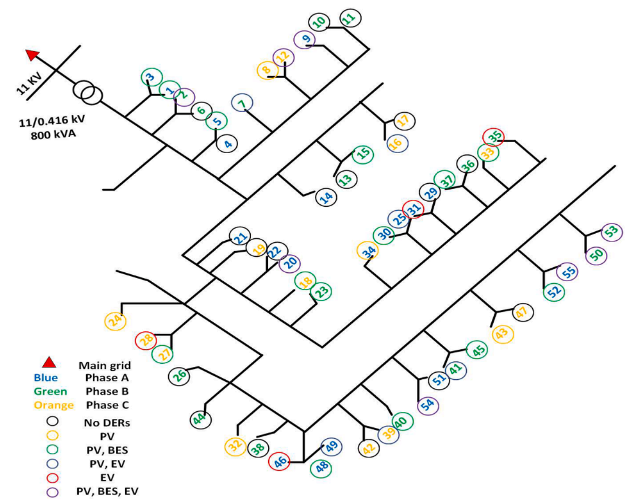

Fig. 2. Single line diagram of the unbalanced low voltage test network.

$$VUF\% = \frac{V_2}{V_1} * 100. \tag{28}$$

3. Case study

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.

3.1. Low voltage distribution network

Fig. 2 depicts a single-line schematic of the investigated imbalanced IEEE European test system that is used as a case study [62]. This test system is widely used as a benchmark for studying distribution networks in Europe since it represents a typical European radial LVDN. It was developed to model real-world LVDNs and assess the impact of DERs and their management approaches. The network has an 800 kVA transformer, transforming the voltage level from 11 kV to 0.416 kV. The network contains 55 one-phase residential houses (i.e., 21 houses at Phase A, 19 at Phase B, and 15 at Phase C). The phase of connection is distinguished by the house number color, as indicated in Fig. 2.

3.2. DERs characteristics

The test network in this study contains flexible devices such as EV

Table 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

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, as indicated in Fig. 2. This study considers an EC with the potential for high adoption rates of different DERs. The PV penetration level is 60 % of the EC houses (i.e., 33 PV). The BES penetration level is 40 % (i.e., 22 BES), and they have 95 % discharging and charging efficiencies. These penetration levels represent the houses willing to install PV and BES. The characteristics of PV [54] and BES [29] used in this study are given in Table 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 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.

The EV penetration level is 33 % (i.e., 18 EVs). They have 24 kWh energy capacity and 3.6 kW charging/discharging power. They have 96 % discharging and charging efficiencies. The color of the circle around the house number distinguishes the installed DERs at each house. For instance, a green circle represents a house with PV and BES. The red circle represents a house with EV only.

3.3. 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 [63].

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 (29). The data for PV generation for Madrid was acquired from Renewables Ninja for one year [64], which provides generation data at hourly resolution based on historical weather conditions. It allows researchers to model realistic PV generation profiles for different locations worldwide. Fig. 3 depicts the normalized PV production profile of a single house for one representative day. The PV generation profile is the same for all houses in the EC.

$$f_b(R^t) = \begin{cases} \dfrac{\Gamma(\alpha^t + \beta^t)}{\Gamma(\alpha^t)\Gamma(\beta^t)} \times (R^t)^{(\alpha^t-1)} \times (1-R^t)^{(\beta^t-1)}, & 0 \le R^t \le 1, \alpha^t, \beta^t \ge 0 \\ 0, & otherwise \end{cases}, \tag{29}$$

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 (30) and (31).

$$\beta^t = (1-\mu^t) \times \left(\frac{\mu^t \times (1+\mu^t)}{(\sigma^t)^2} - 1 \right) \tag{30}$$

$$\alpha^t = \frac{\mu^t \times \beta^t}{1-\mu^t} \tag{31}$$

The probability of solar irradiance ($prob_R^t(G_x)$) for time instant t, and every state x could be determined by (32).

$$prob_R^t\{G_x\} = \int_{R_{x1}}^{R_{x2}} f_b(R^t).dR \tag{32}$$

PV generation could be calculated using (33)-(36).

$$P_{t,x}^{PV} = N \times \frac{V_{MPP} \times I_{MPP}}{V_{OC} \times I_{SC}} \times V_{cell_{t,x}} \times I_{cell_{t,x}} \tag{33}$$

where

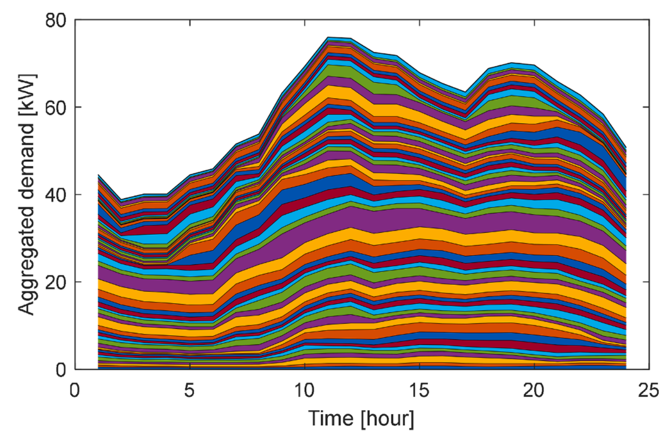

Fig. 4. Aggregated demand of all houses for a representative day.

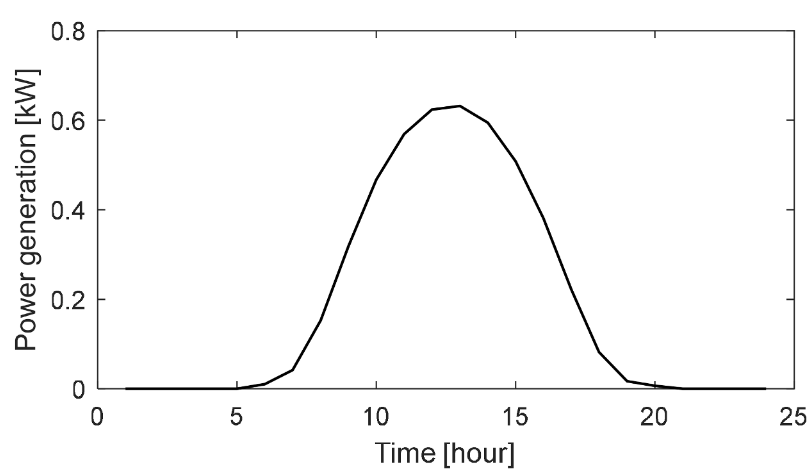

Fig. 3. PV production of a single house for representative day.

$$T_{cell_{t,x}} = T_A + R_{avs}\left(\frac{N_{OT} - 20}{0.8}\right) \quad (34)$$

$$I_{cell_{t,x}} = R_{avs}\left(I_{SC} + K_i\left(T_{cell_{t,x}} - 25\right)\right) \quad (35)$$

$$V_{cell_{t,x}} = V_{OC} - K_v \times T_{cell_{t,x}} \quad (36)$$

- 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. In this study, a normal pdf is used to model the EC houses demand as given in (37). 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. Fig. 4 depicts the aggregated demand of all houses in the EC for one representative day. Each color represents one house. The use of real demand profiles provides several benefits. Real data minimizes the risk of introducing errors or biases that can arise from assumptions in synthetic data generation. Moreover, real data reflects actual user behavior, including peak demand periods, seasonal variations, and unexpected consumption patterns. This results in a more accurate estimation of the optimal size of PV and BES. Moreover, this helps in obtaining accurate insights into the economic viability of DER investments under actual market conditions.

$$f_n(l^t) = \frac{\exp\left[-\frac{\left(l-\mu_l^t\right)^2}{2\left(\sigma_l^t\right)^2}\right]}{\sigma_l^t\sqrt{2\pi}} \quad (37)$$

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 (38).

$$prob_l^t\{G_u\} = \int_{l_{u1}}^{l_{u2}} f_n(l^t).dl \quad (38)$$

- Electricity price modeling

Normal pdf is used to model the uncertainty of energy buying price in Madrid as given in (39). The probability of electricity prices ($prob_b^t(G_y)$) for time instant t, and every state y could be determined by (40). Similarly, a normal pdf is used to model the uncertainty of energy export (i.e., selling) price in Madrid as given in (41). The probability of electricity prices ($prob_e^t(G_z)$) for time instant t, and every state z could be determined by (42). 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) [65]. The retailer prices for one representative day corresponding to one year (i.e., 2022) are depicted in Fig. 5. A 5 % tax is considered for energy buying price [66]. Besides the energy cost, the electricity charges have a cost for the contracted power. In this study, it is defined as the limit for the maximum kW at any time instant. The houses can select the contracted power based on their needs. For the considered houses, the contracted power costs have two values for different hours of the day (i.e., peak and off-peak hours). The contracted power costs are presented in Table 3 [67,68]. Policy costs include the costs of energy policies, such as support for RES and extra Costs of Spanish islands, among others. 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. Real electricity prices reflect actual market conditions, including supply-demand imbalances, fuel costs, and regulatory influences, which synthetic prices may not capture. Moreover, They include time-dependent variations such as peak/off-peak pricing, seasonal trends, and real-time pricing fluctuations, providing a more accurate representation of costs.

Table 3
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
All costs with a 5 % tax (€/kW/year)	**29.8623843**	**1.3448358**

$$f_n(b^t) = \frac{\exp\left[-\frac{\left(l-\mu_b^t\right)^2}{2\left(\sigma_b^t\right)^2}\right]}{\left(\sigma_b^t\sqrt{2\pi}\right.} \quad (39)$$

$$prob_b^t\{G_y\} = \int_{b_{y1}}^{b_{y2}} f_n(b^t).db \quad (40)$$

$$f_n(e^t) = \frac{\exp\left[-\frac{\left(l-\mu_e^t\right)^2}{2\left(\sigma_e^t\right)^2}\right]}{\left(\sigma_e^t\sqrt{2\pi}\right.} \quad (41)$$

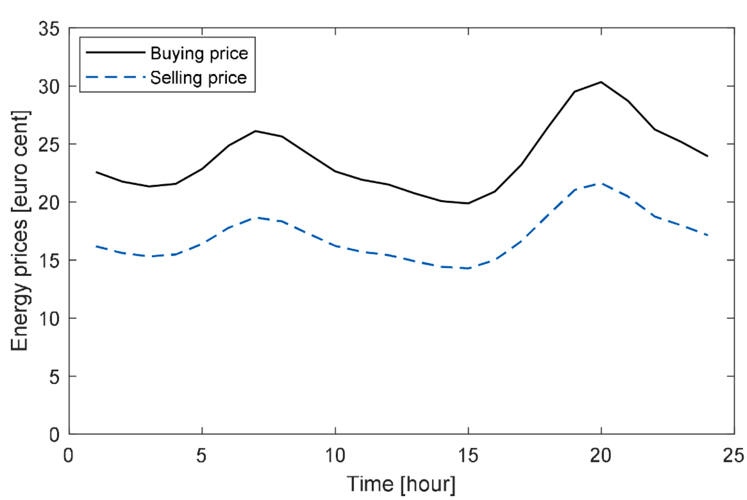

Fig. 5. Houses purchase/sell prices from/to the retailer for representative day.

$$prob_e^t\{G_z\} = \int_{e_{z1}}^{e_{z2}} f_n(e^t).de \tag{42}$$

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

The combined model could be formulated as in (43), 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. Eq. (44) represents the combined probability complete model (ψ). $\mathbb{C}(t,s)$ includes the elements of the combined model derived from the matrix λ.

$$\mathbb{C}(t,s) = prob_R^t\{G_x\} \times prob_l^t\{G_u\} \times prob_b^t\{G_y\} \times prob_e^t(G_z) \tag{43}$$

$$\psi = [\{\lambda_s, \mathbb{C}(t)\{\lambda_s\}\} : s = 1 : n_S] \tag{44}$$

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 prices. Then, the techno-economic performance of three scenarios is discussed. Finally, the assessment of the impacts of three scenarios on unbalanced LVDN is presented.

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.

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 [29]. Additionally, 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.

- Sensitivity analysis with the decrease of BES investment costs

Fig. 6 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). 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 2. 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 energy capacity of BES increase with the decrease in BES investment prices. The optimal BES energy capacity 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.

- 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 Fig. 7. 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

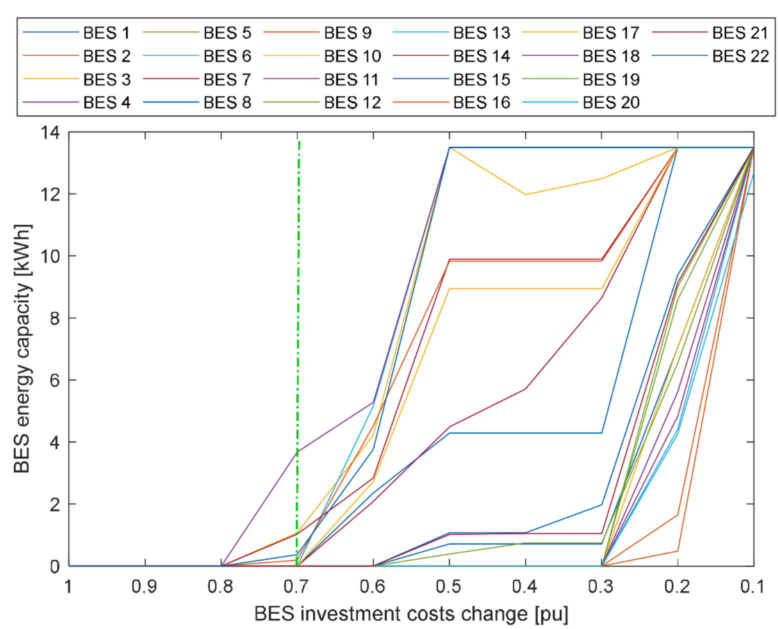

Fig. 6. Sensitivity analysis of the optimal size of the installed BES to the decrease of BES investment costs.

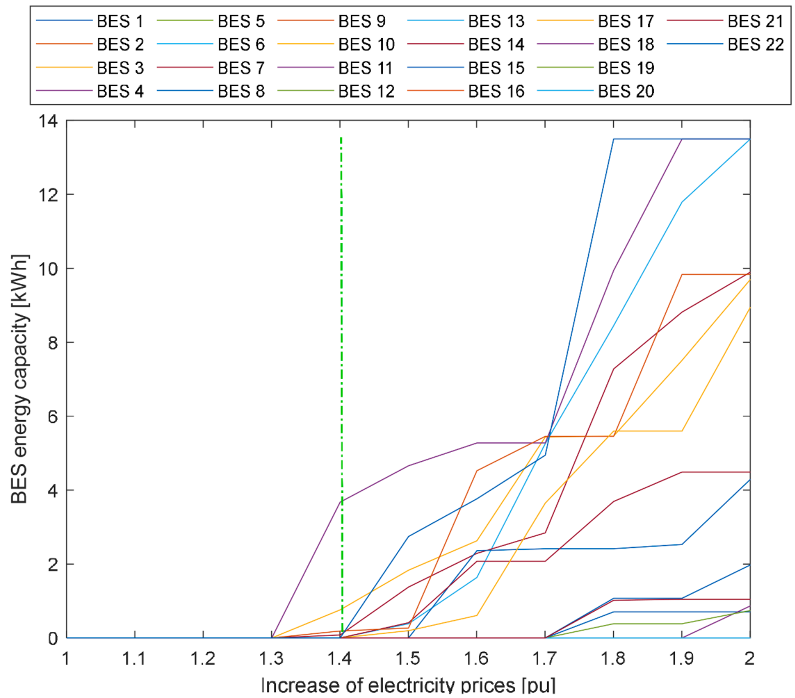

Fig. 7. Sensitivity analysis of the optimal size of the installed BES to the increase of electricity buying and selling prices.

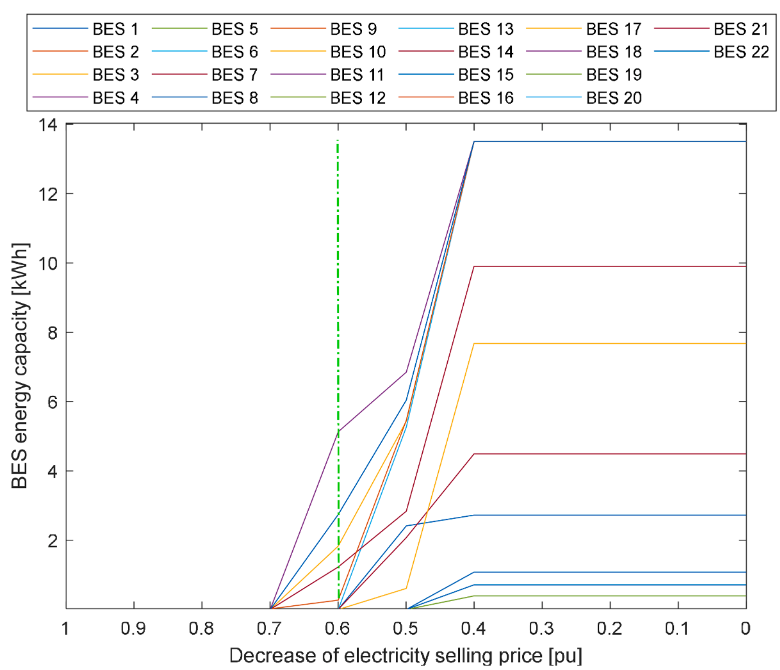

Fig. 8. Sensitivity analysis of the optimal size of the installed BES to the decrease of the electricity selling price.

capacities did 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.

- 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 Fig. 8. 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. The capacities of installed BES in the EC do not change with the price decrease 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.

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 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 (no opt. plan. scenario). 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. LP is used for the optimal operation of EC, considering operational limits. 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 (8).

Scenario 2: Optimal planning (opt. plan. scenario). In scenario 2, LP is used to find the optimal size of PV and BES to minimize the total annual cost of EC represented by (3), considering EC planning and operational limits. 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 (opt. plan. with 0.5 pu BES cost scenario). In scenario 2, LP is used to find the optimal size of PV and BES to minimize the total annual cost of EC represented by (3), considering EC planning and operational limits. Scenario 3 represents the current electricity prices and investment costs of PV (i.e., the same as in scenario 2). 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 BES for this scenario are given in Table 4. 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 simulation results based on LP optimization show that installing PV generation at all houses willing to install PV (i.e., 33 houses) is economically viable, and the optimal value of PV at these houses is 5 kWp (i.e., the maximum limit of the PV size variable). Moreover, it is economically viable for some houses to install BES when the BES investment cost reaches 0.5 pu of its current cost, as indicated in Table 4.

Table 5
Comparison of the three studied scenarios.

	CET without optimal planning (Scenario 1)	CET with optimal planning (Scenario 2)	CET with optimal planning with 0.5 pu BES cost (Scenario 3)
Imports from retailer (kWh)	313,689.11	336,807.37	311,392.96
Exports to retailer (kWh)	0	29,645.68	0
Total local energy trading (kWh)	128,870.46	129,666.53	152,849.61
Demand by retailer (%)	60.07	64.49	59.63
Demand by DERs (%)	39.93	35.51	40.37
Total costs (€)	101,441.34	90,328.65	–
Optimal planning cost reduction (%)	–	10.95	–
Total operation Costs (€)	74,507.09	79,858.34	76,773.69
Costs of imports from retailer (€)	74,507.09	84,246.26	76,773.69
Revenue of exports to retailer (€)	0	4387.92	0

The table shows that the optimal capacities of BES in some houses are the maximum allowed capacities (13.5 kWh and 5.4 kW), as displayed in green. In contrast, the optimal capacities of BES in some houses are zero, as displayed in red. Moreover, the optimal capacities of BES in some houses are between the minimum and the maximum allowed capacities, as displayed in black. This change in the optimal size of BES in different houses depends on the consumption characteristics. For instance, it is good for a house with PV generation and low consumption during day hours and high consumption at night hours to have a BES. The installed BES will enable storing part of PV generation to be consumed at night hours instead of selling it to the retailer at low prices.

Table 5 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. Where red represents the highest performance, green represents the lowest performance, and orange represents the intermediate performance. Opt. plan. with 0.5 pu BES cost scenario has the lowest imports from retailers, followed by No opt. plan. scenario, and Opt. plan. scenario has the largest imports from retailers. The large BES capacities in no opt. plan. scenario enable the importing of larger energy from the retailer than in opt. plan. with 0.5 pu BES cost scenario

Table 4
Optimal BES capacities (kWh and kW) for scenario 3 (i.e., optimal planning with 0.5 pu BES cost). H: house.

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

to minimize operation costs. The presence of BES enables effective usage of PV generation and decreases the imports from the retailer in scenarios no. opt. plan scenario and opt. plan. with 0.5 pu BES cost scenario.

In No opt. plan. scenario and opt. plan. with 0.5 pu BES cost scenario, the EC does 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. The EC in opt. plan. scenario sells part of the PV generation to the retailer because there is no BES installed, and the EVs are used for mobility for most of the day hours.

No opt. plan. scenario 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. Opt. plan. scenario has a slightly higher amount of energy traded locally than no opt. plan. scenario because there are no BES installed and the surplus PV generation can be stored in EVs if they are connected to the charger or sold to other houses in EC or sold to the retailer. The highest amount of energy traded locally is achieved in opt. plan. with 0.5 pu BES cost scenario. No opt. plan. scenario and Opt. plan. with 0.5 pu BES cost scenario cover a larger percentage of demand by EC DERs than Opt. plan. scenario 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 Opt. plan. scenario reduced the total costs (i.e., costs of investments, O&M, and retailer) by 10.95 % compared to No opt. plan. scenario. For fairness, the total costs of opt. plan. with 0.5 pu BES cost scenario are not compared with other scenarios because it represents a 50 % reduction in BES price, which will result in lower total costs. This highlights the financial benefits of DERs optimal planning for EC members since it makes local energy trading more cost-effective. No opt. plan. scenario 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. Opt. plan. with 0.5 pu BES cost scenario has a lower operation cost (because many houses have BES) than Opt. plan. scenario at which no BES are installed in the EC. Opt. plan. scenario has gained revenues from selling surplus energy to retailers. However, No opt. plan. scenario and Opt. plan. with 0.5 pu BES cost scenario have no revenues from selling energy to the retailer because no energy is sold to the retailer for these scenarios.

The obtained results provide important insights for various stakeholders. For EC members, the findings show that higher economic benefits could be obtained from forming ECs if the EC DERs are

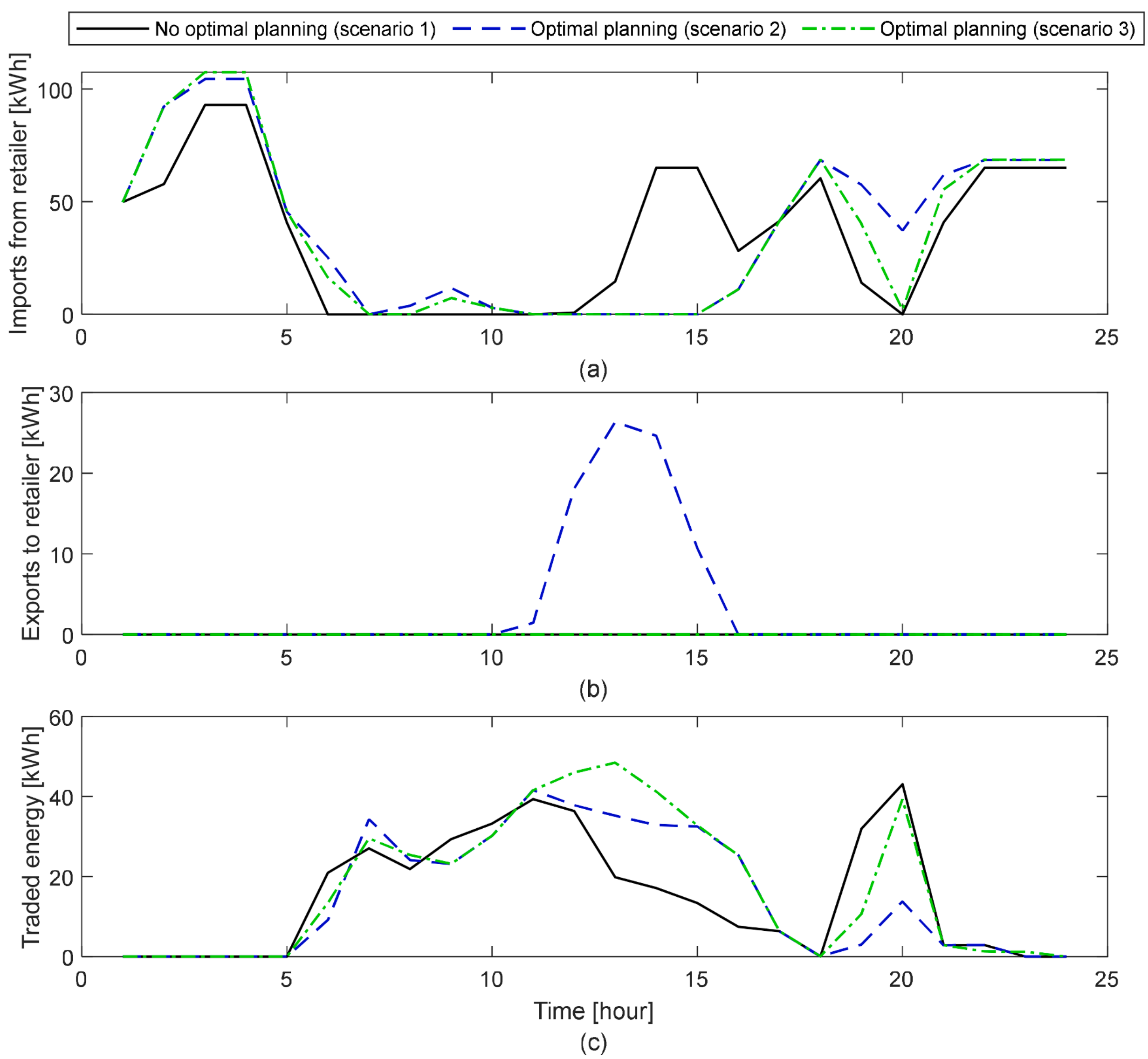

Fig. 9. Comparison of the three scenarios in terms of energy exchange with retailer and locally traded energy.

optimally planned under current conditions, as in scenario 2. However, since the current prices of BES is not economically feasible. The absence of BES in EC results in lower energy independence (i.e., higher energy exchange with the retailer, lower self-consumption, and lower self-sufficiency). These issues could be overcome by the potential future reduction in BES price or incentives by policymakers to support installing BES.

For retailers, The findings show that the formation with EC under current conditions still needs a high energy exchange with the retailer. However, as the price of BES decreases, this energy exchange will decrease (i.e., higher energy independence of ECs), resulting in a decrease in the revenues of retailers. Therefore, retailers need to develop new business models that are suitable for these extreme future variations in the behaviour of end customers.

For policymakers, the findings show the importance of optimal planning of EC DERs in maximizing the economic benefits of members that could foster the adoption of ECs. Moreover, it clarifies the need for incentives to increase the adoption of BES in order to optimize the utilization of local energy in ECs.

Fig. 9(a) shows that EC energy imports from the retailer are very similar in the first hours of the day for opt. plan. scenario and opt. plan. with 0.5 pu BES cost scenario, and no opt. plan. scenario 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 75 % SoC when they leave houses for mobility. Opt. plan. scenario and opt. plan. with 0.5 pu BES cost scenario have higher imports from the retailer at the first 5 h than no opt. plan. scenario because they have a higher charging power of EVs as illustrated in Fig. 10. EVs use this energy to satisfy mobility needs at departure time and avoid buying energy at high prices from the retailer or to sell it to other houses in the EC. Starting from hour 5, the EC energy imports are reduced for all scenarios by taking advantage of PV generation and energy stored in flexible devices to avoid buying from the retailer at high prices. In no opt. plan. scenario, 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 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 grid for charging. The energy imports decreased around hour 20 because of the high electricity price. The EC houses use flexible devices to decrease or avoid buying energy from the retailer. The flexible devices discharge at these hours, as shown in Fig. 10.

Fig. 9(b) shows that in opt. plan. scenario, the EC sells surplus PV generation to the retailer because there is no BES installed, and EVs are used for mobility for most of the hours with high PV generation. On the other hand, the presence of BES in no opt. plan. scenario and opt. plan. with 0.5 pu BES cost scenario enables the use of PV generation within EC, and no energy is sold to the retailer, as shown in Fig. 10.

Fig. 9(c) shows that for Scenarios opt. plan. scenario and opt. plan. with 0.5 pu BES cost scenario, 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. No opt. plan. scenario has similar behavior to other scenarios, but the local energy traded in 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.

Fig. 11 presents a comparative analysis of energy export/import for different houses within the EC under the three studied scenarios. Each scenario has two heatmaps. The one on the left represents the energy exported to peers from each house over 24 h. The one on the right represents the energy imported from peers by each house over 24 h. For all scenarios, it can be seen that the local energy trading is low or nonexistent at first day hours and late night hours. Table 5 shows that scenarios 1 and 2 have similar values in terms of the amount of energy traded locally. However, Fig. 11 clarifies the different behavior of the houses' energy exchange within the EC at different hours. Scenario 1 shows a high energy trade before midday and then a low or no exchange after midday since many houses store the local generation in BES instead of selling it to other houses. In this scenario, the houses take advantage of their large BES capacities. Scenario 2 local energy trading is mainly during day hours when there is PV generation since no BES is installed at

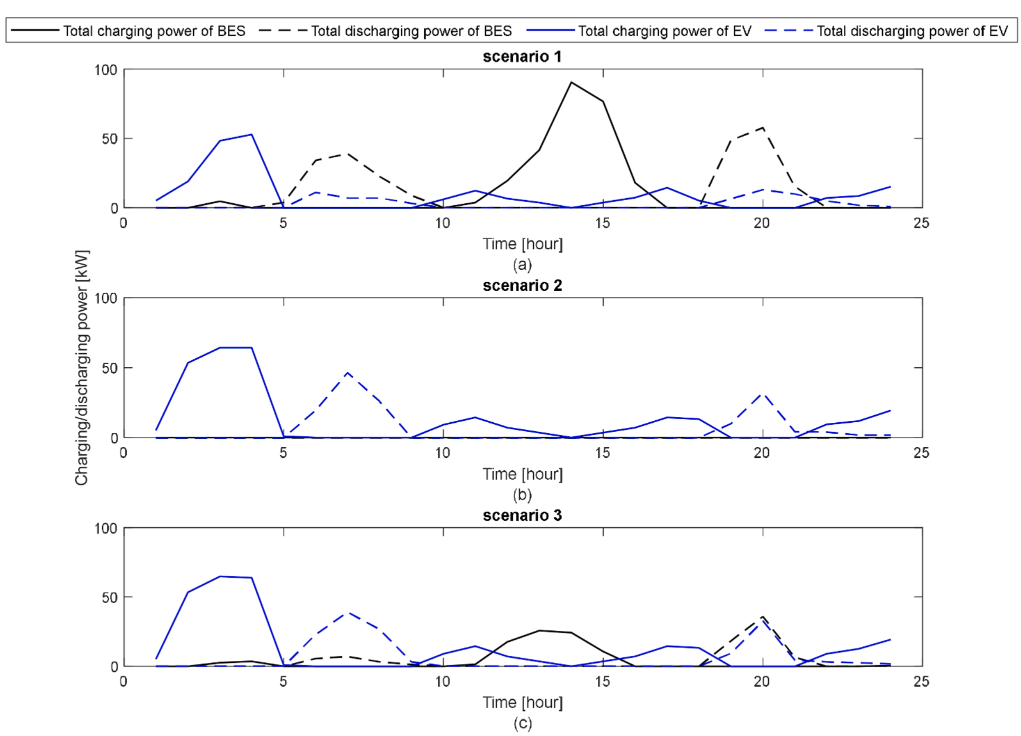

Fig. 10. Total charging/discharging power of BES and EVs for the three scenarios.

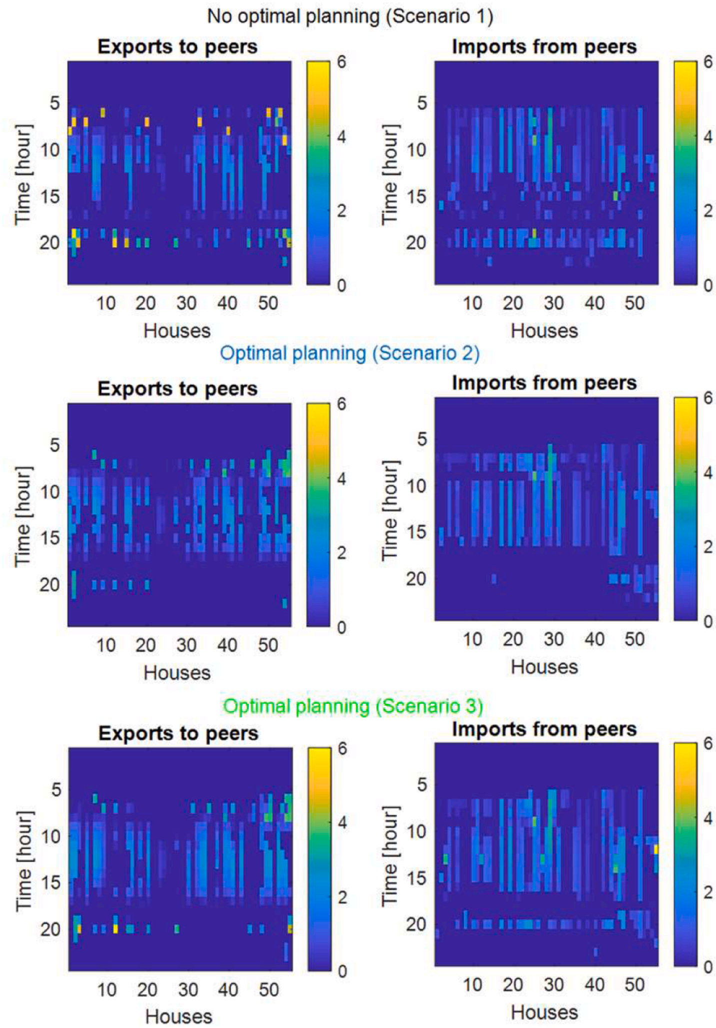

Fig. 11. Local energy trading within the energy community for different houses.

Table 6
Summary of impacts on the studied LVDN.

	CET without optimal planning (Scenario 1)	CET with optimal planning (Scenario 2)	CET 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

any house. There are small energy exchanges in the evening and night hours by the energy stored in EVs. Scenario 3 has higher energy trading than scenario 2, especially at night hours since some houses have BES installed. This clarifies that even a moderate adoption of BES in the EC could enhance local energy trading and the utilization of local generation.

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.

- **Impacts on transformer loading, line loading, and voltage unbalance**

Transformers and lines of LVDNs should operate within acceptable limits to avoid reducing their lifetime or upgrading them, which require high investments. The high DERs deployment could result in violation of limits of LVDNs components like transformers and lines. Therefore, in

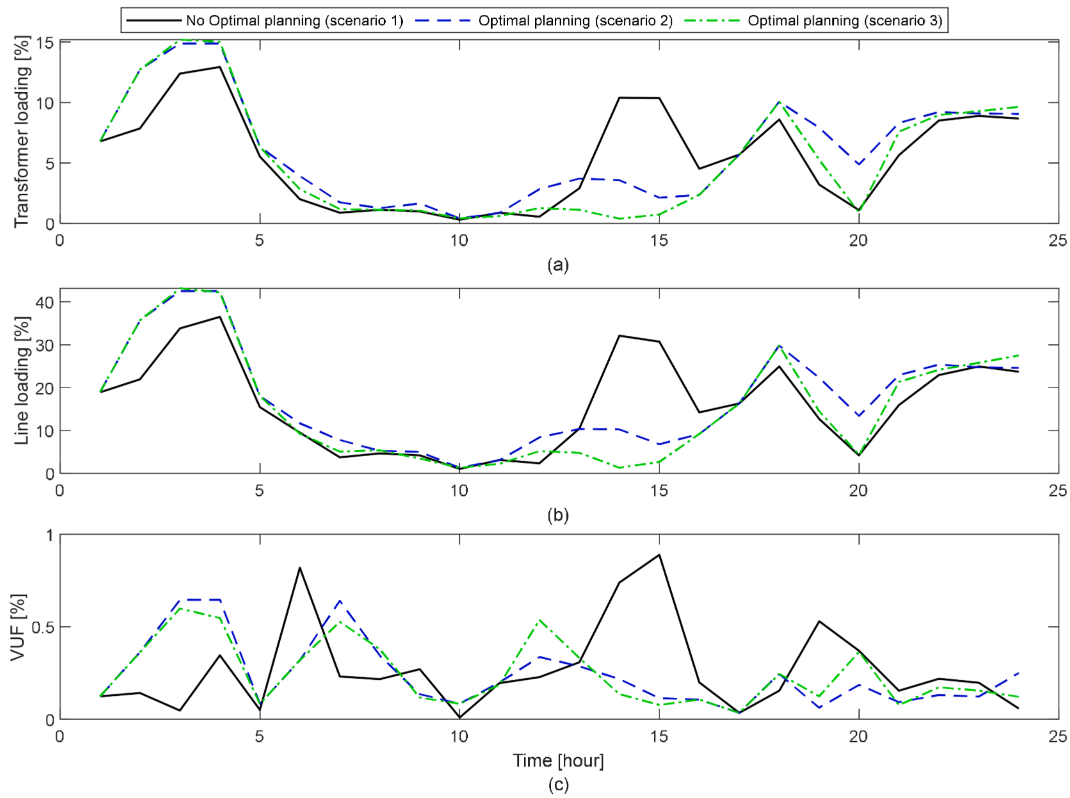

Fig. 12. impacts on LVDN. (a) transformer loading, (b) line loading, (c) voltage unbalance factor.

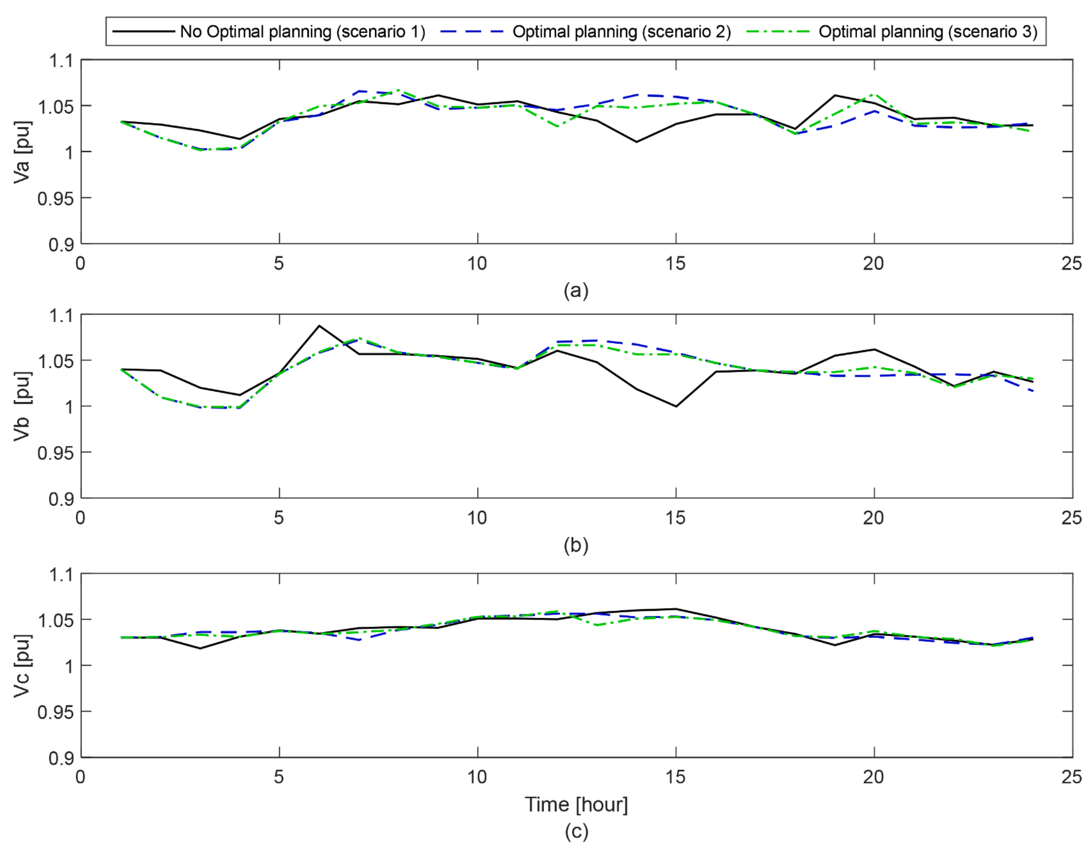

Fig. 13. Variations of phases voltage magnitude. (a) phase a, (b) phase b, (c) phase c.

this subsection, the impacts of the studied scenarios on transformer and line loading are evaluated. Table 6 summarizes the impacts on the LVDN for the studied scenarios. Where red represents the highest impact, green represents the lowest impact, and orange represents the intermediate impact.

Table 6 and Fig. 12(a) show that the MV/LV transformer supplying the EC has a very low loading in the three scenarios. Opt. plan. with 0.5 pu BES cost scenario recorded a 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 opt. plan. with 0.5 pu BES cost scenario recorded a higher line loading than the other two scenarios, as shown in Table 6 and Fig. 12(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 no opt. plan. scenario is higher than the other two scenarios, as shown in Table 6 and Fig. 12(c). The VUF in no opt. plan. scenario has high values at hours when there are simultaneous charging or discharging of EC flexible devices, and the highest VUF is recorded at hour 15. In opt. plan. scenario, there is no BES installed, and in opt. plan. with 0.5 pu BES cost scenario there is less BES installed and with lower capacities compared to no opt. plan. scenario, which prevents or reduces the effect of simultaneous charging or discharging. However, in no opt. plan. scenario, the customers simultaneously exploit the larger BES energy and power capacities installed.

- Impacts on the variation of phases voltage magnitude

Due to their normally radial architecture and not having voltage regulation instruments, LVDNs are more vulnerable to voltage fluctuations than other parts of the grid. Therefore, many researchers studied the effects of the widespread adoption of DERs on voltage variations at the LVDNs. The endpoints of the feeders typically have more voltage variation than other points close to the transformer. Whenever the load is high, the LVDNs may experience a high voltage drop, and if the local production is high, they may experience a voltage rise. According to EN 50,160, the LVDN voltage magnitude should be between 0.90 and 1.10 pu.

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 6 and Fig. 13 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 Fig. 13(c).

The findings of the EC impact on LVDN for the studied scenarios provide important insights for distribution system operators. It can be noticed that the LVDN encounters different loading patterns with the formation of EC with DER deployment compared to the expected loading with inflexible demand only. The presence of a high share of flexible devices such as BES and EVs, in addition to the variation of electricity prices, are significant factors in this loading pattern variations. As a result, there is a need for planning for optimal operation of LVDNs under these significant changes at the distribution level.

5. Conclusion

Energy communities (ECs) is an emerging approach for distributed energy resources (DER) management that has received a large interest in existing studies. However, these studies focused on EC operations assuming the capacities of installed DERs. Existing studies did not address optimal planning of ECs enabling local energy trading that considers uncertainties, impacts on distribution networks, and the unbalanced nature of distribution networks. Therefore, This study introduced a methodology for the optimal planning of the resources within ECs, which can guide investment decisions towards more cost-effective solutions. Linear programming (LP) 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 (PV) generation and battery energy storage (BES). Installing PV in the studied EC is economically feasible in all scenarios and conditions assessed. Under the current operating conditions in Madrid, Spain, it is not economically feasible to install private BES in ECs. Sensitivity analysis shows that, with a 30 % decrease in BES investment costs, a 40 % increase in electricity prices, or a 40 % decrease in the 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. The scenario without optimal planning records the lowest loading of the transformer and lines. However, it results in the highest unbalance compared to scenarios with optimal planning.

While this study focused on an EC in Madrid, Spain, the methodology and several key findings offer valuable insights applicable to other regions and contexts. The proposed LP optimization model provides a flexible and adaptable framework for optimal EC planning and operation. It can be applied to different types of ECs (e.g., residential, commercial, industrial) and can be extended to incorporate additional objectives and constraints relevant to specific regional contexts by changing inputs such as generation profiles, load profiles, prices, regulations, and incentives of DERs deployment. In regions with high solar irradiance similar to Spain, the economic feasibility of PV installations is likely to be pronounced. In areas with higher electricity prices or more favorable regulatory incentives for DERs, the economic feasibility of BES installations could be even higher. Therefore, it is crucial for each EC member to understand his energy needs and the optimal DER investments.

Future studies could consider ECs planning including other objectives (i.e., multi-objective function), like maximizing self-consumption, besides minimizing annual costs. Moreover, demand response programs with controllable loads like heat pumps could be considered. Furthermore, the performance of centralized community BES and decentralized house-owned BES could be compared. Additionally, other ECs containing different types of buildings could be studied. Finally, more research is needed to assess the impacts of ECs on different types of distribution networks.

CRediT authorship contribution statement

Morsy Nour: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **José Pablo Chaves-Ávila:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Matteo Troncia:** Writing – review & editing, Supervision, Methodology. **Álvaro Sánchez-Miralles:** Supervision, Project administration, Methodology, Funding acquisition, Conceptualization. **Abdelfatah Ali:** Writing – review & editing, Validation, Software, Methodology, Investigation, Conceptualization.

Declaration of competing interest

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

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Data availability

The authors do not have permission to share data.

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