Bidding in Local Electricity Markets Considering Low Voltage Grid Constraints

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***Abstract*—Local electricity markets give end-users the ability to trade electricity at the distribution level. However, distributed energy transactions can threaten the correct operation and stability of the grid. This article proposes a local market framework and analyzes the impact of local energy transactions on the grid. A distribution system operator is considered, calculating the power losses and voltage limit violations after the LEM is cleared. The framework is validated considering 55 users and 6 strategic bidders trading energy in a low voltage grid. Results show an improvement in costs and incomes for market participants and network operation when the islanded LEM is considered. Counter intuitively, selecting a plain tariff improves local generation guaranteeing smooth grid operation and energy transactions but affecting consumers' costs. These findings show that more scrutiny of results is needed when several participants with different objectives, including the network operator, are considered in local electricity markets.**

***Index Terms*-- Auction-based market, computational intelligence, local electricity markets, low voltage grid, renewable generation.**

I. Introduction

Local electricity markets (LEM) are attracting the attention of stakeholders at the distribution level, pushing for the decarbonization and decentralization of energy systems[1]. Furthermore, these new market structures enable the participation of end-users as active market players, eager to take full advantage of their generation capabilities (in the form of renewables or distributed generation) and flexibility [2].

While LEMs unlock benefits for several stakeholders (e.g., utilities, system operators, and end-users), different challenges must be overcome before implementation of such systems in practice. Different market structures and frameworks have been proposed in the literature to analyze LEM from different perspectives. For instance, models focusing on energy communities [3], [4], aggregators [2], [5], or DSO-TSO coordination [6], [7], have been proposed in an attempt to find the best means for exploiting market transactions of end-users. From the literature studying LEMs, it is evident that local transactions cannot be decoupled from higher levels of the electricity grid and their impact, primarily in the distribution network (DN), plays a key role in the design and implementation of such systems.

In this article, the interaction between market participants at the local level is considered, taking into account the validation and needs of the distribution network operator (DSO). The proposed framework is constructed following [8], in which different types of players, namely consumers, prosumers, and combined heat and power (CHP) generators, participate in a day-ahead double-auction LEM. In addition to [8], this work considers the IEEE European Low Voltage Test Feeder, a radial distribution topology with 116 buses and 115 lines [9]. In this way, the impact of LEM transactions on the distribution network (DN) can be quantified utilizing power flow assessment. It is assumed that smart grid technologies (e.g., smart meters and management systems) are available for all market participants and the DSO, allowing local energy transactions and network validation accordingly [10].

We formulate a multi-leader single-follower bi-level optimization problem for strategic bidding in the LEM with these considerations. In such a model, competitive agents search for maximization of profits at the upper-level, and the LEM maximizes energy transacted at the lower-level. In addition, keeping DSO and LEM operation decoupled, a postface is considered to quantify DN losses and grid constraints violations in function of LEM response. While such a scenario can be (not easily) solved to optimality under the (not very realistic) assumption of complete perfect information, users would like to preserve private information and perform strategic bidding according to their interests. Therefore, we use the ant colony optimization (ACO) algorithm, a learning approach, to determine the best bidding strategies for producers. While such a technique is a metaheuristic method, it was empirically tested under similar frameworks in [8], [11].

The main contributions of the article are: i) a model for optimization of energy bids in LEM including DN validation; ii) Implementation of a framework and simulation environment including a learning algorithm (the ACO) for strategic bidding in LEMs; iii) Analysis of the impact of LEM transactions on the DN and users' profits considering different grid tariffs.

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II. PROBLEM FORMULATION

We consider a LEM in which consumers, prosumers (with PV generation), and CHP producers transact energy aiming at minimizing costs (in the case of consumers) and maximizing incomes (in the case of prosumers and producers). The innovation of this work is to consider a DSO for the validation of DN constraints. Thus, assuming a sequential interaction between the LEM operator and the DSO, the losses in the DN are considered, searching for energy transactions that favor market participants and guarantee a reduction of DN losses (something in which the DSO is naturally interested). Figure 1 illustrates the scenario considered in this article.

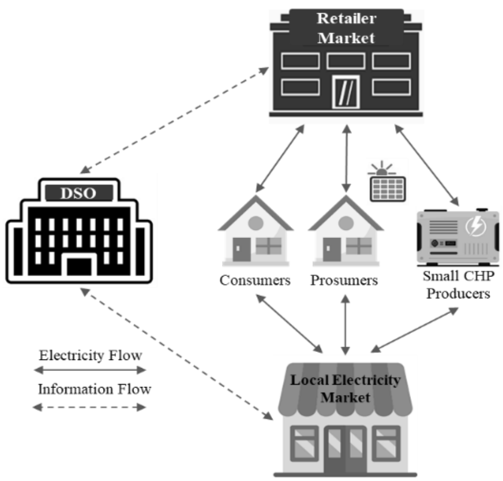

Figure 1. LEM, retailer and DSO interactions.

A. Mathematical model

The modeling of the problem considers a set of consumers $I = \{1,2,\dots,N_c\}$, and producers $J = \{1,2,\dots,N_p\}$. Prosumers act as consumer when their PV generation is not enough to satisfy their total consumption, or as a producer in the periods where they have PV generation surplus. Thus, a bi-level model for strategic bidding is proposed as follows:

1) Upper-level (multiple-followers): The upper-level models the independent costs/profits that market participants expect by putting bids/offers in the LEM. Consumers' bids are characterized as a tuple $(s_{i,t}, d_{i,t})$, where $s_{i,t}$ is a price bid for energy $d_{i,t}$ at time t. Consumers' minimization of costs is modelled as:

$$\min_{s_{i,t},d_{i,t}} C_i = \sum_{t=1}^{T}\left(\sum_{j} cp_t \cdot x_{j,i,t} + c_t^{\text{grid}} \cdot E_{i,t}^{\text{buy}}\right) \tag{1a}$$

st.

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

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

where $x_{j,i,t}$ is the energy bought by agent i from agent j in the LEM (kWh); $E_{i,t}^{\text{buy}}$ is the energy bought by agent i from the grid (kWh); cp_t is the LEM clearing price (EUR/kWh); and c_t^{grid} is the grid tariff (EUR/kWh). (1b) guarantees that the total demand of agent i ($d_{i,t}^{\text{Total}}$) is supplied either by the LEM or the grid; (1c) guarantees that the LEM cp_t is higher than the feed-in tariff c_t^{F}, and lower or equal to the bid price $s_{i,t}$ and the grid tariff c_t^{grid} (making the LEM profitable for consumers). All variables are considered non-negative.

On the other hand, producers' incomes are calculated in function of their offers modeled as a tuple $(s_{j,t}, g_{j,t})$, where $s_{j,t}$ is a price offer for energy $g_{j,t}$ at time t. Thus, producers maximize incomes as:

$$\max_{s_{j,t},g_{j,t}} In_j = \sum_{t=1}^{T}\left(\sum_{i} cp_t \cdot x_{j,i,t} + c_t^{\text{F}} \cdot E_{j,t,s}^{\text{sell}} - \mathbf{C}_{j,t}^{\text{total}}\right) \tag{2a}$$

st.

$$g_{j,t}^{\text{Total}} = \begin{cases} \sum_{i,j\neq i} x_{j,i,t} + E_{j,t}^{\text{sell}} & \text{for PV} \\ \sum_{i,j\neq i} x_{j,i,t} & \text{for CHP} \end{cases} \qquad \forall t \in T \tag{2b}$$

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

where $x_{j,i,t}$ is the energy sold by agent j to agent i in the LEM (kWh); $E_{j,t}^{\text{sell}}$ is the energy sold by agent j to the grid (only PV generation can be injected into the grid) in kWh; cp_t is the LEM clearing price (EUR/kWh); c_t^{F} is the feed-in tariff (EUR/kWh); and $\mathbf{C}_{j,t}^{\text{total}}$ is the total production cost of local generation. Constraint (2b) is used to guarantee that PV generation of player j is transacted in the LEM and fed into the grid, or that CHP production is limited to the one transacted in the LEM; constraint (2c) bounds producers' offers $s_{j,t}$ between the feed-in tariff c_t^{F} and the grid tariff c_t^{grid}. All variables are non-negative. The production cost $\mathbf{C}_{j,t}^{\text{total}}$ is 0 for PV generation and $(2 \cdot b_{CHP} \cdot \sqrt{G_{j,t}})$ for CHP producers, where b_{CHP} is a cost factor and $G_{j,t}$ is the energy produced by the CHP unit.

2) Lower-level (single-follower): The expected costs and incomes of the upper-level problem are directly related to the LEM clearing price cp_t. To solve the lower level problem efficiently, we modelled it as a symmetric pool-based market mechanism [12]. In a first step, the supply curve is obtained by defining GE containing the offers of energy $(s_{j,t}, g_{j,t})$ in ascending order of price, and the demand curve DE containing the bids for energy $(s_{i,t}, d_{i,t})$ in descending order of price. The price at which supply equals demand is known as the equilibrium price (or clearing price) and can modelled as:

$$\max_{d_i^*,g_j^*} \sum_{i=1}^{N_c} \lambda_i^{\text{d}} \cdot d_i^* - \sum_{j=1}^{N_p} \lambda_j^{\text{g}} \cdot g_j^* \tag{4a}$$

st.

$$\sum_{i=1}^{N_c} d_i^* - \sum_{j=1}^{N_p} g_j^* = 0 \qquad : cp_t (\text{dual variable}) \tag{4b}$$

$$0 \le d_i^* \le DE_i, \qquad i = 1,\dots,N_c \tag{4c}$$

$$0 \le g_j^* \le GE_j, \qquad j = 1,\dots,N_p \tag{4d}$$

where d_i^* and g_j^* are the demand bids and supply offers ordered by price (i.e., belonging to the sets DE_i and GE_j), and λ_i^{d} and λ_j^{g} are their corresponding bid/offer prices. Eq. (3a) maximizes the social welfare of players; Eq. (3b) is the balance equation from which the clearing price cp_t can be obtained taking its corresponding dual variable; Equations (3c) and (3d) guarantees that generation/consumption limits are respected. Any commercial mathematical software can solve the corresponding linear model. A reverse procedure is implemented to determine the corresponding LEM transactions $x_{i,j}$ and $x_{j,i}$ from the accepted d_i^* and g_j^*.

B. Network Constraints

The LEM transactions occur at the distribution level, and therefore, decisions on the traded volumes have an impact on the DN performance. Using MATPOWER, we perform a power flow analysis after LEM response to determine DN current and voltages after CHP local production has been committed. It is assumed that the DSO aims at the minimization of voltage violations and network losses as:

$$\min_{g_j^{\text{CHP}}} DN^{\text{impact}} = \sum_{t=1}^{T} \left(\sum_{b \in \Omega_b} B_{t,b} + \sum_{b \in \Omega_b} \theta_{t,b} + \sum_{l \in \Omega_l} L_{t,l} + \sum_{l \in \Omega_l} P_{t,l}^{\text{loss}} + \sum_{l \in \Omega_l} Q_{t,l}^{\text{loss}} \right) \tag{5}$$

where $B_{t,b}/\theta_{t,b}/L_{t,l}$ are set to 1 if a voltage/angle/line limit violation occur in bus b or line l; $P_{t,l}^{\text{loss}}$ and $Q_{t,l}^{\text{loss}}$ are the active and reactive power (kWh) in line l; and DN^{impact} is a unitless measure of the status of the network. We are aware that this value is not a realistic measure of how DSO validate network status but has been used in this work as a simplistic and easy-to-integrate measure of DN status.

III. Simulation and Validation Framework

The resulting bi-level problem with network validation involves different actors with different objectives and private information. To keep all optimization procedures separately (i.e., profits maximization of agents, transacted energy maximization of LEM, and network losses minimization of DSO), we implemented a simulation and validation framework using the ACO algorithm for the strategic bidding of players, a linear-programming (LP) model for market-clearing, and MATPOWER software for DSO power flow validation. The different blocks and their implementation are explained in the following subsections.

A. Metaheuristics for strategic bidding

Players need to find the best strategy for bidding in the LEM and maximize profits. For this first step in the decision process, we define a set of players $K = \{1,2,\ldots,N_k\}$ in which each player k is either a consumer or producer. Each player then defines a tuple $(q_{k,t}, p_{k,t}) \forall k \in K, \forall t \in T$ representing bids/offers of quantity and price, i.e., $(s_{i,t}, d_{i,t})$ or $(s_{j,t}, g_{j,t})$ depending if the player is a consumer or producer in that time step. A sign convention is used to differentiate energy offers (negative value for selling energy) from bids (positive value for buying energy) in variable $q_{k,t}$. Thus, a complete solution to our problem is a vector $\vec{x} = \{[q_{k,t}] \cup [p_{k,t}]\}$, including all bids/offers registered. We use a distributed ACO algorithm to learn/improve players decisions over time. ACO is 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 clear paths to food. In other words, ACO exploits a problem-solving mechanism by reinforcing paths (solutions) that show good performance in a given fitness function [13]. The details on the implementation of distributed ACO for this problem are omitted due to space constraints but can be found in [8].

Important to recall the following: each prosumer k with PV surplus is forced to inject this energy into the grid at the feed-in tariff; CHP offer price $s_{j,t}$ is adjusted to be higher or equal than the resulting $g_{j,t}$ production cost (or set to 0 otherwise); consumers are price takers ($s_{i,t} = c_t^{\text{grid}}$) and inelastic loads ($d_{i,t} = d_{i,t}^{\text{Total}}$); we only focus on the learning process of CHPs. After having all bids and offers from market participants, the lower-level problem is solved by first performing a merit order procedure and solving the LP model from Eq. (4). The results from this step are the accepted bids/offers $x_{i,j,t}/x_{j,i,t}$ and clearing price cp_t.

With all this information, we calculate the costs and incomes for each player using Eqs. (1a) and (2a) as:

$$U_{k,t} = \begin{cases} -C_{i,t} \text{ if } k \text{ is a consumer agent} \\ P_{j,t} \text{ if } k \text{ is a generator agent} \end{cases} \tag{6a}$$

$$U_k^{\text{total}} = \sum_{t=1}^{T} U_{k,t} \tag{6b}$$

where $C_{i,t}$ and $P_{j,t}$ are the objectives of each player optimized independently. The total profits of all agents can be later recorded in a vector $A_{\text{profit}} = [U_1^{\text{total}}, \ldots, U_k^{\text{total}}, \ldots, U_{N_k}^{\text{total}}]$, used for performance calculation.

B. Distribution network validation

After players' bids/offers are set and the LEM has been cleared, we use power flow calculations to determine the DN state in buses and lines. We applied MATPOWER at each iteration, varying the CHP generation in function of the LEM results. Notice that, since consumers are considered inelastic loads, and prosumers are forced to inject their total PV generation into the LEM or grid, the CHP production is the only distributed generation affecting the DN constraints. This also makes the DN validation a very fast procedure since market clearing results can be easily implemented. The results of power flow validation include voltage limit violations in buses and lines, angles, and active and reactive power losses. We define a penalty function using Eq. (5) to define $p_t^{\text{DN}} = DN^{\text{impact}}$. The LEM results and DN validation are combined in the fitness function to have a complete picture of the performance of a solution.

C. *Fitness function including network losses*

The fitness function is modelled to reflect the performance of a solution taking into account the objectives of all the involved players. While this performance metric is not realistic in practice (since players might not be able to share private performance information), it gives you a sense of profit maximization, LEM performance, and DN validation all at once. Thus, the fitness function is defined as:

$$Fit(\vec{x}) = -\mathbf{mean}(A_{\text{profit}}) + \mathbf{std}(A_{\text{profit}}) + \sum_{t=1}^{T} p_t^{\text{LEM}} + \sum_{t=1}^{T} p_t^{\text{DN}} \quad (7)$$

where $A_{\text{profit}} = [U_1, \dots, U_k, \dots, U_{N_k}]$ is the vector with the profits of players; $\mathbf{mean}()$ and $\mathbf{std}()$ are functions that return the mean and standard deviation values; $\sum_{t=1}^{T} p_t^{\text{LEM}}$ is a penalty added to the fitness when the LEM is not cleared ($p_t^{\text{LEM}} = 1e4$, in this work to make pressure towards solutions that clear the LEM); and $\sum_{t=1}^{T} p_t^{\text{DN}}$ is a penalty related to the DN constraints defined in Eq. (5). The implementation of this framework can be found at https://fernandolezama.github.io/publication.

IV. Case Study

We tested the model in an environment considering 61 players bidding in an hourly day-ahead LEM. From the 61players, 13 are consumers, 6 are CHP producers, and 42 are prosumers (with PV generation). The peak power consumption in the network is approximately 140.49 kW with a peak power PV generation of 193.69 kW. The CHP generators have a maximum capacity of 10kW, and a factor $b_{CHP} = 0.20$ EUR/kWh used to calculate their production cost (Eq. (3)). Regarding tariff limits, we assume a flat feed-in tariff of $c_t^{\text{F}} = 0.045 \; \forall t \in T$, and two retail tariffs, namely a plain tariff of 0.158 €/kWh a bi-hourly tariff of 0.1023 €/kWh in off-peak periods, and 0.1924 €/kWh in peak periods (i.e., from 9 to 22).

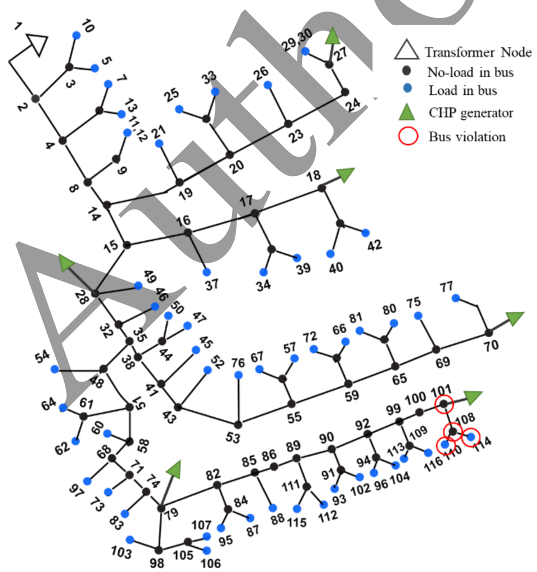

Figure 2. Equivalent model of the IEEE low voltage test feeder adapted from [9].

Fig 2 presents the single line diagram of the IEEE European LV test feeder [9]. The radial network has base frequency of 50 Hz, 55 loads, 114 buses, and 115 lines. It is connected to a medium voltage transformer of 0.8 MVA stepping the voltage from 11kV to 416 kV. For simulations, 42 PV generators are installed in load buses simulating prosumers that use such PV for self-consumption, selling the excess to the grid or the LEM. Finally, 6 CHP units are included in buses 18, 27, 28, 70, 79, and 108.

Table I summarizes the case studies defined to evaluate players' performance under different situations. Base case 1 and Base case 2 are used to quantify the total costs for market participants under two different tariffs when no LEM and DN constraints are considered (i.e., the base cases). Case 1 and Case 2, on the contrary, are defined to analyze the impact of the optimization model and results when LEM and DN constraints are considered.

TABLE I. Analysed cases in this article.

	LEM	**DN**	**Tariff**
Base case 1	no	no	Plain
Base case 2	no	no	Bi-hourly
Case 1	yes	yes	Plain
Case 2	yes	yes	Bi-hourly

Finally, the ACO parameters ρ, α, β are set equal to [8]. The number of iterations and ants (solutions) is set to 500 and 20 respectively. All iterations are performed for the same day with the same network and load initial values. We performed 10 runs for each experiment due to the stochastic nature of the optimizer, reporting the best value found of the metrics. The experiments were implemented in MATLAB 2018a in a computer with Intel (R) Core (TM) i7-8650U CPU@1.90GHz processor with 16GB of RAM running Windows 10.

V. Results and Discussion

Table II shows the results in terms of profits by type of players and in total, the fitness value (Eq. (6b)), the execution time for Base cases 1 and 2, and the best solution found over 10 runs of the ACO. Notice that Base cases 1 and 2 do not include producers' profits since CHP participation is only allowed when LEM are considered. Also, while ACO is a metaheuristic providing different results in each run, we reported just the best value found for the sake of clarity in analyzing the values and plots obtained. The results from Table II indicate that the cost of consumers and prosumers decreases w.r.t. the two base cases, achieving the minimum value when the bi-hourly tariff is considered (i.e., Case 2). In fact, the best incomes for consumers and prosumers are also achieved for Case 2, improving by around 2 EUR compared to Case 1 (plain tariff) and up to 7 EUR compared to Base case 1 and 2 (when no LEM is considered). Analyzing the producer's performance, Case 1 and Case 2 result in similar profits (a difference of just some cents), yet the incomes perceived by the CHP generators are much higher in Case 1 (around 65 EUR higher than Case 2) which indicates CHP produce more in Case 1 (which is actually counterintuitive). While total costs, incomes, and profits impro-

TABLE II. OVERALL COSTS/INCOMES/PROFITS, FITNESS, AND EXECUTION TIME IN EACH CASE.

	Consumers & prosumers (EUR)			Producers (EUR)			Total (EUR)			Fitness	Time (mins)
	Cost	Income	Profit (loss[a])	Cost	Income	Profit (loss[a])	Cost	Income	Profit (loss[a])		
Base case 1	-217.33	13.43	-203.89	-	-	-	-217.33	13.43	-203.89	81.41	-
Base case 2	-203.69	13.43	-190.26	-	-	-	-203.69	13.43	-190.26	80.95	-
Case 1	-209.44	18.79	-190.65	121.58	148.37	26.79	-209.44	45.58	-163.86	18.52	53.48
Case 2	-193.44	20.21	-173.23	56.44	82.81	26.37	-193.44	46.58	-146.86	46.83	57.27

[a] Profits are calculated as Incomes minus Costs. Thus, a negative value of profits indicates a loss (i.e., costs are higher than incomes)

ve in Case 2 w.r.t. Case 1, the fitness value actually increases from 18.52 to 46.83, indicating that the solution found presents higher penalties than the one of Case 1.

To corroborate this, Table III summarizes the limit violations and the losses found on the DN for each case analyzed. Here we can see that Base cases 1 and 2, which are actually equivalent from the perspective of the network, present 14 limit violations in buses 101, 108, 110, and 114 (depicted these violations in Fig. 2 with red circles) and active power losses of 48.36 kWh. When the LEM and a plain tariff are considered (i.e., Case 1), the active power losses are reduced to only 10.57 kWh, and all buses limit violations are mitigated (remember that this is achieved considering a plain tariff that results in higher costs for consumers and prosumers as shown in Table II). When the bi-hourly tariff is considered (i.e., Case 2), the limit violations in buses cannot be fully mitigated, and power losses increase w.r.t. Case 1, confirming that less CHP generation is actually unfavorable from the DSO perspective.

TABLE III. DN CONSTRAINTS RESULTS OBTAINED IN EACH CASE.

	Limit violations (number)			Losses (kWh)	
	Lines	Buses	Angles	Active	Reactive
Base Case 1	0	14	0	48.36	8.74
Base Case 2	0	14	0	48.36	8.74
Case 1	0	0	0	10.57	1.92
Case 2	0	5	0	30.71	5.57

Fig. 3 shows the LEM clearing prices obtained in the reported Case 1 and Case 2 results to go further into the details. We confirmed that, when the plain tariff is used (Fig. 3a), the LEM is cleared in all the periods, with most values near or equal to the grid tariff, which is beneficial for CHPs and prosumers. We can also see that periods 11,14-16 are cleared with low prices (equal to the feed-in tariff), which can be explained by the preference of buying the excess of PV generation in those periods due to its 0 production cost. On the other hand, Fig. 3b shows that LEM is not cleared in periods 1-8 and 23-24. This can be explained by the settings of the CHP production cost, which results in a higher cost than the maximum price they can get from the LEM market in those periods (remember that players attending the LEM are not willing to pay a higher cost than the one set by the grid tariff). The low price of the bi-hourly tariff, in combination with no PV production, makes the LEM useless affecting the performance of the DN.

Finally, Fig. 4 contrasts the energy bought and sold from the grid and LEM and depicts the PV and CHP generation for Cases 1 and 2. The figure supports our previous statements, showing in Fig. 4b that there is no CHP and PV production in periods 1-8, 23-24 for Case 2, resulting in 0 energy traded in the LEM market, and also showing that the excess of PV generation in periods 11-16 affect the CHP production. This situation applies to both Cases (see Fig. 4a and Fig. 4b).

VI. CONCLUSIONS

This paper proposes a framework for strategic bidding in LEM considering DN constraints. We assume that market participants do not share private information, resulting in a competitive LEM with agents striving to maximize profits. We also assume that consumers are inelastic loads and price takers, focusing on the strategic bidding of CHP producers. The results show that the LEM is advantageous for market players and the operation of the DN, minimizing losses and voltage limit violations. Surprisingly, the results also show that the grid tariff (an upper level for the price that CHP producers can offer) limits the participation of local producers in some periods due to the low cost of imported energy from the grid. These results make evident the need of further studies in the design and implementation of LEMs involving the objectives of a variety of market participants. For instance, while the fitness function (that measures the performance of a solution) was utilized in the simulation environment, in practice, agents do not have access to such performance measure. In any case, it is desired that all players search for the maximization of social welfare, so coordination between market participants, LEM operator, and DSO could be a good avenue for future research. In fact, the interconnection of the LEM with the larger system and other markets, and how LEM can provide flexibility to those while not while not violating distribution network constraints is an important topic to study in the future. Another line of research could be related to the analysis of the relation between local production cost, network losses cost, and LEM clearing price to find the best compromise between the involved players. Finally, future work must consider other distributed energy resources (e.g., EVs or storage systems) and time horizons to fully unlock the benefits promised by LEM in practice.

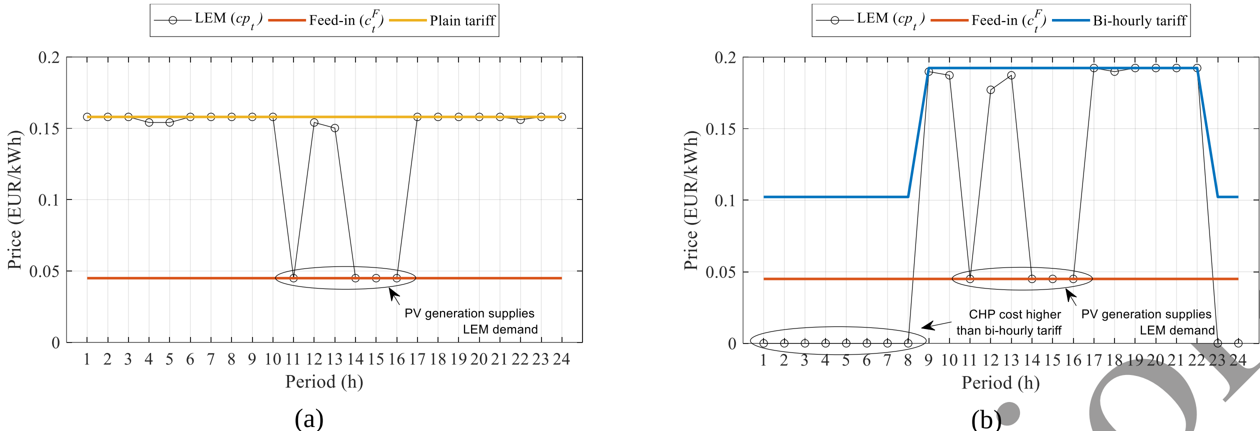

Figure 3. Obtained clearing prices in the LEM. (a) Case 1 – plain tariff; (b) Case 2 – bi-hourly tariff.

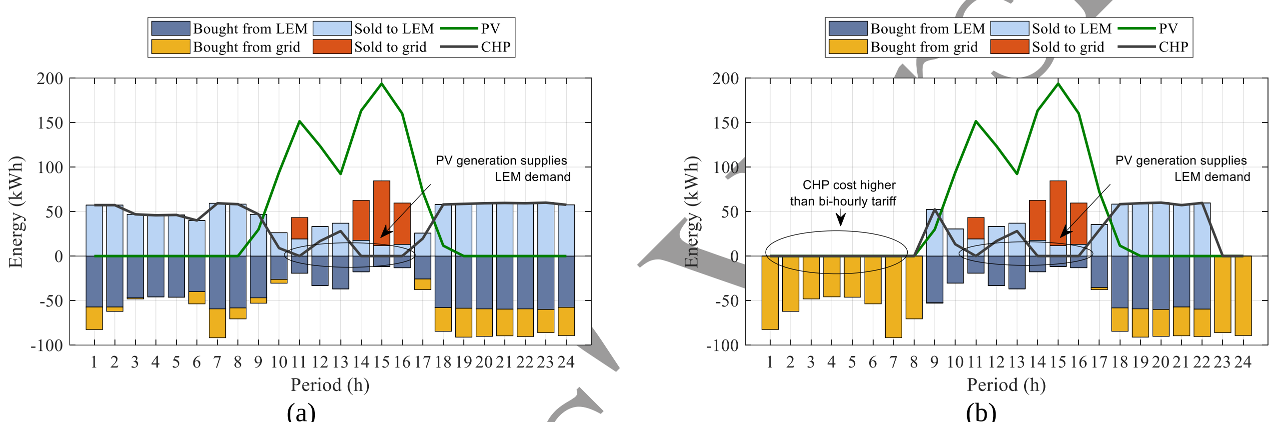

Figure 4. Energy transacted in the LEM and grid as well as PV and CHP production. (a) Case 1 – plain tariff; (b) Case 2 – bi-hourly tariff.

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