

Received December 3, 2020, accepted January 1, 2021, date of publication January 12, 2021, date of current version January 22, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3051004

Optimal Model for Local Energy Community Scheduling Considering Peer to Peer Electricity Transactions

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This work was supported in part by the European Union's Horizon 2020 Research and Innovation Programme under Project DOMINOES 771066; in part by the Fundo Europeu de Desenvolvimento Regional (FEDER) Funds through COMPETE Program; and in part by the National Funds through Fundação para a Ciência e a Tecnologia (FCT) under Project UIDB/00760/2020, Project CEECIND/01811/2017, and Project CEECIND/02814/2017. The work of Ricardo Faia was supported by the Ph.D. Grant from National Funds through FCT under Grant SFRH/BD/133086/2017.

ABSTRACT The current energy strategy of the European Union puts the end-user as a key participant in electricity markets. The creation of energy communities has been encouraged by the European Union to increase the penetration of renewable energy and reduce the overall cost of the energy chain. Energy communities are mostly composed of prosumers, which may be households with small-size energy production equipment such as rooftop photovoltaic panels. The local electricity market is an emerging concept that enables the active participation of end-user in the electricity markets and is especially interesting when energy communities are in place. This paper proposes an optimization model to schedule peer-to-peer transactions via local electricity market, grid transactions in retail market, and battery management considering the photovoltaic production of households. Prosumers have the possibility of transacting energy with the retailer or with other consumers in their community. The problem is modeled using mixed-integer linear programming, containing binary and continuous variables. Four scenarios are studied, and the impact of battery storage systems and peer-to-peer transactions is analyzed. The proposed model execution time according to the number of prosumers involved (3, 5, 10, 15, or 20) in the optimization is analyzed. The results suggest that using a battery storage system in the energy community can lead to energy savings of 11-13%. Besides, combining the use of peer-to-peer transactions and energy storage systems can potentially provide energy savings of up to 25% in the overall costs of the community members.

INDEX TERMS Local electricity market, local energy community, optimization, peer-to-peer transactions, prosumers.

I. INTRODUCTION

Distributed and renewable generation has emerged as a solution for the depletion of fossil fuel energy and for meeting energy sustainability targets, namely the greenhouse gas emissions limits imposed in some areas. For example, the European Union (EU) is targeting a reduction of at

least 40% of greenhouse gas emissions by 2030, an increment of at least 32% share for renewable energy, and an improvement of at least 32.5% in energy efficiency, taking as basis 1990 levels [1]. In 2018, renewable generation accounted for 18.9% of the energy consumed in the EU [2], which already represents about 50% of the imposed levels. At the residential level, households can install smart devices and distributed energy resources (DER) such as photovoltaic (PV) modules, small scale wind turbines, and energy

The associate editor coordinating the review of this manuscript and approving it for publication was Hao Luo¹.

storage including plug-in electric vehicles (EV), to increase energy efficiency and reduce energy bills [3]. However, due to the increasing maturity of renewable energy production capabilities, the feed-in tariff which incentivized local generation sales to the grid is being reduced. In consequence, the reduction of feed-in tariffs may impact the motivation of consumers, slowing down the penetration of renewable sources and ultimately, failing in achieving the agreed targets.

Due to feed-in tariff reduction, in several locations, it is now more attractive for households to use generation surplus for self-consumption than selling to the grid [4]. Self-consumption is different among individuals depending on daily consumption profiles, which can vary with the habits and with the used electrical equipment.

The European Commission Strategic Energy Technology Plan [5] states that energy consumers are envisioned at the center of the future energy systems and shall be encouraged to install energy production sources. Peer-to-peer (P2P) energy trading emerges as a promising solution to empower the role of the end-users in energy systems [6]. Basically, P2P energy trading is a recent technology of energy management mechanism in smart grids [6]. In the scope of an energy community, P2P energy trading enables flexible energy trades between peers. In other words, in a P2P market, the excess of energy generation coming from many small-scale DERs is traded among local customers [7]. The prosumers can achieve a “win-win” situation by searching for a satisfactory trading price and by reaching an agreement in a seamless way. The marginal price of P2P electricity transactions should be cheaper than the retailer tariff and higher than the feed-in tariff (i.e., the price of electricity export to the grid) so that P2P can provide savings for buyers and profit for sellers [8]. The work in [9] highlights potential benefits of P2P energy trading: the maximization of renewable energy usage, the reduction of electricity cost, the shaving of peak load, the empowerment of the prosumers, and the minimization of network operation and investment costs. Although the potential benefits are fairly significant, research on P2P energy trading is still at an early stage and there is no consensus on what type of data sharing and processing infrastructure is more efficient and yields to the best results [3]. It is expected to reach an investment of USD 25 billion in microgrid markets by 2025 in USA [10], which will inevitably lead to the development of P2P market applications to empower prosumers and fulfill the niche market void.

In this article, a P2P market structure is proposed to allow energy transactions between users at a price that provides better benefits than current feed-in tariffs. In this way, consumers become active participants of the local market, having the possibility to take advantage of their surplus electricity without being limited by retailers.

Figure 1 presents the trading architecture proposed for a local community with N prosumers considering a conventional retail electricity market and a P2P market between the community members.

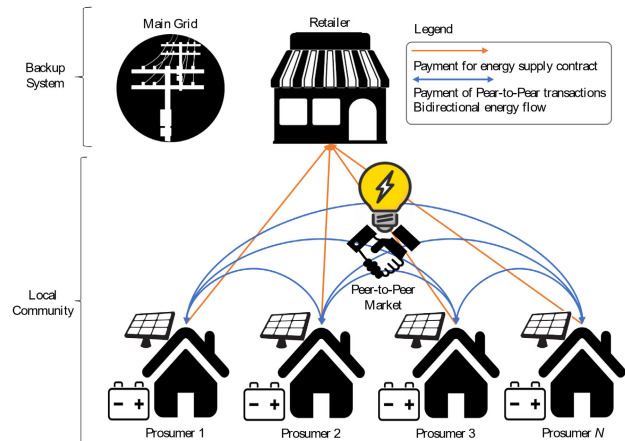


FIGURE 1. Proposed methodology.

As can be seen in Figure 1, we propose a local community scheduling considering the possibility of transacting energy with the retailer and in a market within the community with P2P transactions. The local community is composed by prosumers, each of them with a PV-battery system which is also scheduled in the optimization process. The community members have two different possibilities, namely, buy/sell electricity to the grid or transact energy with other community members. The optimization is used to determine the set of prosumers in each period that performed P2P transactions.

As the main contributions of this work, we highlight five aspects:

- An optimization model that determines the best P2P energy transactions in a local energy community with prosumers equipped with PV generation and energy storage systems;
- A deterministic mixed-integer linear programming (MILP) method, implemented in TOMLAB,¹ to determine the decision-making;
- The model includes realistic constraints, customer load profiles, PV systems, battery energy storage systems and market transactions constraints. Real Portuguese tariffs are used to generate realistic case studies;
- The presented model considers the active involvement of households in the electricity markets, in line with the goals of governmental institutions to reduce energy costs and carbon emissions;
- The proposed methodology considers an optimal solution combining demand side management (DSM) and P2P transactions integrated into the optimization process, characteristic that, to the best of the authors' knowledge and according to the analysis made by the authors in section II, is not proposed in the current literature.

The rest of this paper is divided into six sections: Section 2 presents the background on the DSM and P2P models. Section 3 shows the proposed methodology and the

¹TOMLAB is a language for solving optimization problems considering MATLAB language (<https://tomopt.com/tomlab/>).

mathematical formulation developed in this research work. Section 4 describes the case study used to test the proposed methodology. Section 5 discusses and analyzes the results. Finally, Section 6 presents the conclusion of this work and provides future research directions.

II. BACKGROUND

This section presents a background on the energy costs optimization in smart grids. DSM applications in smart grids can be considered as one of the most innovative steps to minimize the operation costs [11]–[13]. These applications consider the optimization of house consumption by rescheduling the loads to periods when the electricity price is lower [14], [15]. With the installations of PV generators in residential houses and the development of load controlled systems for demand response, more comprehensive and complex approaches are emerging [16]. In previous referred works, authors consider the rescheduling of controllable loads and the use of PV generation and battery storage systems. A similar work is presented in [17], where authors reduce the computational effort by adopting evolutionary computation algorithms to solve the optimization problem. A different technique was implemented in [18] using case-based reasoning based on historical data to determine the reduction value for a demand response application. More recently, works that address the energy commerce between groups within smart grids have been proposed. In [19], a trading environment between neighbor microgrids was presented. In the case study, a smart grid with three microgrids was considered, and apart from the inter-micro-network market, six different markets were analyzed for trading electricity.

Energy transaction between households has emerged in recent years as a promising trend that should be adapted to minimize the costs of the electric bill. Reference [20] introduces a local market into the simulation. The problem was solved using a two-stage stochastic programming approach. The authors optimize the electricity costs of all microgrids members, allowing local transactions between microgrids and the possibility of buying energy into the wholesale market. Publication [21] determines the best portfolio option for the electricity transaction, considering the possibility of transacting electricity in local electricity markets. The authors in [22] consider an energy sharing approach between prosumers. The problem is solved considering a bi-level programming method using a function called demand and supply ratio. A Mixed Integer Non-linear Programming (MINLP) is used in work [23] to determine the P2P transaction considering 2 households and a horizon time of 8 periods (1h each). The influence of battery storage systems in P2P trading within a microgrid was explored in reference [24]. Works [22]–[24] consider the problem of local electricity transaction but do not consider the coordination of DSM with local transaction scheduling. In other words, these works cannot provide a coordinate solution of the local transaction to take the maximum benefits of households loads and storage systems. DSM approaches are used to optimize energy costs

and are typically formulated as linear or non-linear problems [3]. Linear optimization is usually used to solve short periods of time and usually have a very short resolution time when compared with non-linear optimizations resolutions. Researchers to reduce the computation time burden of non-linear models are using approximate methods to reduce the resolution time [25]–[27].

TABLE 1 presents a comparison between works published considering P2P energy trading within an energy community. The proposed work is also included in TABLE 1 highlighting its contributions concerning the current literature.

A similar method to the one presented in this work was proposed in [26]; authors used a distributed approach to implement a DSM system combined with P2P trading. Due to the use of an approximate solution approach the work in [26] does not guarantee optimal solutions to the problem. In contrast, by using a deterministic solution approach (MILP), our method provides an optimal solution considering up to 20 players combining the DSM with P2P transactions. Typically, optimization methods that determine local market transaction using centralised approaches consider a small number of users involved due to the computational burden [22]–[24]. On contrast, methods that consider a large number of users use iterative process [3] or determine the local transaction after the DSM optimization is finished [8], [25].

The current literature reflects a lack of deterministic solution methods that include local electricity transactions considering more than four players. Thus, this work presents a deterministic method that can solve the problem under a case study considering up to 20 players. Our method also considers the coordination between DSM and local transactions, unlike most of the current approaches.

III. MATHEMATICAL FORMULATION

In this section, the mathematical formulation used to obtain the optimal social welfare costs of the community is fully presented. Equation (1) represents the objective function that minimizes the total cost of the energy community. Indeed, the objective function is equivalent to the social welfare of the community members, minimizing their energy costs.

$$\begin{aligned} \text{minimize : } obf = & \sum_{t=1}^{Nt} \sum_{i=1}^{Ni} \left(\pi_{t,i}^{buy Grid} \times P_{t,i}^{buy Grid} \right) \times \frac{1}{\Delta t} \\ & - \sum_{t=1}^{Nt} \sum_{i=1}^{Ni} \left(\pi_{t,i}^{sell Grid} \times P_{t,i}^{sell Grid} \right) \times \frac{1}{\Delta t} \end{aligned} \quad (1)$$

where t represents the period, i represents the prosumer, Nt the total number of periods, Ni the total number of prosumers, $\pi_{t,i}^{buy Grid}$ represents the price of buying electricity from the grid (time-of-use tariff), $P_{t,i}^{buy Grid}$ represents the amount of electricity purchased from the grid, $\pi_{t,i}^{sell Grid}$ represents the selling price of electricity to the grid (feed-in tariff) and $P_{t,i}^{sell Grid}$ represents the amount of electricity sold to the grid.

TABLE 1. P2P energy trading works comparison.

Reference	Year	Method	Solution type	Coordinate DSM with local transactions	Method to determine local marker transactions.	Number of users* involved in the optimization?
[22]	2017	Bi-Level Programming	Approximate	No	Included in the optimization	5
[23]	2017	Mixed Integer Non-linear Programming	Optimal	No	Included in the optimization	2
[24]	2018	Linear Programming	Optimal	No	Included in the optimisation	4
[25]	2018	Constrained Non-linear Programming	Approximate	Yes	After the optimization	3, 100
[3]	2019	Bi-Linear Programming	Near Optimal	Yes	Iterative process (ECO-Trade algorithm)	40
[26]	2019	Alternating Direction Method of Multipliers	Approximate	Yes	Included in the optimization	10
[8]	2020	Mixed-integer Linear Programming	Optimal	No	After optimization using coalition game theory	30
Proposed	2020	Mixed-integer linear Programming	Optimal	Yes	Included in the optimization	3,5,10,15,20

*users can be considered prosumers, consumers, and small producer.

The term Δt is used to adjust the tariff price to the optimization time intervals (e.g., 15 min). Equation (2) represents the power balance for each prosumer.

$$\begin{aligned}
 P_{t,i}^{gen} + P_{t,i}^{buy Grid} + P_{t,i}^{dch} + \sum_{j=1, j \neq i}^{N_j} P_{t,i,j}^{buy p2p} \\
 = P_{t,i}^{load} + P_{t,i}^{sell Grid} + P_{t,i}^{ch} + \sum_{j=1, j \neq i}^{N_j} P_{t,i,j}^{sell p2p} \\
 \forall i \in Ni, \quad \forall j \in Nj, \quad \forall t \in Nt \quad (2)
 \end{aligned}$$

where $P_{t,i}^{gen}$ represents the generated power, $P_{t,i}^{dch}$ is the discharged power of the battery, $P_{t,i,j}^{buy p2p}$ corresponds to the electricity purchased in the P2P market, $P_{t,i}^{load}$ is the load, $P_{t,i}^{ch}$ is the power charged by the battery, $P_{t,i,j}^{sell p2p}$ corresponds to the electricity sold in the P2P market, j is the prosumer and N_j the total numbers of prosumers. The sum of variable $P_{t,i,j}^{p2p}$ over the index j gives the total value of each i buy in P2P transactions for each t index, whereas the sum in i index gives the total value of each j sale. Equation (3) and (4) represent the maximum limits of variables $P_{t,i}^{buy Grid}$ and $P_{t,i}^{sell Grid}$.

$$P_{t,i}^{buy Grid} \leq P_{t,i}^{max buy Grid} \times Bin_{t,i}^{buy Grid} \quad \forall i \in Ni, \quad \forall t \in Nt \quad (3)$$

$$P_{t,i}^{sell Grid} \leq P_{t,i}^{max sell grid} \times Bin_{t,i}^{sell Grid} \quad \forall i \in Ni, \quad \forall t \in Nt \quad (4)$$

where $P_{t,i}^{max buy Grid}$ represents the maximum amount of electricity to buy from the grid, $Bin_{t,i}^{buy Grid}$ is a binary variable that enables purchasing electricity from the grid if it is 1, $P_{t,i}^{max sell grid}$ represents the maximum amount of electricity sold to the grid, and $Bin_{t,i}^{sell Grid}$ is a binary variable that enables selling electricity to the grid if it is 1. Equation (5) is the constraint applied to the binary variables above.

$$Bin_{t,i}^{buy Grid} + Bin_{t,i}^{sell Grid} \leq 1, \quad \forall i \in Ni, \quad \forall t \in Nt \quad (5)$$

Equation (5) restricts the transactions of electricity to either buy or sell energy in the same period for the same prosumer. Equations (6) and (7) represent the maximum limits of variable $P_{t,i,j}^{max buy p2p}$ and $P_{t,i,j}^{max sell p2p}$.

$$P_{t,i,j}^{buy p2p} \leq P_{t,i,j}^{max buy p2p} \times Bin_{t,i,j}^{buy p2p} \quad \forall i \neq j \in Ni, \quad \forall j \neq i \in Nj, \quad \forall t \in Nt \quad (6)$$

$$P_{t,i,j}^{sell p2p} \leq P_{t,i,j}^{max sell p2p} \times Bin_{t,i,j}^{sell p2p} \quad \forall i \neq j \in Ni, \quad \forall j \neq i \in Nj, \quad \forall t \in Nt \quad (7)$$

where $P_{t,i,j}^{max buy p2p}$ corresponds to the maximum limit for P2P purchase transactions, $Bin_{t,i,j}^{buy p2p}$ corresponds to a binary variable that enables purchasing electricity from j to i in P2P mode, $P_{t,i,j}^{max sell p2p}$ corresponds to the maximum limit for P2P electricity sale transactions, and $Bin_{t,i,j}^{sell p2p}$ corresponds to a binary variable that enables selling electricity from i to j in P2P mode. Both indices $i \neq j$ and $j \neq i$ represent prosumers, and must be different since $i = j$ or $j = i$ would represent a prosumer negotiating with himself. Equations (8) and (9) are implemented to restrict actions related to the transactions with the grid and P2P market.

$$Bin_{t,i}^{buy Grid} + \sum_{j=1, j \neq i}^{N_j} Bin_{t,i,j}^{sell p2p} \leq 1 \quad \forall i \in Ni, \quad \forall t \in Nt \quad (8)$$

$$\sum_{j=1, j \neq i}^{N_j} Bin_{t,i,j}^{buy p2p} + Bin_{t,i}^{sell Grid} \leq 1 \quad \forall i \in Ni, \quad \forall t \in Nt \quad (9)$$

Equation (8) imposes that it is not allowed to buy electricity from the grid to sell it in P2P mode, whereas equation (9) imposes that it is not possible to buy electricity in P2P mode to sell to the grid. The above restrictions were implemented assuming that it is always more expensive to buy/sell electricity from the grid than in P2P trading. Equation (10)

corresponds to the balance of the P2P trading market.

$$\sum_{j=1, j \neq i}^{Nj} \sum_{i=1, i \neq j}^{Ni} P_{t,i,j}^{buy p2p} = \sum_{j=1, j \neq i}^{Nj} \sum_{i=1, i \neq j}^{Ni} P_{t,i,j}^{sell p2p} \quad \forall t \in Nt \quad (10)$$

Equation (10) imposes that the total amount of electricity purchased in P2P mode should be equal to the total amount of electricity sold in the same P2P mode. Equations (11) and (12) are applied to model the P2P market transactions.

$$\sum_{i=1, i \neq j}^{Ni} Bin_{t,i,j}^{buy p2p} + \sum_{j=1, j \neq i}^{Nj} Bin_{t,i,j}^{sell p2p} \leq 2 \quad \forall t \in Nt \quad (11)$$

$$\sum_{j=1, j \neq i}^{Nj} Bin_{t,i,j}^{buy p2p} + \sum_{i=1, i \neq j}^{Ni} Bin_{t,i,j}^{sell p2p} \leq 2 \quad \forall t \in Nt \quad (12)$$

Equations (11) and (12) ensure that each prosumer trade with another prosumer in each period. The model does not allow that one prosumer transacts electricity with two or more prosumers.

Equations (13) and (14) represent the limits for charge and discharge of the batteries.

$$P_{t,i}^{ch} \leq P_{t,i}^{max ch} \times Bin_{t,i}^{ch}, \quad \forall i \in Ni, \forall t \in Nt \quad (13)$$

$$P_{t,i}^{dch} \leq P_{t,i}^{max dch} \times Bin_{t,i}^{dch}, \quad \forall i \in Ni, \forall t \in Nt \quad (14)$$

where $P_{t,i}^{max ch}$ represents the maximum charge power, $Bin_{t,i}^{ch}$ is the binary variable associated with the charging state, $P_{t,i}^{max dch}$ represents the maximum discharge power, and $Bin_{t,i}^{dch}$ represents the binary variable associated with the discharge option. Equation (15) represents the limit imposed on the charging/discharging state. With equation (15), the charge and discharge actions are controlled so that they do not occur simultaneously.

$$Bin_{t,i}^{ch} + Bin_{t,i}^{dch} \leq 1, \quad \forall i \in Ni, \forall t \in Nt \quad (15)$$

Equation (16) presents the state of the batteries in each period.

$$E_{t,i}^{Bat} = E_{t-1,i}^{Bat} + P_{t,i}^{ch} \times \eta_i^{ch} - P_{t,i}^{dch} \times \frac{1}{\eta_i^{dch}} \quad \forall i \in Ni, \forall t \in Nt \quad (16)$$

where $E_{t,i}^{Bat}$ represents the state of the battery, $E_{t-1,i}^{Bat}$ represents the state of the battery in period $t - 1$, η_i^{ch} corresponds to the efficiency of charge and η_i^{dch} to the efficiency of discharge. Equations (17) - (29) present the upper and lower bounds for the variables of the problem.

$$0 \leq P_{t,i}^{buy Grid} \leq P_{t,i}^{max buy Grid}, \quad \forall i \in Ni, \forall t \in Nt \quad (17)$$

$$0 \leq P_{t,i}^{sell Grid} \leq P_{t,i}^{max sell Grid}, \quad \forall i \in Ni, \forall t \in Nt \quad (18)$$

$$0 \leq P_{t,i}^{dch} \leq P_{t,i}^{max dch}, \quad \forall i \in Ni, \forall t \in Nt \quad (19)$$

$$0 \leq P_{t,i}^{ch} \leq P_{t,i}^{max ch}, \quad \forall i \in Ni, \forall t \in Nt \quad (20)$$

$$0 \leq P_{t,i,j}^{buy p2p} \leq P_{t,i,j}^{max buy p2p} \quad \forall i \neq j \in Ni, \quad \forall j \neq i \in Nj, \forall t \in Nt \quad (21)$$

$$0 \leq P_{t,i,j}^{sell p2p} \leq P_{t,i,j}^{max sell p2p} \quad \forall i \neq j \in Ni, \quad \forall j \neq i \in Nj, \forall t \in Nt \quad (22)$$

$$0 \leq E_{t,i}^{Bat} \leq E_{t,i}^{max Bat}, \quad \forall i \in Ni, \forall t \in Nt \quad (23)$$

$$0 \leq Bin_{t,i}^{buy Grid} \leq 1, \quad \forall i \in Ni, \forall t \in Nt \quad (24)$$

$$0 \leq Bin_{t,i}^{sell Grid} \leq 1, \quad \forall i \in Ni, \forall t \in Nt \quad (25)$$

$$0 \leq Bin_{t,i,j}^{buy p2p} \leq 1 \quad \forall i \neq j \in Ni, \quad \forall j \neq i \in Nj, \forall t \in Nt \quad (26)$$

$$0 \leq Bin_{t,i,j}^{sell p2p} \leq 1 \quad \forall i \neq j \in Ni, \quad \forall j \neq i \in Nj, \forall t \in Nt \quad (27)$$

$$0 \leq Bin_{t,i}^{dch} \leq 1, \quad \forall i \in Ni, \forall t \in Nt \quad (28)$$

$$0 \leq Bin_{t,i}^{ch} \leq 1, \quad \forall i \in Ni, \forall t \in Nt \quad (29)$$

where $E_{t,i}^{max Bat}$ represents the maximum battery capacity. Equations (17) - (23) bound the continuous variables, while equations (24) - (29) bound binary variables.

The total energy bill (EB) for each prosumer in the P2P market can be calculated according to equation IV.

$$EB_i = \sum_{t=1}^{Nt} \left(\pi_{t,i}^{buy Grid} \times P_{t,i}^{buy Grid} \right) \times \frac{1}{\Delta t} - \sum_{t=1}^{Nt} \left(\pi_{t,i}^{sell Grid} \times P_{t,i}^{sell Grid} \right) \times \frac{1}{\Delta t} + \sum_{t=1}^{Nt} \sum_{j=1, j \neq i}^{Nj} \left(\pi_{t,i,j}^{p2p} \times P_{t,i,j}^{buy p2p} \right) \times \frac{1}{\Delta t} - \sum_{t=1}^{Nt} \sum_{j=1, j \neq i}^{Nj} \left(\pi_{t,i,j}^{p2p} \times P_{t,i,j}^{sell p2p} \right) \times \frac{1}{\Delta t} + FixCost_i \quad \forall i \in Ni, \quad (30)$$

where $\pi_{t,i,j}^{p2p}$ represents the price in the P2P market for the transaction between prosumer i and prosumer j , and $Fix Cost_i$ is the fixed cost that each prosumer must pay to use the network.

EB contains five terms, as equation IV shows. The first term represents the costs of purchasing electricity from the grid; the second term is the revenue of selling electricity to the grid; the third term corresponds to the costs of buying electricity in P2P market; the fourth term represents the revenues of selling electricity in the P2P market and, finally; the fifth term corresponds to fixed costs paid by each prosumer. The fixed costs are paid directly to the retailer, and are defined in the energy supply contract established between retailer and prosumer. In fact, the sum of the EB of each prosumer without the fixed costs represents the objective function of equation (1). The costs and revenues in the P2P market are not implemented in the objective function since the sum of costs/profits over all player is 0.

To obtain the P2P price for the transactions, we chose the mid-market rate method presented in [4]. The method of price determination assumes that the exchange price is the average

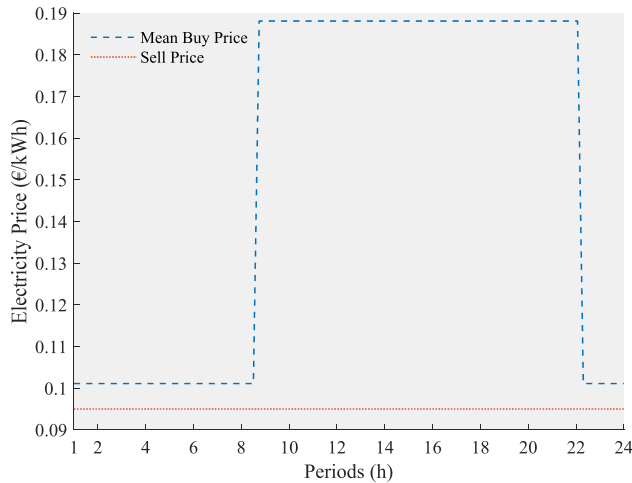


FIGURE 2. Average values of electricity grid prices in the local energy community.

of the electricity buying price and selling price:

$$\pi_{t,i,j}^{p2p} = \frac{\pi_{t,i}^{buy\ Grid} + \pi_{t,i}^{sell\ Grid}}{2}, \quad \forall i \in Ni, \forall t \in Nt \quad (31)$$

When a P2P transaction is executed, the price $\pi_{t,i,j}^{p2p}$ is determined by the seller (i).

IV. CASE STUDY

This section presents a case study to illustrate the use of the methodology proposed in section II. A local energy community with 10 prosumers is considered to presents the main results. To test the scalability of the approach, simulations were executed considering up to 20 prosumers. Each domestic prosumer is equipped with a PV-battery system installed in the household. Figure 2 presents the mean value of electricity prices used to buy and sell electricity within the energy community.

It is assumed that all consumers have contracted a bi-hourly tariff from a retailer. The maximum limit for electricity purchase from the grid is specified in the contract between retailer and prosumers. The prosumer is free to choose this limit but should be considered that higher limits have associated more expensive fixed costs. As can be seen in Figure 2, the buying price correspond to the average price of the ten prosumers. This price is always higher than the selling price. The selling price considered for this case study corresponds to the feed-in tariff defined by Portuguese legislation.² Selling electricity to the main grid is modelled as a constant price (see Figure 1). Each prosumer complying with the current Portuguese legislation, which allows small producers (consumers with local generation) to use their energy to satisfy their own load needs, can inject their surplus of energy to the grid.

²Defined in Portaria n.º 115/2019 of Diário da República n.º 74/2019, Série I de 2019-04-15, <https://data.dre.pt/eli/port/115/2019/04/15/p/dre/pt/html>

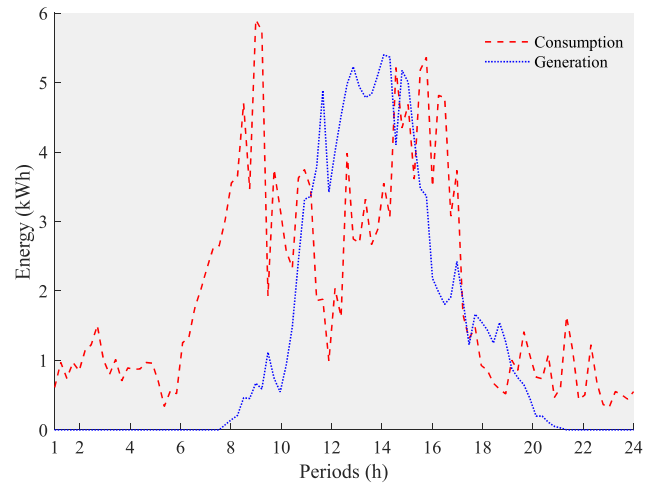


FIGURE 3. Average of consumption and generation in the local energy community.

Figure 3 presents the average consumption and generation profiles.

Figure 3 shows that the average consumption profile presents one peak in the morning (period 8) and another in the afternoon (period 15-17). The generation profile is a classic PV profile with a generation peak near to period 14h. A total of 54 kWh capacity for PV production and 128 kWh of capacity for the battery systems is installed. Each prosumer has a contract with a retailer for a maximum power supply. In the case study, one prosumer has a contract of 3.45 kVA, one 4.6 kVA, two 5.75 kVA, four 10.75 kVA and two 13.8 kVA. The prosumers in the case study pay an average of 0.49 € of fixed costs per day; it is assumed that the retailer has defined these costs. TABLE 2 presents the input variables used in the simulations.

For some parameters two different values appeared in TABLE 2, these correspond to the minimum and maximum values. The input parameters are different for each case study in order to consider prosumers with diverse characteristics.

V. RESULTS

This section presents and discusses the results of the case study presented in Section IV. The experiments were implemented using MATLAB2018a, in a computer with Intel Xeon(R) E5-2620v2@2.1 GHz processor with 16GB of RAM running Windows 10. TOMLAB optimization platform with the solver CPLEX has been used. Four different scenarios are simulated and compared. The scenarios are defined considering the battery usage and the possibility of transacting energy with P2P. The set of scenarios is:

- *Scenario A* – scenario without batteries and without P2P transactions. This scenario is considered the base case;
- *Scenario B* – scenario with batteries and without P2P transaction;

³EDP comercial website: <https://www.edp.pt/particulares/energia/tarifarios/>.

TABLE 2. input parameters of the problem.

Parameters	Designation	Value	Units
Nt	Number of periods	96	-
Ni, Nj	Number of prosumers	10	-
$\pi_{t,i}^{buy Grid}$	Price for buying electricity from the grid*	0.1886 – 0.1008	€/kWh
$\pi_{t,i}^{sell Grid}$	Price for selling electricity to the grid	0.095	€/kWh
Δt	Multiplicative time factor	4	-
$\pi_{t,i,j}^{p2p}$	Prices for p2p transactions	0.1418 – 0.0979	€/kWh
$p_{t,i}^{max buy Grid}$	Limit for buying electricity from grid	3.45 – 13.8	kWh
$p_{t,i}^{max sell Grid}$	Limit for selling electricity to grid	1.725 – 6.9	kWh
$p_{t,i,j}^{max buy p2p}$	Limit for buying electricity in P2P market	3.45 – 13.8	kWh
$p_{t,i,j}^{max sell p2p}$	Limit for selling electricity in P2P market	3.45 – 13.8	kWh
$p_{t,i}^{max ch}$	Limit for battery charge	2 – 8	kWh
$p_{t,i}^{max dch}$	Limit for battery discharge	2 – 8	kWh
$E_{t,i}^{max Bat}$	Maximum capacity of the battery	5 – 20	kWh
$Fix Cost_i$	Fixed costs*	0.7267 – 0.240904	€/day
η_i^{ch}	Battery charge efficiency	0.9	%
η_i^{dch}	Battery discharge efficiency	0.9	%

*values obtained from a Portuguese retailer EDP commercial³.

- Scenario C – scenario without batteries but considering P2P transactions;
- Scenario D – scenario with batteries and with P2P transactions.

The detailed results are presented for a simulation with 10 prosumers. In the end of this section, we have included simulations varying the number of prosumers to analyze the scalability of our approach.

TABLE 3 presents the results of the tested scenarios for 10 prosumers for one day of operation (96 periods of 15-minutes each).

The total costs presented in TABLE 3 correspond to the evaluation of objective function in equation (1). Also notice that consumption and production are considered the same in the four scenarios.

Comparing the scenarios without P2P transactions (Scenario A and Scenario B), Scenario B presents a cost reduction of 4.23 €, i.e. 11%, in comparison with Scenario A. When batteries are considered, there is less energy sold to the grid. This indicates that it is more benefic for prosumers to use the electricity they produce for their own consumption by making use of the batteries than to sell the electricity to the grid. Comparing the two scenarios without battery (Scenario A and Scenario C), Scenario C presents a reduction of 12% in total costs (4.48 €) compared with Scenario A. Without available storage, it is more profitable to sell electricity in P2P market than to sell it to the grid. Considering now the scenarios with battery systems (Scenario B and

TABLE 3. Results considering 10 prosumers.

	No battery	Battery
<i>Without P2P transaction</i>		
	<i>Scenario A</i>	<i>Scenario B</i>
Total costs (€)	37.07	32.84
Consumption (kWh)	482.03	482.03
Production (kWh)	321.38	321.38
Grid supply (kWh)	294.88	268.64
Grid sell (kWh)	129.37	93.46
Savings storage (€)	-	4.23 (11%)
<i>With P2P transactions</i>		
	<i>Scenario C</i>	<i>Scenario D</i>
Total costs (€)	32.59	27.79
Consumption (kWh)	482.03	482.03
Production (kWh)	321.38	321.38
Grid supply (kWh)	250.38	216.45
Grid sell (kWh)	88.40	39.51
P2P transaction (kWh)	44.50	72.53
Savings storage (€)	-	4.80 (13%)
Savings trade (€)	4.48 (12%)	5.05 (15%)
Savings total (€)	4.48 (12%)	9.28 (25%)

Scenario D), Scenario D has a reduction of 5.05 €(15%) compared with Scenario B. In the scenarios with P2P transactions (Scenario C and Scenario D), the battery enables a reduction of 4.80 €(13%) in the total operation cost. Comparing Scenario A with the most complete scenario (Scenario D), savings account for 9.28 €, i.e. 25%, in the later.

TABLE 4 presents the total electricity transaction for each prosumer considering all scenarios for the full considered day.

It is clear that the inclusion of batteries provides additional flexibility to the prosumers, having a direct influence on the electricity transactions and on the total costs.

Figure 4 presents the energy bill value for each prosumer for Scenarios B, and D. EB value is obtained after finalizing the optimization process using equation IV. The value of EB for all prosumers decreases when P2P transactions are enabled. For Scenario B, the average EB for one day of operation is 3.28 €, whereas for Scenario D it is 2.78 €, corresponding to a difference of 0.50 €representing a 15% of reduction.

Notice that in Figure 4, prosumer 9 presents an EB negative value indicating that this prosumer was able to make profits with P2P transactions. Therefore, his energy bill becomes negative. On average, comparing the results of Scenario A with the results of Scenario D, the prosumers have a decrease in cost of 0.93 €/day. If these scenarios are repeated every day of the year, a potential annual savings of 338 €per prosumer can be achieved. Figure 5 presents the contracted power, the battery capacity, and the P2P transactions of each prosumer for Scenario D.

Figure 5 presents two different vertical axes; the left-side vertical axis measures the P2P energy (purchased and sold) transacted in kWh, and the right-side vertical axis measures the contracted power and battery capacity in kW.

As explained before the contracted power limits the transactions between the prosumer and the grid in each period

TABLE 4. Electricity transactions for each individual household considering one day of operation [in kWh].

	Without P2P transaction				With P2P transaction							
	No Battery		Battery		No Battery				Battery			
	SCENARIO A		SCENARIO B		SCENARIO C		SCENARIO D		SCENARIO C		SCENARIO D	
	Grid		Grid		Grid		P2P		Grid		P2P	
	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell	Buy	Sell
Prosumer 1	25.78	2.34	24.73	0.53	16.41	2.34	9.36	0	12.19	0.57	13.21	0.45
Prosumer 2	31.33	8.57	27.90	3.37	26.40	6.47	4.93	2.10	20.60	1.54	8.62	2.90
Prosumer 3	38.01	24.03	35.23	19.87	37.36	15.80	0.65	8.24	36.00	7.78	1.90	14.03
Prosumer 4	12.78	6.63	11.85	5.24	12.49	4.91	0.29	1.72	12.80	2.16	0.41	4.31
Prosumer 5	27.49	13.66	23.61	7.90	25.04	10.82	2.46	2.84	21.65	4.56	3.85	5.19
Prosumer 6	37.37	30.83	34.58	28.15	36.81	16.19	0.56	15.62	35.49	8.81	2.31	22.03
Prosumer 7	18.32	3.14	17.02	1.11	14.06	3.13	4.25	0.01	10.79	1.32	7.32	0.81
Prosumer 8	43.92	10.91	39.67	4.61	33.15	8.91	10.76	2.00	26.47	3.35	17.49	5.08
Prosumer 9	17.92	19.05	16.42	19.13	17.46	11.49	0.47	10.09	16.35	7.07	1.41	14.14
Prosumer 10	41.96	10.21	37.62	3.55	31.18	8.33	10.77	1.88	24.13	2.34	16.00	3.58
Total	294.88	129.37	268.63	93.46	250.36	88.39	44.5	44.5	216.47	39.5	72.52	72.52

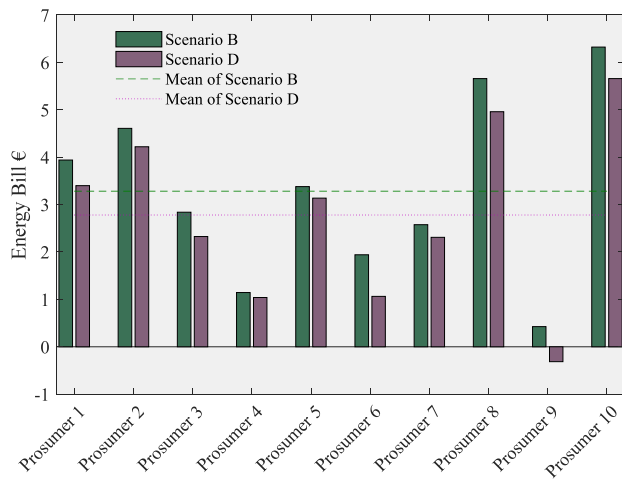


FIGURE 4. Energy Bill results for each prosumer in Scenario B and Scenario D for one day of operation.

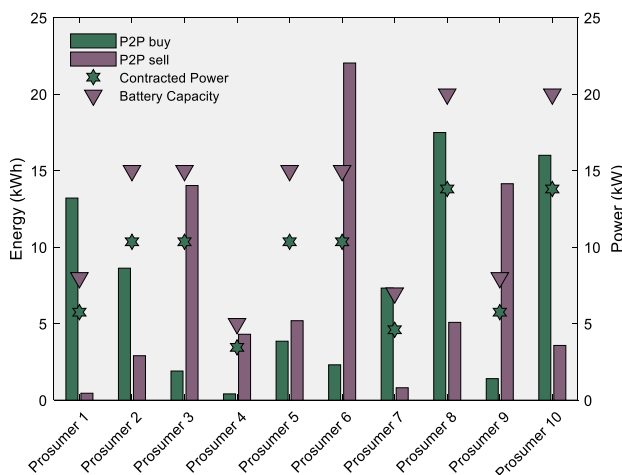


FIGURE 5. P2P trades in Scenario D with the contracted power and battery capacity.

and has a direct influence on the P2P transactions. As can be seen in Figure 5, prosumers 3 and 6 have the same contracted

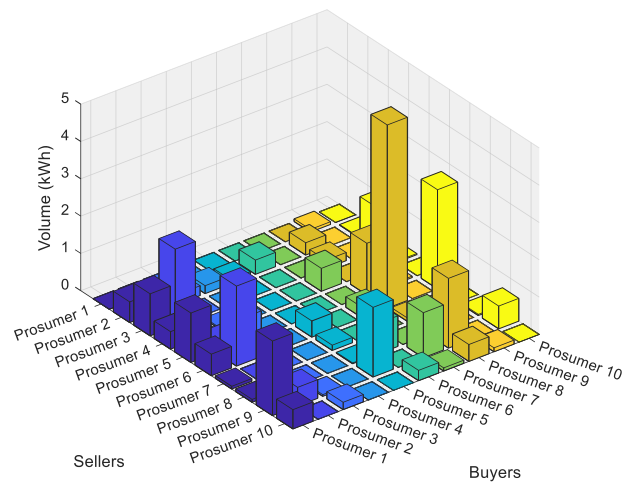


FIGURE 6. Volume of P2P electricity transactions for one day of operation in Scenario D.

power, but prosumer 6 presents a higher volume of electricity sold in the P2P market. Analyzing both figures 4 (showing the *EB*) and 5, prosumers 6 and 9 have the smaller energy bills and the higher values of energy transacted in P2P.

Figure 6 presents the electricity sellers in *yy*-axis, buyers in *xx*-axis and the transacted volume in *zz*-axis corresponding to the volume of electricity transacted between prosumers for the full day in Scenario D. The higher volume of energy transacted occurs between prosumer 8 (as a buyer) and prosumer 6 (as a seller) with a total of 4.91 kWh. Moreover, an average of 3.34 kWh was transacted in the P2P market by each prosumer in the referred day of operation.

Figure 7 presents the electricity purchased from the grid, the electricity sold to the grid, and the P2P transactions for Scenario D.

As can be seen in Figure 7, the tariff peak hours are between 9h to 22h as defined by the bi-horary tariff contracted with the grid/retailer. In these periods, the price of electricity is higher than the rest of periods (off-peak). In turn, the P2P transactions price is also higher in those peak periods.

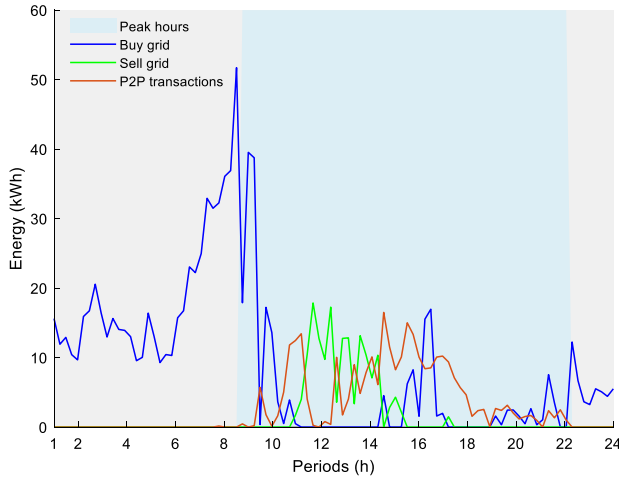


FIGURE 7. Accumulated electricity transactions with the grid and in P2P market for one day of operation in Scenario D.

However, P2P prices are always lower than the retailer’s selling prices. Therefore, the P2P transactions have been realized during the peak periods, as Figure 7 illustrates. Another important fact is that the exceeding PV production from 8h to 20h (Figure 3) can be used to charge the batteries, to be injected to the grid, or to be traded with other prosumers (P2P). As can be seen in Figure 7, electricity is sold to the grid between hours 11h and 16h, which corresponds to the periods with higher PV production (see Figure 3). The P2P market is more attractive for the prosumer to sell the surplus of electricity for a higher profit. However, a part of the surplus electricity is still exported to the grid because prosumers with high PV production reach their maximum battery capacity, and eventually, there are not enough peers to carry out P2P transactions.

The implemented optimization procedure considering 10 prosumers (with total cost of 27.29 €, as showed in TABLE 3) took around 142.83 second. Therefore, to test the scalability of our model, we have run experiments considering 3, 5, 15 and 20 prosumers to obtain a sensitivity analysis of the optimization times. Figure 8 presents the execution time for the optimization process of all scenarios in TABLE 3, varying the number of prosumers from 3 to 20. The yy-axis uses a logarithmic scale. The faster optimization times are obtained with Scenario A considering 3 prosumers (0.81 s). The most time-consuming optimization corresponds to Scenario D with 20 prosumers, that took 15,869.68 s (4.41 h).

As can be seen in figure 8, Scenario D presents a higher optimization time. This is related to the number of variables involved in the optimization process. When the P2P transactions are included in the optimization, it is necessary to include all the possibilities that prosumers have to trade electricity. Also, notice that the number of prosumers does not have an impact in the optimization times for Scenario A and Scenario B, while having a clear impact for Scenario C and Scenario D. In Scenario D, an increment of 4.37 hours was registered in the optimization

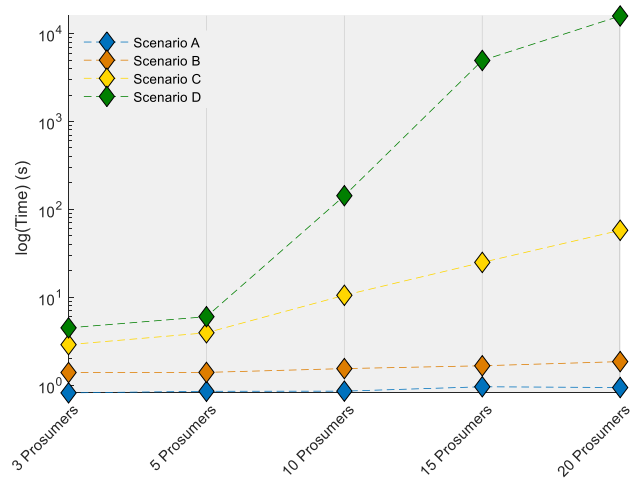


FIGURE 8. Optimization time results for one day of operation.

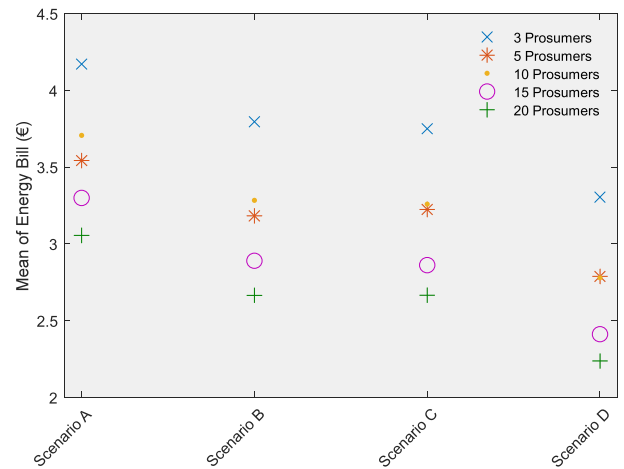


FIGURE 9. Mean results of energy bill considering the scenarios and number of prosumers.

time when the number of prosumers was increased from 10 to 20.

Finally, Figure 9 presents a comparison of the mean energy bill considering the four scenarios and the total set of prosumers number. In each scenario presented in figure 9, five different values are shown corresponding to the different number of prosumers tested. The mean EB value registered a reduction when the numbers of prosumers increased. In the case of Scenario D, corresponding to the scenario with the best results, the mean value considering 20 prosumers registered a decrease of 1.07 €(32%) with regards to the case considering 3 prosumers only.

VI. CONCLUSION

This paper proposes a method for managing the energy resources of a local community considering P2P transactions, PV production, and storage systems. With the inclusion of P2P transactions, looking at the economic aspects, the overall costs of the energy community were lower and each prosumer was able to get a reduction in the energy bill. The best option, as demonstrated by simulation studies, is the combination of

P2P transactions with the usage of batteries (*Scenario D*). In fact, *Scenario D* led to the minimum overall costs for the community members, ensuring an average reduction of electricity costs of 0.93 €/day (9%) per prosumer compared *Scenario D* with *Scenario A*.

The proposed optimization method is consumer-centric having the ability to enable significant user participation in energy trading. Hence, enabling P2P transaction in the energy communities has the potential to encourage households to shift from consumers to prosumers.

The proposed methodology presents some limitations as it requires the existence of bidirectional information and physical energy flows between the involved prosumers. Also, in a real implementation, long execution times can be a drawback that needs to be solved. In the case of 20 prosumers, the optimization time was 4.41 h for the best scenario (*Scenario D*). Therefore, alternative and efficient methods that run near to real-time should be proposed.

In the future, we intend to explore metaheuristic methods (such as evolutionary computation) and decompositions methods (such as Benders decomposition) to solve the proposed problem and reduce the optimization time. In this way, the proposed model can be applied considering a higher number of prosumers.

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