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A MBNLP Method for Centralized Energy Pricing and Scheduling in Local Energy Community

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***Abstract*— This paper proposes a new optimization model for pricing and demand scheduling in a grid-connected local energy community (LEC), including residential homes (consumers and prosumers), and combined heat and power (CHP) generation units. It is assumed that some homes have photovoltaic (PV) generation, electric vehicles (EVs), or both. A central entity is responsible for managing the EVs' charging and discharging process, and for scheduling energy exchanges among homes. Moreover, the central entity is responsible for setting the LEC-price for the energy exchanged between CHP producers and homes, and among homes themselves. We model and solve the problem with a mixed binary non-linear programming (MBNLP) approach with the objective to maximize the total benefit of consumers/prosumers. The LEC-price is set based on demand and supply. The proposed approach is applied to a case study with 100 homes and 5 CHP generation units, and the results are reported for three different electricity grid tariffs A, B, and C. The results suggest 12%, 10% and 23% cost reduction in comparison with not considering the LEC respectively for tariffs A, B, and C.**

Keywords*— *centralized scheduling, energy management system, energy pricing, local energy community, mixed binary nonlinear problem.

I. INTRODUCTION

Local energy communities (LECs) are attracting the attention of stakeholders at the distribution level, pursuing decarbonization and decentralization of energy systems. They allow local energy trading between hundreds or thousands of agents willing to trade energy with their neighbors in order to receive financial benefits [1]. Such an organization of end-users and other stakeholders is also referred to as "local energy market" because the trading occurs nearby (locally), with some sort of economic exchange, i.e., a commodity traded (the "energy"), and a settled price between the buyer and the seller (the market). In this context, each house could be equipped with distributed resources (e.g., photovoltaic (PV) generation and electric vehicles (EVs)), while some independent producers sell energy to nearby consumers within the community.

These new market structures enable the participation of end-users as active players, eager to take full advantage of their generation capabilities (in the form of renewables or distributed generation) and flexibility [3]. In fact, the participation of end-users in the wholesale market is typically limited due to their small volumes of energy (inefficiency) and unpredictable renewable generation (unreliability), a situation limiting their ability to compete against traditional generators in those markets [2]. Thus, LEC have the potential to unlock benefits for several stakeholders (e.g., utilities, system operators, and end-users) under different perspectives [4], [5]. To enable the above scenario, sophisticated communication and energy management algorithms are required to determine the energy trading between participants in order to minimize energy costs for all the involved parties [6] [7].

Several energy management algorithms have been proposed in the literature to overcome diverse challenges, most of which are related to privacy and scalability issues [9]. For instance, Orozco et al. [8] present a day-ahead scheduling decentralized approach for local energy communities with generation, loads, and battery storage systems and compare it with a centralized approach. EVs and grid constraints are not considered in their model and the pricing mechanism is based on a peer-to-peer assignment. A later work from the same authors [10] included an approximation mechanism for grid losses into their original problem formulation. Lezama et al. [11] propose a local electricity market framework with the integration of the wholesale market through an aggregator. The used distributed learning approach appears promising and scalable; however, the work presents some limitations, such as not including uncertainties, EVs, and fairness analysis. In [12], a centralized framework to optimize local trading was proposed showing the benefits that community members can achieve from these market structures. The price is bilateral and not optimized and is used as a parameter of the optimization model. The model in [13] compares the centralized model of [12] with a decentralized approach using rules to achieve convergence. The results indicate a similar optimal cost for the energy community but higher scalability of the decentralized model. From the literature studying energy communities, it is evident that there is a need for novel approaches for energy management in local environments considering the vast amount of distributed resources available and the different objectives of a variety of market participants. For instance, none of the above-related works have considered vehicle-to-grid (V2G) in the context of local market transactions.

Therefore, in the present work, a framework for the optimization of a grid-connected LEC is proposed. The LEC is formed by end-users with PV generation and EVs with the possibility of vehicle to grid (i.e., discharging the vehicle to the grid). Combined heat and power (CHP) local producers are also considered in the LEC, opening the possibility of local energy exchanges among community members. We formulate a mixed binary non-linear programming (MBNLP) model to maximize the benefits of the community members. The main contributions of the article are: i) A model to find the optimal scheduling of energy resources while maximizing the benefits for the community members; ii) Implementation of an MBNLP model and pricing mechanism; iii) Analysis of results over case studies with different characteristics.

Our work is organized as follows: after the introduction in Section I, Section II introduces the problem description and assumptions made. Section III provides an explicit mathematical model of the centralized scheduling of energy resources. After this, the case study used to evaluate the proposed method is introduced in Section IV, and the results are discussed in Section V. Finally, the conclusions of the work are drawn in Section VI.

II. Problem Description

This work considers a grid-connected LEC, including producers, consumers, and prosumers. The producers use CHP generators that can sell energy in the LEC. Consumers are, for instance, residential apartments or commercial buildings with no generation capabilities, whereas a prosumer is a consumer equipped with a PV panel to generate green energy, and with one or more EVs with V2G capability. All the consumers and prosumers are connected to the external utility grid. To minimize the total community cost, a nonprofit community energy manager (CEM) is considered to coordinate the available resources via a centralized approach. The considered LEC in this work is depicted schematically in Fig. 1.

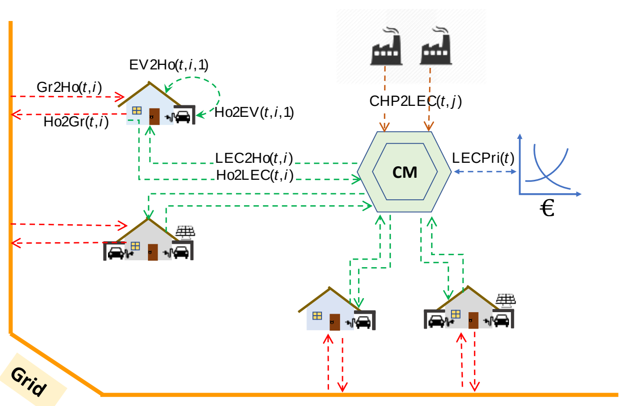

Fig. 1. Structure of the considered LEC and traded energy

In this work, the mentioned LEC is mathematically formulated as an optimization problem to find the optimal scheduling for flow energy among appliances such as PV, EVs, and CHP to maximize the benefits for the community members. The optimization plans one day ahead in 1 hour intervals. In addition, we make the following assumptions:

- Each home has its own contracted power, in which the grid tariff, feed-in and load limit are specified at each time slot.
- The energy generated by PVs is known in advance.
- The arrival and departure times as well as energy demands of EVs are known in advance.
- EVs can charge or discharge during parking at homes.
- The homes' energy demands are known in advance.
- The cost of CHP production is $2b_{CHP}\sqrt{\text{Production}}$, where b_{CHP} is a known parameter and Production is the amount of produced energy.
- The marginal cost of PV generators is supposed to be zero.
- The energy generated by a PV system is consumed by its owner, and the extra power can be sold to the grid or other energyr applicants.
- CHPs cannot sell energy to the grid.

The mathematical model considering the problem description and assumptions is introduced in the next section.

III. Mathematical Model

A centralized framework aiming to find the optimal scheduling of energy resources and the prices of energy transfers between consumers and prosumers in the LEC. In what follows, an MBNLP optimization problem is proposed for scheduling, managing, and pricing.

A. *Decision variables and parameters*

The sets, parameters, and decision variables use in the problem formulation are presented in Table 1, Table 2, and Table 3 respectively.

Table 1: List of sets in mathematical formulation.

Symbol	Sets	Running Index	Description
$\mathbb{T}$	$\{1,..,T\}$	t	Set of time slots from 1
$\mathbb{T}_0$	$\{0,1,..,T\}$	τ	Set of time slots from 0
$\mathbb{I}$	$\{1,..,I\}$	i	Set of Prosumers
$\mathbb{k}$	$\{1,..,EVNu\ (i)\}$	k	Set of cars
$\mathbb{J}$	$\{1,..,J\}$	j	Set of CHPs

Table 2: List of Parameters in mathematical formulation.

Parameter	Index	Description
T		Number of time period
I		Number of Prosumers
J		Number of CHPs
Δ		Duration of each time-slot
TotDem (t)	$t \in \mathbb{T}$	Total Demand in time-slot t
TotSup (t)	$t \in \mathbb{T}$	Total supply in time-slot t
PVGen (t, i)	$t \in \mathbb{T}, i \in \mathbb{I}$	Generated Power by PV i at time t
HoDem (t, i)	$t \in \mathbb{T}, i \in \mathbb{I}$	Power demand of home i at time t
HoSup (t, i)	$t \in \mathbb{T}, i \in \mathbb{I}$	Supply of home i at time t
HoCon (t, i)	$t \in \mathbb{T}, i \in \mathbb{I}$	Consumption of home i at time t
GrSelPri (t)	$t \in \mathbb{T}$	Purchased cost from grid at time t
GrFeedIn (t)	$t \in \mathbb{T}$	Selling Cost to the grid at time t
EVNu (i)	$i \in \mathbb{I}$	The number of EVs for i-th home
AriEV (i, k)	$i \in \mathbb{I}, k \in \mathbb{K}$	Arrival time of k EV from i home
ExiEV (i, k)	$i \in \mathbb{I}, k \in \mathbb{K}$	Exit time of k EV from i home
IniChaEV (i, k)	$i \in \mathbb{I}, k \in \mathbb{K}$	Initial SoC of k EV from home i
SocMax (i, k)	$i \in \mathbb{I}, k \in \mathbb{K}$	Maximum allowable SoC of k EV from i home
SocMin (i, k)	$i \in \mathbb{I}, k \in \mathbb{K}$	Minimum allowable SoC of k EV from i home
PchEV (i, k)	$i \in \mathbb{I}, k \in \mathbb{K}$	Active power for charging of k EV of i home
PdisEV (i, k)	$i \in \mathbb{I}, k \in \mathbb{K}$	Active power for discharging of k EV of i home
EchEV (i, k)	$i \in \mathbb{I}, k \in \mathbb{K}$	The charge efficiency of k EV of i home
EdischEV (i, k)	$i \in \mathbb{I}, k \in \mathbb{K}$	The discharge efficiency of k EV of i home
HoMaxLoad (t, i)	$t \in \mathbb{T}, i \in \mathbb{I}$	The maximum load of i home at t
CHPMaxLoad (j)	$j \in \mathbb{J}$	The maximum load of j CHP
EVLoc (t, i, k)	$t \in \mathbb{T}, i \in \mathbb{I}$	Location of k EV of i home at t (1: in parking)
ConEV (i, k)	$i \in \mathbb{I}, k \in \mathbb{K}$	Consumption of kth EV of Home i

Table 3: List of Decision Variables in mathematical formulation.

Variables	Index	Description
LECPri (t)	$t \in \mathbb{T}$	LEC-price at time t
Ho2LEC (t, i)	$t \in \mathbb{T}, i \in \mathbb{I}$	Power from i-th home to LEC at time t
LEC2Ho (t, i)	$t \in \mathbb{T}, i \in \mathbb{I}$	Power from LEC to i-th home at time t
Ho2Gr (t, i)	$t \in \mathbb{T}, i \in \mathbb{I}$	Power from i-th home to grid at time t
GR2Ho (t, i)	$t \in \mathbb{T}, i \in \mathbb{I}$	Power from grid to i-th home at time t
CHP2LEC(t, j)	$t \in \mathbb{T}, j \in \mathbb{J}$	Power from j-th CHP to LEC at time t
SoCE (τ, i, k)	$\tau \in \mathbb{T}_0, i \in \mathbb{I}$	State of charge of k-th EV of Home i at time τ.
EV2Ho(t, i, k)	$t \in \mathbb{T}, i \in \mathbb{I}, k \in \mathbb{K}$	Power from k-th EV to home i at time t
Ho2EV(t, i, k)	$t \in \mathbb{T}, i \in \mathbb{I}, k \in \mathbb{K}$	Power from home i to k-th EV at time t
α (t, i, k)	$t \in \mathbb{T}, i \in \mathbb{I}, k \in \mathbb{K}$	Binary variable for charging of EV k of home i at t
β (t, i, k)	$t \in \mathbb{T}, i \in \mathbb{I}, k \in \mathbb{K}$	Binary variable for discharge EV k of home i at t
θ(t, j)	$t \in \mathbb{T}, \quad j \in \mathbb{J}$	A binary variable for status of j CHP at t (1: production)

B. *Pricing based on total demand and supply*

In the proposed model, the LEC-price is determined based on the total supply and demand in each time slot. At first, we should achieve a rule for pricing in the LEC. Thus, the following three points are considered:

- The price of buying energy from LEC (LECPri (t)) should be less than the buying price from the external grid ($GrSelPri\ (t)$);
- The price of selling energy to LEC (LECPri (t)) should be greater than the incentive received by selling energy to the external grid $GrFeedIn(t)$;
- The (LECPri (t)) should be considered such that the CHPs have a nonnegative benefit. In this regard, from the initial cost, we have the following constraint for the active CHPs:

$$LECPri(t)CHP2LEC(t,j) - 2b_{CHP}\sqrt{CHP2LEC(t,j)} \geq 0. \quad (1)$$

Now, by simple algebraic manipulation, we find that the minimum LEC-price for active j-th CHP should be greater than $\frac{4b_{CHP}^2}{CHP2LEC(t,j)}$. Note that if j-th CHP is not active, the minimum LEC-price is $\mathrm{GrFeedIn}(t)$. Accordingly, from all active CHPs, the LECPri (t) must be greater than the following $MinLECPri(t)$:

$$MinLECPri(t) \coloneqq \max_{j\in\mathbb{J}, CHP2LEC(t,j)\neq 0,} \sqrt{\frac{4b_{CHP}^2}{CHP2LEC(t,j)}}. \quad (2)$$

In this way, the trading in the LEC becomes attractive and beneficial for homes and CHPs.

After determining the lower and upper bounds for the LEC-price, the LEC-price should be determined. Different rules may be considered for pricing. However, in this paper, we set up the LEC-price based on demand and supply relying on the fact that when the energy demand is high, naturally, the price of energy should be higher than at times with a low demand. Therefore, we set up the LEC-price proportional to demand and supply as follows:

$$LECPri(t) = \frac{TotDem(t)}{TotDem(t)+TotSup(t)}GrSelPri(t) + \frac{TotSup(t)}{TotDem(t)+TotSup(t)}MinLECPri(t). \quad (3)$$

In Fig. 2, the diagram of $LECPri(t)$ is sketched. Note that, if $TotDem(t) = 0$, then $LECPri(t) = MinLECPri(t)$, and if $TotSup(t) = 0$, then $LECPri(t) = GrSelPri(t)$.

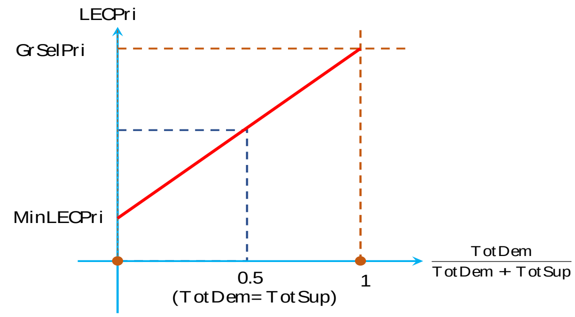

Fig. 2. The LEC-price diagram

We note that $TotDem(t)$ and $TotSup(t)$ are the total homes' demand and supply (including charging/discharging of their EVs), and are determined as follows:

$$HoTCon(t,i) = HoCon(t,i) + \sum_{k\in\mathbb{k}} Ho2EV(t,i,k), \quad (4)$$

$$HoTPro(t,i) = PVGen(t,i) + \sum_{k\in\mathbb{k}} EV2Ho(t,i,k), \quad (5)$$

$$HoDem(t,i) = Max\{0, HoTCon(t,i) - HoTPro(t,i)\}, \quad (6)$$

$$HoSup(t,i) = Max\{0, HoTPro(t,i) - HoTCon(t,i)\}, \quad (7)$$

$$LEM2Ho(t,i) + Gr2Ho(t,i) = HoDem(t,i), \quad (8)$$

$$Ho2LEM(t,i) + Ho2Gr(t,i) = HoSup(t,i), \quad (9)$$

$$TotDem(t) = \sum_{i\in\mathbb{I}} HoDem(t,i), \quad (10)$$

$$TotSup(t) = \sum_{i\in\mathbb{I}} HoSup(t,i). \quad (11)$$

C. *Objective Function*

Some authors have modelled the objective function of similar problems as the minimization of total costs [11], i.e.,

$$Minimize \quad \sum_{i\in\mathbb{I}} Cost(i), \quad (12)$$

where Cost(i) is a decision variable representing the cost of the i-th home defined as:

$$Cost(i) = \sum_{t\in\mathbb{T}} Gr2Ho(t,i) \times GrSelPri(t) - Ho2Gr(t,i) \times GrFeedIn(t) + LEC2Ho(t,i) \times LECPri(t) - Ho2LEC(t,i) \times LECPri(t). \quad (13)$$

However, notice that when $\sum_{i\in\mathbb{I}}\left(LEC2Ho(t,i) - Ho2LEC(t,i)\right) = 0$, the objective function (12) is independent of the value of LECPri. To overcome this drawback, the following objective function is proposed in this work:

$$Maximize \quad \sum_{i\in\mathbb{I}}\left(Cost(i) - cost0(i)\right)^2, \quad (14)$$

where $cost0(i)$ is the optimal cost of the i-th home not participating in the LEC. Note that our aim is to minimize $Cost(i)$ or, equivalently, maximize $\left(Cost(i) - cost0(i)\right)^2$. In other words, the objective function (14) is the sum of squared (2-norm) of benefits of homes. Like least-square problem (Gauss problem) which the sum of squared error (SSE) is minimized. Moreover, by considering the sum of squared benefits, we can resolve the independency of objective function to LEMPri.

The benefit of each end-user is the reduction of the costs when attending to LEC compared to not attending the LEC.

D. *Constraints*

In this section, the problem assumptions and physical restrictions of resources are expressed as constraints for the proposed MBNLP model. Thus, the constraints corresponding to EVs are outlined:

$$SoCEV(\tau+1,i,k) = SoCEV(\tau,i,k) + Ho2EV(\tau,i,k) \times EchEV(i,k) - \frac{EV2Ho(\tau,i,k)}{EdchEV(i,k)}, \ \tau \in \mathbb{T}_0 \in \mathbb{T}, i \in \mathbb{I}, k \in \mathbb{K}, \quad (15)$$

$$Ho2EV(t,i,k) \leq \alpha(t,i,k) \times PchEV(i,k), \ t \in \mathbb{T}, i \in \mathbb{I}, k \in \mathbb{K}, \quad (16)$$

$$EV2Ho(t,i,k) \leq \beta(t,i,k) \times PdchEV(i,k), t \in \mathbb{T}, i \in \mathbb{I}, k \in \mathbb{K}, \quad (17)$$

$$SoCEV(0,i,k) = IniChaEV(i,k), i \in \mathbb{I}, k \in \mathbb{K}, \quad (18)$$

$$SoCEV(T,i,k) \leq IniChaEV(i,k), i \in \mathbb{I}, k \in \mathbb{K}, \quad (19)$$

$$SoCMinEV(i,k) \leq SoCEV(\tau,i,k) \leq SoCMaxEV(i,k), \quad (20)$$

$$\alpha(t,i,k) + \beta(t,i,k) \leq EVLoc(t,i,k), t \in \mathbb{T}, i \in \mathbb{I}, k \in \mathbb{K}, \quad (21)$$

The state of the charge (SoC) for each EV is updated in equation (15). The amount of charge and discharge for the k-th EV of the i-th home is limited by constraints (16) and (17). Constraints (18) and (19) set the initial and final SoC, respectively, for the k-th EV of the i-th home. Constraint (20) sets the lower and upper bounds of SoCs. Finally, constraint (21) guarantees that the EV charging and discharging process do not occur simultaneously and only in time steps when the EV is parked at home. The constraints corresponding to the homes are as follows:

$$Cost(i) \leq \mathrm{cost0}(i), \quad (22)$$

$$0 \leq Gr2Ho(t,i) \leq HoMaxLoad(i), \quad (23)$$

$$0 \leq Ho2Gr(t,i) \leq HoMaxLoad(i), \quad (24)$$

$$\sum_{i \in \mathbb{I}} LEM2Ho(t,i) = \sum_{i \in \mathbb{I}} Ho2LEM(t,i) + \sum_{j \in \mathbb{J}} CHP2LEM(t,j), \quad (25)$$

$$CHP2LEM(t,j) \leq \theta(t,j) \times CHPMaxLoad(t,j), t \in \mathbb{T}, j \in \mathbb{J}, \quad (26)$$

$$CHP2LEM(t,j) \geq \theta(t,j) \times CHPMinLoad(t,j) \coloneqq \frac{4 \times B_{CHP}(j)^2}{LECPri(t)^2}, \quad t \in \mathbb{T}, j \in \mathbb{J}, \quad (27)$$

Constraint (22) guarantees for each home that the cost does not increase by attending the LEC. The possibility of prosumer i to buy or sell energy is limited by the constraints (23) and (24). The constraint (25) represents the equilibrium between the energy sold and purchased to/from the LEC in time step t. Constraints (26) and (27) represent the maximum and minimum allowed energy production for the j-th CHP, where $\theta(t,j)$ is a binary variable that stands for the production status of the j-th CHP at time t. In other words, $\theta(t,j) = 1$ means that the j-th CHP produces energy in time t, and in this case, we set: $CHPMinLoad(t,j) = \frac{4 \times B_{CHP}(j)^2}{LECPri(t)^2}$.

In summary, to determine the LEC-price and schedule the demand, we maximize the objective function (14), subject to the constraints (2)-(11), (13), and (15)-(27).

IV. Case study

We evaluate our proposed approach in a case study considering a LEC composed of 100 households from which 30 are considered low-level income, 60 medium level income, and 10 high-level incomes. The medium and high-level income have PV units installed. Regarding the EV, we assume that one of every two medium-level income household has one EV, and each high-level income household has two EVs. Thus, in total, 50 EVs are considered within the LEC. According to the Portuguese legislation, each household must have a contracted term with retailers that defines the electricity price and the contracted peak power level defining the allowed import/export power limit values. The planning horizon considered is 24 hours with 1 hour resolution.

Fig. 3 shows three different tariffs for buying electricity: a flat tariff (Tariff A), a bi-hourly tariff (Tariff B), and a tri-hourly tariff (Tariff C)[1]. For all three tariffs a constant grid feed-in price is considered. Fig. 4 presents the households load and generation profiles used in the case study without EVs charging and discharging actions. The presented profiles consider a mean within elements of the same income group.

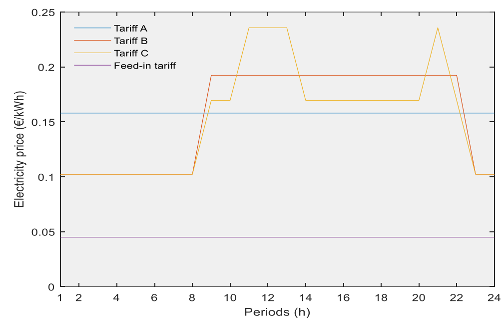

Fig. 3. Tarrif used in the simmulations

As can be seen in Fig. 4, the high income households have higher load and generation profiles than the other households.

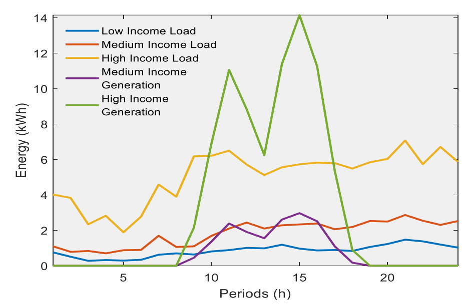

Fig. 4. Load and generation mean profiles

Fig. 5 shows the number of EVs and models used in the case study. Nine different models are used in the case study. For the EV models three different price segments were defined. The Dacia and VW are considered to be in the low segment, the Renault, Nissan and Honda in the medium segment, and finally Tesla, Porsche, Mercedes and Jaguar in the high segment[2]. The EV characteristics such as charging rate, battery capacity for each model have been obtained in the data available in the Bjorn Nyland website[2].

We assume that households belonging to the medium income segment have EVs within the low and medium EV price segment (i.e., Dacia – 9 units, WV – 7 units, Renaut – 6 units, Nissan – 5 units and Honda – 3 units). On the other hand, high income households can have medium and high EV price segment (i.e., Nissan – 6 units, Honda – 4 units, Tesla – 3 units, Porsche – 2 units, Mercedes – 2 units and Jaguar – 3 units). In the case study, 5 CHP units are considered.

[1] Data from SU Eletricidade Retailer www.sueletricidade.pt

[2] Based on the data provided by Bjorn Nyland, Kris Rifa, Batterylife, NAF, Elektro bay, Rsymons, Recharging, et al. Online at https://bit.ly/3qUPyw7

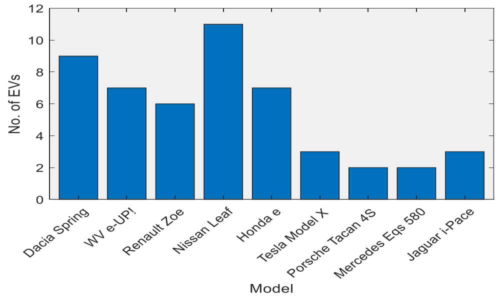

Fig. 5.EV models used

Fig. 6 shows the production cost function considered for all CHPs having a maximum production capacity of 10kW, the constant b_{CHP} is set to 0.2€/kWh.

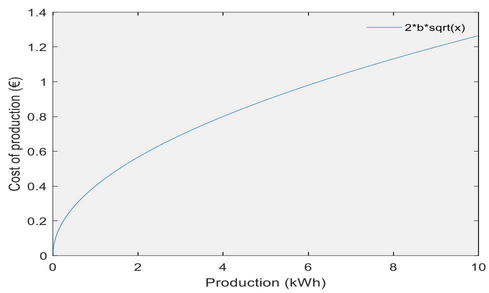

Fig. 6. Chp production cost function

V. SIMULATION RESULTS

In this section, the results of the proposed model on the described case study are presented and discussed. We have implemented the method in MATLAB in a MacBook Pro, 2.7 GHz Quad-Core Intel Core i7, 16 GB 2133 MHz LPDDR3. The final mathematical problem is solved by KNITRO [14], interfaced with the AMPL modeling language and setup with a maximum of 200 iterations.

TABLE 4: OVERALL RESULTS (COST, INCOME, AND PROFITS) CONSIDERING THREE DIFFERENT TARIFFS.

Tariff		Consumers/prosumers (€)			Producers (€)			Total (€)			CPU
	LEC	Cost	Income	Profit (loss)	Cost	Income	Profit (loss)	Cost	income	Profit (loss)	time (sec.)
A	No	522.57	11.91	-510.66	--	--	--	522.57	11.91	-510.66	11
	Yes	544.46	80.48	-463.98	123.82	139.55	15.74	668.28	220.03	-448.25	251
B	No	468.39	11.91	-456.48	--	--	--	468.39	11.91	-456.48	12
	Yes	533.14	106.75	-426.40	55.23	64.78	9.55	588.38	171.52	-416.86	274
C	No	459.57	11.91	-447.66	--	--	--	459.57	11.91	-447.66	11
	Yes	517.84	152.34	-364.66	43.36	45.53	2.17	560.36	197.87	-362.49	300

In Table 4, the obtained cost, income and profit of consumers/prosumers and producers are reported. The last column shows the runtime for solving the model. It can be seen that the total cost, and the cost of agents are better with Tariff B (bi-hourly) and Tariff C (tri-hourly) compared to Tariff A (flat). The same holds for the total profit.

Fig. 7 depicts the LEC-prices resulting from the proposed model over the 24 time periods for tariffs A, B, and C. Additionally, the considered grid tariff for buying energy from the grid (upper-bound) and the feed-in tariff for selling energy to grid (lower-bound) are illustrated in the figure. The green, red, and brown triangle symbols show the low-, high- and medium-price periods, respectively, for the different tariffs. As it can be seen, with tariff A, the LEC-price has low variations because the energy price is constant at all time slots. These variations are due to variations in demand and supply. Moreover, in the high-level periods of tariffs B and C, the price is higher than in medium-level periods, and the LEC-price in the medium-level periods is higher than in low-level periods. This fact can confirm the validity of the method because when demand increases, the generators produce more energy to supply the demand required by consumers, and naturally the LEC-price to increases and so their profits. In contrast, the generators decrease their production in the low demand time, and the LEC-price decreases.

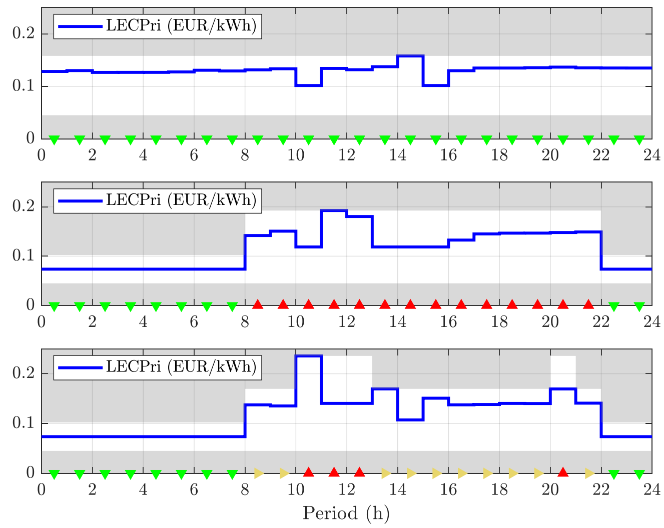

Fig. 7. Feed-in tariff, energy tariff, and the obtained LEC-prices considering three different tariffs: Tariff A (Top), Tariff B (Middle) and Tariff C (Bottom).

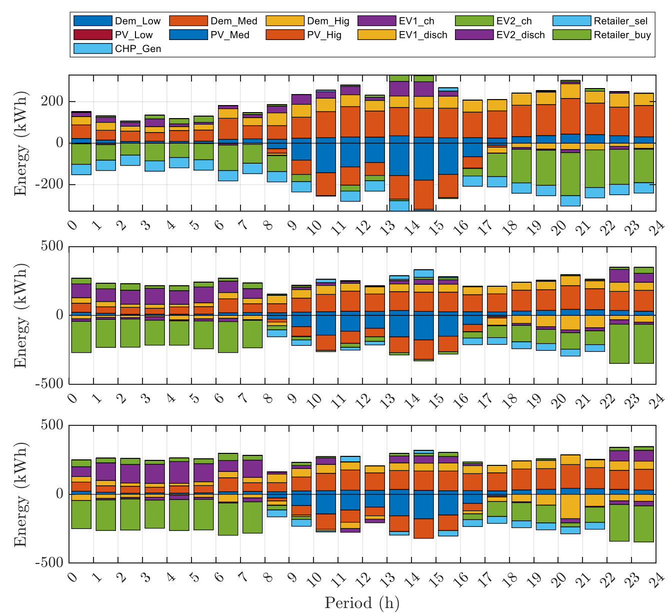

Fig. 8. Energy resource management results considering different tariffs: tariff a (top), tariff b (middle) and tariff c (bottom)

Fig. 8 shows the net demand in positive bars and generation scheduling in negative bars for low, medium, and high-income levels, and EVs and also grid load for Tariffs A, B, and C. In Fig. 9 , the states of EVs are depicted. In the left axis of this figure, the number of arrivals and departure EVs is shown from periods 1 to 24. Moreover, the number of EVs parking at home is shown. In the right y-axis of Fig. 9, the total charge of parking EVs is plotted. As it can be seen, the total SoC is proportional to the number of parking EVs . Moreover, in Tariffs B and C, EVs tend to charge at initial low-demand times, and consequently, at high-demand times less charging is done.

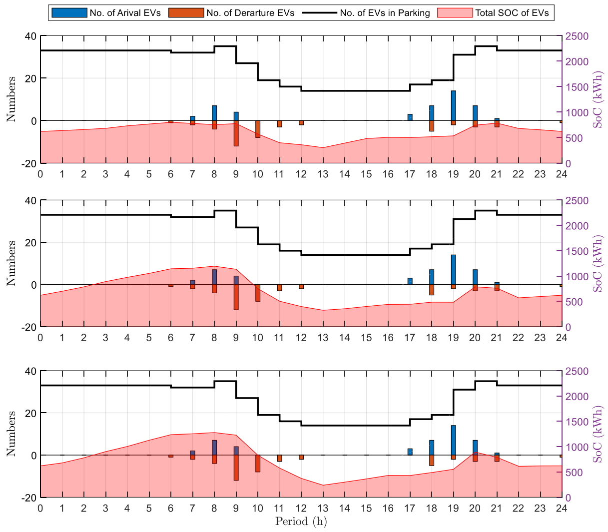

Fig. 9. Number of arrival, departure and total soc of evs: tariff a (top), tariff b (middle) and tariff c (bottom)

VI. CONCLUSION AND FUTURE WORK

In this paper, a MBNLP is presented to mathematically formulate the pricing and demand scheduling for a LEC. The main objective is to maximize the total benefit of homes in the LEC. In addition, the goal is to optimally schedule the charging/discharging of electric vehicles , and to manage the exchange of energy among the homes. Finally, the model determines the trading price (LEC-price) between homes and combined heat and power producers. The LEC-price is obtained based on the value of total demand and total supply. Note that this model has a significant drawback. The model is an un-convex MBNLP, which is an NP-Hard problem. This means that we face difficulties in solving it with a large number of agents. As a future research work, we can use the idea of decomposition methods to overcome this challenge. Another possibility for further research is to adopt reducing model order techniques.

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