Energy & Buildings 310 (2024) 114078

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enbuild

Smart coordination of buildings to incentivise grid flexibility provision: A virtual energy community perspective

Naser Hashemipour [a], Raquel Alonso Pedrero [a,*], Pedro Crespo del Granado [a], Jamshid Aghaei [b]

[a] Department of Industrial and Technology Management, Norwegian University of Science and Technology, Trondheim, Norway
[b] School of Engineering and Technology, Central Queensland University, Rockhampton, QLD, Australia

ARTICLE INFO

Keywords:
Energy communities
Distribution grid
Mathematical optimisation
Power flow analysis
Particle swarm optimisation

ABSTRACT

Energy communities (ECs) play a crucial role in promoting the adoption of renewable energy resources and establishing local energy markets for sharing and trading energy among end-users (e.g., residential buildings) and prosumers (plus energy buildings). However, since end-users are connected to distribution grids, their energy transactions can sometimes lead to reversed power flows and potential power quality issues, such as over-voltage. This paper introduces the concept of Virtual Energy Communities (VECs) as a coordination mechanism designed to align the goals of ECs with the flexibility requirements of the distribution grid operator. The smart coordination of buildings employs a Particle Swarm Optimisation algorithm to identify optimal VEC configurations that effectively manage potential trading activities to adhere to power grid constraints. The tool's performance is evaluated with a focus on voltage levels and voltage imbalance factors across various case studies. The results demonstrate that smart building coordination efficiently mitigates overvoltage and voltage imbalances by implementing VECs, all while causing minimal disruption to energy sharing opportunities. This is of significant importance, as providing grid flexibility on its own is not economically viable. Therefore, this coordination offers a valuable win-win solution for both ECs and grid flexibility.

1. Introduction

The transition towards a decarbonised power system must ensure affordable and secure energy [1]. Distributed energy resources (DERs) like photovoltaic (PV) panels, energy storage systems, smart controlled appliances and electric vehicles (EVs) are playing a key role in achieving this goal. These assets bolster consumers' autonomy, reduce the dependence on upstream generation, and enhance energy security through decentralisation [2]. These DERs are gradually rewriting the landscape of energy production and consumption. For example, the European Union has committed to promoting a more consumer-centric power system that empowers end users to manage their generation and consumption actively and endorses the implementation of Energy Communities [3,4].

Energy communities (EC) are groups of end users (e.g., residential buildings) who group to engage in energy-related projects. One of the main activities proposed in ECs is enabling energy sharing among members. Inspired by the concept of sharing economies [5], these initiatives motivate the monetisation of under-utilised energy resources. They do so by adopting coordination platforms that enhance the exchange of energy services [6].

Despite the benefits, large-scale adoption of ECs encounters technical challenges. The existing infrastructure was not originally designed for bidirectional power flows and volatile voltage levels, necessitating reactive power compensation and voltage control [7]. As a result, community transactions must adhere to the grid's stringent technical constraints [8].

Distribution Grid Operators (DSOs) can use optimal power flow (OPF) analysis to ensure their power system operations are within safe and reliable limits at minimum costs. However, integrating DER operations in OPF algorithms results in complex, nonlinear and dynamic operations that require significant computational resources [9,7]. Also, crude solutions like upgrading grid capacity or limiting further distribution assets have been proposed to facilitate the adoption of DERs. However, these come at the expense of high installation costs and potential reduction in value for end users [9].

Hence, there is a pressing need for innovative techniques to align the technical requirements of DSOs and the operations within ECs [10]. While ECs focus on energy sharing or trading among community members, there is a growing body of literature advocating the benefits of providing flexibility services to other agents in the system, like grid

* Corresponding author.
E-mail addresses: raquel.a.pedrero@ntnu.no, raquel.alonso.pedrero@gmail.com (R. Alonso Pedrero).

https://doi.org/10.1016/j.enbuild.2024.114078
Received 25 December 2023; Received in revised form 22 February 2024; Accepted 11 March 2024

Available online 19 March 2024

operators [11] and retailers [12]. However, offering flexibility should provide sufficient economic value for adjusting the operations of DERs.

To this end, this paper explores the following research questions:

1. What minimum incentive is required to encourage ECs to provide flexibility services to grid operators?
2. Is it feasible for ECs to offer flexibility services while keeping their energy-sharing activities?

This paper presents a coordination architecture to determine close-to-optimal economic dispatch of ECs considering the underlying network constraint. It was designed such that it is only required to perform a Power Flow (PF) analysis, removing the need to solve nonlinear optimisation problems (i.e., OPF). The underlying idea of the algorithm is to meet network constraints by modifying the trading options within the community. This is done by introducing the concept of a Virtual Energy Community (VEC), a replicate of the initial community where the participants are grouped into clusters that function independently from each other. The algorithm uses Particle Swarm Optimisation (PSO) to find the VEC whose cluster composition optimises a community's financial result within the physical constraints set by the DSO.

The paper is structured as follows: the subsequent section reviews the literature on EC that considers network constraints and highlights this paper's contributions. Then, the coordination architecture and the PSO method are presented. Sections 4 and 5 present the case study and the results of applying the proposed method. Section 6 summarises concluding remarks.

2. Literature review

ECs are commonly classified based on their coordination scheme, which dictates how community members interact. This can occur through a central authority, such as a central market operator [13], or a central manager overseeing all assets [14]. Alternatively, ECs may employ bilateral trading, also known as peer-to-peer markets, to facilitate direct interactions among participants and eliminate third-party intermediaries, preserving privacy [15]. The choice between these coordination approaches depends on community members' specific needs and preferences. While centralised approaches lower the involvement demands of residents, bilateral trading offers more privacy to community members.

The real-life implementation of EC is subject to its physical viability, which can raise concerns about how to combine the economic and technical layers effectively. To gain insight into potential grid issues caused by local energy transactions, Dynge et al. [16] conducted a feasibility study of a centralised market with different DER adoption rates. The authors highlighted that grid problems varied significantly depending on the system setup. Similarly, Azim et al. [17] demonstrated that high levels of rooftop penetration, driven by peer-to-peer transactions, could lead to overvoltage issues. These findings underscore the importance of considering grid-related factors when implementing ECs. For example, Oprea et al. [12] present a Stackelberg game model to define dynamic tariffs that optimise the electricity consumption of end users to mitigate peak demand.

Building upon the concept of using flexibility capabilities for grid management, AC OPF extends the scope of optimisations to include more detailed network constraints, such as overvoltage [18]. These optimisation problems are typically computationally challenging to solve given that they are nonlinear problems and they involve a large number of assets. To tackle these challenges, AC OPF problems can be implemented using approximations and convex relaxations. For instance, DC OPF is an extended approximating method that makes the problem tractable by neglecting voltage magnitudes, power losses and reactive power. Baroche et al. [19] deployed DC OPF in combination with exogenous network charges to avoid congestion issues. With the same goal, Khorasany et al. [20] applied the primal-dual gradient method to solve the DC OPF in a distributed manner. Despite the computational benefits DC OPF offers, it omits physical factors that might be required to be regulated by the system operator. Another option is the second-order cone relaxation technique from Farivar and Low [21], which handles specific nonlinear constraints (e.g., voltage limits, line flow limits) to transform the AC OPF problem into a more tractable and convex form. This technique was applied by Kim & Dvorkin [22] to ensure that different coordination schemes meet voltage and congestion thresholds. In their proposal, the grid operator calculates Distributed Locational Marginal Prices (DLMPs) to capture the costs caused by the trading and induce a price signal to consumers. However, DSOs are highly regulated entities, so inducing new network charges does not align with current regulations. Another option for solving AC OPF is the Alternating Direction Method of Multipliers (ADMM), a decomposition technique for handling convex and nonlinear constraints. The ADMM algorithm has been applied to the context of ECs engaged in bilateral trading, given its ability to optimise in a distributed fashion, which might be desirable to preserve agents´ privacy. Babgheibi et al. [23] applied ADMM to solve an AC OPF problem where the end users provide congestion management services to the DSO.

Other studies suggest solving the market and the physical layer separately, avoiding computationally challenging problems and applying AC power flow (AC PF). Unlike OPF, the AC power flow is just a feasibility study based on a specific set of system parameters and not an optimisation problem. This approach is used by Guerrero et al. [24], who define three sensitivity coefficients derived from the AC PF analysis. These coefficients are used to discard bilateral transactions that could cause voltage issues. In an extension work, Guerrero et al. [9] show the method's versatility by applying it to three different trading arrangements: open market, division of the market in zones based on physical infrastructure and one-to-one transactions. The use of PF analysis usually entails the development of iterative algorithms, which allows for considering the grid network in detail while updating the energy-sharing activities of ECs.

Table 1 shows key studies focused on solving grid issues generated from integrating EC and characterise them based on the market or business model adopted by the EC, the method used to meet network constraints, the type of power flow analysis (i.e., AC PF, AC OPF, DC OPF) and the network issues addressed.

Furthermore, recent studies highlight the significant economic potential for energy communities to provide flexible services with the right incentive structures and market mechanisms [25]. Coordination tools for building flexibility management should ensure that end users are economically better off after providing flexibility services and should reflect the actual cost of activating flexibility. The work in [26] notes that the value of flexibility of residential buildings is important in the European transition but highlights that the incentive to activate it is overall low. Despite a consensus on the importance of grid flexibility, diverse views exist on how to price and reward it. Authors in [27] highlight the need for agreements guaranteeing individual rationality and incentive compatibility of end users.

However, most studies focus on quantifying the value of flexibility from the grid operators' perspective (i.e., deferred investments), often neglecting the benefits or costs to the end user. For instance, while studies like [28] and [29] analyse system cost reductions and grid operators' profitability, they do not explore the economic impact on end users. This gap in the research is pointed out in other studies [30,31], questioning the economic attractiveness of grid flexibility from the perspective of end users. Hence, there are remaining questions on whether or not the EC incentive to provide grid flexibility is economically attractive and what should be the actual incentive to reward flexibility [32].

The novel coordinating tool presented in this paper decouples the network and market models and adopts an iterative approach to link them. Such separation is key to surpassing the computational challenges of nonconvexity inherent in other studies applying AC OPF. Further-

Table 1
Some related papers solving or analysing network issues arising from local energy trading.

Paper	EC/Market	Method	Grid analysis	Network issues
[20]	P2P	Primal-dual gradient method for market clearing with linked flow constraints	DC OPF	Line congestion
[22]	P2P & centralised	DLMPs	Relaxed AC OPF	Line congestion and voltage control
[19]	P2P	Exogenous network charges	DC OPF	Line congestion
[17]	P2P	Feasibility study	AC PF	Line congestion and voltage control
[24]	P2P	Sensitivity coefficients to discard transactions	AC PF	Line congestion and voltage control
[33]	Centralised	LFM to purchase grid services	AC PF	Line congestion and voltage control
[16]	Centralised	Feasibility study	AC PF	Line congestion and voltage control
[23]	Centralised	ADMM	AC OPF	Line congestion and voltage control
[34]	P2P	Grid service flexibility	-	Peak control
[35]	P2P	Network charges	DC OPF	Line and equipment losses

more, applying PF analysis instead of approximation techniques allows a detailed grid analysis, which may be desirable for grid operators. The method addresses network constraints by clustering community members into groups to establish a VEC. Instead of predetermined clusters or areas as presented in [9], our approach dynamically optimises cluster formation using a PSO algorithm. This optimisation process, using only the community cost and a technical signal from the PF analysis, ensures nearly optimal economic benefits for the community while adhering to network restrictions. By only necessitating a technical signal, the framework offers versatility to the grid operator in deciding the technical factor to solve. Another novel aspect of the study is the application of PF analysis to three-phase unbalanced distribution grids, expanding the scope of energy community studies.

The core strategy of the proposed method is to prioritise energy sharing within ECs, treating grid flexibility as a beneficial by-product of coordination. By quantifying the cost of this by-product for the community, the grid operator can compensate this cost for the flexibility provided, fostering a mutually beneficial relationship. This strategy encourages the integration of grid flexibility with minimal disruption to community economic outcomes. Hence this framework aims to positively incentivise grid flexibility from ECs. This contrasts with another approach present in the literature that relies on imposing penalties for activating grid flexibility. Such penalties could, in turn, diminish the attractiveness of participating in ECs, thereby hindering adoption and engagement.

The paper contributes to the literature as follows:

- Introducing the concept of Virtual Energy Communities (VECs) for coordination of communities within network constraints.
- A framework that allows the provision of flexibility services without disrupting the local energy sharing operations that incentivise local adoption of generation assets in buildings.
- Quantification of the economic outcomes for a community of residential buildings forming an EC and the minimum incentive to provide flexibility to grid operators.
- A novel algorithm that reorganises operations at the local level to avoid violating network constraints and provide economic benefits to community members.
- A methodology that approximates an optimal unbalanced three-phase AC power flow without requiring complex solution methods.

3. Methodology

3.1. Coordination framework: energy sharing and the value of grid flexibility

ECs can optimise their operations to minimise the operational costs of importing electricity. Such cost reductions are possible when communities increase their self-sufficiency, for instance, through energy sharing. However, maximising community efficiency may be constrained if the community aims to provide grid services, as they would need to restrict their local operations.

Given the trade-off between flexibility provision and optimal operation, the minimum economic incentive for communities to assist grid operators equals the *opportunity cost* incurred from deviating from the optimal operational plan. This opportunity cost is computed as the difference between the *optimal cost*, which represents the cost under optimal operations, and the *adjusted cost*, calculated as the cost for the entire community after adapting to the grid's requirements.

To calculate the *optimal cost*, the framework incorporates an energy management model that optimises energy sharing and asset utilisation among community members without accounting for network constraints. The model delivers a set of energy rates for both energy injection and withdrawal for each building within the community.

The subsequent step in the framework involves conducting an AC power flow analysis using the energy rates generated by the energy management model. This analysis checks whether the optimal operations are in compliance with the network's technical constraints. If no disruption to grid operations is found, there is no need to calculate the opportunity cost, as the community can proceed with optimal operations. Conversely, if a network violation is detected, the framework initiates a process to reorganise operations and resolve the grid issue by limiting sharing options.

To restrict energy sharing, the framework proposes dividing the buildings into clusters to form a VEC. Each possible combination of clusters within the community yields a unique VEC. Fig. 1 exemplifies three alternative VECs (b, c and d) for a community composed of eighteen members. The colours identify a particular cluster in each configuration. Within a VEC, the energy management model is executed for each individual cluster, such that energy sharing between buildings from other clusters is not an option. In doing so, the framework narrows the feasible space for energy sharing, thereby influencing the grid's technical parameters.

A crucial element of this coordination is identifying the VEC that best achieves the objective of minimising the opportunity cost. While

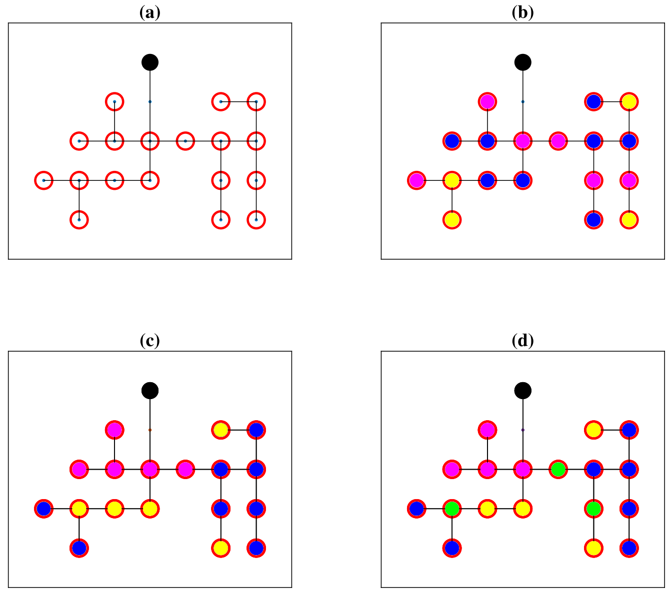

Fig. 1. Illustrative representation of VECs with each circle symbolising a building. Figure (a) depicts a conventional grid topology without the formation of a VEC. Figures (b), (c), and (d) showcase various configurations of VECs. The black circle signifies the point of connection to the upper grid. The other circles are colour-coded to indicate the specific cluster to which each building is assigned. (For interpretation of the colours in the figure(s), the reader is referred to the web version of this article.)

randomly generating a VEC could fortuitously solve the technical issues, it is unlikely to ensure the minimum adjusted costs and, therefore, the minimum willingness of the community to provide flexibility services. To address this, the framework employs PSO algorithm to identify the most suitable VEC.

The PSO algorithm iteratively updates the clustering configuration based on data gathered from both the energy management model and the AC power flow analysis. The management model yields the total operational costs under a given VEC, while the power flow analysis indicates whether the decided operations cause any grid issues. This grid issue is quantified using a signal that correlates with the severity of the issue analysed (e.g., voltage issues, congestion). Using both the operational costs and the technical signal, the PSO algorithm suggests new VECs that reduce both metrics. This iterative procedure continues until a specific convergence criterion is met (e.g., a number of iterations). Upon convergence, the VEC with the minimal cost calculated associated and technical signal equal to zero is considered for actual operations. Subsequently, its associated opportunity cost can be charged to the grid operator.

This framework not only outlines a coordination tool for flexible neighbourhoods but also offers a systematic approach for quantifying the minimum incentive required for ECs to provide flexibility to grid operators.

The remainder of the section delves into the details of the algorithms forming the coordination framework. First, the energy optimisation model for deciding the energy sharing for the entire community and the clusters within VECs is presented. Then, its connection with the AC power flow analysis and the PSO algorithm is described in more detail. The nomenclature used in the rest of the paper is included in Appendix A

It is worth noting that the EC considered in this study is a centralised system wherein a central manager optimises all building assets. However, this model could be substituted by any other market or community structure, as the only information for the next steps is the injection and withdrawal energy rates and the resulting costs.

3.2. Energy community model

Consider a group of buildings $\mathcal{N} = \{1, \dots, h\}$ organised together as an EC. These households can be clustered forming a set $C = \{C_1, \dots, C_n\}$, where n is the number of clusters and each element is a subset of $\mathcal{N}$, $C_i \subseteq \mathcal{N}$. Every building is associated to a cluster C_i following that $\bigcup_{i=1}^{n} C_i = \mathcal{N}$ and $C_i \cap C_j = \emptyset$. Note that with $n = 1$, the set C equals $\mathcal{N}$. Thus, the EC becomes a VEC with $n > 1$.

The objective of any cluster of buildings, C_i, is to minimise the cost of purchasing electricity from the main grid, G, throughout an operational time horizon T, which is priced at the retailer price p^G. The minimum operational cost is calculated as shown in Equation (1).

$$OF(C_i) = \min \sum_{h \in C_i} \sum_{t \in T} p_t^G \cdot G_{t,h} \tag{1}$$

To ensure the proper operation of the group, each building's energy supply must be equal to or greater than its demand at all times. This is guaranteed through Equation (2) where the left-hand side of the equation includes electricity supply from the main grid, renewable production from generation assets in the building, $res_{t,h}$, EV discharge, $D_{t,e}^{EV}$, and energy imported from peer buildings, $I_{t,h}$. On the other hand, the energy demand, $dem_{t,h}$, EV charging load, $C_{t,e}^{EV}$, and energy exports to other peers, $X_{t,h}$ define the consumption part of the nodal equation. All components in Equation (2) are energy-related.

The storage technologies considered are EV batteries associated with each building. For each building $h \in C_i$, we define a set of EVs E_h associated with that particular building. Clarifications on the mathematical notation can be found in Appendix A (see Tables A.4–A.6).

$$\begin{aligned} &G_{t,h} + res_{t,h} + \sum_{e \in E_h} D_{t,e}^{EV} + I_{t,h} \geq \\ &dem_{t,h} + \sum_{e \in E_h} C_{t,e}^{EV} + X_{t,h} \end{aligned} \qquad \forall h \in C_i, \forall t \in T \tag{2}$$

Moreover, electricity sharing is accounted for through Equations (3)-(6). These ensure that all the local electricity remains within the neighbourhood, quantify distribution losses and maintain import/export balance. It is important to note that because the power rates are input data for the PF model, grid losses do not need to be factored in the energy management model. However, the loss factor, ψ, is set to $1 - \epsilon$ with $\epsilon << 1$ to preserve the community model's features.

$$I_{t,h \leftarrow p}^{P} = \psi \cdot X_{t,p \rightarrow h}^{P}, \qquad \forall h \in C_i, p \in C_i \setminus \{h\}, \forall t \in T \tag{3}$$

$$X_{t,h} = \sum_{p \in C_i \setminus \{h\}} X_{t,p \rightarrow h}^{P}, \qquad \forall h \in C_i, \forall t \in T \tag{4}$$

$$I_{t,h} = \sum_{p \in C_i \setminus \{h\}} I_{t,h \leftarrow p}^{P}, \qquad \forall h \in C_i, \forall t \in T \tag{5}$$

$$\sum_{h \in C_i} I_{t,h} = \sum_{h \in C_i} \psi \; X_{t,h}, \qquad \forall t \in T \tag{6}$$

Constraints related to EV storage operations are also considered. For every $e \in E_h$, Equation (8) defines its state-of-charge, considering their previous state-of-charge and the charge/discharge electricity volumes, namely $C_{t,e}^{EV}$ and $D_{t,e}^{EV}$. Change in the state of charge only occurs at times when the vehicles are connected to the distribution grid, contained in set T_e^C. However, at times when the EVs connect to the charging station, defined by set T_e^A, the state of charge depends on its usage outside the community and on the owner's usage of the vehicle. Equation (9) captures this dynamic and sets an initial state of charge as parameter $s_{t,e}^A$. Similarly, Equation (7) guarantees that the state of charge at $t = 1$ builds upon the last state of batteries before running the algorithm. Furthermore, to avoid the batteries getting totally discharged at the end of the time horizon, we introduce Equation (10) that forces it to finish with a minimum state-of-charge. This avoids compromising the potential usage in the next instance. Note that if the algorithm is run one instance after the other, the initial state of charge, $s_{t,e}^I$, for the later instance equals $\bar{s}_{t,e}$ of the previous one. Moreover, the same equation is enforced to guarantee that before delivery the batteries are charged. The ratio γ would be set according to individual preferences. Finally, the EVs' charging and discharging volumes and the maximum state of charge allowed are constrained by Equations (11)-(12). The parameters α and β are derived from the power rating of the EVs and the temporal resolution of the model to translate the power capabilities into energy volumes that can be charged and discharged in a single timeslot, t.

$$S^{EV}_{t,e} = s^{I}_{t,e} + \eta^{c}_{e} \cdot C^{EV}_{t,e} - \frac{1}{\eta^{d}_{e}} \cdot D^{EV}_{t,e}, \qquad t = 1, \forall e \in E_h, \forall h \in C_i \quad (7)$$

$$S^{EV}_{t,e} = S^{EV}_{t-1,e} + \eta^{c} \cdot C^{EV}_{t,e} - \frac{1}{\eta^{d}} \cdot D^{EV}_{t,e}, \quad \forall t \in T^{C}_{e}, \forall e \in E_h, \forall h \in C_i \quad (8)$$

$$S^{EV}_{t,e} = s^{A}_{t,e} + \eta^{c}_{e} \cdot C^{EV}_{t,e} - \frac{1}{\eta^{d}_{e}} \cdot D^{EV}_{t,e}, \quad \forall t \in T^{A}_{e}, \forall e \in E_h, \forall h \in C_i \quad (9)$$

$$S^{EV}_{t,e} = \gamma\ \bar{s}_{t,e}, \qquad \forall t \in T^{D}_{e} \cup t = |T|, \forall e \in E_h, \forall h \in C_i \quad (10)$$

$$S^{EV}_{t,e} \le \bar{s}_{t,e}, \qquad \forall t \in T^{C}_{e}, \forall e \in E_h, \forall h \in C_i \quad (11)$$

$$0 \le C^{EV}_{t,e} \le \alpha_e, \qquad \forall t \in T^{C}_{e}, \forall e \in E_h, \forall h \in C_i \quad (12)$$

$$0 \le D^{EV}_{t,e} \le \beta_e, \qquad \forall t \in T^{C}_{e}, \forall e \in E_h, \forall h \in C_i \quad (13)$$

The cost obtained when running the EC model for the entire community, that is $C_i = \mathcal{N}$, is the optimal cost for the EC (see Equation (14)). On the other hand, the adjusted costs from VECs are defined as the sum of the optimal costs of clusters C_i forming the VEC with structure C (see Equation (15)).

$$\lambda^{opt} = OF(\mathcal{N}) \quad (14)$$

$$\lambda^{adj} = \sum_{C_i \in C} OF(C_i) = OF(C) \quad (15)$$

3.3. Power flow analysis

For the PF analysis, decisions defined in the energy management model are translated into power injection/consumption in each feeder. The energy injected/withdrawn at each node is computed as

$$E_{t,h} = G_{t,h} + I_{t,h} - X_{t,h}, \quad \forall h \in \mathcal{N}, \forall t \in T \quad (16)$$

The buildings forming the community only exchange active power, but computing the reactive power is necessary for the PF analysis. Equation (17) calculates it at each node, assuming the renewable generation has a unit power factor. Hence, the demand is the only contributor to the reactive power. Note that, whether or not the community has been divided into clusters, the PF analysis is performed considering the operations of the entire community $\mathcal{N}$.

$$Q_{t,h} = dem_{t,h} \times \sqrt{\frac{1}{PF^2} - 1}\ \frac{|T|}{24}, \forall t \in T, \forall h \in \mathcal{N} \quad (17)$$

With this information, the PF analysis can be performed for the whole time horizon (e.g., a whole day). This study employs the three-phase unbalanced Forward-Backward Sweep Power flow proposed by Eminoglu & Hocaoglu [36].

Upon the PF analysis, the next step is to translate any physical constraint violations (i.e., overvoltage) caused by the operations of the entire community into input data for the PSO algorithm. This is done by calculating a technical signal, F, which is proportional to a heuristic penalty factor, PE, and a value specific to the technical factor violated.

Equation (18) presents the technical signal that penalises overvoltage, F^{OV}, which is proportional to the difference between the upper threshold of voltage magnitude and the maximum voltage level incurred in the feeder. If there are no grid issues, the term becomes zero, while the higher the over-voltage, the larger the number of the technical signal.

$$F^{OV} = PE^{OV} \times \left(\sum_{t} \max\left(V_t - V^{max}, 0\right) \right) \quad (18)$$

3.4. Particle swarm optimisation

As a metaheuristic algorithm, PSO was designed to solve optimisation problems with continuous nonlinear functions in a quick and effective manner. Developed by Kennedy and Eberhart [37], its core idea involves a grouped-based search for the optimal solution. This method involves defining a set of potential solutions called particles, which continuously adjust their positions by learning from their own history of solutions and the best strategies of others.

Each particle, p, is characterised by a set of decision variables, referred to as the particle's position, x_p, a velocity, v_p, and a fitness value f. The algorithm refines these attributes iteratively, with each iteration represented by the subscript k. The adjustment of each particle's decision variables and velocity across iterations proceeds as follows:

$$v_{p,k} = \omega v_{p,k-1} + c^1 r^1_k (pbest_{p,k-1} - x_{p,k-1}) + c^2 r^2_k (gbest - x_{p,k-1}) \quad (19)$$

$$x_{p,k} = x_{p,k-1} + v_{p,k} \quad (20)$$

Equation (19) includes ω as the inertia weight. The constants for acceleration are coefficients c^1 and c^2 that influence the particle's movement towards its personal best and the global best solution, respectively. The variables r^1 and r^2 are stochastic components, each sampled from a uniform distribution ranging from 0 to 1. The $pbest_p$ and $gbest$ are the particle's and global best positions, respectively. The best-known position of any particle, $pbest_p$, is updated in each iteration based on Equation (21).

$$pbest_{p,k} = \begin{cases} pbest_{p,k-1} & \text{if } f(x_{p,k}) \ge f(pbest_{p,k-1}), \\ x_{p,k} & \text{if } f(x_{p,k}) < f(pbest_{p,k-1}). \end{cases} \quad (21)$$

The algorithm proceeds to iteratively adjust each particle's decision variables over a predefined number of iterations, K, or until it meets convergence criteria. This iterative process drives the algorithm towards optimal or near-optimal solutions in the problem space.

Within the proposed coordinating framework, the PSO algorithm aims to account for the nonlinear network constraints of the PF analysis to restrict decision-making in the energy community model. Thus, it would be initiated whenever the technical signal $PF(\mathcal{N}) > 0$, as it reflects that the scheduled operations of the community do not comply with technical limits. The goal is to find the best combination of clusters of members within the EC, that is the best VEC, that minimises the economic costs and eliminates network issues.

The PSO starts by defining a number of random particles, P, representing potential VECs such that $C^p_k = \{C^p_{1,k}, \dots, C_{n,k}\}$ indicates the set of building clusters forming particle p. The number of sets of clusters $n \ge N$, where N is a predefined maximum number of clusters. The operational decisions for each particle and iteration are a vector $x_{pk} = [x_{pk1}, \dots, x_{pkh}, \dots, x_{pk|\mathcal{N}|}]$ with $|\mathcal{N}|$ variables, one per building in the community. The decision variables, in this case, can only take the integer values between $[1, \dots, n]$, and they indicate the number of clusters corresponding to each building. These vectors x_{pk} are translated to C^p_k, which is the set of clusters in particle p. For instance, let us define a community with five buildings and a particle whose position in a given iteration is $x_{pk} = [1, 2, 2, 3, 1]$, this indicates a potential VEC whose set of clusters is formed by $C^p_{1,k} = \{1, 5\}$, $C^p_{2,k} = \{2, 3\}$ and $C^p_{3,k} = \{4\}$.

To ensure the definition of integers in the PSO algorithm, at each iteration, the positions x_{pk} for every particle get rounded off to the closest integer [38]. Also, maximum and minimum values on decision variables are set to 1 and N, respectively. It is important to note that the higher the number of clusters, the more restricted the feasible space of the community is. Essentially, having more clusters implies fewer opportunities for accounting for members' operational synergies.

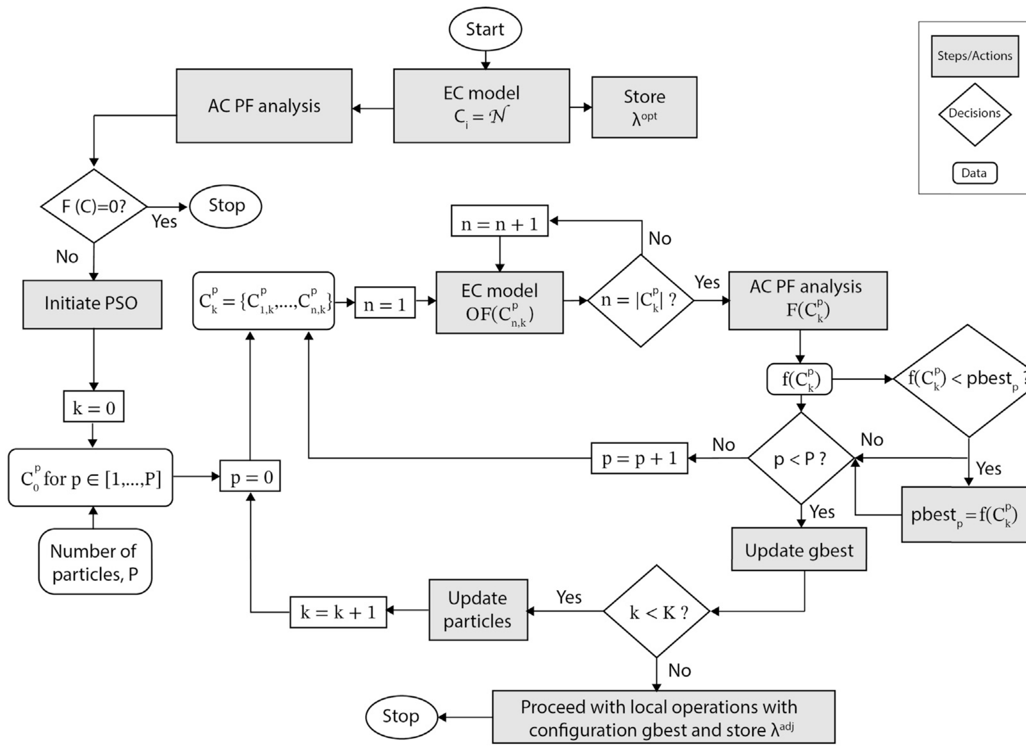

Fig. 2. Flowchart of the algorithm.

The fitness value for each particle and iteration is calculated as the sum of the operational cost, $OF(C^p)$, and the technical signal from the power flow analysis, $F(C^p)$, such that

$$f(C_k^p) = OF(C_k^p) + F(C_k^p) \tag{22}$$

At each iteration, the EC model and the PF analysis are executed for each particle. Note that the penalty factor PE constructing the technical signal $F(C_k^p)$ needs to be set at a value large enough to encourage the PSO algorithm to prioritise minimising this component of the fitness function. Also, as a metaheuristic method, enough iterations are required to find a solution that sets the physical signal to zero. The PSO algorithm will find the particle with the combinations of clusters with the minimum fitness value f.

Fig. 2 illustrates the proposed framework for a time horizon T. Note that computing the fitness values in the PSO algorithm can be performed in parallel computing to speed up the process.

3.5. Other potential technical signals: voltage unbalance factor

The technical signal described in Equation (18) ensures voltage control. However, this signal can be adapted to incorporate other physical factors depending on the variables the grid operator wants to regulate. An example of a physical factor that can be considered is the voltage unbalance factor (VUF). The VUF is defined as the ratio of the negative sequence to the positive sequence of voltage [39], as expressed in Equation (23).

$$F^{VU} = PE^{VU} \times \min\left(\max_{b,t} \frac{|V_n(b,t)|}{|V_p(b,t)|} \times 100\right) \quad \forall\, t \in T, b \in B \tag{23}$$

The negative and positive sequences are defined for each bus $b \in B$ and time t according to Equations (24) and (25), respectively.

$$V_n(b,t) = \frac{V_{ab}(b,t) + a^2 \times V_{bc}(b,t) + a \times V_{ca}(b,t)}{3} \tag{24}$$

$$V_p(b,t) = \frac{V_{ab}(b,t) + a \times V_{bc}(b,t) + a^2 \times V_{ca}(b,t)}{3} \tag{25}$$

Here, $a = 1\angle 120°$ and $a^2 = 1\angle 240°$. Also, V_{ab}, V_{bc}, and V_{ca} are line-line voltages.

4. Data and case study

To examine the coordination tool for aligning local electricity sharing with the grid and determining the minimum incentive for providing flexibility services, three different scenarios are examined within a residential building neighbourhood:

- ***No sharing***: In this case, prosumers and consumers operate their assets individually, without any interaction or energy exchange between them.
- ***Sharing - No Clustering***: The energy community model determines the cost-optimal operations, and a power flow analysis is performed to examine their effect on the grid. However, the algorithm does not generate VECs to solve the grid issues. This case illustrates a situation where there is no possibility of solving grid issues.
- ***Clustering***: In this scenario, the algorithm uses the PSO to find the VEC and the minimal economic incentive needed to provide flexibility services.

Moreover, the study encompasses a sensitivity analysis to evaluate the algorithm's performance in future scenarios where communities have widely adopted EVs and renewable energy sources. Also, the entire process is performed at the beginning of each day. This implies that the VEC selected is kept until the next day when a new analysis is performed.

4.1. Distribution grid and community set-up

All the cases are evaluated using the IEEE European Low Voltage Test Feeder. As depicted in Fig. 3, this three-phase unbalanced grid is a benchmark for low voltage feeders typically found in Europe [40]. The nominal voltage and frequency of the grid are 416 V (phase-to-phase) and 50 Hz, respectively. Furthermore, the feeder, which is connected to

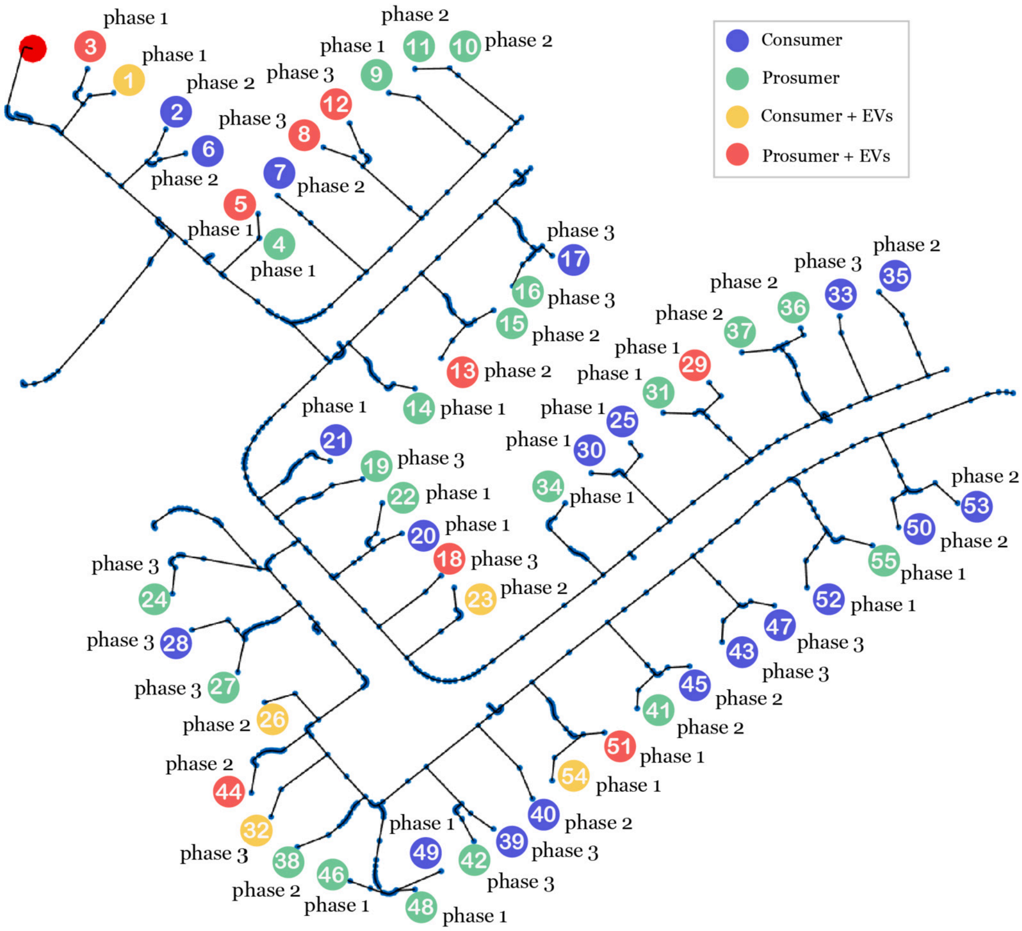

Fig. 3. Single-line diagram of the IEEE European Low Voltage Test Feeder identifying each member of the community. (For interpretation of the colours in the figure(s), the reader is referred to the web version of this article.)

the upper grid via an 11/.416 kV transformer, supplies 55 households. These households comprise thirty prosumers (nine with EVs) and fifteen consumers (five with EVs). The specific member types and their connection to different grid phases are included in Fig. 3.

4.2. Prosumers and consumers' profiles

The demand profiles for each household are obtained from the Low Carbon London project.[1] This dataset contains measured half-hourly energy consumption for different households in London (UK), collected in 2013. This study assumes that consumers and prosumers are equipped with smart meters, enabling them to react to a real-time tariff with an average price of 14.2 pence/kWh per year. These profiles span nine months of electricity consumption, from January to September (275 days), where each day is divided into 48 time periods.

4.3. Renewable technologies

Of the thirty prosumers, twenty-five are assumed to own photovoltaic systems, while the rest possess small wind turbines. Considering only self-consumption, these renewable resources cover 24.3% of the total community demand.

Synthetic solar profiles are generated assuming 4 kW solar units with 21% efficiency and a tilt angle of 35°, tailored for the London area, as suggested in [41]. The same wind generation profile is assumed for the five turbines. The profile was generated using a polynomial power curve, as detailed in [42], representing the output power of a 2.3 kW turbine.

4.4. EVs

Fourteen households are assumed to grant permission for the community to utilise their EVs as a source of flexibility. All EVs have a nominal storage capacity of 50 kWh and a round-trip efficiency of 96%. This is the average value drawn from the capacity of the Nissan Leaf, Volkswagen e-Golf, and Tesla S as documented by Sæther et al. [11]. Furthermore, a maximum charging and discharging rate of 32 A is assumed, which is approximately equivalent to 7.3 kW in a 230 V grid. The arrival and departure times of the EVs are estimated using an algorithm developed by Lakshmanan & Bjarghov [43].

4.5. PSO parameters

As discussed in Section 3.4, the adjustment of each particle's decision variables depends on several parameters, including the inertia weight and the constants for acceleration. The inertia weight ω is a dynamic parameter that, rather than being static, gets updated at each iteration. Its value starts at 0.9 in the first iteration and decreases with the number of iterations, a strategy used to balance the exploration of solutions. This will force the algorithm to update the velocity of the particles to a lesser degree as it approximates the final solution. This allows the algorithm to fine-tune its search around more promising solutions. Paremeters c^1 and c^2 were set to 2 as originally stated in the seminal work of Kennedy and Eberhart [37].

[1] https://data.london.gov.uk/dataset/smartmeter-energy-use-data-in-london-households.

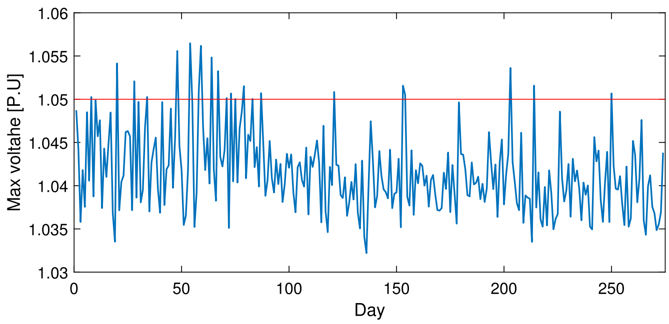

Fig. 4. Impact of energy sharing on the grid's maximum voltage over nine months for the *Sharing - No Clustering* case.

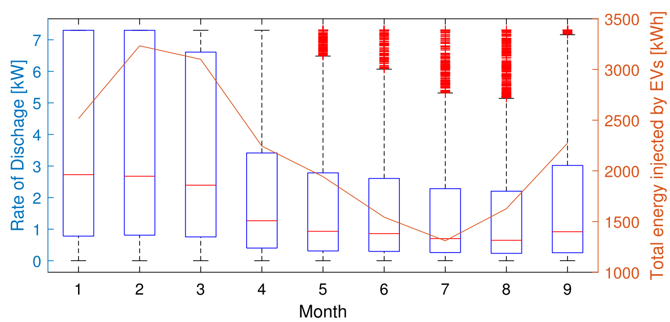

Fig. 5. Rate and total volume of energy injected to the grid by EVs in the local interactions in the *Sharing - No Clustering*.

5. Results and discussion

This section delves into the impact of the residential neighbourhood's energy sharing on grid voltage levels. It also evaluates the effectiveness of the proposed algorithm to manage potential overvoltage events. Then, the economic incentives for providing voltage regulation services are assessed together with the algorithm's performance under increased renewable production, energy consumption, and EV integration.

Fig. 4 illustrates that optimising energy sharing at the EC level, as in the Sharing - No Clustering Case, jeopardises grid operations by inducing overvoltage. Over the nine-month period considered, voltage levels exceeded the maximum safe threshold of 1.05 P.U. on several days. However, these overvoltage events were not uniformly distributed over time. They occurred most frequently during the second and third months, attributable to higher energy injection rates by EVs. This increase in injection was prompted by specific demand conditions, fluctuating energy prices, and variable energy generation rates during these months. The distribution of discharge events of EVs for each month is depicted in Fig. 5.

5.1. Algorithm evaluation to manage overvoltage

The algorithm's primary objective is to manage overvoltage within the community grid while facilitating energy exchanges. Fig. 6 provides a comparison of the highest voltage levels observed over the course of a selected day in March for the Sharing - No Clustering case and the Clustering case. The results demonstrate the algorithm's effectiveness in mitigating overvoltage issues. For example, at timestep 37, voltage levels were reduced to within acceptable limits, thereby avoiding exceeding the 1.05 P.U. limit.

Also, the algorithm's consistency is confirmed by the three-phase voltage profiles illustrated in Fig. 7 for timestep 37. Without energy sharing, the voltage falls along the feeder in the three phases due to the absence of energy feed-in. Conversely, in the Sharing - No Clustering case, the total energy exported by the houses connected to phase 1 is

Table 2
KPIs for the three cases obtained for the selected 30 days in March.

	No sharing	Sharing - No Clustering	Clustering
Total cost [£]	1989	1697 ↓ 14.7%	1698 ↓ 14.6%
Total grid cons. [kWh]	13311	11657 ↓ 12.4%	11660 ↓ 12.4%
RES curtailment [kWh]	2436	699 ↓ 71.3%	702 ↓ 71.2%
RES curtailment [%]	43	12	12
Days with overvoltage	0	8	0
EV P2P Export [kWh]	-	3031	3021
EV P2P Import [kWh]	-	771	763

2.7 times higher than the average of the other phases, resulting in overvoltage. The integration of the algorithm keeps phase 1 beneath 1.05 P.U.

Furthermore, to validate the correct functioning of the algorithm, it is necessary to check whether the estimated energy imported from the main grid from the energy community model equals the one calculated by the AC PF analysis. Fig. 8 compares the results of both models for each case. As expected, when there is no trading, the demand is inflexible, and the market and power flow model are coincident (Fig. 8 (a)). This alignment is also observed in the other two cases, reinforcing that the algorithm ensures model consistency.

Moreover, Fig. 9(b) illustrates the energy export for all buildings under both optimal operation and after implementing the algorithm. Remarkably, the algorithm managed to solve the overvoltage issues by reducing the energy exported from two crucial households, buildings 51 and 54, by 76% and 73%, respectively. Interestingly, the algorithm allowed most other households to actually increase their electricity exports via their EVs, resulting in a negligible impact on the community's total daily energy exports.

However, this result raises questions of equity within the EC. The analysis reveals that buildings connected to the grid at standard voltage levels were more likely to increase their energy exports. This implies that some households, due to their advantageous connection points, could potentially obtain greater rewards from the trading. Such disparity could introduce elements of unfairness within the community, necessitating governance measures.

5.2. Minimum economic incentive for overvoltage services

The application of the algorithm to solve overvoltage issues entails adjustments to the optimal schedule of buildings, resulting in different economic and technical outcomes for the EC. Several Key Performance Indicators (KPIs) for the three scenarios are presented in Table 2.

Electricity trading among buildings led to a substantial decrease in both renewable curtailment and electricity imports from external sources, compared to the No Sharing scenario. The algorithm proposed in this study maintains these reduced levels of imports and curtailments, as shown in the Clustering case. Additionally, it effectively eliminated the days with overvoltage, going from eight instances to none, without significant changes in EV exports.

The optimal cost for the community throughout the month was 14% lower than when the community did not engage in energy-sharing activities (No Sharing scenario). Implementing the voltage restriction in the Clustering case resulted in an adjusted cost of only one pound higher than the optimal cost. This value indicates the minimum economic incentive required for the EC to offer voltage services. This cost is expected to be lower in other months when voltage issues are less frequent than in March.

5.3. Performance under futuristic scenarios

The following section evaluates the robustness of the algorithm and the incentives for providing grid services under futuristic scenarios characterised by high EV and renewable energy penetration. This hypothetical future scenario assumes nearly complete EV ownership among

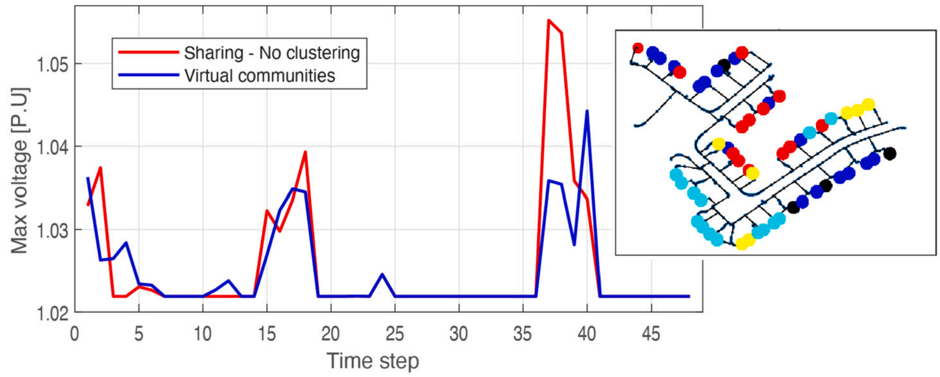

Fig. 6. Comparison of the maximum voltage of the grid (P.U.) over a day with voltage issues in March.

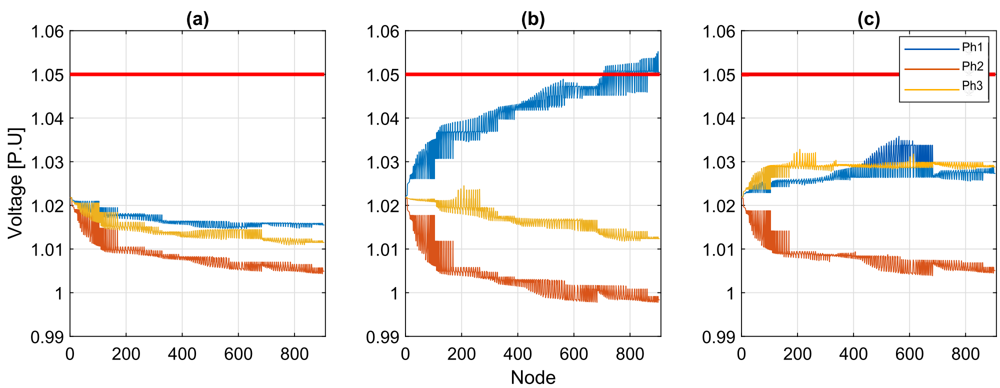

Fig. 7. Voltage profile for the (a) "No sharing", (b) "Sharing - No Clustering", and (c) "Virtual Energy Communities" cases at time step 37 on the selected representative day.

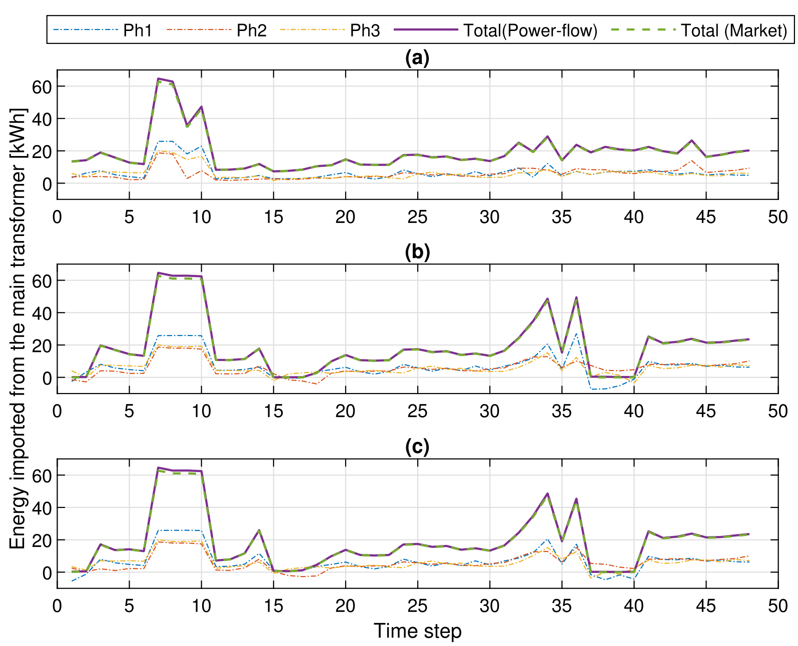

Fig. 8. Comparison of the energy withdrawn from the main grid in the community and power flow models for (a) No sharing, (b) Sharing - No Clustering, and (c) Clustering cases.

participating buildings, with the exception of five houses. Additionally, the scenario doubles the number of exiting solar PV units by adding 20 additional panels.

Hainsch et al. [44], which analyses various decarbonisation pathways, suggests that high electrification rates are likely in multiple sectors, including residential buildings. Based on these findings, the futuristic scenario explores 20% and 100% load increase.

Fig. 10 displays the maximum grid voltage during March when the electricity load increases. The results reveal that higher consumption levels exacerbate overvoltage events throughout the entire day by

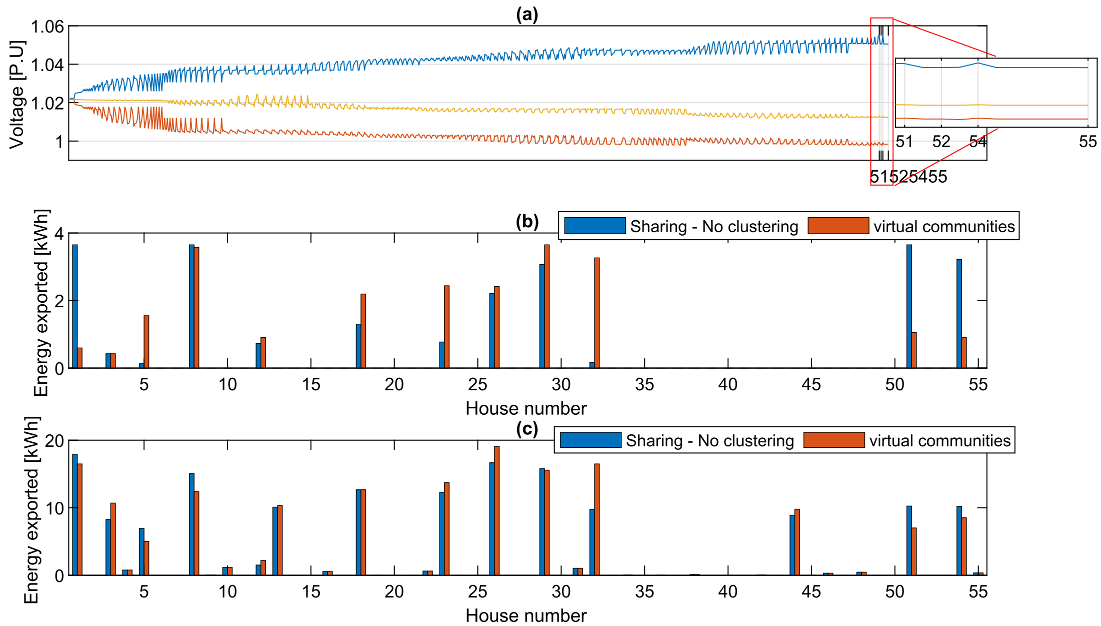

Fig. 9. Representation of the (a) three-phase voltage profile, (b) the individual energy export from various prosumers, and (c) the cumulative energy export from these prosumers, all captured at timepoint 37 on the selected representative day.

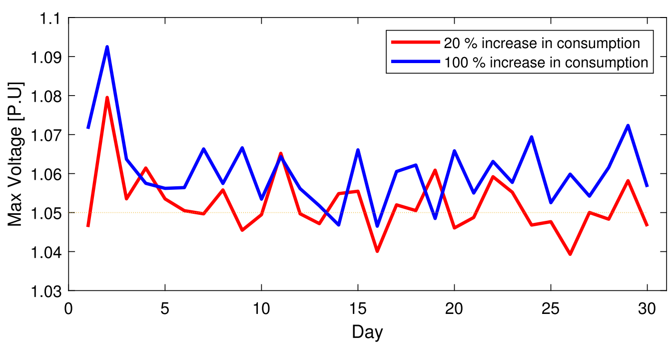

Fig. 10. Maximum daily overvoltage in March for the futuristic scenarios with assumed load growth.

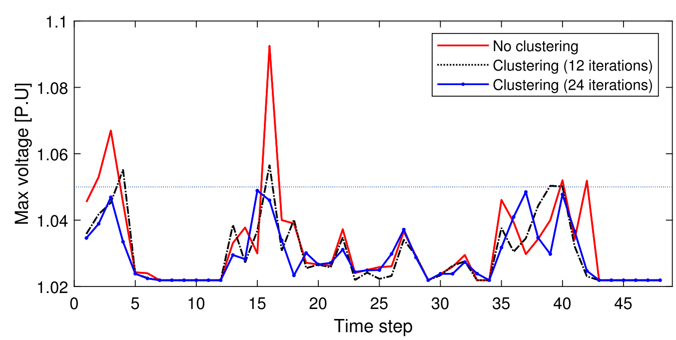

Fig. 11. Comparison of the maximum voltage level for the Sharing No Clustering case and the Clustering cases with $K = 12$ and $K = 24$ for the 2[nd] of March.

necessitating more frequent local energy sharing and, consequently, increased power injection from EVs into the grid.

Two different stopping criteria for the PSO algorithm were tested to assess its effectiveness under higher overvoltage occurrences. This was tested on a selected day from the scenario with 100% consumption growth when there is higher pressure on the grid. Initial attempts with $K = 12$, consistent with prior cases, managed to reduce both the frequency and magnitude of overvoltage events but could not eliminate them entirely (see Fig. 11). The second attempt successfully maintained voltage levels within acceptable limits by setting $K = 24$. This adjustment allowed the PSO algorithm to continue its search for an optimal solution over a longer period, thereby managing to identify a VEC configuration that mitigated all overvoltage events that were not identified by setting the number of iterations to $K = 12$. By adjusting the iterations, the algorithm is capable of maintaining voltage levels effectively under a range of conditions, underscoring its robustness under changes in demand and levels of distributed asset penetration.

Finally, Table 3 presents the KPIs for $K = 12$ and $K = 24$ for the representative day. The results reveal that in futuristic scenarios, regulating voltage restricts community trading such that it diminishes costs and benefits. Interestingly, the economic incentive for voltage regulation is £3 just for a single day, which is approximately 1% of the total costs. This number is considerably higher than one pound per month, resulting in prior cases. However, this number can be interpreted as an

Table 3
Results of the sensitivity analysis of increasing the number of iterations of the algorithm using the overvoltage signal.

	Sharing	Clustering	
	No Clustering	$K = 12$	$K = 24$
Total cost [£]	278	282	281
Total grid consumption [kWh]	949	962	956
Max. Voltage [P.U]	1.0925	1.0567	1.0489
Max. VUF	1.950	1.950	1.950
Local energy [kWh]	204	171	170

upper threshold of the minimum incentive as the day selected presents more overvoltage occurrences than other days of the year.

6. Conclusion

This study introduces the concept of VECs as a novel coordination mechanism to align the interests of EC and grid operators. The essence of the proposed method lies in the strategic formation of smaller, independent clusters within ECs, which allow for the optimisation of energy sharing and storage operations in a manner that adheres to the constraints imposed by the grid. This is achieved through the implementation of a PSO algorithm, which is able to identify configurations of VECs that not only yield close-to-optimal economic benefits for the EC but also comply with network constraints.

By leveraging the concept of VECs, the proposed coordination tool limits the potential energy sharing within ECs, thereby aligning their activities with the grid needs. This balance is achieved without the need for executing optimal power flows, simplifying the analysis of three-phase unbalanced AC grids, which pose significant optimisation challenges. The coordination tool is tailored to encourage ECs to evaluate and offer their flexibility at the lowest possible cost while simultaneously motivating DSOs to support energy-sharing initiatives within the community framework.

The findings of this paper shed light on the first research question addressing the minimum incentive required to motivate grid flexibility from ECs. The coordination tool calculates it as the difference between the cost under optimal operations and the cost incurred after activating grid flexibility through VECs. The results suggest that the minimum incentive to encourage ECs to provide flexibility services for mitigating overvoltage issues is relatively low, and position the coordination tool as a potentially more cost-effective solution than traditional grid upgrades. However, the variability in minimum incentives across different community setups presented in this study underscores that the attractiveness of the coordination tool may be dependent on the specific circumstances. This variability arises from varied factors, such as grid infrastructure, the geographical distribution of the assets, and the specific energy use patterns. Therefore, a more comprehensive analysis is required to evaluate these two alternatives effectively. Thus, future work should compare these alternatives across a spectrum of scenarios. Such an approach will enable grid operators and energy communities to identify the most economically viable solutions for enhancing the feasibility of ECs.

The paper also tackles the second research question of whether ECs can provide flexibility service effectively by proposing a novel coordination tool. Using a case study, the method has been proven to manage ECs' activities to offer flexibility to grid operators while still engaging in energy-sharing. This balance is achieved by optimising the operations with communities within grid limitations, ensuring they can maintain their core operations without compromising the grid's stability. Also, the coordination tool is not restricted to mitigating overvoltage issues and can adapt to varying situations. On the one hand, grid operators can choose the physical factor(s) to tackle by defining the technical signal to compute and consider in the platform. Conversely, the tool can adapt to different community structures (e.g., local energy market) as the information required to reorganise operations is not specific to any particular setting. An extension of this work should focus on examining how different community structures could be implemented in the proposed framework.

Furthermore, the coordination tool is designed to ensure that both agents have incentive compatibility. Firstly, it encourages the community to value its flexibility at the lowest possible cost. Secondly, it promotes the grid operator to facilitate energy sharing within communities. The framework guarantees also individual rationality by remunerating the community based on its minimum incentive. This ensures that its economic outcome is at least as favourable as it would be if it engaged in energy sharing under any grid restrictions.

While the proposed coordination mechanism shows promising results in enhancing grid flexibility and optimising energy distribution, it has several limitations. Firstly, the PSO algorithm, by its heuristic nature, does not guarantee the identification of the optimal configuration for VECs that minimises the cost of flexibility provision. This limitation is particularly pronounced in nonconvex optimisation problems, where the algorithm's capacity to reach global optima cannot be assured. Further research should compare the tool's performance with precise solutions like AC OPF. Despite this limitation, the coordination tool offers a computationally efficient method to solve a nonconvex problem that usually requires high computational capacity.

Additionally, the iterative nature of the algorithm necessitates defining adequate stopping criteria. This involves finding an equilibrium between the computational efficiency - reflected in the maximum number of iterations - and the quality of the solution obtained. Also, the PSO algorithm's ability to explore the search space is significantly affected by the parameters selected, including the inertia weight and the constants for acceleration. Further work should concentrate on refining the stopping criteria as well as the algorithm's parameterisation. For instance, another approach to defining the stopping criteria could involve iterative solving until finding a VEC that manages the technical signal to zero. Such adjustment would ensure minimising the number of iteration that addresses grid concerns, thereby enhancing the computational efficiency of the method.

Another promising direction to expand the present study is the integration of stochastic optimisation techniques that could accommodate the uncertain nature of renewable generation and consumption dynamics. The methodology presented in this paper assumes complete information for the entire operational time horizon, overlooking real-world scenarios. Developing the tool to account for uncertainties will identify a more secure VEC that could reflect actual grid conditions.

Lastly, another potential limitation of approaches based on restricting trading options like the one proposed in this paper is their social consequences. This study has highlighted instances where the physical location of households' connections to the grid has resulted in differential treatment among community members. This variance in treatment manifests by restricting the ability of some households to engage fully in community trading activities. This raises social concerns regarding fair participation and treatment of members within communities and could pose social challenges in their adoption. Therefore, addressing this challenge is a key aspect of implementing coordination tools between energy communities and grid operators.

CRediT authorship contribution statement

Naser Hashemipour: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Raquel Alonso Pedrero:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **Pedro Crespo del Granado:** Writing – review & editing, Writing – original draft, Supervision, Resources, Funding acquisition. **Jamshid Aghaei:** Writing – review & editing, 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.

Data availability

Data will be made available on request.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Grammarly in order to improve the language of the paper. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Acknowledgements

We gratefully acknowledge the BEYOND - Blockchain-based ElectricitY trading for the integration Of National and Decentralized local markets" project (Grant Agreement No. 775970) which has received funding from the initiative ERA-Net Smart Energy Systems, with support from the European Union's Horizon 2020 research and innovation programme.

Appendix A. Mathematical notation

Table A.4
Indexes and Sets.

Notation	Description
$\mathcal{N}$	Set of buildings forming the EC
C	Set of clusters in a VEC
n	Number of clusters in C
N	Maximum number of clusters allowed
h, p, e	Building index
i, j	Cluster index
$C_i \in C$	Set of buildings
E	Set of EVs
E_h	Subset of EVs associated to building h
e	EVs
T	Set of time periods
t	Timer periods
$T_e^C \subset T$	Subset of time periods when the EV in building e is connected to the grid
$T_e^A \subset T$	Set of time periods when the EV in building e arrives to the EC
$T_e^D \subset T$	Set of time periods when the EV of building e departs from the EC
P	Number of particles for the PSO
p	Particles
K	Number of iterations for the PSO
k	Iteration

Table A.5
Indexes and Sets.

Notation	Description
p_t^G	Electricity price for importing from the main grid
$res_{t,h}$	Renewable electricity generated (kWh)
$dem_{t,h}$	Demand electricity (kWh)
ψ	Loss factor for trading electricity
η_e^c	EV charging efficiency factor
η_e^d	EV discharging efficiency factor
$s_{t,e}^A$	State of charge of EV e at time of arrival
$\overline{s}_{t,e}$	Fixed ratio to define the minimum state of charge of EV e at departure time
$\overline{s}_{t,e}$	Maximum capacity of EV e
α_e	Maximum charging rate
β_e	Maximum discharge rate
F	technical signal from the grid operator
F^{OV}	technical signal from the grid operator for overvoltage
F^{VU}	technical signal from the grid operator for voltage unbalance
PF	Power factor
PE	Penalty factor
PE^{OV}	Penalty factor for overvoltage
PE^{VU}	Penalty factor for voltage unbalance
V^{max}	Maximum allowed voltage level at the feeder (V)
c_p^1 and c_p^2	Acceleration coefficients
ω	Inertia

Table A.6
Variables.

Notation	Description
λ^{opt}	Optimal cost of the EC
λ_C^{opt}	Adjusted cost of the EC under the VEC C
OF	Objective value of the EC
$G_{t,h}$	Electricity imported from main grid (kWh)
$D_{t,e}^{EV}$	Discharged electricity from EV e (kWh)
$C_{t,e}^{EV}$	Charged electricity by EV e (kWh)
$I_{t,h}$	Total imported electricity from peers (kWh)
$X_{t,h}$	Total exported electricity to other peers (kWh)
$I_{t,h\leftarrow p}^P$	Imported power by building h from peer p (kWh)
$X_{t,p\rightarrow h}^P$	Exported power by building h to peer p (kWh)
$S_{t,e}^{EV}$	State-of-charge of EVs in e (kWh)
$E_{t,h}$	Injected/withdrawn energy (kWh)
$P_{t,h}$	Injected/Withdrawn power (kW)
$Q_{t,h}$	Reactive power (VAR)
V_t	Voltage level at the feeder (V)
$v_{p,k}$	Velocity
$x_{p,k}$	Position or decision variable
$pbest_p$	Best particle's position
$gbest$	Best position found

References

[1] IEA, World Energy Outlook 2022, Report, International Energy Agency, 2022.
[2] D. Pudjianto, G. Chin Kim, V. Stanojevic, M. Aunedi, P. Djapic, G. Strbac, Value of integrating distributed energy resources in the UK electricity system, in: IEEE PES General Meeting, 2010, pp. 1–6.
[3] E. Parliament, Directive (EU) 2018/2001 of the European Parliament and of the council of 11 December on the 2018 on the promotion of the use of energy from renewable sources, 2018.
[4] E. Parliament, Directive (EU) 2019/944 of the European Parliament and of the Council of 5 June 2019 on common rules for the internal market for electricity and amending Directive 2012/27/EU, Off. J. Eur. Union L 158 (2019).
[5] J.J. Cuenca, E. Jamil, B. Hayes, State of the art in energy communities and sharing economy concepts in the electricity sector, IEEE Trans. Ind. Appl. 57 (2021) 5737–5746, https://doi.org/10.1109/tia.2021.3114135.
[6] J.M. Zepter, A. Lüth, P. Crespo del Granado, R. Egging, Prosumer integration in wholesale electricity markets: synergies of peer-to-peer trade and residential storage, Energy Build. 184 (2019) 163–176, https://doi.org/10.1016/j.enbuild.2018.12.003.
[7] M. Caramanis, E. Ntakou, W.W. Hogan, A. Chakrabortty, J. Schoene, Co-optimization of power and reserves in dynamic t&d power markets with nondispatchable renewable generation and distributed energy resources, Proc. IEEE 104 (2016) 807–836, https://doi.org/10.1109/JPROC.2016.2520758.
[8] H.S. Ahn, B.Y. Kim, Y.H. Lim, B.H. Lee, K.K. Oh, Distributed coordination for optimal energy generation and distribution in cyber-physical energy networks, IEEE Trans. Cybern. 48 (2018) 941–954, https://doi.org/10.1109/TCYB.2017.2669041.
[9] J. Guerrero, A.C. Chapman, G. Verbic, Trading arrangements and cost allocation in p2p energy markets on low-voltage networks, in: 2019 IEEE Power & Energy Society General Meeting (PESGM), 2019, pp. 1–5.
[10] T. Sousa, T. Soares, P. Pinson, F. Moret, T. Baroche, E. Sorin, Peer-to-peer and community-based markets: a comprehensive review, Renew. Sustain. Energy Rev. 104 (2019) 367–378, https://doi.org/10.1016/j.rser.2019.01.036.
[11] G. Sæther, P. Crespo del Granado, S. Zaferanlouei, Peer-to-peer electricity trading in an industrial site: value of buildings flexibility on peak load reduction, Energy Build. 236 (2021) 110737, https://doi.org/10.1016/j.enbuild.2021.110737.
[12] S.-V. Oprea, A. Bâra, G.A. Ifrim, Optimizing the electricity consumption with a high degree of flexibility using a dynamic tariff and Stackelberg game, J. Optim. Theory Appl. 190 (2021) 151–182, https://doi.org/10.1007/s10957-021-01876-1.
[13] S. Xu, Y. Zhao, Y. Li, Y. Zhou, An iterative uniform-price auction mechanism for peer-to-peer energy trading in a community microgrid, Appl. Energy 298 (2021) 117088, https://doi.org/10.1016/j.apenergy.2021.117088.
[14] A. Lüth, J.M. Zepter, P. Crespo Del Granado, R. Egging, Local electricity market designs for peer-to-peer trading: the role of battery flexibility, Appl. Energy 229 (2018) 1233–1243, https://doi.org/10.1016/j.apenergy.2018.08.004.
[15] E. Sorin, L. Bobo, P. Pinson, Consensus-based approach to peer-to-peer electricity markets with product differentiation, IEEE Trans. Power Syst. 34 (2019) 994–1004, https://doi.org/10.1109/tpwrs.2018.2872880.
[16] M.F. Dynge, P. Crespo del Granado, N. Hashemipour, M. Korpås, Impact of local electricity markets and peer-to-peer trading on low-voltage grid operations, Appl. Energy 301 (2021) 117404, https://doi.org/10.1016/j.apenergy.2021.117404.
[17] M.I. Azim, S.A. Pourmousavi, W. Tushar, T.K. Saha, Feasibility study of financial p2p energy trading in a grid-tied power network, in: 2019 IEEE Power & Energy Society General Meeting (PESGM), 2019, pp. 1–5.
[18] S. Frank, S. Rebennack, An introduction to optimal power flow: theory, formulation, and examples, IIE Trans. 48 (2016) 1172–1197, https://doi.org/10.1080/0740817x.2016.1189626.
[19] T. Baroche, P. Pinson, R. Latimier, H. Ben Ahmed, Exogenous approach to grid cost allocation in peer-to-peer electricity markets, IEEE Trans. Power Syst. (2018), https://doi.org/10.1109/TPWRS.2019.2896654.
[20] M. Khorasany, Y. Mishra, G. Ledwich, A decentralized bilateral energy trading system for peer-to-peer electricity markets, IEEE Trans. Ind. Electron. 67 (2020) 4646–4657, https://doi.org/10.1109/TIE.2019.2931229.
[21] M. Farivar, S.H. Low, Branch flow model: relaxations and convexification—part i, IEEE Trans. Power Syst. 28 (2013) 2554–2564, https://doi.org/10.1109/TPWRS.2013.2255317.
[22] J. Kim, Y. Dvorkin, A p2p-dominant distribution system architecture, IEEE Trans. Power Syst. 35 (2020) 2716–2725, https://doi.org/10.1109/TPWRS.2019.2961330.
[23] M. Babagheibi, S. Jadid, A. Kazemi, An incentive-based robust flexibility market for congestion management of an active distribution system to use the free capacity of microgrids, Appl. Energy 336 (2023) 120832, https://doi.org/10.1016/j.apenergy.2023.120832.
[24] J. Guerrero, A.C. Chapman, G. Verbic, Decentralized p2p energy trading under network constraints in a low-voltage network, IEEE Trans. Smart Grid 10 (2019) 5163–5173, https://doi.org/10.1109/tsg.2018.2878445.
[25] A. Bâra, S.V. Oprea, A holistic view on business model-oriented energy communities, Kybernetes ahead-of-print, https://doi.org/10.1108/K-07-2023-1235, 2023.
[26] M. Barani, S. Backe, R. O'Reilly, P. Crespo del Granado, Residential demand response in the European power system: no significant impact on capacity expansion and cost savings, Sustain. Energy Grids Netw. (2023) 101198, https://doi.org/10.1016/j.segan.2023.101198.

[27] T. Haring, G. Andersson, Contract design for demand response, in: IEEE PES Innovative Smart Grid Technologies, Europe, 2014, pp. 1–6.

[28] M. Askeland, S. Backe, S. Bjarghov, K.B. Lindberg, M. Korpås, Activating the potential of decentralized flexibility and energy resources to increase the ev hosting capacity: a case study of a multi-stakeholder local electricity system in Norway, Smart Energy 3 (2021) 100034, https://doi.org/10.1016/j.segy.2021.100034.

[29] E. Bjørndal, M. Bjørndal, M. Buvik, C.N. Børke, E. Gramme, End-user flexibility in the local electricity grid–blurring the vertical separation of market and monopoly?, in: 52nd Hawaii International Conference on System Sciences, IEEE Computer Society, 2019, pp. 3560–3570.

[30] S. Pearson, S. Wellnitz, P. Crespo del Granado, N. Hashemipour, The value of tso-dso coordination in re-dispatch with flexible decentralized energy sources: insights for Germany in 2030, Appl. Energy 326 (2022) 119905, https://doi.org/10.1016/j.apenergy.2022.119905.

[31] R. Alonso, V.V. De Lestrade, J. Specht, P.C. Del Granado, Value and effects of adopting residential flexibility in the European power system, in: 2023 IEEE Power & Energy Society General Meeting (PESGM), 2023, pp. 1–5.

[32] Z. Afroz, M. Goldsworthy, S.D. White, Energy flexibility of commercial buildings for demand response applications in Australia, Energy Build. 300 (2023) 113533, https://doi.org/10.1016/j.enbuild.2023.113533.

[33] R. Faia, T. Pinto, Z. Vale, J.M. Corchado, A local electricity market model for dso flexibility trading, in: 2019 16th International Conference on the European Energy Market (EEM), 2019, pp. 1–5.

[34] Z.E. Lee, K.M. Zhang, Regulated peer-to-peer energy markets for harnessing decentralized demand flexibility, Appl. Energy 336 (2023) 120672, https://doi.org/10.1016/j.apenergy.2023.120672.

[35] H. Ruan, H. Gao, H. Qiu, H.B. Gooi, J. Liu, Distributed operation optimization of active distribution network with p2p electricity trading in blockchain environment, Appl. Energy 331 (2023) 120405, https://doi.org/10.1016/j.apenergy.2022.120405.

[36] U. Eminoglu, M.H. Hocaoglu, Distribution systems forward/backward sweep-based power flow algorithms: a review and comparison study, Electr. Power Compon. Syst. 37 (2008) 91–110.

[37] J. Kennedy, R. Eberhart, Particle swarm optimization, in: Proceedings of ICNN'95 - International Conference on Neural Networks, vol. 4, 1995, pp. 1942–1948.

[38] E.C. Laskari, K.E. Parsopoulos, M.N. Vrahatis, Particle swarm optimization for integer programming, in: Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No. 02TH8600), vol. 2, 2002, pp. 1582–1587.

[39] P. Pillay, M. Manyage, Definitions of voltage unbalance, IEEE Power Eng. Rev. 21 (2001) 49–51, https://doi.org/10.1109/MPER.2001.4311362.

[40] K.P. Schneider, B.A. Mather, B.C. Pal, C.W. Ten, G.J. Shirek, H. Zhu, J.C. Fuller, J.L.R. Pereira, L.F. Ochoa, L.R. de Araujo, R.C. Dugan, S. Matthias, S. Paudyal, T.E. McDermott, W. Kersting, Analytic considerations and design basis for the ieee distribution test feeders, IEEE Trans. Power Syst. (2017) 1.

[41] N. Hashemipour, P. Crespo del Granado, J. Aghaei, Dynamic allocation of peer-to-peer clusters in virtual local electricity markets: a marketplace for ev flexibility, Energy 236 (2021) 121428, https://doi.org/10.1016/j.energy.2021.121428.

[42] P. Crespo Del Granado, S.W. Wallace, Z. Pang, The value of electricity storage in domestic homes: a smart grid perspective, Energy Syst. 5 (2014) 211–232.

[43] V. Lakshmanan, S. Bjarghov, Versatile electric vehicle charging profile generation tool for home charging scenarios for regional case study, https://doi.org/10.5281/zenodo.4599634, 2021.

[44] K. Hainsch, K. Löffler, T. Burandt, H. Auer, P.C. del Granado, P. Pisciella, S. Zwickl-Bernhard, Energy transition scenarios: what policies, societal attitudes, and technology developments will realize the eu green deal?, Energy 239 (2022) 122067, https://doi.org/10.1016/j.energy.2021.122067.