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Bidding in local electricity markets with cascading wholesale market integration

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ABSTRACT

Local electricity markets are a promising idea to foster the efficiency and use of renewable energy at the distribution level. However, as such a new concept, how these local markets will be designed and integrated into existing market structures, and make the most profit from them, is still unclear. In this work, we propose a local market mechanism in which end-users (consumers, small producers, and prosumers) trade energy between peers. Due to possible low liquidity in the local market, the mechanism assumes that end-users fulfill their energy demands through bilateral contracts with an aggregator/retailer with access to the wholesale market. The allowed bids and offers in the local market are bounded by a feed-in tariff and an aggregator tariff guaranteeing that end-users get, at most, the expected cost without considering this market. The problem is modeled as a multi-leader single-follower bi-level optimization problem, in which the upper levels define the maximization of agent profits. In contrast, the lower level maximizes the energy traded in the local market. Due to the complexity of the matter, and lack of perfect information of end-users, we advocate the use of evolutionary computation, a branch of artificial intelligence that has been successfully applied to a wide variety of optimization problems. Throughout three different case studies considering end-users with distinct characteristics, we evaluated the performance of four different algorithms and assessed the benefits that local markets can bring to market participants. Results show that the proposed market mechanism provides overall costs improvements to market players of around 30–40% regarding a baseline where no local market is considered. However, the shift to local markets in energy procurement can affect the conventional retailer/aggregator role. Therefore, innovative business models should be devised for the successful implementation of local markets in the future.

1. Introduction

Recent investments in renewable generation at the distribution level are contributing to decentralization, decarbonization, and motivation for new market models [1,2]. In this scenario, local electricity markets (LEM) will provide a new framework for players to trade energy (most often of renewable type) and thus, contribute to lower carbon emissions. To fully realize the potential of LEMs, it is required sophisticated technology to be in place, namely, smart grid communications and smart meter data [3,4]. By doing so, end-users can be empowered to take a large part in the energy community and promote the transition to a sustainable energy system [1]. It is expected that the competition between the smart grid agents (or players) fostered by LEMs, will allow local small producers and prosumers to participate and obtain more significant profits than the current policy allows, usually with feed-in tariff approaches. Local consumption will also contribute to postpone grid investments and reduce grid losses, increasing the overall operational efficiency [5].

Taking into account the recent literature, we develop an approach that integrates LEMs and central wholesale market (WSM) using easy to implement computational intelligence techniques. We consider a distribution grid in which agents of different types (i.e., consumers, producers, and prosumers) can trade energy in the LEM. It is assumed that agents have access to smart grid technologies to fulfill energy transactions. A market operator (e.g., a service provider or a DSO) is put in place to coordinate the local trading between market participants and

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avoid grid violations. It is also considered an aggregator/retailer with access to the WSM for trading the excess/deficit of energy required by the agents after the LEM is cleared.

The problem is formulated as a bi-level optimization model searching for the maximization of profits of independent agents (i.e., a non-cooperative model). However, solving the mathematical formulation resulting from our market mechanism using classic deterministic approaches might present two main drawbacks: i) the practical implementation of such solution method is only permissible under the assumption of having access to perfect information from agents that is not openly available in LEMs; ii) the computational burden and execution times dealing with large instances of the problem could be prohibited in some scenarios (i.e., scalability limitations). Those two drawbacks are the main motivation to evoke the use of approximate methods based on evolutionary computation (EC). In this article, we evaluate the performance of four different state-of-the-art evolutionary algorithms over three case studies considering agents with distinct characteristics.

The main contributions of the paper are: i) an optimization and simulation framework for the maximization of profits of agents participating in the LEM; ii) a coordination mechanism for interoperability between LEM and WSM through the role of an aggregator; iii) the implementation and use of evolutionary computation to solve the optimization problem; iv) the analysis of case studies based on real data to assess the impact of LEM participation.

2. State of the art on LEM

Several works have been proposed to implement LEM structures using decentralized approaches and to focus on services such as flexibility for distribution system operators (e.g., blockchain, transactive energy, and peer-to-peer trading using ICT) [6–8]. Research is also paying attention to the interactions between LEMs and central markets [9,10]. Mengelkamp et al. [11] presents a comprehensive market design and simulation of a LEM between 100 residential households using private blockchain technology to ensure data and energy trading without the need of a centralized entity. However, the blockchain-based market remains to be investigated concerning real-world feasibility since regulatory changes will be crucial for its development. The work of Olivella-Rosell et al. [9] explains how the WSM and local flexibility market can be coupled to enable interaction between transmission and distribution. It discusses the possibility of prosumers as flexibility providers. The main stakeholders are the distribution system operator (DSO) and balance responsible parties that could be interested in buying this flexibility from aggregators and flexible devices. The work lays some foundations for the operation of LEMs and WSM but does not provide evidence on the benefits and gains of the coupled market. Tohidi et al. [10] provides a systematic review of the coordination schemes categorized as DSO leader, DSO follower, transmission system operator (TSO)-DSO interaction, and independent LEMs without interaction with central electricity markets. According to this work, the coordination scheme that provides higher social welfare is the TSO-DSO interaction. However, such a platform is challenging to realize in practice since optimal TSO-DSO dispatch of all resources is computationally expensive while decentralized approaches can be deployed with less burden and complexity, leading to higher levels of reliability.

Interactions and competition of market participants have been studied from different perspectives in the literature (e.g., agent-based systems, game-theoretic approaches, machine learning, etc.) [12,13,14,15]. The work proposed by Paudel et al. [15] is based on evolutionary game theory to model LEM and peer to peer energy trade. The price competition between sellers is modelled as a non-cooperative game and is used to model the dynamics of the buyers for selecting sellers. The work highlights that this kind of LEMs is an alternative to cost-intensive energy storage systems while providing significant financial and technical benefits to the community. Most of the current studies make several assumptions, for instance, regarding available information or technologies to tackle realistic scenarios. The bidding in electricity markets can be modelled as a bi-level optimization problem taking into account different stakeholders and network constraints [16]. Such bi-level formulations can be solved using, for instance, KKT conditions [17], dual theory, or as a mixed complementarity problem under certain assumptions [18,19]. The work from Nezamabadi and Vahidinasab [17] proposes a microgrid bidding strategy in the context of transactive energy. The problem is a bi-level optimization with interval concept to model the uncertainty of renewable energy sources and load. The results suggest an improvement of around 10% in the profits each 24 hours. The work neglects the grid distribution cost allocation.

Lüth et al. [20] analyze the prosumers benefits of electricity storage in the presence of P2P trade in LEMs. The work highlights that decentralization of storage offers more flexibility of utilization than central approaches. Nevertheless, the storage utilization lowers energy costs in both situations. The work also suggests that future research should explore the integration of LEM into the WSM regime, a feature which we attempt in our work. Subsequent work from the authors in [21] proposes peer-to-peer (P2P) trading with an exchange platform called STEP to integrate prosumers and make the interface between the WSM and prosumer communities. The work uses a two-stage stochastic programming framework to address the underlying uncertainty, namely renewable generation and spot prices of the WSM. The authors claim that P2P trade with battery storage may lead to savings of almost 60%. Zhang et al. [22] proposes a novel P2P model to tackle energy trading and uncertainty simultaneously. The novel aspect of the work is that it considers uncertainty associated with the trading simultaneously. This favors the integration of PV power and motivates the use of accurate forecasts. Tackling uncertainty constitutes an important step in this field because most of the traded energy in LEM comes from uncontrollable sources of energy generation. Also, price fluctuations are larger in small markets due to lower volume of energy. In our proposal, we adopt a sequential cascading market integration. The aggregator can help to reduce the risk and uncertainty of LEM trading, i.e., by providing prosumers with the possibility to trade energy (not previously traded in LEM) in the WSM.

Since classic approaches are plagued with scalability issues (more detailed in Section 3.3), we adopt methods inspired in a line of research that follows the use of evolutionary computation (EC), a novel and efficient artificial intelligence branch used to tackle complex optimization problems. For instance, in Ma et al. [23], an EC algorithm called particle swarm optimization (PSO) is used to solve the bi-level producer surplus maximization problem. Authors make use of an EC because the objective function is not concave, and there are nonlinear complementarity terms to represent the market clearing. Similarly, a PSO-based algorithm is used in Zhang et al. [24] to solve a bi-level model for the strategic bidding of generation companies in the day-ahead electricity market. A more complete formulation was developed in Zhang et al. [25] , where a multileader-one-follower nonlinear bilevel (MLNB) optimization concept to analyze the strategic bidding behavior of generating companies in the day-ahead electricity market was provided. The decision model was solved using a PSO algorithm again. A hybrid-method, combining PSO and simulated annealing (SA) was proposed by Soleymani [26] also to predict the bidding strategies of generation companies, but this time considering the incomplete information and market mechanism of opponents.

Despite several EC approaches have been applied to electricity market problems, e.g. [25,26], very few have attempted to solve the optimal bidding problem in LEM. More recently, in [27], authors have adopted the framework of bi-level optimization but applied to LEM. Due to the complexity of the problem, the authors compared and assessed different EC algorithms under a case study with producers, consumers, and prosumers with renewable generation acting in a day-ahead LEM. In this paper we solve this problem by proposing Ant colony and other EC methods with proven superiority over standard EC approaches. Ant colony optimization has the ability to be implemented in a decentralized manner with learning features [28].

3. LEM mechanism and bi-level optimization problem

In this section, we introduce the main parts of our approach, consisting in: Section 3.1) the LEM mechanism including the simulation employed method; Section 3.2) the LEM bi-level optimization formulation; Section 3.3) the solution method based in evolutionary computation.

3.1. Market mechanism design

In this article, we have considered a LEM in which agents of different types (i.e., consumers, prosumers, and small producers) in an energy community submit bids and offers into the LEM to maximize their profits (i.e., cost minimization for consumers, and income maximization for producers). The LEM framework assumes that agents have access to the main grid energy through a bilateral contract with an aggregator/retailer. The aggregator, in turn, has access to the WSM to acquire the energy needed by the community. In this way, the aggregator might use an accurate forecast of market prices to set a tariff for its customers. With these considerations, similar to [29,30], agents can trade energy in the LEM considering prices within the range of the feed-in tariff (lower bound c_t^{F}) and the aggregator/retailer tariff (upper bound c_t^{agg}). It is assumed that $c_t^{\mathrm{F}} < c_t^{\mathrm{agg}}$ and therefore buy/sell energy from the aggregator/retailer is less beneficial to agents than transacting energy in the LEM.

Fig. 1 illustrates the LEM considered in this work. The analysis has been carried out considering the day-ahead market under the assumption that advanced metering infrastructure is available for such a task. The framework can be easily applied to consider other time horizons (such as intra-day or real-time) by modifying the available input data, as long as the proper infrastructure is in place.

The LEM mechanism is developed based on the following assumptions:

•The model relies on the high accuracy of load forecasts. It is assumed that prosumers' home energy management systems (HEMS) can predict PV generation profiles with small errors by implementing the models developed in [31,32]. The aggregator also has similar available tools to forecast market prices and determine fair tariffs for its clients.

•The agents in the energy community are equipped with adequate infrastructure (for instance HEMSs as in [33]) to determine the best bidding strategies with the available information provided by the market facilitator.

•The aggregator, as the LEM facilitator, operates under the power limits established by a distribution system operator (DSO), who is able of actively controlling the network, monitoring its conditions and guaranteeing the optimal operation of the grid. This assumption also is used to neglect grid constraints, although those can be considered in future work.

•The aggregator is able to trade energy in the WSM. This could represent other external entities or aggregators in extensions of this work.

Regarding the coordination mechanism to integrate the LEM into existing WS/retailer markets, we consider the sequential diagram showed in Fig. 2. Since the local area cannot most likely maintain self-sufficiency in energy, and to avoid excessive partial optimization in the local area, which can be harmful to the total system optimum, the local users have to be able to acquire energy with external sources. Thus, the energy should be procured from where it can be produced at the cheapest cost to maintain an efficient system while considering network losses and limitations. It can be assumed that from a system optimum perspective, it is beneficial to prefer hierarchical cascading markets, where the initial trading is done locally, and further resources can be forwarded to larger WSMs. Different network tariffs might apply to access the local and external markets. Also, social aspects (e.g., community trading) and the ability to consider local network congestion can be contributing factors. The cascading approach allows the local resources to be used to their full potential through the value chain. Therefore, after the LEM has been cleared, the remaining resources can be aggregated to the external markets through, e.g., an aggregator. Multiple aggregators can also perform the WSM trading in the role of the traditional retailers of the end-customers. The aggregator (or retailers) can aggregate the bids of these local resources to their existing bids aimed at the national WSMs. Further similar cascading intraday markets to compensate deviations due to forecasting errors, or to trade flexibility during the

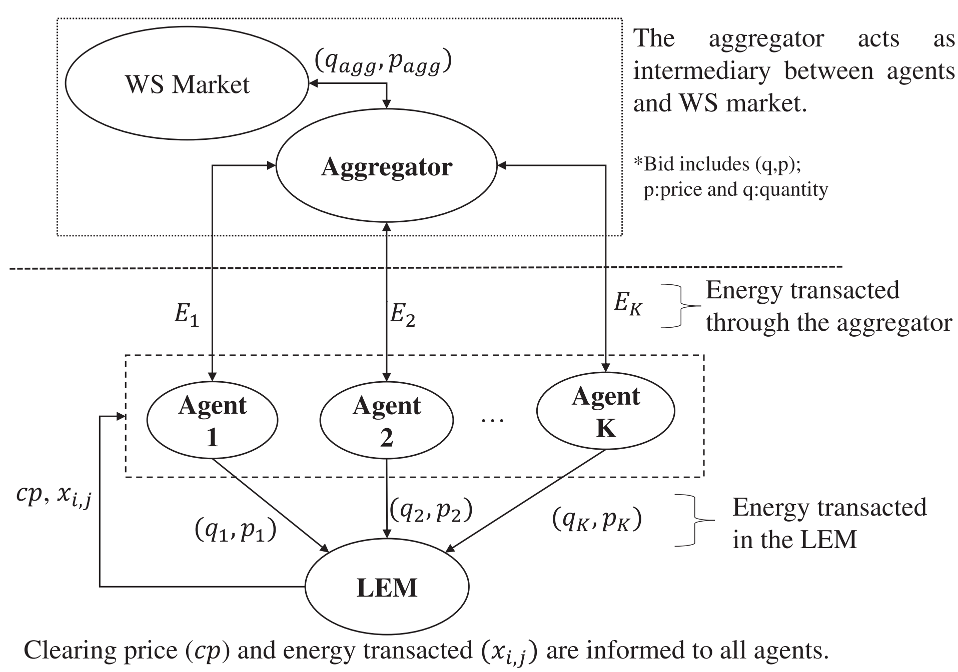

Fig. 1. Considered LEM and market participants.

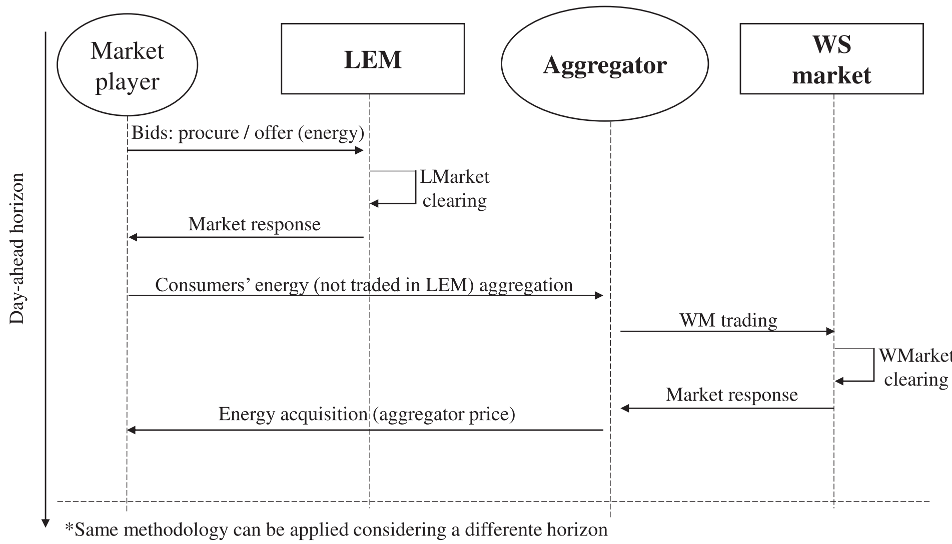

Fig. 2. Sequential diagram of LEM with cascading WSM integration.

operating day, could also be envisioned. Balance responsibility of these intraday trades could be implemented on a system-wide level, where imbalance costs (due to, e.g., forecasting errors) of the local end-users are based on national imbalance costs. Alternatively, a separate model for local balance responsibility could be constructed in addition to the existing models.

3.2. LEM Bi-level optimization

The optimization of LEM transactions is modeled as a bi-level optimization problem [34]. The upper problem corresponds to the maximization of profits (or minimization of costs) of agents participating in the LEM. The lower problem corresponds to the market response mechanism in which the objective is to maximize the amount of energy traded concerning the bids/offers of agents. The profits/costs of agents (upper problem) depend on the market-clearing price (lower problem). The solution to the bi-level problem is not trivial since the strategic competition of agents in such a scenario is hard to achieve. Also, restrictions in the available information can pose difficulties if distributed agents and incomplete information are considered. In this scenario, machine learning or computational intelligence can provide near-optimal solutions to the problem under more realistic assumptions (e.g., considering the private information of agents).

Consider a set of consumer agents $I = \{1, 2, ..., N_c\}$, and producer agents $J = \{1, 2, .., N_p\}$, where each agent i wants to minimize its costs while each agent j wants to maximize its profits. Producers and consumers act under the premise that the LEM will react to their bids and offers. Every consumer bid is characterized by a tuple $(s_{i,t}, d_{i,t})$, where $s_{i,t}$ is a price bid for the amount of energy $d_{i,}$ at time t. Similarly, producers offer are characterized as $(s_{j,t}, g_{j,t})$, where $s_{j,t}$ is a price offer for the amount of energy $g_{j,t}$ at time t.

Thus, the optimization problem for each consumer agents (minimization of costs) can be formulated as:

$$\text{minimize } C_i = \sum\nolimits_{i=1}^{t} \left(\sum_{j} cp_t \cdot x_{j,i,t} + c_t^{\text{agg}} \cdot E_{i,t}^{\text{buy}} \right) \tag{1a}$$

st.

$$d_{i,t}^{\text{Total}} = \sum_{j,j \neq i} x_{j,i,t} + E_{i,t}^{\text{buy}} \quad \forall t \in T \tag{1b}$$

$$0 \le c_t^{\text{F}} \le cp_t \le s_{i,t} \le c_t^{\text{agg}}, \quad \forall t \in T \tag{1c}$$

$$x_{i,j,t}, E_{i,t}^{\text{buy}}, s_{i,t}, d_{i,t} \ge 0, \quad \forall t \in T \tag{1d}$$

where cp_t is the LEM clearing price, $x_{j,i,t}$ contains the energy bought by agent i to agent j in the LEM, c_t^{agg} is the aggregator tariff, and $E_{i,t}^{\text{buy}}$ is the energy buy by agent i from the grid, at each time $t \in T$. Constraint (1b) guarantees that the total demand $d_{i,t}^{\text{Total}}$ of agent i is supplied by either the LEM, the aggregator, or a combination of both; constraint (1c) guarantees that bid price $s_{i,t}$ (bounded by the feed-in tariff c_t^{F} and the aggregator tariff c_t^{agg}) is higher than the cp_t and therefore matched on the LEM ; and constraint (1d) guarantees non-negative values for the variables.

On the other hand, producer agents try to maximize their profits considering their marginal production cost as follows:

$$\text{maximize } P_j = \sum_{t=1}^{t} \left(\sum_{i} cp_t \, x_{j,i,t} + c_t^F * E_{j,t}^{sell} - c_t^m * G_{j,t} \right) \tag{2a}$$

st.

$$g_{j,t}^{\text{Total}} = \sum_{i,i \neq j} x_{j,i,t} + E_{j,t}^{\text{sell}} \quad \forall t \in T \tag{2b}$$

$$0 \le c_t^{\text{F}} \le s_{j,t} \le cp_t \le c_t^{\text{agg}}, \quad \forall t \in T \tag{2c}$$

$$x_{i,j,t}, E_{j,t}^{\text{sell}}, s_{j,t}, g_{j,t} \ge 0, \quad \forall t \in T \tag{2d}$$

where cp_t is the LEM clearing price (equal for buyers and sellers), $x_{j,i,t}$ contains the energy sold by agent j to agent i in the LEM, c_t^{F} is the feed-in tariff, $E_{j,t}^{\text{sell}}$ is the energy sold by agent j to the grid, and $c_t^{\text{m}} \cdot G_{j,t}$ represents the marginal cost associated to producer j. Constraint (2b) guarantees that the generation of agent j is transacted in the LEM or feed into the grid; constraint (2c) guarantees that the producer bid $s_{j,t}$ (bounded by the feed-in tariff c_t^{F} and the aggregator tariff c_t^{agg}) is allocated in the LEM ; and constraint (2d) guarantees non-negative values in the variables.

We assume that $c_t^{\text{m}} = 0$ for PV generation, and $c_t^{\text{m}} = C^{\text{CHP}}(G_{j,t})$ (i.e., the marginal cost associated to a combined heat and power (CHP) generator) is defined as a monotone decreasing function [34]:

$$C^{\text{CHP}}(G_{j,t}) = \frac{b_{\text{CHP}} \cdot \sqrt{G_{j,t}}}{G_{j,t}} \tag{3}$$

where b_{CHP} is a cost factor of the CHP generation unit and $G_{j,t}$ is the energy produced by the CHP.The agents' profits/costs are influenced by the LEM clearing price cp_t, which in turns is determined in the lower level problem and depends on the bidding process. The lower level problem is modelled here as a symmetric pool market mechanism in which bids and offers of agents are allocated using a merit order procedure to determine the supply and demand curves for energy [35]. The price at which supply equals demand is known as the *equilibrium price*:

$$\text{maximize } X^{\text{LEM}} = GE_v \cup DE_w \tag{4a}$$

st.

$$cp_t = \max(s_j(GE_v)) \tag{4b}$$

$$cp_t, X^{\text{LEM}} \geq 0, \tag{4c}$$

where X^{LEM} is the amount of energy transacted in the LEM; GE contains the offers of energy g_j in ascending order of price; DE contains the bids for energy d_i in descending order of price; GE_v and DE_w describe the aggregated amount of offers and bids that comply with $s_v \leq s_w$ (i.e., when the supply and demand curves intersect). In this way, the clearing price at each time t (cp_t) is determined by the highest offer still accepted in the LEM merit order mechanism.

3.3. Evolutionary computation approach

The bi-level optimization problem from Section 3.2 can optimally be solved under the assumption of perfect competition and complete information using, for instance, a diagonalization approach [34]. However, such an optimal solution would only represent an upper limit of profits (equivalent to the stable Nash equilibrium solution) of the non-cooperative model proposed in this work. In other words, the optimal solution of such a market represents the higher profits agents can get considering open access to complete information of demand, generation, and marginal costs. That information, however, is not available in LEM and can only be estimated by observations of past decisions and data. Moreover, it is expected that the LEM, apart from increasing agent profits, will be designed to empower customers and give them the option of trading their energy with peers as they decided to (in some cases, even without pursuing solely monetary benefits).

Solving the mathematical formulation using deterministic approaches might present two main drawbacks: i) one related to scalability, since solving such model might present difficulties related to computational burden and execution times dealing with large instances of the problem; ii) the assumption of perfect competition and access to complete information from all users (e.g., demand, generation, and marginal costs) are not realistic in the considered model. Thus, we evoke the use of approximate methods based on evolutionary computation (EC). EC is one of the most successful branches of computational intelligence (CI), encompassing a set of algorithms for global optimization inspired by biological and evolutionary processes [4]. Typically, evolutionary algorithms (EA) are population-based solvers that act over an initial set of candidate solutions (i.e., a population or swarm) that is iteratively updated. A given fitness function measures the performance of solutions. At each iteration/generation, solutions with inferior performance are stochastically removed, whereas new solutions (generated through a specific operator) are introduced into the population. It is expected that by the principles of natural/artificial selection, the population will gradually evolve towards the optimal fitness value [4].

To use EC methods, we need to define a fitness function and a solution representation that can be evaluated in such a function. Thus, assuming we have $K = \{1, 2, ...N_k\}$[1] agents, it is clear that we are trying to determine the best tuple $(q_{k,t}, p_{k,t})\ \forall k \in K, \forall t \in T$ representing the optimal price and quantity to bid in the LEM. Therefore, we define a vector $\vec{x} = \{[q_{k,t}] \cup [p_{k,t}]\}$ including the bids for quantity and price that the kth agent will send to the LEM. To avoid separating the agents by consumer and producer types, we use a sign convention in which a positive quantity represents a bid (i.e., buying in the market), and a negative quantity represents an offer (i.e., selling in the LEM). Therefore, we can control the agent action by defining variable bounds in which consumer agents can send bids to the LEM within the bounds $[0, d^{\text{Total}}_{i,t}]$ (i.e., between 0 and their maximum consumption); and producer agents can send offers within the bounds $[-G^{\max}_{j,t}, 0]$ (i.e., between 0 and their maximum production capacity). The bounds for prices are the same for all agents and within the range $[c^{\text{F}}_t, c^{\text{agg}}_t] \forall t \in T$.

Such solutions $\vec{x}$ should be evaluated in an objective/fitness function. Notice that in this work, following a non-cooperative model would result in a multi-objective formulation since the calculation of profit would be independent for each agent. In fact, individual distributed profits for each agent can be computed using Eqs. (1a) and (2a) retrieving the required information from $\vec{x}$:

$$U_k = \begin{cases} -C_i & \text{if } k \text{ is a consumer agent} \\ P_j & \text{if } k \text{ is a generator agent} \end{cases} \tag{5}$$

where $C_{i,t}$ and $P_{j,t}$ are conflicting objectives since agents want to achieve the best result for themselves. In this paper, we adopt two different perspectives for solving the problem. In the first, we use a learning approach (based in the ant colony optimization technique) to solve the problem in a distributed manner. This perspective allows the optimization and simulation of the market as a non-cooperative model preserving private information of agents (i.e., considering bids in closed form). In the second, we approximate the optimal solution of the cooperative model (i.e., the average profits for agents) by using the sum over all agents profits and considering such sum Pareto optimal [36]. In this way, we avoid a multi-objective formulation of the problem modelling the fitness function as:

$$Fit(\vec{x}) = -\mathbf{mean}(A_{\text{profit}}) + \mathbf{std}(A_{\text{profit}}) \tag{6}$$

where $A_{\text{profit}} = [U_1, ..., U_k, ..., U_{N_k}]$ is a vector that includes all the profits (calculated with Eq. (5)) achieved by the agents considering bids/offers encoded in the solution $\vec{x}$; $\mathbf{mean}()$ and $\mathbf{std}()$ are functions that compute the average and standard deviation of the profits of all agents. The negative sign in the first term is used to transform the problem of profits maximization into a minimization problem. The less the value in Eq. (6), the better the mean profits achieved by all agents.

The fitness function, either distributed or centralized, should perform a series of steps in order to be evaluated. First, for each time step t, bids and offers are decoded from the vector solution $\vec{x}$ and a market clearing function that uses a merit order mechanism determines the clearing price (Cp_t) and the energy transacted between agents (see Eq. (4a)). After this, the individual profit of agents can be calculated using Eqs. (1a) and (2a). A simple deterministic mechanism is implemented internally to determine the amount of energy traded through the aggregator (i.e., variables $E^{\text{buy}}_{i,t}$ and $E^{\text{sell}}_{j,t}$ in Eqs. (1a) and (2a)). For instance, in the case of consumer i, $E^{\text{buy}}_{i,t} = d^{\text{Total}}_{i,t} - \sum_j x_{j,i,t}$ which is equal to the remaining energy not obtained in the LEM to satisfy its demand. On the other hand, for producers we have two possible situations that need to be handle in different ways. The first situation is when producer k is a small CHP generator; in that case, a restriction is imposed not allowing those type of generators to sell energy to the grid at the feed-in tariff (since that situation is simply not realistic). The second situations occurs when producer k corresponds to a prosumer with excess of PV generation; in that case, the prosumer is forced to inject the excess of energy that was not traded in the LEM into the grid at the feed-in tariff (i.e., the$E^{\text{sell}}_{j,t} = g^{\text{Total}}_{j,t} - \sum_{i, i \neq j} x_{j,i,t}$). Besides, a direct repair mechanism is implemented in the algorithms to avoid that CHP generators put a bidding price $s_{j,t}$ lower than the resulting marginal cost of their generation bid $g_{j,t}$. Finally, a penalty is added to the resulting fitness value

[1] Notice that, different from Section 3.2, in which producers and consumers are separated in two groups, this K set includes all agent

each time the market is not cleared. This penalty is necessary to direct the search towards feasible solutions that clear the LEM.

Fig. 3 shows the flowchart and steps required to evaluated encoded solutions in the EAs. The process can also be seen as a blackbox that receives a group of solutions and return the results concerning bids/offers, LEM clearing prices, LEM transactions, and overall profits achieved by agents.

Now that we defined the encoding of individuals and the fitness function, we can apply different EA to solve the problem. In this paper, we have chosen a distributed version of the ant colony optimization (ACO) [30], a variant of the well-known differential evolution (DE) called HyDE-DF [37], a single-solution vortex search (VS) algorithm [38], and an estimation distribution algorithm (EDA) called CUMDANCauchy++ [39]. The algorithms were selected due to its success in different applications and ease of implementation. Also, notice that from the selected algorithms, one belongs to the class of swarm intelligence (ACO), two to the class of population-based approaches (HyDE-DF and CUMDANCauchy++), and one to the class of single-solution based approach (VS).

Fig. 4 shows the generic flowchart of the whole process proposed in this paper. Notice that the flowchart shows a high-level evolutionary cycle that can be applied to HyDE-DF, VS, and CUMDANCauchy++ due to their similar frameworks of applications. The main difference of these approaches is the way in which they generate new solutions, applying a particular operator in the process. Also, it is important to remark that distributed ACO has an entirely different evolutionary process (in fact, it is a learning process instead), so we present the flowchart of ACO in the following subsection. In addition, we introduce the basics of the algorithms and point out the references for the reader to consult more details of the used approaches.

3.3.1. Distributed ACO

Ant Colony Optimization (ACO) is an EA classified as a swarm intelligence approach that mimics the social behavior of ant species. To do so, learning matrices are programmed to represent the process of ants depositing pheromone on the ground to mark favorable paths to food. In other words, ACO exploits a problem-solving mechanism reinforcing paths (solutions) that show good performance in a given fitness function [40].

Originally, ACO was proposed for solving discrete combinatorial optimization problems, and for a model $P = (S, \Omega, f)$ consisting of:

- a search space S defined over a finite set of discrete decision variables $X_i, i = \{1, ..., D\}$ (with D as the dimension of the problem);
- a set Ω of constraints among the variables;
- an objective function$f : S \in \mathbb{R}^+$

The generic variable X_i can take values over the set $V_i = \{v_i^1, ..., v_i^{|V_i|}\}$. A feasible solution $s \in S$ is a complete assignment of values that satisfies constraints in Ω. A solution $s^* \in S$ is optimal iff: $f(s^*) \leq f(s) \forall s \in S$. The application of ACO to solve the optimal bidding problems in LEM was explored in [28], making a discretization of the continuous bidding variables for the bids/offers of quantity and prices (i.e., M ants of each agent construct a solution selecting the quantity and price for bidding over a discrete set of options). Since the optimization problem searches for the optimal bidding of independent agents in the LEM, and individual learning matrix can be employed for each market player, a distributed ACO that is applied to each agent independently was proposed.

Fig. 5 presents the flowchart of the distributed ACO process. In an initialization step, a pheromone matrix containing the discrete set of options for bids/offers of quantity and price is defined for each agent. After that, for each ant m_k belonging to agent k, a bid/offer of price and quantity $[q_k, p_k]$ is constructed independently based on its pheromone matrix trail. The bids/offers of all ants/agents are combined and evaluated in the fitness functions, and the pheromone matrices are updated according to the fitness response (i.e., the profits achieved by the agent due to its decision of bid/offers). The distributed process is repeated for each ant of each agent, until the maximum number of iterations is reached. The readers can be referred to [28,30] for details on the implementation of the distributed ACO.

The distributed method has the advantage of guarantee private information since each agent has their own pheromone/learning matrix and reinforce such matrix as a function of their independent profit/cost. Other advantages of the distributed ACO are related to the use of parallel computing to overcome scalability issues when systems of large size are considered.

3.4. HyDE-DF

HyDE with decay function (HyDE-DF) is an improved version of the recently proposed HyDE [37]. Inspired by the well-known differential evolution algorithm [41], HyDE-DF incorporates a decay function to perform a transition in the iteration process from the main operator of HyDE [37] to the generic basic operator of DE for the generation of new solutions. This transition allows an enhanced phase of exploration in the early stage of evolution and stresses the exploitation in later stages of the optimization.

HyDE-DF uses a population (Pop) of individuals $\vec{x}_{j,i,g} = [x_{1,i,g}, ..., x_{D,NP,g}]$, where g is the current generation, and $i = [1, ..., NP]$ is the number of individuals in the population, to optimize a function of dimension D (i.e., with D variables to optimize). As with most EAs, a population ofNP solutions is generated randomly within lower and upper ranges $[x_{lb,j}, x_{ub,j}]$ of variables (i.e., for this problem between $[0, d_{i,t}^{\text{total}}]$ for bid quantities $[-G_{j,t}^{\max}, 0]$ for offer quantities, and $[c_t^{\text{F}}, c_t^{\text{agg}}]$ for prices). After that, HyDE-DF creates new solutions at each iteration applying mutation and recombination operators and selecting the best solutions to survive for the next iteration (i.e., performing elitist selection for the next generation).

The reader can be referred to [37] and [42] for a detailed explanation of HyDE-DF. To remark that HyDE-DF achieved third place (out of 36 algorithms) in the international 100-digit challenge held at CEC/GECCO 2019 [42].

3.5. Vortex search

Vortex search (VS) was applied in this work due to its simplicity and open available code [38]. VS is classified as a single-solution based metaheuristic, although its framework is very similar to other EAs. The algorithm was employed in [27] to solve the optimal bidding problem, and its performance was compared against other well-known EAs. Briefly explained, in each iteration, N given number of neighbor solutions are generated using a multivariate Gaussian distribution around the initial solution. Those N solutions are evaluated in the fitness function, and the single-solution is updated with the best solution found. This process is iteratively repeated until a stop criterion is achieved.

In VS, and generally in single-solution methods, the generation of new solutions in the neighborhood of the single-solution is critical for the success of the algorithm. The main property searched in a neighborhood is locality. A weak locality (i.e., large effect on the solution) is required in the initial steps to favor exploration. Once the algorithm converges to a promising region of the search space (e.g., to a near-optimal solution), strong locality (i.e., small changes on the solution) is preferred. In VS, this balance is achieved decreasing the radius of the neighborhood around the best solution iteratively (emulating a vortex phenomenon). Another feature of VS is the use of "poor memory" since only the best solution is stored in each iteration, resulting in a quite simple EA.

The reader can consult [38] for a detailed explanation of the VS algorithm, and [27] for an example of the application of VS to the optimal bidding problem.

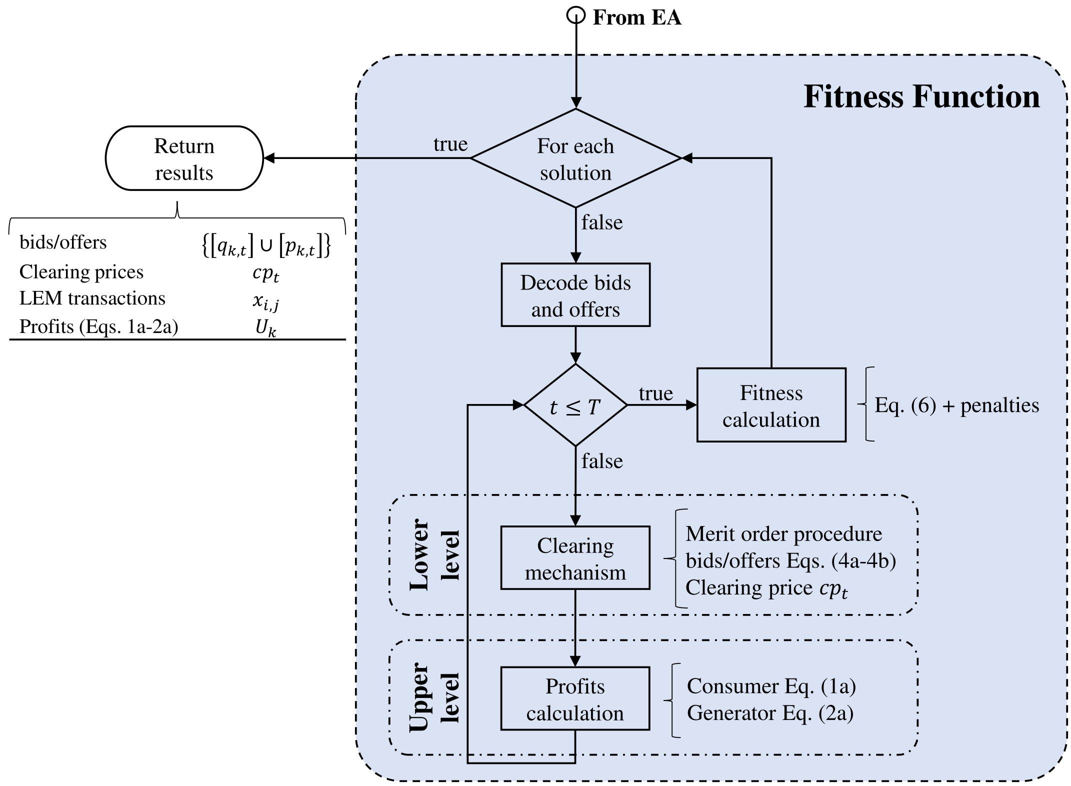

Fig. 3. Fitness function flowchart.

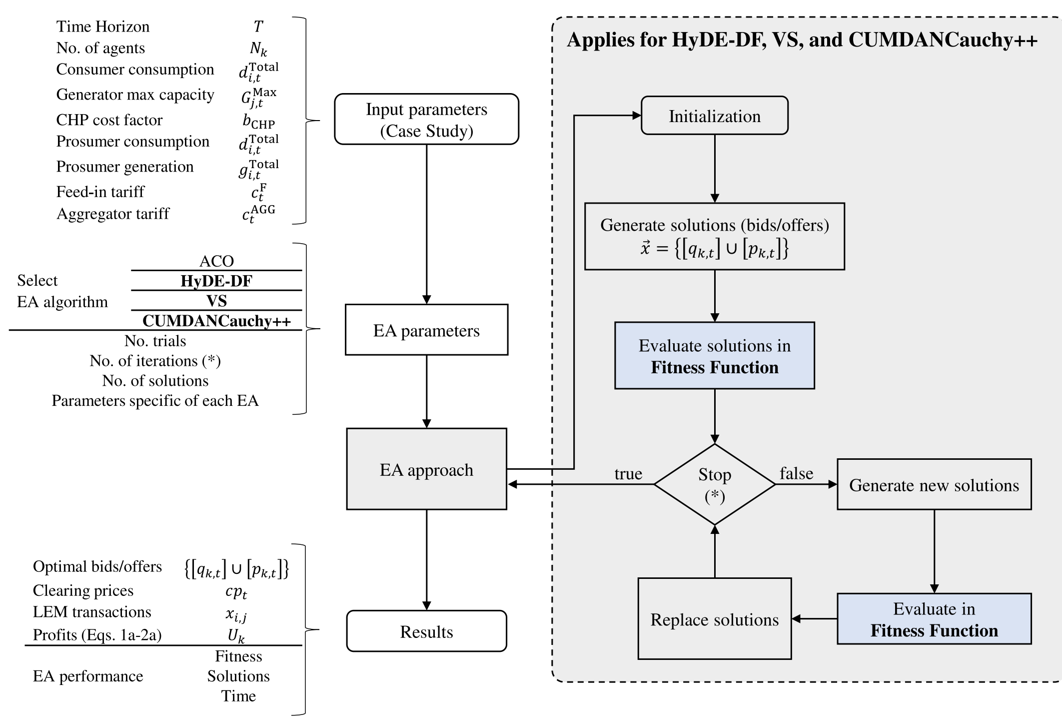

Fig. 4. HyDE-DF, VS, and CUMDANCaychy++ flowchart.

3.6. *CUMDANCauchy++*

CUMDANCauchy++ is a newly proposed EA that combines estimation distribution algorithms (EDAs) [43] with cellular evolutionary algorithms [44]. EDAs is a set of EAs that, instead of using typical crossover and mutation operators, uses estimation and sampling to determine the most feasible probability distribution of variable from the selected individuals [43]. On the other hand, in cellular EAs, individuals cannot mate arbitrarily, so that individuals in a population can only interact with its closest neighbors [44]. The combination of these two approaches gives rise to cellular EDAs, [45].

CUMDANCauchy++ obtained the first place at the “2020

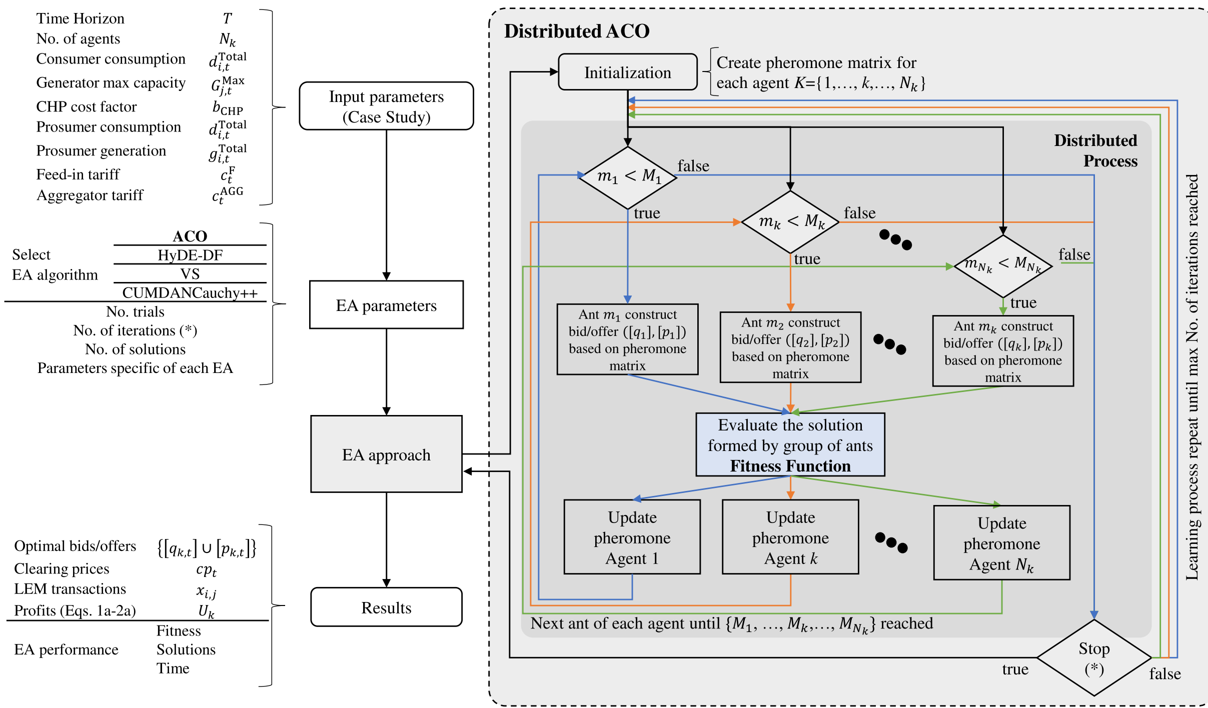

Fig. 5. Distributed ACO flowchart.

Competition on Evolutionary Computation in the Energy Domain: Smart Grid Applications", solving a complex energy resource management problem with uncertainty, and a bidding problem in LEM. The reader is referred to [39] for further details on the implementation of this algorithm.

4. Case Study, Scenarios, and algorithms settings

In this section, we present the case studies and scenarios used to evaluate the framework developed in this paper. We adopt three different case studies and two different scenarios for each of them, resulting in six scenarios to be evaluated. Table 1 presents an overview of case studies and scenarios considered.

To build the case studies and scenarios, three types of players are considered: consumers, prosumers (consumers with PV generation) and producers (small CHP generators). The case studies (**C1, C2, and C3**) are referred to the data and number of players/agents, while the scenarios (**A - FreeM and B - Ptakers**) correspond to a variant in the setting of how consumers behave within the LEM. FreeM - "free market scenario", corresponds to a scenario in which consumer agents are able to put free bids of quantity and price into the LEM. Such scenario is ideal in the sense of free participation of agents but does not reflect the reality of low short-term price elasticity of demand. In fact, it is generally accepted that price elasticity of demand is very low [46]. Therefore, Ptakers - "price takers scenario", assumes that consumers have no elasticity for the price and demand, making their bids into the LEM equal to the required energy at the market price. Notice that in this scenario, producers become the price-setters and need to compete to be able of selling their energy into the LEM (i.e., producers became price setter due to the merit order mechanism used in the LEM). The list of the six analyzed scenarios is present below:

- C1.A - nine players, from which three are consumers (with freedom of bidding quantity and price), three are prosumers, and three are producers - FreeM case;
- C1.B - nine players, from which three are consumers (with no elasticity of price and quantity), three are prosumers, and three are producers, - Ptakers case;
- C2.A - thirty players, from which twenty five are consumers, and five are producers, - FreeM case;
- C2.B - thirty players, from which twenty five are consumers, and five are producers, - Ptakers case;
- C3.A - thirty players, from which five are consumers, twenty are prosumers, and five are producers, - FreeM case;
- C3.B - thirty players, from which five are consumers, twenty are prosumers, and five are producers, - Ptakers case.

Regarding the details of the data used, Table 2 summarizes the consumption and generation values of the case studies. In each case study, we present the values for consumers and prosumers divided into consumption (load), and generation (PV gen). Five different metrics are used to characterize power and energy: i) maximum power value achieved in all periods(i.e., the Peak); ii) the accumulated energy over the 24 h (Energy); and mean power and energy values corresponding to iii) the mean power value per hour (p/h column), iv) mean energy value per agent over the whole 24 periods, and v) the mean power value per hour per each agent.

Table 2 shows that C1 is the case study with the smallest quantity of energy consumption and generation due to the low number of agents presented in the system. On the other hand, C2 only consider consumers

Table 1
Scenarios used to evaluate the proposed methodology.

		No. of players	Consumers	Prosumers	Producers
C1 A – FreeMB - Ptakers	A – FreeM B - Ptakers	9	3	3	3
C2 A – FreeMB - Ptakers	A – FreeM B - Ptakers	30	25	0	5
C3 A – FreeMB - Ptakers	A – FreeM B - Ptakers	30	5	20	5

Table 2
Summary of consumption and generation characteristics of agents.

			Peak (kW)	Energy (kWh)	Mean power and energy p/h	p/agent	p/agent and h
C1	3 Consumers		2.52	21.98	0.92	7.33	0.31
	3 Prosumers	Load	3.06	22.36	0.93	7.45	0.31
		PV gen	2.81	20.96	0.87	6.99	0.29
C2	25 Consumers		44.59	390.04	16.25	15.60	0.65
	0 Prosumers	Load					
		PV gen					
C3	5 Consumers		8.00	71.48	2.98	14.30	0.60
	20 Prosumers	Load	36.59	318.56	13.27	15.93	0.66
		PV gen	61.71	321.60	13.40	16.08	0.67

with no PV generation; thus, the values of prosumers do not appear in the table. This case presents values around sixteen times higher than C1 in terms of consumption. Finally, C3 splits the consumption into consumers and prosumers, and add PV generation into the mix.

Regarding market participants data, sample power profiles of residential houses and PV systems are built using the open datasets available at PES ISS website[2]. Fig. 6 presents the profiles used to create the case studies. As can be seen in Fig. 6, four different types of consumption profiles and two different types of PV production were used as a basis to generate the rest of the profiles. A randomized function with a uniform distribution, 20% around the base profiles was employed to generate agents. For instance, to create the case study C1, the consumption profiles of houses 1, 2, 3, and the PV production profile of house 1 were used. Case study C2 and C3 were created similarly, considering the consumption profile of house 4, and the generation profile of house 2, to generate the rest of agents. Also, our case studies consider small producer modeled as CHPs generators with a maximum production capacity of 2 kW and a marginal cost calculated with Eq. (3) with a factor $b_{\text{CHP}} = 0.10$ EUR/kWh [34]. Concerning the bounding tariffs of the LEM, a flat feed-in tariff of $c_t^{\text{F}} = 0.095\ \forall t \in T$ has been set considering the Portuguese scenario, whereas the aggregator tariff c_t^{agg} has been set considering an aggregator fee of 0.15 EUR/kWh plus the average WSM price through the day (which in average was 0.05 EUR/kWh in the MIBEL market during the week of 5–9/08/2019). We assume that such tariff already includes network fees (like for instance taxes, transportation, distribution [47]) and a margin of profit for the aggregator.

4.1. EAs parametric settings

Now that we defined the encoding of individuals and the fitness function, we can apply different EA to solve the problem. In this paper, we have chosen a distributed version of the ant colony optimization (ACO) [30], a variant of the well-known differential evolution (DE) called HyDE-DF [37], a single-solution vortex search (VS) algorithm [38], and an estimation distribution algorithm (EDA) called CUMDANCauchy++ [39]. The algorithms were selected due to its success in different applications and ease of implementation. Also, notice that from the selected algorithms, one belongs to the class of swarm intelligence (ACO), two to the class of population-based approaches (HyDE-DF and CUMDANCauchy++), and one to the class of single-solution based approach (VS). We introduce the basics of the algorithms and point out the references for the reader to search for more details.

We have implemented and compared the performance of the four state-of-the-art EAs introduced in Section 3.3 to solve the optimal bidding problem. The algorithms include a distributed version of ACO [30], an improved version of the well-known DE called HyDE-DF [37,42], the VS [38], and an EDA called CUMDANCauchy++ [39]. All the tested algorithms perform a number of function evaluations (FE) equal to the size of the population in each iteration. From the selected algorithms, ACO is classified as a swarm intelligence approach, with the particularity that can be implemented in a distributed manner, with a mechanism that resembles machine learning techniques. Also, VS is not strictly speaking a population-based approach but evaluates at each iteration a given number of neighbor solutions, which results in the same number of FE per iteration as the other selected algorithms.

For the experiments, we have set the particular parameter of the algorithms, as concluded in their original studies. The size of generated solutions (i.e., population/neighbors/ants) has been set accordingly to result in 10,000 function evaluations (FE) in total.

Table 3 presents the values of parameters used to perform the experiments. Notice that VS and CUMDANCauchy++ do not need any parameter setting apart from the number of solutions and iterations. We do not include a thorough description of the selected EAs for space limitations, but the reader can consult the cited references in Section 3.3 for further details.

5. Results and discussion

In this section, we present the results of our simulation and the respective discussion. We applied our methodology to the case studies (i.e., C1, C2, and C3) presented in Section 4. First, we present a comparison of the performance of algorithms in terms of costs (overall and by group of agents) in all the scenarios. After that, we present a more comprehensive analysis of the impact of LEM transactions, renewable penetration, and clearing prices, using the best results found in each case study.

The algorithms and experiments were implemented in MATLAB 2018a in a computer with Intel(R) Core(TM) i7-8650U CPU@1.90 GHz processor with 16 GB of RAM running Windows 10. Due to the stochastic nature of EAs, 30 trials have been performed to validate the overall performance of the algorithms. The mean, standard deviation, and the best values were recorded for each algorithm.[3]

5.1. Results

Table 4 presents the overall costs of agents, the costs by group of agents (i.e., consumers, prosumers, and producers), and the average fitness, standard deviation, and time required by each algorithm (notice that the reported values correspond to the average of the 30 runs of each

[2] Open data online at http://sites.ieee.org/pes-iss/data-sets/

[3] For the sake of reproducible research, case study data and complete experimentation files can be found in https://fernandolezama.github.io./publication

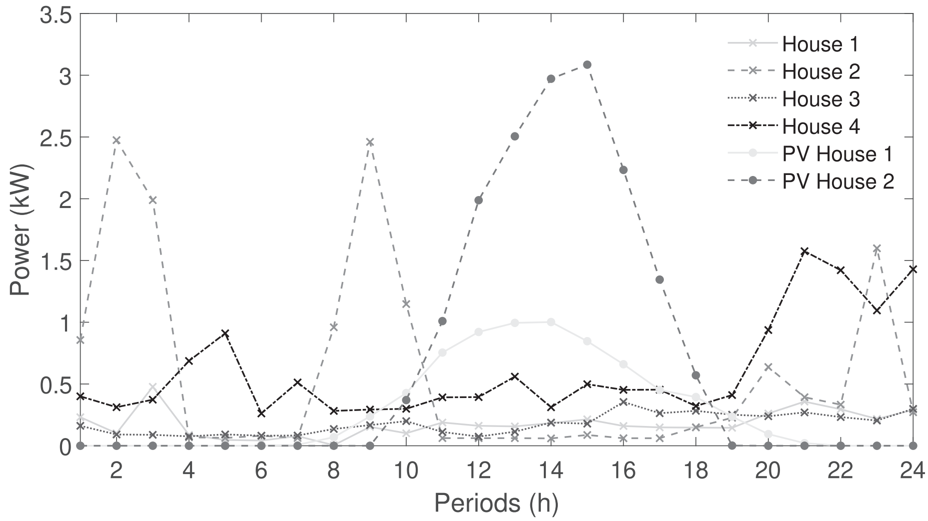

Fig. 6. Base profiles used to create the case studies.

Table 3
Parameters used in the experiments.

	Parameters	Value	Solutions	Iterations	FE
ACO	ρ, α, β	0.3, 0.5, 0.5	20	500	10,000
HyDE	F, Cr	0.5, 0.5	5	2000	10,000
VS	N/A	N/A	5	2000	10,000
CUMDANCauchy++	N/A	N/A	125	80	10,000

algorithm). The table also includes the results of the baseline case, i.e., the cost agents attain in the absence of an LEM, as well as a column with the percentage of improvement w.r.t that baseline case (Imp column). It can be seen that for the case in which consumer agents have the freedom to put bids of quantity and price (i.e., FreeM case). VS achieves the best overall costs for the system. In fact, VS achieves a 19.58% of improvement compared to the baseline, the lowest cost for consumer and prosumer agents, and the higher profits for producers (notice that the negative value represent profits in the table). It can be noticed, however, that VS presents a high fitness value and std compared to the other algorithms, which indicates that the algorithm found unfeasible solutions in some of the runs (unfeasible solutions have a higher fitness due to penalties added). On the other hand, when consumers are considered price takers with no price elasticity to put the bid price (i.e., Ptakers case), ACO presents the best performance achieving an improvement of 68% w.r.t. the baseline case. ACO can achieve the best profits for generators, taking advantage that consumers are willing to pay the higher price of the LEM (i.e., price takers). Finally, it is worth mentioning that, in the baseline, producer agents achieve 0 profits due to the restriction imposed on small CHP generators avoiding selling energy to the aggregator at a feed-in tariff. In fact, CHP generators have a marginal cost associated, which results in a higher price than the feed-in tariff. This principle of 0 profits for generators in the baseline case is applied to all the cases.

Table 5 presents the overall costs of agents for the case study C2 − 30 agents without PV generation. In this case, five generators compete in the LEM to sell energy to 25 consumers. It can be noticed that better overall costs are achieved when consumers are considered price takers (see the rows "Ptakers" in Table 5). The best percentage of improvements w.r.t. the baseline case is achieved with VS (32%) followed very close by ACO (30%). Also, despite the increase in the number of consumers and the absence of prosumers, considering consumers as price takers results in an advantage for the whole system. This can be explained by the fact that generators are able to sell more energy in the LEM and competition by generators (reducing their price for the possibility of selling more energy) results in clearing prices that also benefit consumers. In fact, the gap in percentage improvement between the FreeM case and Ptakers case is higher compared to the C1 − 9 agents case.

The case study C3 can be contrasted with the previous results since it is a very similar case in which 80% of the agents (i.e., 20 of the consumers) become prosumers with PV generation. Table 6 presents the overall costs for this case. The performance of the algorithms presents similar behavior than the previous C2 case, with VS and ACO showing the best performance (around 45% of improvement w.r.t. the baseline) when consumers are considered price takers. Overall, costs are reduced almost by half due to the penetration of PV generation. In fact, that PV penetration is responsible also for a decrease in the profit of producers (w.r.t. C2 case) since some of the energy traded in the LEM now comes

Table 4
C1 − 9 agents case study. Costs/profits by group of agents (EUR).

	EA	Overall Costs	Costs		Profits	Fitness	Std	Time (mins)	Imp (%)
			Consumers	Prosumers	Producers				
FreeM	**ACO**	5.63	4.19	1.71	−0.27	3.28	0.05	2.49	9.64
	HyDE	5.81	4.19	1.69	−0.07	3.30	0.06	2.79	6.63
	VS	5.01	3.89	1.52	−0.40	18.79	16.14	3.77	19.58
	CUMDAN	6.03	4.26	1.80	−0.03	3.41	0.04	2.13	3.10
Ptakers	**ACO**	1.97	3.94	1.37	−3.34	2.51	0.04	3.28	68.33
	HyDE	3.80	3.39	1.43	−1.02	2.66	0.13	3.15	38.91
	VS	3.38	3.56	1.45	−1.63	7.66	5.34	4.45	45.65
	CUMDAN	5.22	3.76	1.63	−0.16	3.07	0.13	2.31	16.10
Baseline	**No LEM**	6.23	4.36	1.86	0.00	0.00	0.00	0.00	0.00

Table.5
C2 − 30 agents without PV generation. Costs/profits by group of agents (EUR).

	EA	Overall Costs	Costs		Profits	Fitness	Std	Time (mins)	Imp (%)
			Consumers	Prosumers	Producers				
FreeM	**ACO**	73.12	75.66	0.00	−2.54	4.91	0.11	3.31	5.60
	HyDE	70.76	74.68	0.00	−3.92	4.64	0.19	4.92	8.64
	VS	68.12	73.85	0.00	−5.73	4.31	0.08	5.75	12.05
	CUMDAN	66.88	74.25	0.00	−7.37	4.22	0.84	2.56	13.65
Ptakers	**ACO**	53.76	76.99	0.00	−23.24	2.06	0.18	6.60	30.59
	HyDE	56.62	75.67	0.00	−19.06	2.53	0.17	4.64	26.90
	VS	52.33	75.77	0.00	−23.44	1.88	0.08	5.33	32.43
	CUMDAN	56.91	69.58	0.00	−12.67	3.08	1.10	2.98	26.52
Baseline	**No LEM**	77.45	77.45	0.00	0.00	0.00	0.00	0.00	0.00

Table 6
C3 − 30 agents with 80% PV penetration. Costs/profits by group of agents (EUR).

	EA	Overall Costs	Costs		Profits	Fitness	Std	Time (mins)	Imp (%)
			Consumers	Prosumers	Producers				
FreeM	**ACO**	35.52	13.42	24.09	−2.00	6.33	0.09	3.22	9.91
	HyDE	32.24	13.03	23.29	−4.08	5.88	0.23	4.82	18.22
	VS	31.10	12.79	22.77	−4.45	5.70	0.08	5.53	21.10
	CUMDAN	28.46	12.64	22.56	−6.74	5.35	0.53	2.62	27.80
Ptakers	**ACO**	21.42	13.61	23.82	−16.00	4.41	0.04	4.81	45.66
	HyDE	24.17	11.10	23.58	−10.51	4.52	0.13	4.02	38.69
	VS	21.46	11.07	23.39	−13.00	4.12	0.08	4.52	45.56
	CUMDAN	29.15	10.17	23.27	−4.29	5.26	0.68	2.72	26.05
Baseline	**No LEM**	39.42	14.19	25.23	0.00	0.00	0.00	0.00	0.00

from the excess of prosumers PV generation.

It can be seen that all algorithms are able to provide feasible solutions for the problem in a reasonable amount of time (between 2 and 5 min). Also, considering consumers as price takers is actually beneficial for the whole system. From the algorithms tested, VS and ACO present the best performance. However, ACO is an algorithm that can be implemented in a distributed environment, which has two main advantages over the other tested algorithms, namely 1) ACO allows agents to keep private information by being a distributed approach, and 2) can be implemented using distributed computing tools allowing better scalability.

For the next set of experiments, we have taken the best solution found with the algorithm that achieved the best performance in each case. This was done since we were interested in analyzing the real profits achieved by each agent (and by a group of agents) instead of the average values over a set of runs (as was done for Tables 4, 5, and 6).

Fig. 7 presents the energy bought/sell in the LEM and to the aggregator by each agent. The depicted result corresponds to the best solution found with VS (for the FreeM scenario) and ACO (for the Ptakers scenario). It can be seen that when consumers are set as price takers (Fig. 7a), generators are able to sell more energy in the LEM. In fact, for this scenario, consumers can acquire almost all the energy needed in the LEM. Even one prosumer (bar number 5 in Fig. 7a) is able to trade some of its excess of PV generation in the LEM.

Fig. 8 depicts the resulting LEM clearing prices for FreeM and Ptakers scenarios of C1 over the 24 periods. Besides, we include the considered "aggregator plus WSM tariff" (upper bound) and the considered feed-in tariff (lower bound). Clearing prices of 0 represent situations in which the market was not able to be cleared. As can be seen, when consumers are able to bid quantity and price (FreeM scenario), the clearing price is lower compared to the Ptakers scenario. Moreover, there are some periods (e.g., periods 4-to-7 and 17) in which the LEM was not able to be cleared. This seems to indicate that when consumers are able to put bids of price and quantity, competition takes agents to situations in which clearing prices are low, including situations in which the offer cannot meet the demand prices. On the other hand, when consumers become

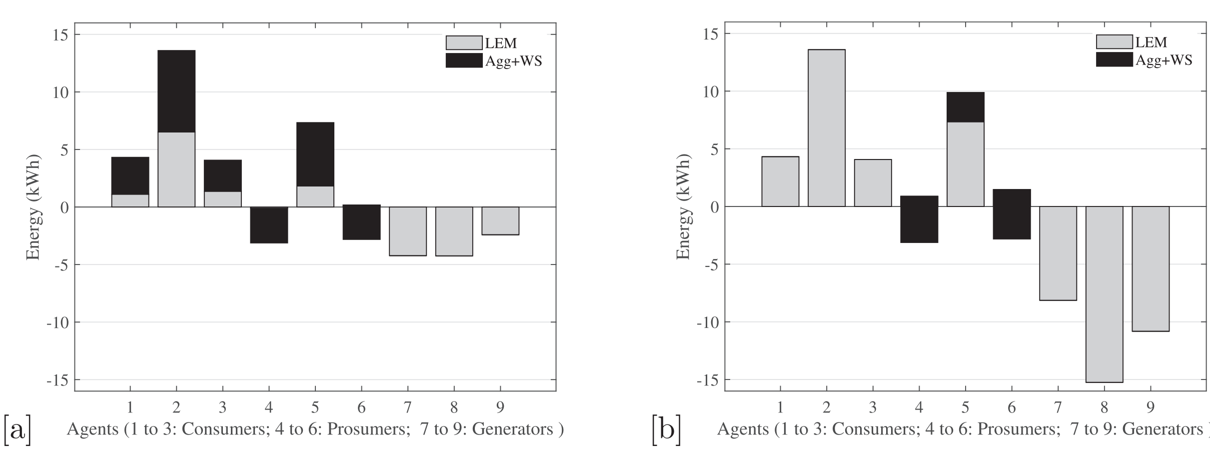

Fig. 7. C1 − 9 agents. Comparing overall LEM and Agg + WSM transactions. [a] Transaction considering consumers as FreeM (free market). [b] Transactions considering consumers as Ptakers (price takers).

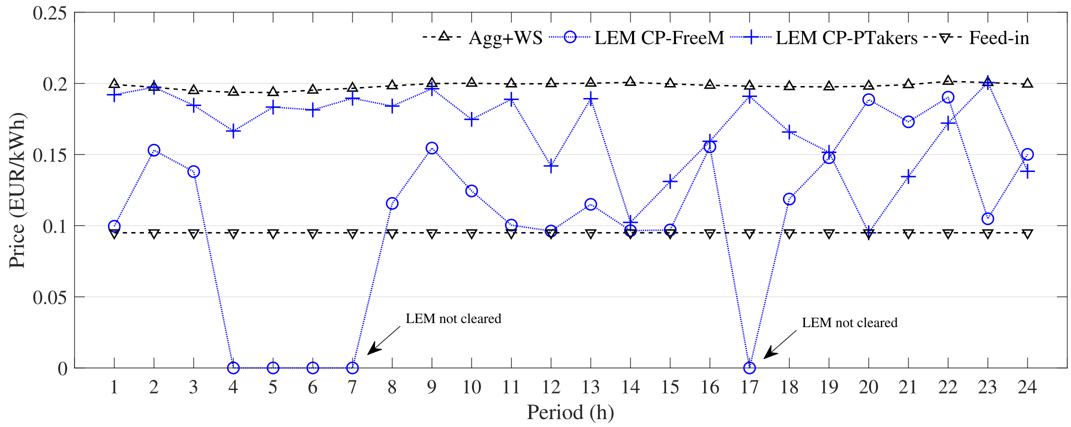

Fig. 8. C1 – 9 agents. Resulting LEM clearing prices in each period considering free market and price takers scenarios. The figure also shows the considered aggregator plus WSM price and the feed-in tariff.

price takers, the competition of generators to supply the demand results in higher clearing prices, and in addition, market clearing is guaranteeing.

We performed the same analysis for cases C2 and C3 to confirm the trends observed for the small case study using nine agents. Figs. 9 and 10 show the energy transacted in the LEM for C2 and C3 case studies. Remember that both cases consider 25 consumers, with the difference that 20 of those 25 consumers have PV generation in case C3. To presents plots with a uniform structure that can be compared between cases C2 and C3, we have grouped five consumers in column 1, and the other 20 consumers in column two as prosumers without PV generation for Fig. 9, and with PV generation in 10. Fig. 9 depicts the results of the best solutions found with CUMDAN algorithm (for the FreeM scenario) and VS (for the Ptakers scenario). It can be noticed, again, that setting the consumers as price takers result in more energy transacted in the LEM, and therefore, lower prices for consumers and higher profits for producers. When PV penetration is considered (i.e., Fig. 10), the energy transacted is lower due to lower demand of consumers, but the trend is maintained, and considering consumers as price takers gives the best response of the market for the whole systems (e.g., as can be seen in Fig. 10b).

Finally, Figs. 11 and 12 presents the clearing prices obtained for the C2 and C3 case studies. It is confirmed that the Ptakers scenario results in slightly higher clearing prices. Also, it can be noticed in Fig. 12 that the presence of PV generation results in lower demand for energy, affecting the LEM clearing prices consequently. For instance, the clearing prices are lower in periods in which there is an excess of PV generation (i.e., periods 11 to 18). This is a clear consequence of demand and supply market rules, in which generators have to low their prices to be able to compete in a market in which demand is low.

5.2. Discussion and future work

The results of the previous subsection illustrate that the presence of LEM greatly reduces the overall system cost (around 30–40% in general, with a case of up to 60% for the nine agents case study). It was shown that the improvement is more pronounced if consumers are set as price takers (Ptakers scenario), always willing to pay the aggregator tariff and to search for their whole supply of energy in the LEM. The aggregator sells energy to consumers/prosumers at a variable price and acts as a supply backup following the WSM prices. The work suggests that LEM could significantly shift the procurement of energy from the traditional form (simulated as the aggregator assuming the role of a retailer) to local transactions. Thus, this could indicate that the conventional retailer/aggregator activity can be largely affected by the implementation and introduction of LEMs since their energy sales can drastically be reduced and shift towards local markets (changing from Business-to-Consumer to Consumer-to-Consumer). Thus, these companies will have to adapt and improve their business model in order to thrive. LEM operators could, for instance, provide the platform and charge a fee for the LEM trades. In this way, these companies can have a source of income in the new LEM paradigm, while partially replacing the current business models of retailer companies. Retailers and aggregators can improve their results by adopting demand response programs and intelligent energy

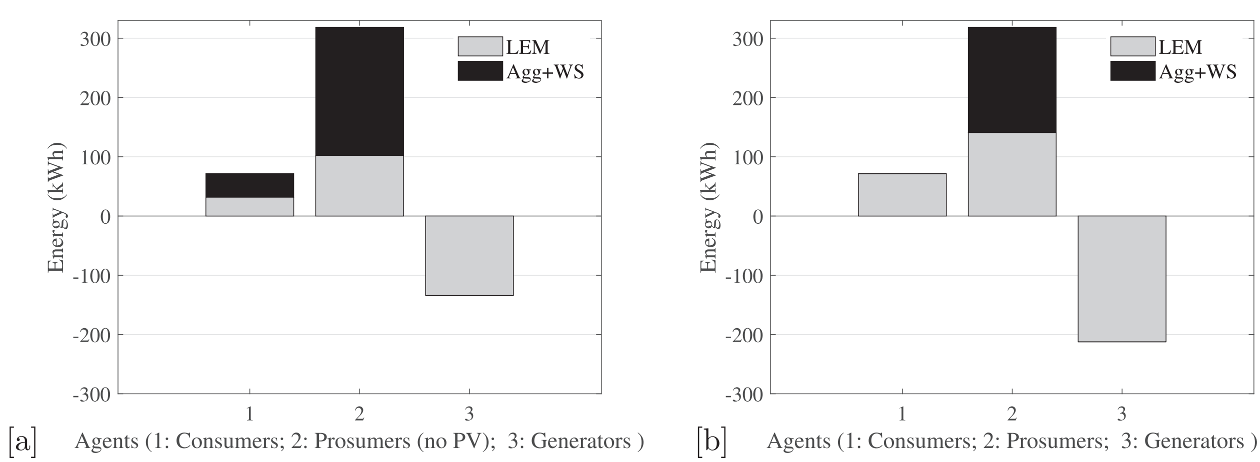

Fig. 9. C2 – 30 agents without PV. Comparing overall LEM and Agg + WSM transactions. [a] Transaction considering consumers as FreeM (free market). [b] Transactions considering consumers as Ptakers (price takers).

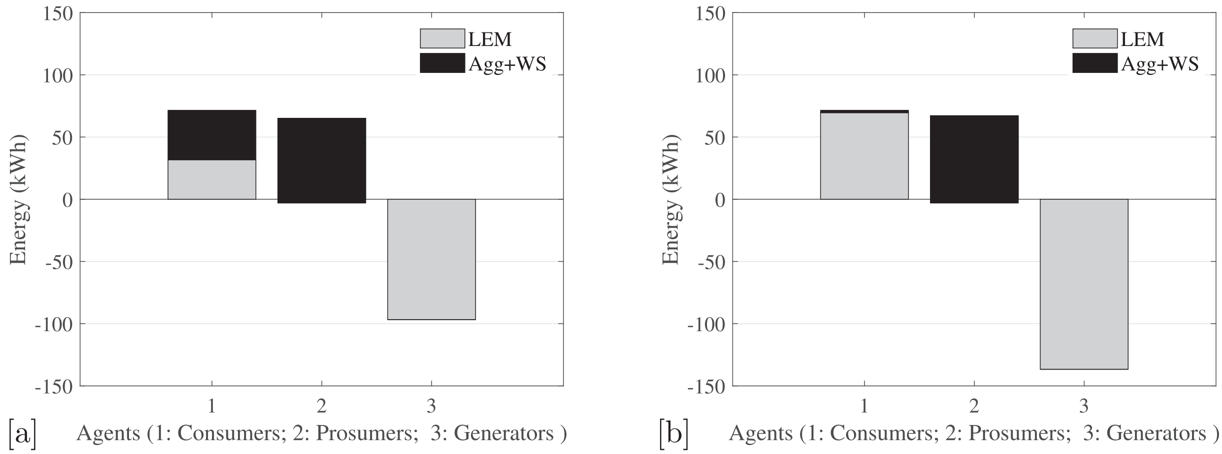

Fig. 10. C3 – 30 agents with PV penetration. Comparing overall LEM and Agg + WSM transactions. [a] Transaction considering consumers as FreeM (free market). [b] Transactions considering consumers as Ptakers (price takers).

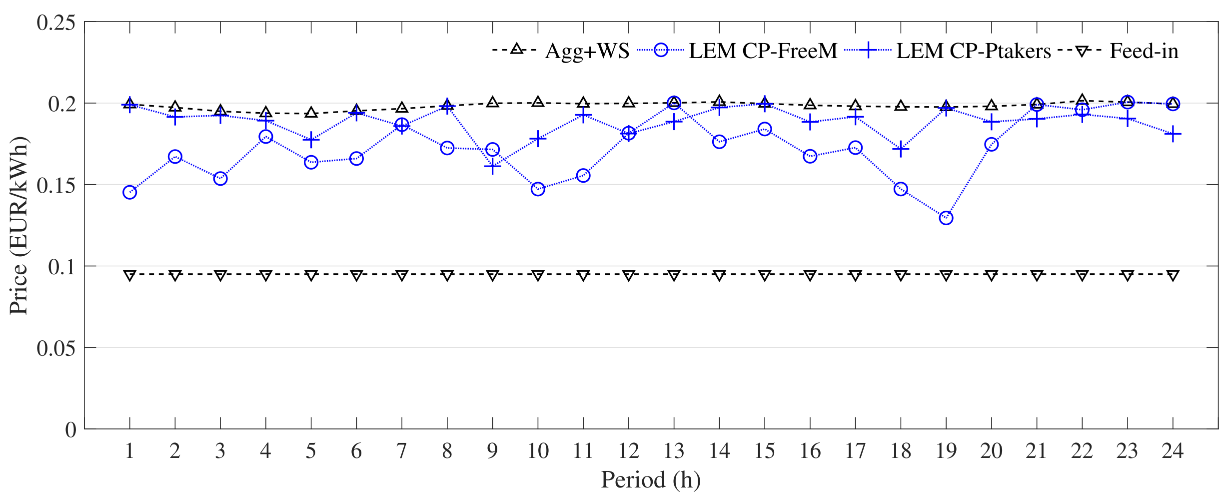

Fig. 11. C2 – 30 agents without PV generation. Resulting LEM clearing prices in each period considering free market and price takers scenarios. The figure also shows the considered aggregator plus WSM price and the feed-in tariff.

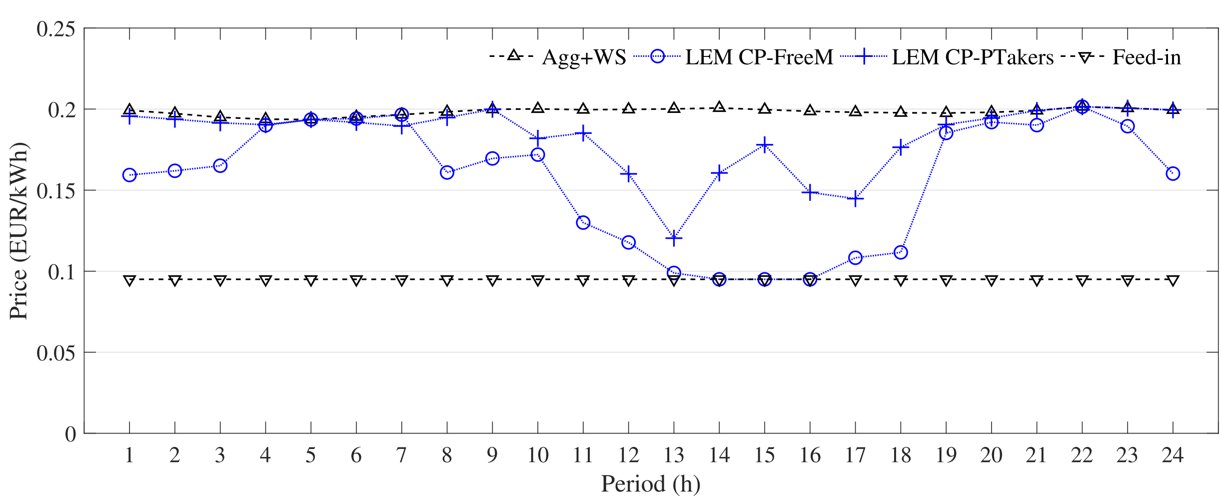

Fig. 12. C3 – 30 agents with PV penetration. Resulting LEM clearing prices in each period considering free market and price takers scenarios. The figure also shows the considered aggregator plus WSM price and the feed-in tariff.

management systems because they will have new mechanisms to compete with LEMs. Also, while our framework was tested for the day-ahead market and considering accurate forecasting, it can be easily extended to manage sequential markets, in which a second round of bidding in the intra-day/balancing market can be implemented both at the local and wholesale level. Such extension needs to deal with uncertainties of renewables and voltage fluctuations and with the requirements of infrastructure that algorithms need to work on a near to real-time basis. Finally, the consideration of flexibility markets is now of interest in energy networks to monitor flows and create market signals that can result in changes in energy supply and demand, integration of smart metering systems, adoption of renewables and energy-efficient resources, etc. Despite the efforts (by for instance the European Commission) promoting flexibility markets, it is still required a high level of digitalisation and automated communication and control, as well as an adaptation of the regulatory framework to support such transition in an efficient manner. The involvement of big players of the market (such as DSO and TSO) is crucial to allow and motivate the participation of new players (including end-users) in this emerging market structures. Despite the promising features of LEMs, which apparently reduce energy costs by a high margin (at least when seen as a whole), our study presents some drawbacks that need some attention in future research. This means that our discussion's narrative can eventually change if these drawbacks are addressed and taken into account. The drawbacks include: 1) The network costs of the distribution network are neglected but can have an impact on the profitability and viability of LEM; 2) the voltage fluctuations and modeling of the distribution network is an aspect that may affect the performance of the system, especially if real-time/flexibility markets and large penetration of distributed energy resources is considered; 3) transaction fees of LEM operator are not taken into account; 4) Geographical location and political decisions (e.g., feed-in tariff) may affect the performance of LEM; 5) Different generation mixes and renewable penetration may also highly influence the LEM results; 6) Interoperability of markets is an open issue that is addressed in this article coupling LEM and WSM, but the integration with other markets, such as intra-day, balancing, or even flexibility markets, might have an impact in the resulting profits of the system. Having said this, our research presents promising results for the integration of LEMs in distribution networks. However, more research is certainly required to extend and complete our discussion.

6. Conclusion

LEMs can be beneficial for end-users, utilities, and the system as a whole. However, the interactions between agents and the penetration of fluctuating distributed resources will pose new challenges regarding the operation and management of distribution grids. Exploring how LEM can be integrated into existing structures of electricity markets (i.e., the WSM) is crucial to take full advantage of energy traded at the local level. In this paper, we have studied a possible LEM framework with a cascading coupling to the WSM. We showed that LEMs can reduce user costs and increase the profits of small producers in realistic case studies. This is achieved due to the better price obtained in the LEM compared to the one provided by the utility/aggregator. We assume an aggregator fixed tariff calculated using the forecast of the WSM prices. This constitutes a risk for the aggregator in case prices in the WSM increase, or when renewable and local generation is able to supply the whole energy required by users (although this situation requires large capacity for generation locally, which is not yet likely to occur). Thus, the aggregator needs to adapt its business models, for instance, opting for the development of contracts with the end-users to secure energy when balancing or supply issues are present (for instance due to high variability of renewable production). Overall, if the LEM and WSM work as expected, benefits for both users and the aggregator are achieved. Notice, however, that such activity might impact the current business model of the utility since local transactions can drastically reduce the use of the grid when enough generation can be procured locally. Therefore, utilities need to take this into account and adapt to the situation by re-thinking the distribution grid models to take the most from LEM. As future work, different lines for research can be followed. For instance, the model of an aggregator that also considers flexibility resources to bid into external markets (e.g., multi-level markets) can be further studied. By considering flexibility markets, other resources such as energy storage systems (including electric vehicles) and demand response should be integrated into the model. Such considerations will certainly increase the complexity of the model since the distribution of profits and the optimal market offers into such markets are not straightforward. Therefore, adapting the framework by modeling a local market of flexibility in which user agents are willing to modify their load profile in exchange for monetary incentives is a natural step towards the implementation of LEM. In addition, another line of research is to consider network constraints and network fees. We have neglected those aspects by assuming that LEM transactions are done withing a voltage limit and that the aggregator tariff offered to the consumers considers grid fees somehow. However, the comprehensive modeling of these aspects should be incorporated into further work to validate the proposed framework in a more realistic and comprehensive manner. Finally, while we have assessed the effectiveness of metaheuristic algorithms solving the problem in reasonable times, adapting the framework will impose a higher degree of complexity into the model, so that the study of efficient algorithms will be key to achieve acceptable results for players involved, and ultimately, achieve real implementation of LEM.

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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References

[1] Lezama F, Soares J, Hernandez-Leal P, Kaisers M, Pinto T, Vale Z. Local energy markets: Paving the path toward fully transactive energy systems. IEEE Trans Power Syst 2018;34:4081–8.
[2] Munné-Collado Í, Bullich-Massagué E, Aragüés-Peñalba M, Olivella-Rosell P. Local and micro power markets. Micro Local Power Markets 2019:37–96.
[3] Chakraborty S, Hernandez-Leal P, Kaisers M. Coordinating distributed and flexible resources: A case-study of residential cooperatives. In: IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe); 2018. p. 1–6.
[4] Soares J, Pinto T, Lezama F, Morais H. Survey on complex optimization and simulation for the new power systems paradigm. Complexity 2018;2018.
[5] Olivella-Rosell P, Bullich-Massagué E, Aragüés-Peñalba M, Sumper A, Ottesen SØ, Vidal-Clos J-A, et al. Optimization problem for meeting distribution system operator requests in local flexibility markets with distributed energy resources. Appl Energy 2018;210:881–95.
[6] Abrishambaf O, Lezama F, Faria P, Vale Z. Towards transactive energy systems: An analysis on current trends. Energy Strategy Rev 2019;26:100418.
[7] Sousa T, Soares T, Pinson P, Moret F, Baroche T, Sorin E. Peer-to-peer and community-based markets: A comprehensive review. Renew Sustain Energy Rev 2019;104:367–78.
[8] Faia R, Soares J, Pinto T, Lezama F, Vale Z, Corchado JM. Optimal model for local energy community scheduling considering peer to peer electricity transactions, IEEE. Access 2021.
[9] Olivella-Rosell P, Torbaghan SS, Gibescu M. Coupled local power markets. Micro and Local Power Markets 2019:165–91.

[10] Tohidi Y, Farrokhseresht M, Gibescu M. A review on coordination schemes between local and central electricity markets. In: International Conference on the European Energy Market (EEM); 2018. p. 1–5.
[11] Mengelkamp E, Notheisen B, Beer C, Dauer D, Weinhardt C. A blockchain-based smart grid: Towards sustainable local energy markets. Computer Sci-Res Develop 2018;33:207–14.
[12] Santos G, Pinto T, Morais H, Sousa TM, Pereira IF, Fernandes R, et al. Multi-agent simulation of competitive electricity markets: Autonomous systems cooperation for european market modeling. Energy Convers Manage 2015;99:387–99.
[13] Mengelkamp E, Staudt P, Garttner J, Weinhardt C. Trading on local energy markets: A comparison of market designs and bidding strategies. In: International Conference on the European Energy Market (EEM). IEEE; 2017. p. 1–6.
[14] Ottesen SØ, Tomasgard A, Fleten S-E. Multi market bidding strategies for demand side flexibility aggregators in electricity markets. Energy 2018;149:120–34.
[15] Paudel A, Chaudhari K, Long C, Gooi HB. Peer-to-peer energy trading in a prosumer-based community microgrid: A game-theoretic model. IEEE Trans Ind Electron 2018;66:6087–97.
[16] David AK, Wen F. Strategic bidding in competitive electricity markets: a literature survey. In: IEEE Power Engineering Society Summer Meeting (Cat. No. 00CH37134). vol. 4; 2000. p. 2168–73.
[17] Nezamabadi H, Vahidinasab V. Micro-grids bidding strategy in a transactive energy market. Scientia Iranica 2019;26:3622–34.
[18] Celebi E, Fuller JD. A model for efficient consumer pricing schemes in electricity markets. IEEE Trans Power Syst 2007;22:60–7.
[19] Bahramara S, Moghaddam MP, Haghifam M. A bi-level optimization model for operation of distribution networks with micro-grids. Int J Electr Power Energy Syst 2016;82:169–78.
[20] Lüth A, Zepter JM, del Granado PC, Egging R. Local electricity market designs for peer-to-peer trading: The role of battery flexibility. Appl Energy 2018;229:1233–43.
[21] Zepter JM, Lüth A, del Granado PC, Egging R. Prosumer integration in wholesale electricity markets: Synergies of peer-to-peer trade and residential storage. Energy Build 2019;184:163–76.
[22] Zhang Z, Li R, Li F. A novel peer-to-peer local electricity market for joint trading of energy and uncertainty. IEEE Trans Smart Grid 2020;11:1205–15.
[23] Ma Y, Jiang C, Hou Z, Wang C. The formulation of the optimal strategies for the electricity producers based on the particle swarm optimization algorithm. IEEE Trans Power Syst 2006;21:1663–71.
[24] Zhang G, Zhang G, Gao Y, Lu J. A bilevel optimization model and a PSO-based algorithm in day-ahead electricity markets. In: IEEE International Conference on Systems, Man and Cybernetics; 2009. p. 611–6.
[25] Zhang G, Zhang G, Gao Y, Lu J. Competitive strategic bidding optimization in electricity markets using bilevel programming and swarm technique. IEEE Trans Ind Electron 2010;58:2138–46.
[26] Soleymani S. Bidding strategy of generation companies using PSO combined with SA method in the pay as bid markets. Int J Electr Power Energy Syst 2011;33:1272–8.
[27] Lezama F, Soares J, Vale Z. Optimal bidding in local energy markets using evolutionary computation. In: IEEE International Conference on Intelligent System Application to Power Systems (ISAP); 2019. p. 1–6.
[28] Lezama F, Faia R, Soares J, Faria P, Vale Z. Learning bidding strategies in local electricity markets using ant colony optimization. IEEE Congress on Evolutionary Computation (CEC; 2020. p. 1–8.
[29] Mengelkamp E, Gärttner J, Weinhardt C. Intelligent agent strategies for residential customers in local electricity markets. In: Proceedings of the Ninth International Conference on Future Energy Systems; 2018. p. 97–107.
[30] Lezama F, Soares J, Faia R, Faria P, Vale Z. Learning bidding strategies in local electricity markets using a nature-inspired algorithm. In: International Conference on the European Energy Market (EEM); 2020. p. 1–6.
[31] Lago J, De Ridder F, Vrancx P, De Schutter B. Forecasting day-ahead electricity prices in Europe: the importance of considering market integration. Appl Energy 2018;211:890–903.
[32] Gonçalves C, Pinson P, Bessa RJ. Towards data markets in renewable energy forecasting. IEEE Trans Sustainable Energy 2020.
[33] Zhou B, Li W, Chan KW, Cao Y, Kuang Y, Liu X, et al. Smart home energy management systems: Concept, configurations, and scheduling strategies. Renew Sustain Energy Rev 2016;61:30–40.
[34] Mengelkamp EM. Engineering Local Electricity Markets for Residential Communities. Ph.D. thesis. Karlsruher Institut für Technologie (KIT); 2019. https://doi.org/10.5445/IR/1000095229. 37.06.01; LK 01.
[35] Parsons S, Marcinkiewicz M, Niu J, Phelps S. Everything you wanted to know about double auctions, but were afraid to (bid or) ask. Department of Computer & Information Science, University of New York 2006.
[36] Sandgani MR, Sirouspour S. Coordinated optimal dispatch of energy storage in a network of grid-connected microgrids. IEEE Trans Sustain Energy 2017;8:1166–76.
[37] Lezama F, Soares J, Faia R, Pinto T, Vale Z. A new hybrid-adaptive differential evolution for a smart grid application under uncertainty. In: IEEE Congress on Evolutionary Computation (CEC); 2018. p. 1–8.
[38] Dogan B, Olmez T. A new metaheuristic for numerical function optimization: Vortex search algorithm. Inf Sci 2015;293:125–45.
[39] Martínez-López Y, Rodríguez-González AY, Quintana JM, Mayedo MB, Moya A, Santiago OM. Applying some EDAs and hybrid variants to the ERM problem under uncertainty, in. Genetic and Evolutionary Computation Conference Companion (GECCO) 2020:1–2.
[40] Dorigo M, Birattari M, Stutzle T. Ant colony optimization. IEEE Comput Intell Mag 2006;1:28–39.
[41] Das S, Suganthan PN. Differential evolution: A survey of the state-of-the-art. IEEE Trans Evol Comput 2011;15:4–31.
[42] Lezama F, Soares J, Faia R, Vale Z. Hybrid-adaptive differential evolution with decay function (HyDE-DF) applied to the 100-digit challenge competition on single objective numerical optimization. New York, NY, USA: ACM; 2019. p. 7–8.
[43] Larranaga P, Etxeberria R, Lozano J, Pena J, Pe J, et al. Optimization by learning and simulation of bayesian and gaussian networks. Citeseer 1999.
[44] Alba E, Madera J, Dorronsoro B, Ochoa A, Soto M. Theory and practice of cellular umda for discrete optimization. In: Parallel Problem Solving from Nature-PPSN IX. Springer; 2006. p. 242–51.
[45] Martnez-López Y, Madera J, Rodrguez-González AY, Barigye S. Cellular estimation gaussian algorithm for continuous domain. J Intell Fuzzy Syst 2019;36:4957–67.
[46] Fan S, Hyndman RJ. The price elasticity of electricity demand in south australia. Energy Policy 2011;39:3709–19.
[47] Burger S, Chaves-Ávila JP, Batlle C, Pérez-Arriaga IJ. A review of the value of aggregators in electricity systems. Renewable and Sustainable Energy Reviews 2017;77:395–405.