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Dynamic allocation of peer-to-peer clusters in virtual local electricity markets: A marketplace for EV flexibility

Naser Hashemipour [a, b], Pedro Crespo del Granado [a, *], Jamshid Aghaei [c, b]

[a] Dept. of Industrial Economics and Technology Management, Norwegian University of Science and Technology, Trondheim, Norway
[b] Dept. of Electrical Engineering, Shiraz University of Technology, Shiraz, Iran
[c] School of Energy Systems, Lappeenranta-Lahti University of Technology (LUT), Lappeenranta, Finland

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ABSTRACT

Local Electricity Markets (LEM) and peer-to-peer trading are new mechanisms to encourage the uptake of solar PV and to support the emergence of consumer-centric electricity markets. However, the coordination to trade between consumers and prosumers has different definitions depending on the context and features of the energy system. This paper introduces a new vision: creating virtual LEMs by cooperatively mixing (optimal matching) different load and renewable profiles that complement each other. Since consumer and prosumer profiles change every day (weather conditions or demand behaviors), the dynamic formation of virtual LEMs changes daily. To reward flexibility, Electric Vehicles (EV) are also pooled into forming a virtual LEM. That is, we investigate: What is the value of creating virtual local markets (via clustering)?, and what is the impact of EV flexibility on the creation of virtual LEMs? Through implementing a LEM optimization model with a clustering approach, we analyze the formation of LEMs for a set of end-users in London. Results indicate that a single large LEM (no clustering) is comparatively similar to multiple LEMs (clustering). EV flexibility obtains more revenue in this new marketplace. Findings are encouraging as dynamic virtual LEMs can enable, accelerate and bring scalability for a ubiquitous deployment of LEMs.

1. Introduction

Sharing or selling power surplus from home solar PV systems over to neighbors (or fellow consumers) is becoming an attractive scheme to incentivize the adoption of renewables, and to make the end-user a more active participant in providing flexibility. In this regard, the literature and interest in local electricity markets (LEM), peer-to-peer (P2P) trading schemes, and energy communities has rise remarkably in the last years [1–4].

However, the wider deployment of LEM, its acceptance, and integration to the energy system is in its early stages. Market-regulatory frameworks have yet to be in place to open-up the possibilities to validate new market designs. For example, extending the definition of local or 'communal' market to notions of virtual consumer-prosumer markets would facilitate: i) the participation of a larger pool of end-users beyond geographical limitations, ii) more opportunities to trade or share RES at a better price, and iii) accelerate the decentralization and democratization of energy. That is, similar to virtual power plants concepts [5] that take advantage of cloud-based services, but designed to be consumer-centric with the support of blockchain related technologies for example [6–8]. A formation of a virtual LEM would allow new visions on integrating end-use flexibility and open new business model ideas for LEM. Aside from market-regulatory uncertainty, LEM uptake might also face some techno-economical challenges, for example:

- Scalability: LEM might encompass an immense pool of customers that would like to engage in P2P. A huge LEM might face some computational challenges in calculating the optimal allocation and the market (P2P) trading settlement.
- LEMs as a marketplace to reward flexibility. Batteries from Electrical Vehicles could provide flexibility given the right economic conditions. That is, designing LEMs should consider rewards and signals to be an attractive marketplace for flexibility providers.
- Coordinate LEM operations with the local Distribution System Operator (DSO) for power quality problems. Some LEMs

* Corresponding author.
E-mail address: pedro@ntnu.no (P. Crespo del Granado).

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operations might incur on not ideal behavior from the grid operator perspective. For example, in some parts of the distribution network certain LEM resulting operations might be beneficial to manage losses while in other parts of the network is the opposite. Here a join coordination between virtual LEMs and a DSO would guide P2P decisions based on the network's topology conditions.

In this paper, we propose a new vision on how to address the above challenges and to study new opportunities in the formation of *virtual LEMs*. Under the hypothesis of large scale adoption of LEM and P2P schemes, it is fair to assume that there will be a multitude (e.g., around 1 million homes already have solar panels in the United Kingdom) of prosumers and consumers ready to tap on LEM opportunities. This will present scalability issues on how to organize prosumer and consumers into LEMs. Should a virtual LEMs be based on geographical boundaries? Could a prosumer with a small wind turbine in Scotland be able to sell its surplus to a solar PV prosumer in London who is experiencing a rainy day? A situation that might change the next day in the opposite direction based on weather conditions or household energy demand behaviors. That is, each day there will be different circumstances on demand profiles and RES availability. Some days, LEM for a local setting might not have the best match among its peers, hence combining peers from other regions in a dynamic fashion might offer a further business case for the formation of *dynamic virtual LEMs*. In this sense, to understand the formation of virtual LEMs, the paper is centered on these research questions:

- What is the value of creating dynamic virtual local electricity markets (via clustering)? How does a 'virtual LEM' incentivize P2P trade, flexibility, self-sufficiency and integration of RES?
- What is the impact of Electrical Vehicles' flexibility on the creation of virtual LEMs? What benefits would this marketplace bring?

To answer these questions, we have developed a P2P-clustering model that forms dynamic LEMs based on a pool of consumers and prosumers. It is dynamic in the sense that it creates multiple LEMs based on the features of the consumer and prosumer profiles. It matches and allocates participants by clustering them in virtual LEMs that change every day. That is, we assume a high degree of automation that smartly matches prosumers and consumers and creates daily marketplaces. Fig. 1 epitomizes this idea. A community of 25 houses with different characteristics might belong to a neighborhood where a 'Dynamic-P2P' market pairs prosumer and consumers to form virtual LEMs. In this example, for a particular day in the month of May, five clusters (virtual LEMs) are formed. Here the value of EV flexibility complements the P2P-cluster formation by charging from surplus RES and by selling it back (discharging) to consumers based on day-night load patterns.

The following section presents related literature and outlines the contribution of the paper. Next, Section 3 presents the P2P modelling approach and the clustering concept. A case study of residential buildings is presented in Section 4 along with data details. Section 5 discusses results and Section 6 closes the paper with concluding remarks.

2. Related literature

The intermittency and uncertainty of wind and solar power production are creating opportunities for consumers to actively participate in the operation of the power system [9]. Consumers might change their energy consumption pattern to deal with the renewable resources' uncertainty [10] or support congestion management in the grid [11]. This and demand side management schemes have raised a number of business models that could facilitate the coordination of end-users in providing flexibility [12]. For example, the emergence of local flexibility market promises the establishment of new marketplaces in which different participants like DSO, Balance Responsible Party, aggregators, and end-users trade electricity or provide flexibility services [9]. Here, a central facilitator is the coordinating role of the aggregator. That is, since consumers or prosumers are not big enough to participate individually in a market, in so-called flexibility market structures, aggregators coordinate several consumers and provide services for the other parties [13]. So, the aggregation of these houses and controlling their assets enable flexibility for the grid or opens their participation in wholesale markets [14,15]. The aggregators can control demand response assets to adjust the flexible loads like smart buildings [16], or electric vehicles [17]. In this regard, parking lots can also provide the flexibility potential of many EVs to the grid as an aggregator [18,19]. Brinkel et al. propose a framework in which an aggregator mitigates the impact of the PV fluctuations using the grid-connected EVs' potential [20]. This aggregated flexibility can eventually act as a balance responsible party and trade flexibility in balancing markets [21].

In the last years, flexibility in local electricity markets have been exploring how different prosumers or consumers can trade energy [4,7] or other services like peak capacity under a P2P market [22]. These interactions have been categorized under different market structures like P2P trading [4,23], community-based trading [7,24], and hybrid P2P trading [25]. The fully P2P market structure is based on bilateral contracts between different market participants. It enables to model the attributes of participants individually (e.g. Ref. [26]) but it might face scalability challenges for a large pool of end-users or agents [27]. In the community-based design (similar to smart neighborhoods or micro-grids), the community handler manages the transactions centrally [28]. But the community-based models do not reflect individual preferences which allows faster and more robust implementation than fully P2P structures on larger scales [27]. Here, the results of [29] show that optimizing the size of PV systems for energy communities increases the potential of cost-saving compared to doing it for buildings individually. Lastly, the hybrid approach is a combination of the previous methods with a hierarchical structure. In hybrid methods, the trades can happen at different levels. For example, in Ref. [30], the exchanges are organized in three sets, i.e., between some cells in the grid, micro-grids in the same cell, and a community market within each micro-grid.

In general, the motivation of these papers is to define a local market to a specific context or problem at hand. A relatively under research area is the idea of creating virtual LEMs (via clustering) driven by enabling technologies such as the digitization of power systems and the automatization of transactions via smart contracts [31,32]. For example [33], proposes the dynamic clustering of prosumers to minimize the imbalance cost resulting from the renewable forecast errors. This clustering focuses on the flexibility bids to gather and manage demand response capability. Pinto et al. organized buildings in different clusters to increase the flexibility of the whole collection instead of one single consumer [34]. There and other papers note the premise that several challenges will appear in decentralizing the market when a high number of consumers or prosumers participate in P2P trading [35]. In this context, setting boundaries for different sub-markets by neighborhood clustering can facilitate the cooperation of the houses on bigger scales [36]. In Ref. [37], the players are assigned to different clusters after submitting their bids to the market. The market is then cleared for each segment separately to reduce the data exchange and

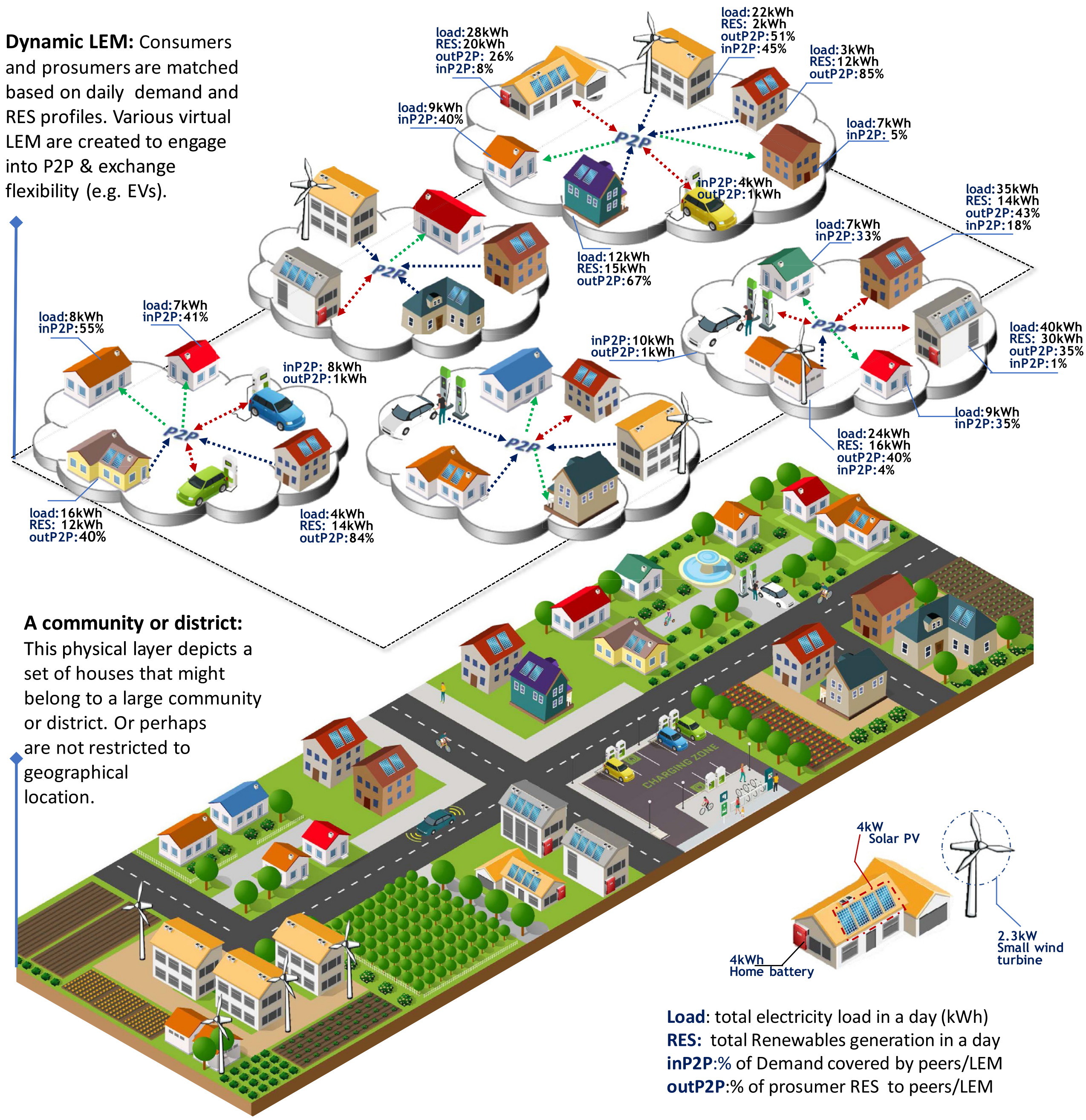

Fig. 1. A set of consumer and prosumers engage in the formation of virtual LEMs. The (upper) virtual layer coordinates the formation of dynamic P2P clusters based on a pool of participants from a community or district (lower layer). LEMs matches EV flexibility with the allocation (best match) of consumers and prosumers profiles. The figure represents the actual features of the case study implemented in this paper (see Table 1). For some clusters, results illustrate the total daily amount of P2P traded, load, and RES production for a day in the month of May.

communication overheads. There a K-means algorithm performs the clustering based on the energy volume and price announced by the bids of market participants. However, in the k-means algorithm, the number of clusters needs to be specified in advance. Other algorithms, such as Hierarchical cluster analysis (HCA) that have resolved this issue are widely used in energy applications [38]. Similar ideas have been applied to virtual micro-grids where the approach is to group the physically constrained energy prosumers [39–41], and the networked micro-grids by operating a bunch of micro-grids that are physically interconnected [42]. Vergados et al. [43] proposed an approach to organize the energy prosumers in virtual clusters participating in energy markets. The objective of the proposed clustering is to minimize the relative forecasting error for each collection. A similar study proposes an aggregation framework by grouping the prosumers to form a target prosumption pattern requested by a market actor [44].

Overall, the status of the existing literature has not directly address the creation of daily virtual LEMs. The objective of this paper is to understand how to form dynamic virtual LEMs so that each agent is assigned to a cluster with the best match of the demand and renewable profiles. So, each agent finds the highest possibility of energy trading with the other members in that cluster. Also, the impact of clustering on the behavior of EVs participating in P2P transactions is a new contribution to the literature. To summarize, the paper's novelty fills relevant research gaps in the literature with these key contributions: i) a new notion on defining virtual LEMs, ii) proposition of a framework of clustering prosumer and consumers that is comparatively efficient versus a perfect market case (a large optimal cluster), iii) design a marketplace for EV-flexibility to understand how virtual LEMs (via clustering) benefit from EVs, and iv) discussion on the potentials of virtual LEM in the design of future consumer-centric electricity markets.

3. Modelling framework

To analyze the formation of dynamic local electricity markets, two main mathematical programming based models were developed to represent the interactions between local RES, demand profiles, P2P trading, batteries, and EVs presence. In a nutshell, the models are as follows:

- **LEM and P2P model:** The objective of the local market is to optimally use the RES production by prioritizing a 'shared' self-consumption between prosumers and consumers via P2P. The LEM model minimizes the overall cost for a set of houses ($h \in H$). It assumes perfect market competition and determines the P2P trading. For example, this LEM model in Refs. [7,15] analyses the role of batteries in P2P trading while in Ref. [22] it focuses on a set of industrial buildings interested in joint peak management via P2P.
- **P2P-Clustering based model:** The clustering approach applies an optimization model that provides the partitioning (houses allocation) into various LEMs. This is based on matching demand profiles, EVs availability, and renewable generation. Then, the P2P model determines the local market trading and supply-demand operations of each cluster.

Both modelling features are described in the following.

3.1. Local electricity market and P2P modelling

Consider a set of houses ($h \in H$) that have diversity on demand and generation profiles. Each house balances its supply and demand. That is, supply from renewable generation $res^{(t,h)}$, grid consumption $G^{(t,h)}$, battery discharge $D^{(t,h)}$ and direct P2P purchase $I^{(t,h)}$ should match the sum of demand $dem^{(t,h)}$, battery charge $C^{(t,h)}$ and P2P sales $X^{(t,h)}$ for each house $h \in H$ in each time step t under a horizon T (e.g., hourly intervals for a horizon of one day or more). In short, the supply-demand balance equation[1] is:

$$\overbrace{res^{(t,h)} + G^{(t,h)} + D^{(t,h)} + I^{(t,h)}}^{\text{RES + Grid + Battery disch. + P2P buy}} \geq \overbrace{dem^{(t,h)} + C^{(t,h)} + X^{(t,h)}}^{\text{Demand + Battery charge + P2P sale}} \tag{1}$$

The virtual local market provides prosumers or consumers a direct trade of electricity with their fellow peers. That is, in the model, the overall sales quantity $X^{(t,h)}$ for each house $h \in H$ is defined as the sum of all electricity flows $X_p^{(t,h\to p)}$ from this house $h \in H$ to its peers $p \in H$. This is equation (2):

$$X^{(t,h)} = \sum_{p\neq h} X_p^{(t,h\to p)} \tag{2}$$

Given that

$$I_p^{(t,h\leftarrow p)} = \psi^{P2P} \cdot X_p^{(t,p\to h)} \qquad \forall\, p\neq h, \tag{3}$$

the change of the flow direction indicates a purchase $I_p^{(t,h\leftarrow p)}$ of one house $h \in H$ from its peer $p \in H$. In each P2P transaction, the energy imported by one house is equal to the export of its peer while considering some network losses (ψ^{P2P}). The overall purchased quantity per house, $I^{(t,h)}$, is then specified by eq. (4).

$$I^{(t,h)} = \sum_{p\neq h} I_p^{(t,h\leftarrow p)} \tag{4}$$

As no grid feed-in is considered, the sold and purchased quantity stays within the community. The sum of sales over all houses is equal to the purchases while considering network losses, this is as follows in eq. (5):

$$\sum_h \psi^{P2P} \cdot X^{(t,h)} = \sum_h I^{(t,h)} \qquad \forall\, t \in T. \tag{5}$$

In this model, the main costs arise when a prosumer or consumer procures electricity from the grid or buys from a fellow peer. However, in the P2P trade, the selling peer earns money and thereby reduces the costs of electricity for the overall community. As the amount someone pays and the other one earns will cancel out in the objective function, these terms are not included in the optimization. Thus, the objective function in this model minimizes the total grid consumption $G^{(t,h)}$ costs, eq. (6).

$$\min\left\{ \sum_h \left(\overbrace{\sum_t \left[p_G^{(t)} \cdot G^{(t,h)} \right]}^{\text{Grid consumption}} \right) \right\} \tag{6}$$

This cost minimisation is subject to the supply-demand balance, eq. (1), the trade constraints, eqs. (2)–(5), and restrictions for the private battery.

The private batteries underlie certain physical characteristics. A lower bound $\underline{s}$ and an upper bound $\overline{s}$ limit the storage level $S^{(t,h)}$ per battery according to eq. (7).

$$\underline{s} \leq S^{(t,h)} \leq \overline{s} \tag{7}$$

The battery's charging and discharging is limited to a specified rate of α and β, respectively. The rates are mathematically represented as follows:

$$0 \leq C^{(t,h)} \leq \alpha \tag{8}$$

[1] All equations hold true for all $h \in H$, $t \in T$. Note that the equation can also be represented as an equality by adding a curtailment variable on the supply side.

$$0 \leq D^{(t,h)} \leq \beta \tag{9}$$

The overall storage level[2] for the battery in a time step t is determined by eq. (10) with the charge $C^{(t,h)}$ and discharge $D^{(t,h)}$ in this period being subject to the efficiency coefficients η^c and η^d.

$$S^{(t,h)} = S^{(t-1,h)} + \eta^c \cdot C^{(t,h)} - (1 / \eta^d) \cdot D^{(t,h)} \tag{10}$$

3.2. Clustering approach

Clustering techniques such as k-means [45] and spectral clustering [46] aim to sort specific data points based on a similarity measure that cluster them in smaller groups. Arranging the energy consumers in smaller clusters to find the best match of the energy consumption, energy production, and the available assets like storage and EVs is the interpretation of clustering in this paper. In this context, a non-effective or 'poor' match of the consumers would create a higher operational costs to the participants by not considering the best P2P trading opportunities. Since there are different flexibility sources such as storage units, EVs, and P2P trading in the community, the clustering is formulated as an optimization problem taking the impact of the flexibility sources into account dynamically. Then, an evolutionary algorithm is employed to solve the formulated problem. Decision variables, constraints, and objective function as main parts of the optimization-based clustering are introduced in the following sections.

3.2.1. Decision variables

The purpose (decision variable) of the clustering is to assign n houses to the N_{cl} clusters with the lowest cost. An indexing vector ($[IV]_{1\times n}$) with integer elements between 1 and N_{cl} can model this set of decisions. The value of ith element in IV expresses the cluster that i-th house belongs to it.

3.2.2. Objective function

As mentioned, a non-effective or poor match between the prosumers and consumers induces higher costs to the cluster (formed virtual LEM). Therefore, the clustering is looking for a configuration that yields the lowest operational cost. That is, similarly to Eq. (6), each cluster has the objective to minimize its cost as represented by Equation (11) (c is the number of clusters):

$$\min\left\{\sum_{i=1}^{|c|}\left(\sum_{h}\left(\overbrace{\sum_{t}\left[p_G^{(t)}\cdot G^{(t,h)}\right]}^{\text{Grid consumption}}\right)\right)\right\} \forall t\in T, h\in c \tag{11}$$

3.2.3. Constraints

In general, each house can be assigned to any cluster. So, each element of the IV should take a number between 1 to N_{cl}. So, 1 and N_{cl} are the lower and upper bounds of each element, respectively. Equation (12) shows this constraint.

$$\underline{IV} \leq IV \leq \overline{IV} \tag{12}$$

$\underline{IV}$, and $\overline{IV}$ represent the vectors of lower and upper bound of IV.

[2] Note that this is a stylized modelling of storage that does not consider detailed operational costs or storage cycles. It is based on similar work in Refs. [7,15].

3.3. Model for P2P clustering and local markets

The clustering splits a large pool of prosumers and consumers into smaller clusters; So, equations (1)–(10) apply likewise to each cluster (c) along with the objective function in Eq. (12). But, how the optimal clusters are specified? At the first stage, a central unit randomly generates different clustering configurations. As there is no interaction between the participants of different clusters, the operating cost of each one is calculated separately. Fig. 2 illustrates this concept. The generated clusters and relevant information are communicated to decentralized computing units (clusters value calculation). The calculated operating costs are then sent back to the central unit. The central unit, equipped with an evolutionary algorithm, updates the configurations of the previous step. This procedure is repeated based on the employed algorithm until a stopping criteria is satisfied. Note that the algorithm only requires the total cost of the virtual LEM (cluster) corresponding to each setup to move toward better solutions. In addition, the ideal size of clusters can be considered as a penalty factor to adjust the priority of the solutions for the algorithm.

In a virtual LEM, P2P electricity trading is a source of flexibility to uptake RES generation. Prosumers can export their energy surplus to avoid curtailment or an unattractive feed-in tariff. This implies that there is a high tendency for P2P trading between the houses in high periods of RES production like summer. In this situation, the clustering tends to put all houses in one single cluster. To overcome this challenge and ensure a balanced allocation of clusters, the unwanted configurations with empty or small clusters are penalized by adding the term $PF \times N_p$ to the objective function in Eq. (11). Where PF is a penalty factor and N_p is the threshold size of small clusters. Appendix B presents a more detail implementation of the proposed method based on the Teaching Learning Based Optimization (TLBO) algorithm [47].

Throughout the paper this is mentioned as the P2P + Cluster problem. With the introduced objective function and constraints, a set of consumers and prosumers are allocated in some clusters (see Figs. 1 and 10 as examples).

3.4. Adding and modelling EVs

As noted in the introduction, the charging points of electrical vehicles participate in the LEM. The objective is to allow that a set of

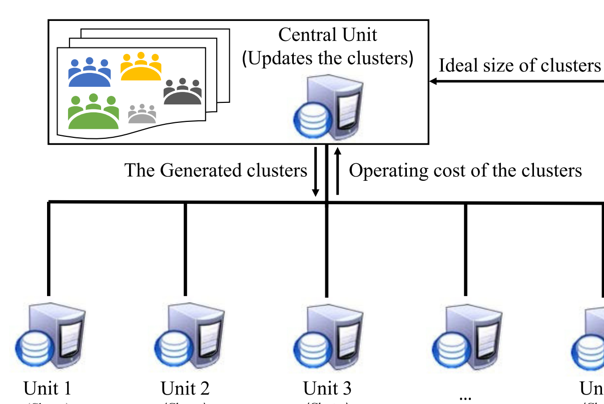

Fig. 2. The procedure happening in the virtual layer to determine the optimal clusters.

EVs ($e \in E$) trade electricity with other EVs or houses during their availability. The availability patterns of the EVs depend on owner behaviors. For example, some of the EV owners prefer to charge in coordination with their working hours. Others charge the EVs at home, mostly evening until the next day's morning. Regardless of the behaviors, a minimum state of charge for EVs at their arrival time-step it is assumed. Also, they must get fully charged at their departure time. Equations (13)–(17) describe the model of the EV which follows a similar logic as stationary batteries but subjected to availability (departure and arrival times).

$$S_{EV}^{(t,e)} = S_{EV}^{(t-1,e)} + \eta_{EV}^{c} \cdot C_{EV}^{(t,e)} - (1 / \eta_{EV}^{d}) \cdot D_{EV}^{(t,e)} \tag{13}$$

$S_{EV}^{(t,e)}$, $C_{EV}^{(t,e)}$, $D_{EV}^{(t,e)}$, η_{EV}^{c}, and η_{EV}^{d} are state of charge, charging, discharging, charging efficiency, and discharging efficiency, respectively. This equation holds for the second time step (after arrival) until the last time step of the availability. The EVs are assumed to be connected to the charging point with a minimum state of charge and depart with the fully charged battery. Equations (14) and (15) reflect this:

$$S_{EV}^{(t,e)} = S_{EV\ _{Arrival}}^{(e)} + \eta_{EV}^{c} \cdot C_{EV}^{(t,e)} - \left(1 / \eta_{EV}^{d}\right) \cdot D_{EV}^{(t,e)}\ ; \quad \forall t\ Arrival\ time \tag{14}$$

$$S_{EV}^{(t,e)} = S_{EV\ _{Departure}}^{(e)}\ ; \quad \forall t\ Departure\ time \tag{15}$$

Where parameters $S_{EV\ _{Arrival}}^{(e)}$ and $S_{EV\ _{Departure}}^{(e)}$ are the EV arrival and departure state of charge. With equations (16) and (17), the charging and discharging rates are limited to the corresponding upper bounds α_{EV} and β_{EV}.

$$0 \le C_{EV}^{(t,e)} \le \alpha_{EV} \tag{16}$$

$$0 \le D_{EV}^{(t,e)} \le \beta_{EV} \tag{17}$$

In some cases, the arrival and departure times are in two days. As the model is based on the day ahead calculations, in such situations, the model discharges the EV to a specified state of charge on the arrival day and charge it again the next day. Eq. (18) shows the energy balance of the EV nodes.

$$\overbrace{G^{(t,e)} + D_{EV}^{(t,e)} + I^{(t,e)}}^{\text{Grid + EV discharge + P2P purchase}} \ge \overbrace{C_{EV}^{(t,e)} + X^{(t,e)}}^{\text{EV charge + P2P sale}} \tag{18}$$

In the allocation of dynamic P2P clustering, the EVs are also included on the pool of participants that will be clustered. A more in depth explanation and examples of the overall clustering approach is available in Appendix B.

4. Data and implementation

Two main cases are setup to understand the effect of clustering in forming local electricity markets. The first case, named *'Dynamic P2P'*, focuses on P2P analysis while the second case (called *'Match EV + P2P'*) introduces EVs into the clustering decisions. These cases use real-life datasets based on a large pool of housing data from London in the United Kingdom. The consumption profiles are smart metering data that took part in the low Carbon London project[3] between 2011 and 2014. The datasets cover nine months of electricity consumption (January to September). These have a half-hour resolution. Hence, the multi-period models solve 275 days instances separately for a time horizon of 48 periods. That is, each day, a new set of clusters are setup by applying the model and the cases features. The description of all the specifications of these datasets, assumptions, and implementation are introduced in the following subsections. As part of this paper, all the data and the P2P model are openly available, see Appendix A.

Table 1
Information about the set of 25 houses.

	Affluent	Comfortable	Adversity	total
Houses considered	11	6	8	25
2.3 [kW] Wind	3	0	1	4
2 [kW] PV	6	1	1	8
4 [kW] PV	2	1	0	3
4 [kWh] storage	2	1	0	3

4.1. Prosumer and consumer profiles

Table 1 summarizes the features of the set of 25 different house profiles that represent a diverse pool of demand patterns. The energy consumption behaviors of these households are based on these categories: affluent, adversity, or comfortable. These consumer classes are determined based on demographic data, social factors, population, and consumer behavior. The average monthly demand in the affluent category is around 916 kWh while in the Adversity category is 374 kWh. Hence, affluent resembles large – well off – households and adversity represents small households. In between, there is the comfortable category with an average monthly demand of 745 kWh. For all the houses, it is assumed that smart metering is available and hence the end-user buys electricity (P_G in Eq. (6)) at wholesale price plus network charges and other costs. This price had an average prices of 15 pence/kWh and is in line with previous studies, assumptions, and data (see Refs. [7,15,22]).

4.2. Solar PV and small wind turbine

The solar power profile has been derived by converting the London area's solar irradiation and temperature data ([48,49]) to the generated power of a 4 kW PV panel with an efficiency of 21% and a tilt angle of 35°. This procedure creates a time-series covering nine months with a resolution of 30 min. To diversify the generation profiles, several new profiles mimicking the primary time-series' behavior are created. So, ten scenarios for the solar profiles are developed based on the autoregressive moving average (ARMA) method to capture solar data's stochasticity [50]. The standard deviation of the power generated at each time-step of scenarios is calculated. It leads to covering the solar fluctuations for each time-step separately. Finally, the lower and upper bounds of the solar unit's output power are determined based on a confidence level equal to the calculated standard deviation. Multitude number of solar profiles can be randomly generated between the upper and lower bounds. Fig. 3 illustrates the generated PV profiles for nine months.

As for the features of a small wind turbine in buildings, the power profile has been calculated based on fitting a curve to the power-to-wind-speed profile of a small 2.3 kW turbine [51]. The

[3] For further information, please refer to https://data.london.gov.uk/dataset/smart-meter-energy-use-data-in-London-households.

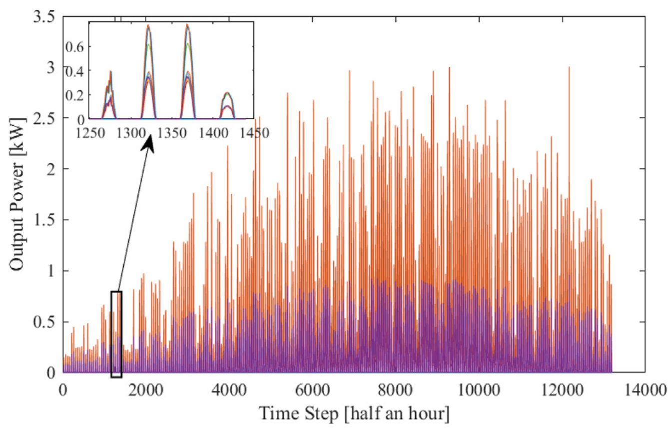

Fig. 3. The profiles of solar power generation for nine months (January to September).

wind speed data belongs to an area near London (data retrieved from Refs. [7,15]).

The total energy production by renewable sources is approximately 61,000 kWh/year that covers around 35% of the 25 houses electricity demand.

4.3. Batteries

Three units of SonnenBatterie battery with a capacity of 4 kWh and one-way efficiency of 98% [52] are employed as the storage model in case studies. Also, connecting the batteries to 2.5 kW inverters with maximum efficiency of 96% leads to a charging/discharging time of 100 min.

4.4. EV availabilities

EVs have different behavioral patterns based on their arrival and departure times, see Refs. [53,54]. Some EVs are charged at charging stations during the day. Others might be charged near their homes or workplaces between their arrival and departure times. This paper considers two EV behavioral characteristics: “Charge Near Home” (CNH) and “Charge Near Work” (CNW). Five EVs are included in the formation of LEMs. Three of them belong to CNH behavioral cluster, and the rest behave similar to CNW cluster. The main difference between these patterns is the arrival and departure times. Cars in the first group connect to the home charging stations in the evening and disconnect when they leave home in the morning. The second group models the behavior of the EV owners that charge their cars during working hours (morning to afternoon). This behavior is in line with the people that charge their vehicles close to their offices. The impact of the seasons, as well as the difference caused by weekends or weekdays, are taken into account. For example, the working hours are affected by daytime which varies seasons and days of the week. Hence, the arrival and departure times may change a bit in both CNH and CNW patterns features.

5. Results and analysis

The analysis focuses on two main cases:

- **Dynamic P2P** case: The prosumers and consumers (described in Table 1) engage into P2P trading.
- **Match EV + P2P** case: In addition to the 25 houses, this case includes the participation of five individual EVs (not part of the house set $h \in H$) in forming LEMs.

For each case, the objective is to analyze specific scenarios to understand and compare the impact of dynamic LEM formation (clustering). This is as follows: i) a scenario without P2P nor clustering, ii) a scenario with P2P but without clustering, and iii) a scenario with both P2P and clustering presence. In short, scenario i) represents the optimal operation from a single house perspective (i.e., no sharing) while scenarios (ii) and (iii) introduce P2P under a clustering assumption.

5.1. Dynamic P2P case

In this case, the objective is to observe how a dynamic allocation of consumer and prosumers affect the value and formation of dynamic virtual LEMs. For instance, by forming a single ‘big’ LEM that considers the participation of all consumers and prosumers, this would obtain the maximum value of P2P and energy sharing. From a consumer perspective, this scenario has more options for P2P trading as it has a large pool of prosumers to choose from. Now, comparing it to a scenario that partitions (clusters) the ‘big’ LEM into smaller virtual LEMs will result in a reduced overall welfare value of P2P. To understand these effects and results, Fig. 4 and Table 2 provide the following insights:

- P2P trading reduces procuring from the grid (or electricity retailer). In the scenario *P2P-NoClusters*, the grid imports and costs are lower than the *NoP2P scenario* as Fig. 4 (a) and (b) illustrate.
- These figures illustrate that the clustering scenario (i.e., ‘smaller communities’) has a very close performance to the *P2P-No clusters scenario* regarding the grid import and the daily total cost. Note that due to the low RES production and a hence less opportunity for P2P trading over the winter period (first 50 days of the year), the cost and grid imports are similar in all cases.
- In the summer months, clustering configuration is challenged as there is more RES production. Nonetheless, the *P2P-Cluster* scenario provides very close results to the perfect competition model in *P2P - No clusters* scenario.
- Table 2 compares the three scenarios. The *P2P - No clusters* scenario reduces the community cost by 14.8%, the grid import by 13.3%, and the RES curtailment (or grid feed-in) by 76.9% compared to the reference scenario (No-P2P). As for the savings obtained by introducing clustering, there is a 12.7% reduction which is again similar to the 14.8% of the open P2P scenario. This is mainly because of P2P contribution to demand slims down from 25.5% to 21.9% as clustering reduces the optimization and possibility space.
- To understand how these costs savings is shared between the LEM participants in *P2P + Cluster* case, the results of three houses are analyzed: (i) a consumer, (ii) a prosumer with solar PV, and (iii) a prosumer with solar-wind combo and storage. Following a similar ex-post calculation procedure as in Refs. [15,22], house (i) and (ii) can respectively attain a 7.3% and 5% cost reduction over nine months. House (iii) experience a 21.6% reduced expenses.

In short, the *P2P + Cluster* scenario creates several smaller clusters instead of a large one (i.e., all the participants into one). The

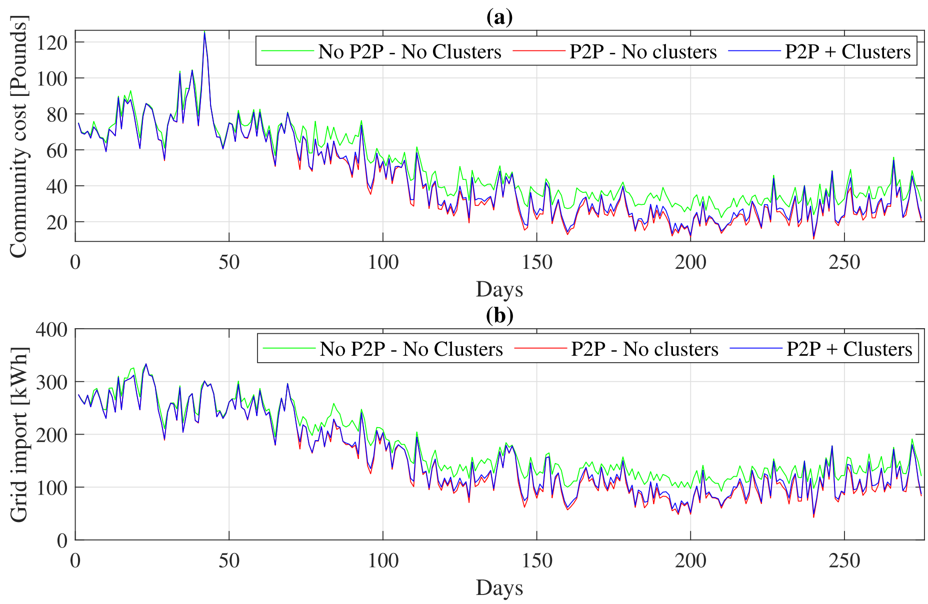

Fig. 4. Comparison of the (a) Community cost, (b) Daily grid consumption of the community between the No P2P - No Clusters scenario, P2P - No clusters scenario, and P2P + Clusters scenario.

Table 2
Summary of the results to compare three scenarios in the *Dynamic P2P case*.

	No P2P (Scenario i)	P2P - NoClusters (Scenario ii)	P2P + Clusters (Scenario iii)
Total cost [£]	6915	5890 ↓ 14.8%	6037 ↓ 12.7%
Total grid consumption [kWh]	49144	42621 ↓ 13.3%	43497 ↓ 11.5%
RES curtailment [kWh]	9388	2165 ↓ 76.9%	3140 ↓ 66.5%
RES curtailment (or feed-in) [%]	36.5	8.4	12.2
% of P2P contribution to demand	–	25.5%	21.9%

typical number of clusters formed throughout the 9 months is between 4 and 5. For these 25 houses, the number of participants in each cluster varies from up to 7 participants in a cluster to down to 3 participants. The details on the number of clusters and sensitivity on the performance of the cluster algorithm is elaborated in Appendix B. All in all, these are very positive results that demonstrate that dynamic LEM via P2P clusters in a daily basis works fairly well compared to a 'perfect market' competition or optimal centralized large community. In other words, a central implication of these results is that the scalability of LEM (via clustering) is feasible as the clustering has an acceptable performance.

5.2. Match EV + P2P

This case mainly concentrates on the impact of clustering based on the EV behavior. The analysis is focused for the month of May since there is a high level of renewable production this month. The cases examines how the energy community's operation gets affected by involving EVs in the P2P transactions. As noted earlier, it considers five individual EVs to the set of houses introduced in Table 1. Three of these EVs have arrival and departure times similar to the CNH pattern. The availability of the next two complies with CNW. The nominal storage capacity for all EVs is set to 50 kWh to provide the average size of Nissan Leaf, Volkswagen e-Golf, and Tesla S models [22]. Also, a round-trip efficiency of 96% is assumed

Table 3
Results for the 'Match EV + P2P' case.

	EV-No P2P (Scenario i)	EV-P2P (Scenario ii)	EV-P2P-Clustering (Scenario iii)
Total cost [£]	689	509 ↓ 26.1%	529 ↓ 23.2%
Total grid import [kWh]	5063	4120 ↓ 18.6%	4175 ↓ 17.5%
Average community Peak [kW]	30.3	49.3 ↑ 62.7%	41.5 ↑ 36.9%
Maximum community Peak [kW]	45.4	83.3 ↑ 83.5%	68 ↑ 49.8%
RES curtailment [kWh]	1173	28 ↓ 96.8%	142 ↓ 85.2%
RES curtailment (or feed-in) [%]	37.9	0.9	4.58
EV Grid Import [kWh]	732	1329 ↑ 81.6%	1033 ↑ 41.1%
EV P2P Export [kWh]	–	910	618
EV P2P Import [kWh]	–	352	342

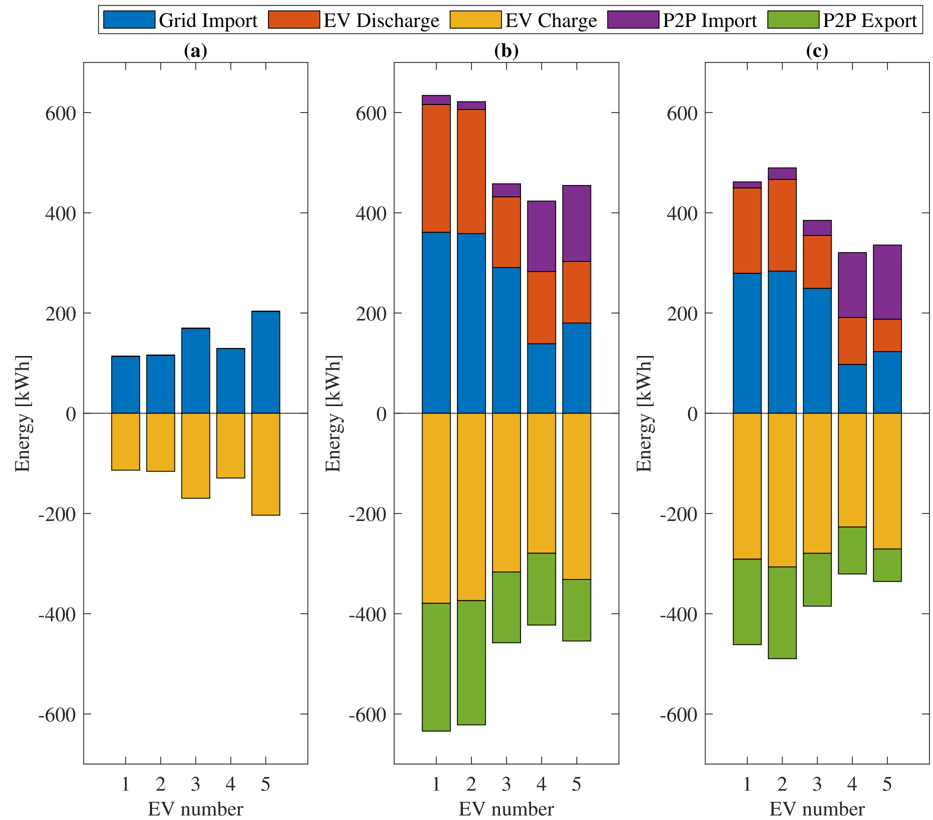

Fig. 5. Energy balance of the five EVs: (a) EV-No P2P, (b) EV-P2P, and (c) EV-P2P-Clustering. The first three EV numbers on the x-axis stand for CNH EVs, and the rest express CNW EVs.

for all of them.

Similar to the previous case, the results presented in Table 3 show that *EV-P2P-Clustering* yields comparable performance to the *EV-P2P* scenario. The following points detail some insights on the examined scenarios:

- The flexibility provided by P2P trading affords a potential of 26.1% in cost savings compared to optimizing each agent separately. It is the maximum potential of cost reduction for the whole community. Clustering contributes a considerable proportion of this potential by reducing the neighborhood's cost from £689 to £529. Similar achievements are present in reducing the energy imported from outside of the community and the renewable energy curtailment (or feed-in) since the EVs absorb a high share of the local energy production.
- Due to the high capacity of EVs' battery, the peak energy consumption increases at periods with a low spot price. This situation can be intensified when the EVs find the possibility of P2P trading, as shown in Table 3. However, the clustering restricts the peak increment since the EVs participate in smaller energy communities.
- Fig. 5 illustrates the aggregated energy balance of the EVs over one month (May). There, likewise, the bigger the community is, the higher possibility of P2P energy export exists for the EVs. There charging Near Home (CNH) provides more availability and flexibility than charging Near Work (CNW).
- Although the EVs' engagement in P2P trading increases their grid import and the overall peak, the dependency of the virtual LEMs to the outside decreases. Fig. 6 provides more insights into the total operational costs or benefit of the EVs' at different P2P prices. The average electricity price from the grid (or retailer) is 14.3 [Pence/kWh]. It is expected that the P2P price is lower than this average. So, the *relative benefit* of the EVs at different prices lower than 14.3 [Pence/kWh] is calculated[4] for *EV-P2P* and *EV-P2P-Clustering* scenarios. The relative benefit of the EVs at prices lower than 11.7 [Pence/kWh] is negative in the *EV-P2P* scenario. It means that it does not worth sharing their energy at prices lower than this threshold. However, this threshold is 11 [Pence/kWh] in *EV-P2P-Clustering* scenario.
- It is assumed that vehicule-to-grid (V2G) is possible in this analysis. However, how would the impact of collaborative energy consumption from EVs be affected without the option of discharging (i.e. no V2G)? By performing a sensitivity analysis that considers no-EV discharging, the total energy import of the EVs remains the same as the EVs should get charged to a specified level. Also almost 30% (210 kWh) of the import comes from P2P transactions. So, it yields the lowest grid import and peak of energy compared to the other cases as it cannot engage in energy arbitrage. Regarding the energy cost, collaborative consumption offers a 21% lower cost (£545) than the EV-No P2P case.

To understand further the detail results of this case, Fig. 7 shows the configuration of the formed clusters in one arbitrary day (May 5th in this case, due to high renewable generation, also refer to Fig. 1). The algorithm creates five clusters with 6, 5, 7, 8, and 4 members on this day. The aggregated electricity demand and production of the consumer/prosumer belonging to each cluster are illustrated in Fig. 7 (a)–(e), respectively. It shows that the first,

[4] To calculate the total operational cost of the EVs, the revenue is based on a range of that P2P price (11-to-13 pence per kWh).

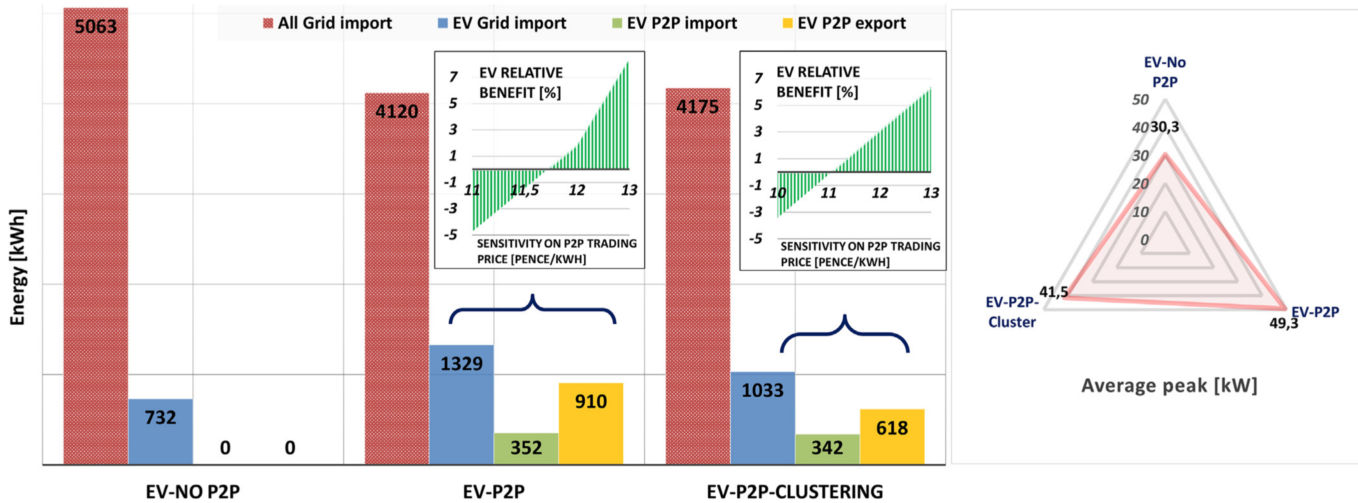

Fig. 6. In the 'Match EV + P2P case', EVs achieve a net benefit of 5% savings compared to the no-P2P scenario under the assumption that the P2P price is 13 pence per KWh. Also the clustering scenario manages better the load peaks.

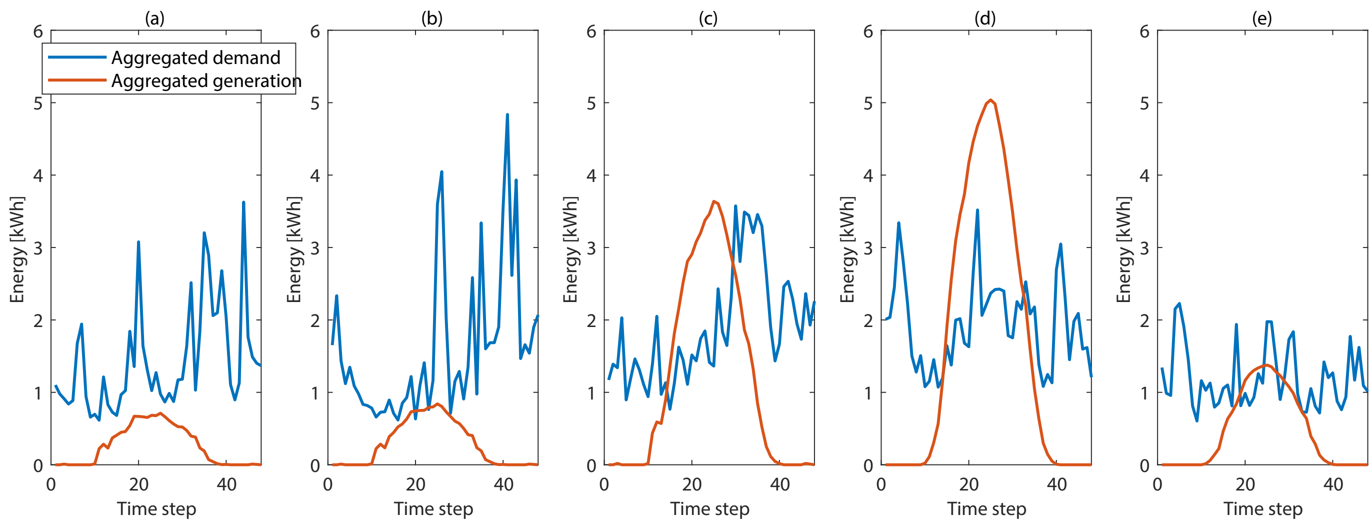

Fig. 7. The aggregated consumption & production of the clusters on the 5th of May (a) Cluster 1, (b) Cluster 2, (c) Cluster 3, (d) Cluster 4, (e) Cluster 5.

second, and fifth clusters do not have a considerable energy surplus. So, it does not assign stationary energy storage (EV) to these clusters. However, due to the concurrence of peak energy demand and high spot price between 20:30 and 21:30, an EV is allocated to cluster 2 during this period (one of the CNH EVs). This EV helps the cluster to pass this period with a lower price. Besides, it finds a high chance to export energy to the other cluster members. Since clusters 3 and 4 have an energy surplus, the battery storage, and the other EVs are distributed between them. Hence, storing energy in a considerable fraction of the 24 h is possible that maximizes the self-sufficiency of the virtual LEMs.

6. Conclusion

This paper analyzes the impact of dynamic P2P clusters and the role of the EVs in the creation of virtual LEMs. Two cases, namely a case including different prosumers and consumers located in London and the same case plus EVs participation are assessed to understand the value of virtual LEM formation.

Results indicate that enabling the P2P energy trading for participants in the virtual LEM, on average, reduces both the electricity costs and the dependency on the grid by £114 and 725 kWh per month. Integration of EVs in the P2P transactions, especially in the periods with higher renewable production, increases these numbers to £180 and 943 kWh per month. Although the clustering breaks the whole set of end-users into smaller virtual LEMs, the results show that the dynamic clustering (virtual LEM formation) achieves a similar outcome to the second scenario (no clustering). Also, results point out that the clustering reduces the peak load which is mainly caused by EVs. The maximum peak of the grid import in the EV-P2P-Clustering scenario is around 20% lower than the EV-P2P scenario. Moreover, a benefit for EVs depends on the sensitivity of the P2P price. Here, the analysis indicate that EVs participation in local virtual LEMs is not profitable at prices lower than around 12 pence/kWh. This threshold is smaller under the clustering scheme. It means that the EVs in the virtual LEMs have a competitive advantage over the EVs in participating in the no-clustering case. This is an important aspect to reward and value flexibility which encourages a sustainable end-user engagement.

In short, the idea of dynamic virtual LEM holds promising features on stimulating the consumer-centric energy transformation. To further analyze the realization of virtual LEMs, future research

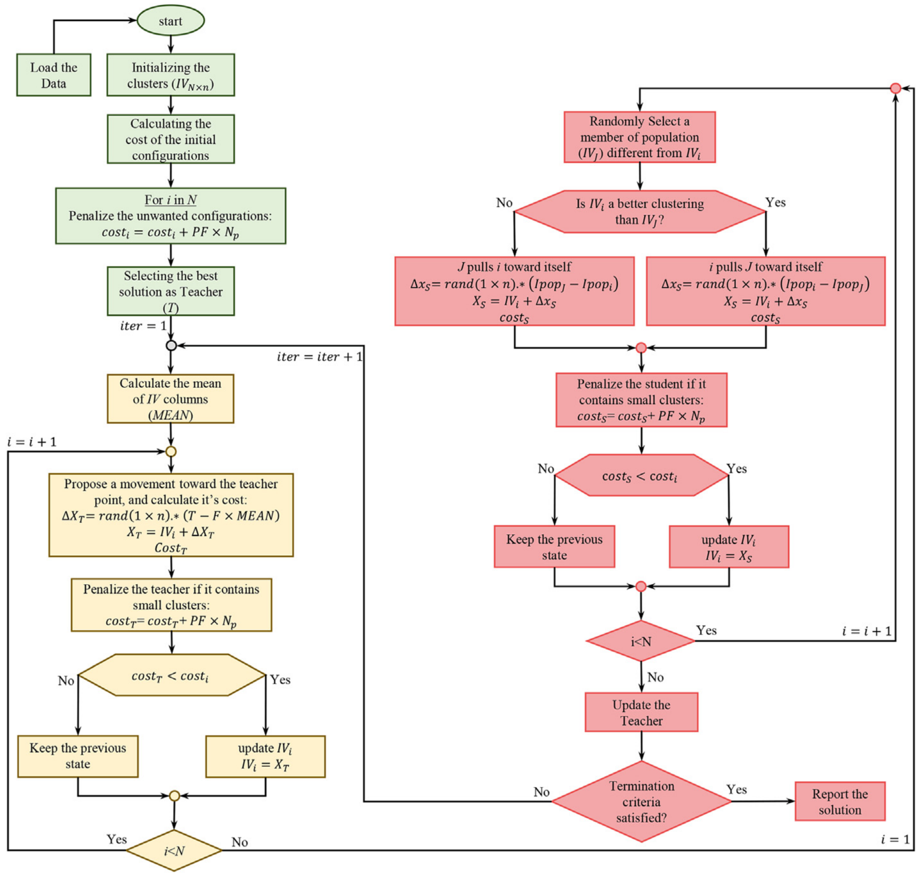

Fig. 8. Flowchart of the P2P clustering.

should consider:

- Analyzing the impact of the formation of the clusters on the operations of the distribution grid. So, introduce a coordination between the formation of the P2P market and power flow features. This framework would consider the grid situation and forms friendly clusters in line with the requirements of the grid.
- The clusters can be created based on the requirements demanded by different market participants, such as flexibility market operator. Investigating the value of orchestrating the prosumers and consumers based on tailored flexibility services is another interesting research question.

In addition to these points, a central aspect to implement P2P and LEM is to have relevant market-regulatory frameworks. For example, an important step to allow the implementation of these concepts would be that retail markets enable P2P transactions among prosumers and consumers. Also, the Renewable Energy Directive 2018/2001 [55] notes that there should be a clear role definition on coordinating energy communities and DSOs, a fair compromise on the network charges, and other potential regulatory barriers. In Refs. [56,57] authors analyze the regulatory frameworks of some countries in Europe, concluding that regulation at the EU level provides an overall progressive framework for collaborative energy consumption. These studies show that France, Germany, the Netherlands, and the United Kingdom are forerunners in Europe. Spain and Portugal also changed their restrictive regulations in 2019. In Italy, Croatia, and Belgium, despite hosting many active energy cooperatives, there is no legal definition for renewable energy communities while Austria has made moves toward updating the regulations (renewable expansion act). All in all, the most critical regulatory challenges are the complicated process of establishing legally energy communities, lack of incentives, and the phase out of existing incentives (e.g. Feed-in tariffs) [57].

CRediT author statement

Conceptualization: Pedro Crespo del Granado. **Methodology:** Pedro Crespo del Granado, Naser Hashemipour. **Software:** Naser Hashemipour. **Validation:** Pedro Crespo del Granado, Naser Hashemipour. **Formal analysis:** Pedro Crespo del Granado, Naser Hashemipour. **Investigation:** Pedro Crespo del Granado, Naser Hashemipour. **Resources:** Pedro Crespo del Granado. **Data Curation:** Naser Hashemipour. **Writing - Original Draft:** Pedro Crespo del Granado, Naser Hashemipour. **Writing - Review & Editing:** Pedro Crespo del Granado, Naser Hashemipour, Jamshid Aghaei. **Visualization:** Pedro Crespo del Granado, Naser Hashemipour. **Supervision:** Pedro Crespo del Granado, Jamshid Aghaei. **Project administration:** Pedro Crespo del Granado. **Funding acquisition:** Pedro Crespo del Granado, Jamshid Aghaei.

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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Appendix A. Supplementary data

We provide the full input data containing the solar and wind profiles, spot prices, as well as the electricity consumption of the 25 houses. Also, we include for download the Matlab code of the community-based P2P trading under the MIT license. This is publicly available on GitHub: https://github.com/LocalEnergyMarkets/PCDGModel-LocalCommunities.

Appendix B. Clustering implementation

In the following, we detail the implementation of the clustering algorithm and provide some examples.

Clustering algorithm

We have employed the Teaching Learning Based Optimization (TLBO) [47] algorithm to solve the P2P-Clustering problem. TLBO can outperform most of the well-known approaches in terms of robustness as well as optimality. Also, there is no parameter to be tuned in this algorithm. Fig. 8 illustrates the process of the P2P clustering based on the TLBO algorithm. There, the algorithm starts finding the best configuration after loading the input data. The whole process can be divided into three parts called initialization, teacher phase, and student phase. Different colors distinguish parts. In the initialization part, the algorithm randomly generates N indexing vectors and calculates the corresponding cost of each one based on eq. (11). Also, to eliminate the unwanted configurations in the algorithm's process, it penalizes the corresponding cost of the structures containing small clusters, similar to adding the term $PF \times N_p$ to eq. (11). Among the initial clusters, the indexing vector obtaining the lowest cost is picked as the teacher and called T. In the teacher phase, the T tries to improve the status of the other clustering configurations by pushing them toward itself. Finally, each member's position gets updated if its move toward the T leads to a lower cost. In the student phase, each indexing vector is considered as a student. The students, two by two, try to improve their positions. So, the ith student randomly finds a companion and goes in its direction if it corresponds to a lower cost and vice versa. Similar to the teacher phase, the outcome of each movement must get evaluated. The new position for the ith member gets accepted if it leads to a better clustering arrangement. At the end of each iteration, the new best indexing vector is assigned to the teacher, and the same procedure is repeated until fulfilling the stopping criteria.

Illustrative examples on clustering results

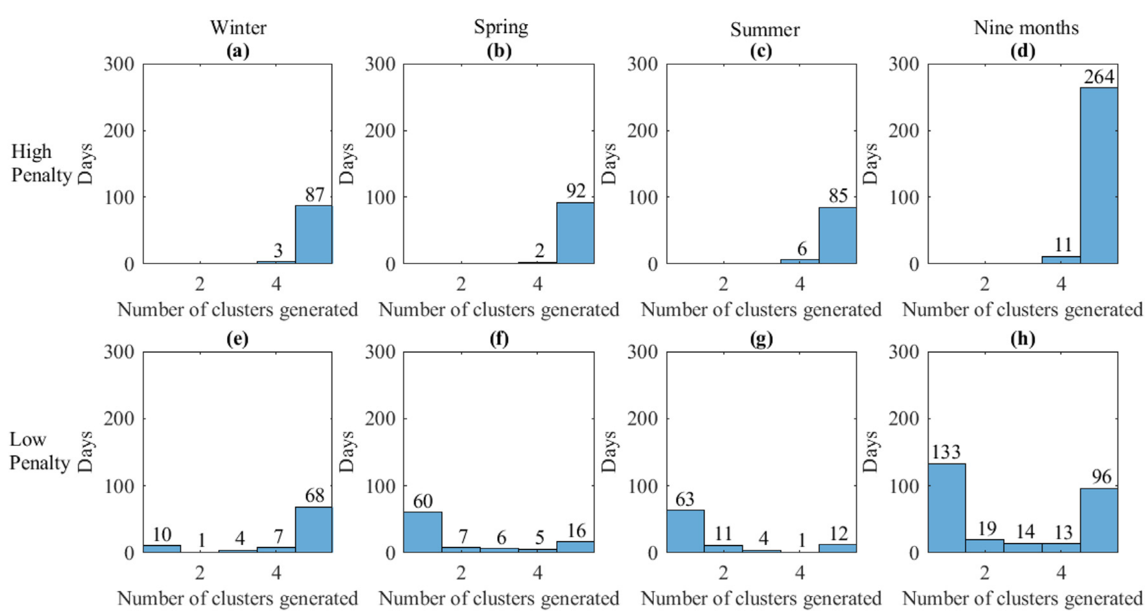

Fig. 9. Seasonal and global histograms for the number of the clusters for: (a) Winter, (b) Spring, (c) Summer, and (a) nine months with high penalty factor, (e) Winter, (f) Spring, (g) Summer, and (h) nine months with low penalty factor.

As discussed in section 3.3, the unwanted configurations can be penalized in the clustering algorithm. A cluster with lower than N_p members is an example of such unsatisfying configurations. So, to analyze the impact of the penalty term, we set the N_p and PF to 4 and 40, respectively. It means that a punishment equal to £40 per cluster is imposed on the clustering configurations that contain clusters with lower than four members. The maximum number of clusters in each day is set to 5. Since 40 is a relatively large penalty, the small clusters can barely be seen in the simulation days. In 264 days out of 275 days of the simulation, five full-clusters (clusters with more than four members) are created with these settlements. In the rest of the days, the proposed method makes four full-clusters each day. In other words, the proposed method leads to an average of 4.96 full-clusters per day in the period of the study that is nine months. Fig. 9(a)–(d) illustrate the distribution of the generated clusters in the optimization period in terms of number of clusters per day. As can be seen, the tendency to form 5 clusters per day more or less is the same in different seasons. Also, each cluster, on average, contains five members (in the community with 25 houses). But, if the penalty factor is set to a low value, the opportunity of P2P trading affects the clusters' size, as shown in Fig. 9(e)–9(h).

To give an overview of the virtual clusters in one month, the dynamic clusters created for the EV-P2P-Clustering are illustrated in Fig. 10. The combination of the colors in each column shows the optimal configuration for the corresponding day. The houses with the same color belong to the same virtual cluster and can trade energy. The configuration of the clusters changes every day.

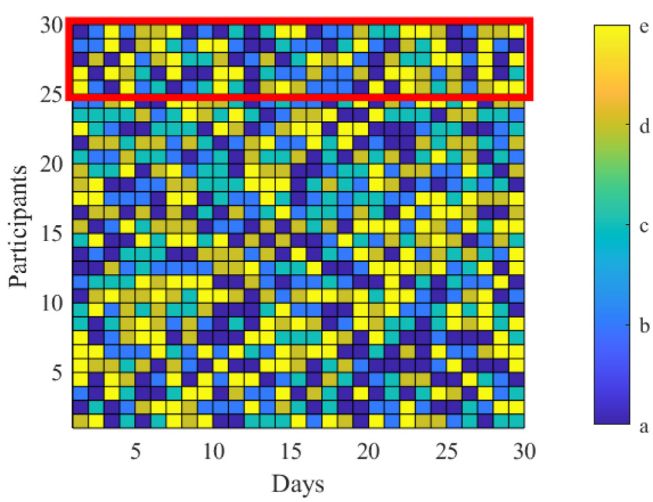

Fig. 10. Dynamic clusters for the 'Match EV-P2P' case. Participants 1-to-25 are prosumers/consumers while participants 25-to-30 are EVs nodes.

Appendix C. Scalability

In P2P trading schemes, each participant can potentially trade with all other members. In other words, $\frac{n!}{2!(n-2)!}$ P2P transactions can take place in a LEM with n members. So, the number of participants dramatically affects the feasibility of up-scaling. For instance, 300 P2P interactions per time-step are probable in a community with 25 houses. This value surges up to 1225 in the case of 50 participants in the LEM. For example, in the case of 1 million end-users, organizing the participants in 1000 clusters reduces potential transactions to lower than 1% compared to the full community (no clustering). So, calculating the optimal configuration of the clusters yields a considerable achievement. This rises an important question, is the clustering algorithm scalable, as well?

In this regard, evolutionary algorithms (such as TLBO) consists of "objective evaluation" and "generation update" parts. The generation update consists of the multiplication or summation of different vectors. A regular computer can efficiently perform such calculations in a fraction of a second for thousands or millions of participants. The challenging part is to calculate the fitness of different members of the population. If one computer is in charge of performance evaluation for all clusters, it can become time-consuming. Here, a favourable feature of the proposed framework is that each cluster is independent of the others and can be evaluated by a separate computer. Here, the concept of asynchronous computing (sometimes also referred to as concurrent programming)[5] can play a significant role. In this structure, different computing units together solve the problem in parallel. Each cluster is evaluated by a separate computer, and the objective value is transmitted to a central computer. Then, the central unit updates the populations only based on the costs received from the other computers. Different controlling signals can be fed to the central computer at this stage to organize the clusters to fulfill the operator's specific requirements.

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