# A Data-Driven Methodology to Design User-Friendly Tariffs in Energy Communities

Akmaral Tlenshiyeva[1], Marcos Tostado-Véliz[1], Hany M. Hasanien[2,3], Nima Khosravi[4], Francisco Jurado[1,*]

1. Department of Electrical Engineering, University of Jaén, 23700, Linares, Spain (e-mail: at000038@red.ujaen.es (A.T.), mtostado@ujaen.es (M.T.-V.), fjurado@ujaen.es (F.J.)).
2. Electrical Power and Machines Department, Faculty of Engineering, Ain Shams University, Cairo 11517, Egypt (e-mail: hanyhasanien@ieee.org).
3. Faculty of Engineering and Technology, Future University in Egypt, Cairo 11835, Egypt.
4. Department of Electrical and Instrumentation Engineering, R&D Management of NPC, Tehran, Iran (e-mail: nimakhosravi64@gmail.com).

* Correspondence: fjurado@ujaen.es

**Abstract.** In recent years, energy communities have emerged as a feasible solution to empower domestic end-users to engage in local power trading with their neighbours, in an attempt to improve the efficiency and economy of residential consumers. From a mercantilist point of view, launching local markets with eventual local electricity prices might be beneficial for community users as they are inhibited from external volatile prices and possible market imperfections. However, local pricing strategies should take into account users' preferences and avoid undesirable effects of response fatigue (i.e. excessive number of response signals within a short-time period). This way, local electricity tariffs should be stable and send coherent response signals easily interpretable by users. In this sense, the necessity of developing proper designing tools for local electricity tariffs is clear. This paper focuses on this issue. In particular, the main novelties of this paper are twofold: on the one hand, the developed tool designs community tariffs over a year basis instead of daily spot prices, as made in existing approaches. Thereby, the resulting tariff keeps stable yearly similar to conventional tariffs offered by retailers worldwide. Secondly, the designed tariff takes into account the negative effects of response fatigue, so that the considered pricing mechanism limits the number of pricing signals sent to consumers, taking this feature as an external parameter. This way, the designer is able to tune up the total number of pricing signals that users received within a time period, thus ensuring that they are not discouraged to partake in the community. The proposed design approach is raised as a data-driven framework, taking advantage of real databases collecting demand, renewable generation and retailer prices. Such profiles serve as inputs for a designed bi-level Stackelberg-based problem, in which the reaction of prosumers is implicitly assumed. A case study is conducted on a benchmark energy community. Different tariff mechanisms are analysed such as flat, time-of-use and happy hours tariffs. The results obtained serve to validate the new proposal as well as analyse the effect of local market mechanisms in energy communities.

**Keywords.** Electricity tariff; Energy community; Response fatigue; Stackelberg game.

**Nomenclature**

| *Acronyms* | |
|---|---|
| BES | Battery energy storage |
| EC | Energy community |
| KKT | Karush Kuhn Tucker |
| MILP | Mixed integer linear programming |
| MPCC | Mathematical problem with complementarity constraints |
| PV | Photovoltaic |
| RTP | Real-time pricing |
| SDT | Strong duality theorem |
| SOC | State of charge |
| SOS | Special ordered set |
| TOU | Time-of-use |
| *Indices (sets)* | |
| $d(\mathcal{D})$ | Day |
| $r(\mathcal{R})$ | Representative day |
| $\Omega_r$ | Cluster of the $r^{th}$ representative day |
| $i(\mathcal{I})$ | Prosumer |
| $t(\mathcal{T})$ | Time |
| *Superscripts* | |
| $EC$ | Energy community |
| $b/s$ | It refers to power imported (bought)/exported (sold) |
| $PV$ | Photovoltaic |
| $S, c/d$ | Storage system in charging/discharging mode |
| $D$ | Non-controllable (non-flexible) demand |
| $F$ | Flexible demand |
| $M$ | Community manager |
| $G$ | External grid (distribution network) |
| *Parameters and constants* | |
| $\Delta\tau$ | Time step [h] |
| $\omega$ | Number of representative days over a year [-] |
| $\eta$ | Efficiency [pu] |
| Z | Total daily demand of flexible loads [kWh] |
| $M$ | Large positive value [-] |
| $T$ | Total number of periods of time-of-use tariffs [-] |
| $K$ | Total number of prices of time-of-use tariffs [-] |
| $k$ | Minimum number of hours for each section of time-of-use tariffs [hour] |
| $H$ | Total number of happy hours over a day [-] |
| *Decision variables (primal)* | |
| $p$ | Power [kW] |
| $\lambda$ | Energy price [€/kWh] |
| $\epsilon$ | Energy stored [kWh] |
| $\theta^{\downarrow}$,$\theta^{\uparrow}$, $\vartheta^{\uparrow}$, $\vartheta^{\downarrow}$, $\zeta$ | Auxiliary binary variables [-] |
| $\rho$ | Auxiliary integer variable [-] |

| *Decision variables (dual)* | |
|---|---|
| $\phi$ | Dual variable linked to equality constraints [-] |
| $\underline{\mu}, \overline{\mu}$ | Dual variables linked to inequality constraints [-] |
| $\psi^{\downarrow}, \psi^{\uparrow}$ | Auxiliary variables to linearize complementarity terms [-] |

## 1 – Introduction

### *1.1 – Context & Motivation*

Energy communities (ECs) have emerged as a regulatory framework that enables market participation of end consumers (principally residential installations). The EU Legislation introduced the concept of EC in [1], thus paving the path for the active participation of end-users in different electricity sectors like generation, distribution, supply, consumption, storage, aggregation and sharing [2]. In addition, ECs can launch local market mechanisms [3]. Thus, local power trading is performed under local prices and thus community users are inhibited from prices fixed by retailers, which might be expensive or eventually volatile. Furthermore, local market strategies encourage to efficiently manage local resources such as photovoltaic (PV) panels and small-scale storage assets.

However, it is important to establish market mechanisms that do not discourage users to partake in the community. Such pricing strategies should not uniquely respond to economic factors, but also to limit the effects of the so-called response fatigue [4]. This well-reported phenomenon makes mention to the number of pricing signals that end-users receive from the pricing-maker agent. Thus, if local transactions are performed under volatile tariffs that frequently varies within a short-time period, users may be reluctant to partake in the community due to the excessive number of signals received.

In this sense, it is important to establish local mechanisms that take into account such negative effects. This paper addresses this issue. Specifically, we propose in this paper a novel optimization framework for user-friendly tariff designing in ECs. In this sense, we understand that a tariff (or pricing) mechanism is user-friendly when its implantation does not discourage users to partake in the community.

### *1.2 – Local Markets in ECs: Current Practises & Research*

Behind the concept of EC underlies the idea of cooperative interaction among participants, enabling prosumers to directly engage in energy trading with their neighbours without pursuing an economic profit [5]. Under this concept, local markets are disabled assuming that energy trading always pursue the collective welfare and therefore all the participants would improve their economy in consequence.

The idea of cooperative communities has been profusely studied in the literature. There exist a number of remarkable references that address local energy management in cooperative ECs. Thus, Lilla et al [6] propose a decentralized energy management strategy for communities formed by prosumers in which each peer is responsible on solving her own energy management problem, exchanging boundary information with the rest of prosumers in the community. In this regard, the authors of this paper developed an optimization algorithm based on the alternating direction of multipliers, which was posteriorly improved in [7] to include intraday decisions. The role of collective energy storage has been addressed in a number of papers. In particular, the works of Guedes et al [8, 9] focus on establishing access mechanism by which the users can leverage collective energy storage, whereas [10, 11] focus on collective storage based on hydrogen technologies. On the other hand, the authors in [12] optimally integrate ECs with intelligent parking lots through a multi-stage optimization strategy.

In addition to the researches above, the idea of cooperative ECs has been put on practise in various real projects in different countries like Belgium [13], Sweden [14] or Spain [15]. However, cooperative energy trading does not establish any monetary incentive and may demotivate to install own generation and storage, which may hide some opportunities brought by local power exchanges. Moreover, enabling local market power discloses some advantages and serves as a barrier for volatile energy prices fixed externally. By these reasons, local markets in ECs are gaining attention in recent years. To promote a fair energy trading in ECs, there is a widespread consensus on the necessity of developing proper market mechanisms that unlock flexibility from all the actors implied in the system. The idea of local energy markets is not new and have been already applied to diverse energy systems. For example, a Mixed Integer Linear Programming (MILP) model for market-driven price-setting in gas supplying of rural areas was developed in [16]. In [17], a planning framework for large-scale storage systems partaking in distribution electricity markets was proposed, showing that storage agents can pursue an individual benefit under local marginal prices. Similarly, [18] studies the integration of ECs into deregulated distribution networks. In [19], an equilibrium model was developed, for optimal price-setting in multi-microgrids systems while [20] accounts for privacy concerns in these systems. Moghaddam et al [21] proposed an optimization model for deriving nodal prices in an integrated traffic-power network, with focus on avoiding traffic congestions. Likewise, the authors in [22] proposed a dynamic charging tariff for charging stations.

The local market principles above are being applied to ECs nowadays. Notable examples are the so-called Market Model 3.0 [23], recently launched by the Danish Energy Agency. Other key examples are being implemented in UK and southern Norway, through the so-called Piclo Flex [24] and NorFlex [25] market initiatives. When ECs agree a local market mechanism, peer-to-peer energy trading is performed under local prices, which are cleared by a local central entity (commonly called community manager).

Although we have cited some real examples, the concept of local market in EC is still an open topic and a number of researches are being conducted on investigating novel market mechanisms for ECs. Nevertheless, most of these works simply assume that local prices are fixed by a central local entity following some preestablished cost allocation mechanism. Within this category, different billing strategies for ECs are proposed and studied in [26]. In particular, this reference discusses different repartition rules, some of them based on optimization and approaches while other are based on the so-called keys of repartition. Other body of research follow heuristic rules to derive local energy prices. Specifically, local prices are derived based on game theory in [27], however, the whole optimization model is solved using metaheuristic techniques, which does not ensure the optimality of the solution. On the other hand, an iterative bisection method is proposed in [28], by which the final pricing strategy is calculated as the equilibrium point where the agents are not able to improve their profit beyond a limit. Finally, it is worth mentioning some references that simply consider the local electricity price as a parameter, without detailing how that price is derived. Some examples are [29], which deals with systems involving virtual power plants formed by prosumers and distributed generators, and [30], where an optimal participation strategy of prosumers in multi-market communities is developed.

Although the references above suppose notable contributions in the field of local energy markets in ECs, it is worth remarking the number of researches conducted by Kazempour et al, and Conejo et al. These works rely on Stackelberg-based approaches to derive local prices. This approach is considered more suitable in local markets as the resulting local price is optimal in the Nash sense, and therefore establishes an analytical equilibrium among the community manager and prosumers. In particular, a local pricing mechanism was proposed in [31] based on spot and real-time market products. The main novelty of this market mechanism is the inclusion of specific financial products for risk trading based on the so-called Arrow Debreu securities. This way, prosumers have access to not only energy-based products, but also to risk exchanges thus incrementing the possibilities of enhancing the economy of users. In [32], a local pricing mechanism for enabling flexibility through limitation services was developed. On the other hand, [33] and [34] focus on deriving market products for collective storage utilization based on access rights. In particular, physical and financial access rights to storage were studied and discussed.

Finally, a distribution market mechanism involved prosumers was discussed in [35], deriving an equilibrium analysis based on Stackelberg game principles.

*1.3 – Research Gaps*

Although local market mechanisms might bring important benefits for community users, the related literature is still scarce and further research is needed in a variety of fields. Actually, most of the up-to-date references regarding ECs are devoted on cooperative interactions and therefore the implications of local markets have not been deeply discussed yet.

Regarding those references focused on local markets, it is worth noting that most of them oversimplify the derivation of local prices. For example, [26] recurs to preestablished repartitions mechanisms while [28] states a simple heuristic methodology. In this sense, the works by Kazempour et al, and Conejo et al suppose an exception, developing well-established price-setting strategies based on game theory, that eventually seek for an equilibrium solution among the agents partaking in the community.

However, the references studied do not take into account the negative effects of response fatigue when deriving local prices. For example, the studied references establish day-ahead clearing mechanisms by which local prices are revealed daily. This way, each prosumer receives different pricing signals each day, thus increasing not only the number of signals received, but also the volatility of local prices. Under such assumptions, the resulting pricing strategy may be counterproductive and could discourage users to partake in the community. This work is specifically devoted on this issue, as explained in the following section.

*1.4 – Our Contributions*

We further follow the idea of local markets in ECs by developing a novel optimization framework for local pricing in ECs. In contrast to existing approaches, which focus on day-ahead price clearing mechanisms, we propose a data-driven planning methodology, which is aimed at designing a tariff for community users over a year basis. There are two main reasons for developing a year-based pricing mechanism instead of other short-term strategies:

- Firstly, developing a year-based tariff voids uncertainty in prices, thus allowing users to reduce the associated risk when engaging in energy trading. In addition, this approach aligns with conventional tariffs offered by retailers, which are normally agreed for a one-year period.
- Secondly, the effect of response fatigue is minimized, as the number of pricing signals is kept below a preestablished bound. This way, the users can schedule their own assets on the basis of limited and easily interpretable response signals, thus avoiding discouraging due to the effect of frequent and repetitive signals sent by the coordinator.

Thus, the new proposal is considered more suitable than other approaches, assuming that users are keen on deterministic and stable tariff mechanisms rather than volatile pricing approaches based on real-time signals (e.g. see [36]). Actually, this work supposes (to the best of our knowledge) the first attempt to consider response fatigue in the tariff design process in ECs. For the sake, of simplicity, the main contributions of this paper are listed below:

- Developing a data-driven optimization framework for tariff design in ECs. Following common ideas in other references, the new model is raised as a bi-level Stackelberg framework, so that the resulting tariff mechanism is assumed to be an equilibrium point in the Nash sense.
- Including additional modelling principles that eventually keep the number of pricing signals below a preestablished bound. It allows designers to carefully tune up the number of response signals that the users receive within a time period thus reducing the effects of response fatigue.

- Modelling and studying three different tariff strategies. In particular, we develop optimization models for flat, time-of-use (TOU) and happy hours tariffs, while their implications, advantages and disadvantages are discussed on a benchmark case study.

### *1.5 – Paper Organization*

In the rest of this paper, Section 2 provides the necessary background. Section 3 introduces the mathematical models for prosumers and community manager. Section 4 develops the proposed data-driven framework for optimal tariff design. A case study with results is described in Section 5. Finally, the paper is concluded with Section 6.

## 2 – Preliminaries

### *2.1 – Energy Communities*

According to [31], we conceive an EC as an aggregation of a few prosumers that are located in the same geographical area and treated as a single entity for an upper-level agent (potentially a retailer or distribution system operator).

In order to establish coherent and equilibrated energy trading among peers, we assume that each prosumer owns PV panels and small-scale battery energy storage (BES). Moreover, each prosumer is capable to adapt her own consumption according to price signals, in a practise known as flexible demand, which results feasible nowadays by optimally managing smart appliances or thermostatically-controlled devices [37].

### *2.2 – Local Market Structure and Agents*

Fig. 1 sketches the structure for the proposed local market framework. This market model encompasses three-levels. In the lower level, prosumers trade energy among them and with the community under a pre-established community tariff mechanism (i.e. $g(\lambda^{EC})$). Actually, the main aim of this paper is determining this tariff mechanism. Note that each prosumer could eventually export power to the community through own generation and storage.

In the middle-level, the community manager coordinates interactions among peers and serves as link between the lower and upper levels. In this sense, the manager trades energy with the local retailer, who establishes energy prices at the grid-scale level. In this paper, we assume that the EC agrees a tariff mechanism with the retailer based on real-time-pricing (RTP), so that market signals are directly translated to the community manager, but not to prosumers, who agree a tariff mechanism based on $g(\lambda^{EC})$.

In the proposed market structure, the community manager gathers the role of spatial arbitrageur and price-setter (see [31] for further information). Thus, besides trading energy with the local retailer, the community manager is responsible of determining community prices. However, in contrast to other approaches (e.g. [31, 32]), community prices are determined on a year basis in this paper, instead of being revealed daily. This way, possible volatility on community prices is eliminated.

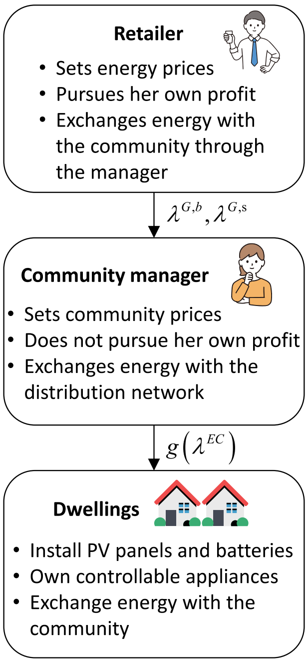


Fig. 1 – The proposed local market mechanism

*2.3 – Representative Days Selection*

This paper proposes a data-driven methodology for tariff design in ECs, which is sketched in Fig. 2. The proposed methodology assumes that data regarding demand and PV generation has been collected for a period of one year (or longer). These data serve as input for the methodology developed in Section 4. However, such database may encompass a large number of samples, which may suppose intractability issues in conventional software and computers. To circumvent this issue, we use clustering techniques with the aim of reducing the original database to a minimum set of representative scenarios. This practise is known as representative day selection as has been widely used in planning tools on different fields [38, 39].

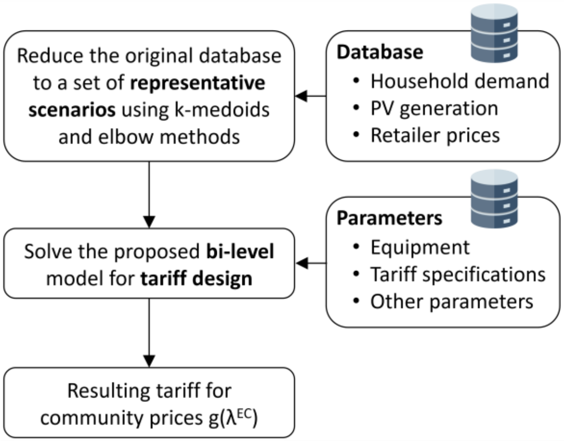


Fig. 2 – Flowchart of the developed tariff design methodology

In particular, we consider in this paper the k-medoids method, due to its good overall features [40]. The k-medoids technique is based on the traveller problem and gathers the original scenario-space (denoted by $\mathcal{D}$) into clusters, which are represented by a unique member called medoid. In practise, the medoid is considered an accurate representation of the whole cluster. In consequence, results obtained by just considering the medoids should be similar to those obtained considering the whole space $\mathcal{D}$.

Therefore, by using the k-medoid method, the original scenario-space is reduced into a representative scenario-space (denoted by $\mathcal{R}$), which is typically formed by 5-15 samples [41].

Nevertheless, one of the main difficulties in applying k-medoids is the necessity of determining the number of medoids (i.e. clusters) a priori, which may be difficult. To solve this issue, we use the elbow method, as described in [42]. Finally, the probability of occurrence for each scenario on a year basis can be calculated, as follows:

$$\omega_r = \frac{\mathrm{size}(\Omega_r)}{\mathrm{size}(\mathcal{D})}; \forall r \in \mathcal{R} \tag{1}$$

*2.3 – Assumptions*

In subsequent models, we assume perfect market competition. This way, all the prosumers partaking in the community assume a price-taker strategy and the prices are fixed uniquely by the community manager. Note that, under this assumption, any of the market agents exercise market power.

On the other hand, the community manager is taken as an economy-neutral agent. In this way, this agent does not pursue her own monetary profit and therefore her monetary balance will be always positive (higher expenditures than incomes). Note that this is a common assumption in ECs [32].

Finally, due to prosumers are assumed to be located near each other, networks constraints are only enforced by exportable and importable power bounds, while branch losses or voltage imbalances are assumed to have a marginal impact and therefore neglected.

## 3 – Mathematical Models

We next describe the mathematical modelling for the agents involved in the community (i.e. prosumers and community manager). Note that dual variables are given at the right-hand side of their corresponding equation.

*3.1 – Prosumers Modelling*

Prosumers aim at minimizing their own cost while trading energy with the community and managing own assets (PV, BES and flexible loads). Thereby, the optimization model for the *i*^th^ prosumer in the EC reads as

$$\min_{\Theta_i} F_i = \Delta\tau \sum_r \left\{ \omega_r \sum_t \left\{ g(\lambda^{EC}) \left( p_{i,r,t}^{EC,b} - p_{i,r,t}^{EC,s} \right) \right\} \right\} \tag{2a}$$

Subject to:

$$p_{i,r,t}^{EC,b} + p_{i,r,t}^{PV} + p_{i,r,t}^{S,d} = p_{i,r,t}^{EC,s} + p_{i,r,t}^{D} + p_{i,r,t}^{S,c} + p_{i,r,t}^{F} : \phi_{i,r,t}; \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{2b}$$

$$\epsilon_{i,r,t}^{S} = \epsilon_{i,r,t-1}^{S} + \Delta\tau \cdot \left( p_{i,r,t}^{S,c} \eta_i^S - p_{i,r,t}^{S,d} / \eta_i^S \right) : \phi_{i,r,t}^{S}; \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \backslash t = 1 \tag{2c}$$

$$\epsilon_{i,r,1}^{S} = \epsilon_{i,r,|\mathcal{T}|}^{S} : \phi_{i,r}^{S\_Cycle}; \forall r \in \mathcal{R} \tag{2d}$$

$$\Delta\tau \sum_t p_{i,r,t}^{F} = \mathrm{Z}_i : \phi_{i,r}^{F}; \forall r \in \mathcal{R} \tag{2e}$$

$$0 \le p_{i,r,t}^{EC,x} \le \overline{p}^{EC} : \underline{\mu}_{i,r,t}^{EC,x}, \overline{\mu}_{i,r,t}^{EC,x}; \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \wedge x \in \{b, s\} \tag{2f}$$

$$0 \le p_{i,r,t}^{S,x} \le \overline{p}_i^{S} : \underline{\mu}_{i,r,t}^{S,x}, \overline{\mu}_{i,r,t}^{S,x}; \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \wedge x \in \{c, d\} \tag{2g}$$

$$\underline{\epsilon}_i^{S} \le \epsilon_{i,r,t}^{S} \le \overline{\epsilon}_i^{S} : \underline{\mu}_{i,r,t}^{\epsilon}, \overline{\mu}_{i,r,t}^{\epsilon}; \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{2h}$$

$$0 \le p_{i,r,t}^{F} \le \overline{p}_{i,t}^{F} : \underline{\mu}_{i,r,t}^{F}, \overline{\mu}_{i,r,t}^{F}; \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{2i}$$

where $\Theta_i = \left[ p_{i,r,t}^{EC,b}, p_{i,r,t}^{EC,s}, p_{i,r,t}^{S,c}, p_{i,r,t}^{S,d}, p_{i,r,t}^{F}, \epsilon_{i,r,t}^{S} \right]$ are the decision variables for the $i^{th}$ prosumer in the EC.

The objective function (2a) implies energy cost minimization by trading energy with the community under the price mechanism $g(\lambda^{EC})$, whose design is discussed in Section 4. Note that (2a) is calculated over a year basis by multiplying each representative scenario by $\omega_r$, which equals to the number of days within the $r^{th}$ cluster. Thereby, results are evaluated over a year basis.

The set of constraints in (2) is formed by equality constraints (2b)-(2e) and operational limits (2f)-(2i). In particular, (2b) represents the power balance involving PV generation, BES, power exchanged with the community, as well as flexible and non-flexible demand. Note that PV generation and non-flexible demand are considered parameters whereas the rest of variables can be controlled. This way, those parameters are considered inputs of the problem and assumed to be modelled by representative days. On the other hand, (2c) represents the instantaneous state-of-charge (SOC) of the BES systems while (2d) establishes coherency in the charging-discharging daily cycle of batteries. Finally, (2e) enforces that total consumption of flexible loads (i.e. $\mathrm{Z}_i$) is fully satisfied. In this case, we consider a simple flexible load model [43], which avoids the use of binary variables.

Regarding power bounds, (2f) and (2g) limit the power that can be exchanged with the community and BES systems, respectively. Note that limitations in imports and exports can be imposed to avoid network congestions, while power bounds for batteries are determined by auxiliary equipment and the energy-to-power ratio [44]. The capacity of the BES is upper limited by nominal values and depth-of-discharge settings in (2h). Lastly, (2i) limits the instantaneous flexible demand, assuming that flexible loads cannot demand beyond their rating power.

*3.2 – Community Manager Modelling*

The community manager is responsible of trading energy with the local grid (through the retailer), as well as determining community prices. Thus, we consider $g(\lambda^{EC})$ in the variable-space of the manager, whose decision vector is given by $\Theta^M = \left[p_{r,t}^{G,b}, p_{r,t}^{G,s}, g(\lambda^{EC})\right]$. The community manager seeks for reducing the total cost for the EC, which motivates the following optimization problem

$$\min_{\Theta^M} F^M = \Delta\tau \sum_r \left\{ \omega_r \sum_t \left\{ \lambda_t^{G,b} p_{r,t}^{G,b} - \lambda_t^{G,s} p_{r,t}^{G,s} \right\} \right\} \quad (3a)$$

Subject to:

$$p_{i,r,t}^{G,b} + \sum_i p_{i,r,t}^{EC,s} = p_{i,r,t}^{G,s} + \sum_i p_{i,r,t}^{EC,b} \,; \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \quad (3b)$$

$$0 \le p_{r,t}^{G,x} \le \overline{p}^{G} ; \forall r \in \mathcal{R} \wedge t \in \mathcal{T} \quad (3c)$$

$$\underline{\lambda}^{EC} \le \lambda_t^{EC} \le \overline{\lambda}^{EC} ; \forall t \in \mathcal{T} \quad (3d)$$

$$F^M \ge 0 \quad (3e)$$

$$F_i \le \Delta\tau \sum_r \left\{ \omega_r \sum_t \left\{ \lambda_t^{G,b} p_{r,t}^{EC,b} - \lambda_t^{G,s} p_{r,t}^{EC,s} \right\} \right\} ; \forall i \in \mathcal{I} \quad (3f)$$

Tariff modelling (3g)

The objective (3a) seeks for minimizing the cost of trading energy with the grid under RTP mechanism. Note that those prices are imposed by the retailer on the basis of real-time signals, and therefore the community agents cannot decide on them. Thereby, the grid prices $\lambda_t^{G,b}$ and $\lambda_t^{G,s}$ are considered parameters and modelled by representative days.

The manager modelling is completed by (3b), which establishes the power balance in the community including peer-to-peer exchanges among prosumers, while (3c) limits the power that can be exchanged with the grid, similar to (2f). On the other hand, (3d) imposes upper and lower bounds on the community prices. Note that we have to include limits on prices since regularization is not considered in the objective function [31]. Moreover, we consider the community prices as a function of time, assuming that a dynamic scheme can be adopted for the designed tariff, as discussed later.

The constraints (3e) and (3f) focus on establishing economy coherency. In particular, (3e) ensures that the community manager is a neutral player who does not pursue any economic profit. On the other hand, (3f) ensures that prosumers gain by partaking in the community, forcing the total cost for each prosumer to be lower than the cost in which a prosumer would incur trading directly with the retailer. Finally, (3g) encompasses the constraints related to tariff modelling, which are described in the following sub-section.

*3.3 – Tariff Modelling*

The designed community tariff scheme should be stable, thus sending few and easily interpretable pricing signals to users. This way, the resulting pricing strategy reduces the effects of response fatigue, which may eventually discourage users to partake in the EC. In this sense, we consider three different tariff models (see Fig. 3), which align with common tariffs offered by retailers [45]. In subsequent paragraphs, we describe each tariff as well as their mathematical models, which can be incorporated as constraints in (3).

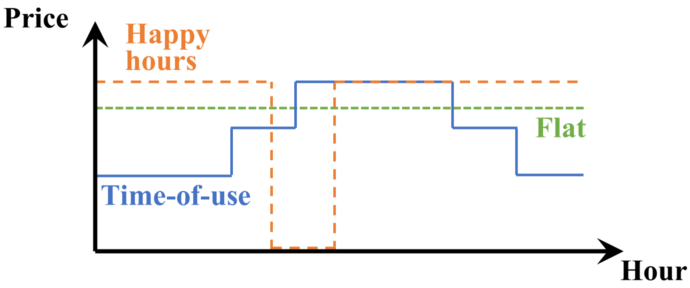


Fig. 3 - Sketch of the considered tariff models

Flat tariff

Flat tariffs are very simple and have been typically offered by retailers until the emergence of renewables and smart devices. Essentially, a flat tariff establishes the same price over a day, which is modelled by declaring the energy price independent of the time, as follows

$$\lambda_t^{EC} \rightarrow \text{constant}\ \forall t \tag{4}$$

TOU tariff

TOU tariffs are likely the most common product offered by retailers nowadays. This kind of tariffs contemplate different energy prices over a day, encouraging to shift demand to valley (i.e. lowest prices) periods. Thereby, each pricing slot is known as a period, during which the price takes a constant value. Consequently, pricing variations are only allowed within transitions from one period to another. However, to avoid incur in repetitive and frequent price signals, the total number of periods is limited to $T$, as follows

$$\sum_t \left(\theta_t^{\downarrow} + \theta_t^{\uparrow}\right) = T \tag{5}$$

$$\theta_t^{\uparrow}, \theta_t^{\downarrow} \in \{0,1\}; \forall t \in \mathcal{T} \backslash t = 1 \tag{6}$$

In (5), auxiliary binary variables $\theta_t^{\downarrow}$ and $\theta_t^{\uparrow}$ model price variations, so that one of them is activated during transitions between periods, as said (7)-(10).

$$M \cdot \theta_t^{\uparrow} \geq \lambda_t^{EC} - \lambda_{t-1}^{EC}; \forall t \in \mathcal{T} \backslash t = 1 \tag{7}$$

$$M \cdot \left(1 - \theta_t^{\uparrow}\right) \geq \lambda_{t-1}^{EC} - \lambda_t^{EC}; \forall t \in \mathcal{T} \backslash t = 1 \tag{8}$$

$$M \cdot \left(1 - \theta_t^{\downarrow}\right) \geq \lambda_t^{EC} - \lambda_{t-1}^{EC}; \forall t \in \mathcal{T} \backslash t = 1 \tag{9}$$

$$M \cdot \theta_t^{\downarrow} \geq \lambda_{t-1}^{EC} - \lambda_t^{EC}; \forall t \in \mathcal{T} \backslash t = 1 \tag{10}$$

Note that by imposing (5)-(10), prices are only allowed to vary between transitions, keeping constant the rest of time slots. We consider that a TOU tariff can take $K$ different prices resulting in different periods. Nonetheless, the price is not allowed to vary within a period, which is enforced by

$$\lambda_t^{EC} = \underline{\lambda}^{EC} + \rho\left(\frac{\overline{\lambda}^{EC} - \underline{\lambda}^{EC}}{K}\right); \forall t \in \mathcal{T} \tag{11}$$

$$\rho \in \{1,2, \dots, K\} \tag{12}$$

Indeed, (11) splits the pricing range $\left[\underline{\lambda}^{EC}, \overline{\lambda}^{EC}\right]$ into $K$ sections, and the integer variable $\rho$ enforces that energy price remains constant within a period is activated. In addition, (13) ensures that a period must remain active for at least $k$ hours.

$$\sum_{t+k/\Delta\tau}\left(\theta_t^{\uparrow} + \theta_t^{\downarrow}\right) \leq 1; \forall t \in \mathcal{T} \backslash t = 1 \tag{13}$$

Finally, (14) imposes symmetry in the tariff (same positive and negative variations in prices) whereas (15) enforces that the same period is activated for the first and final time slots.

$$\sum_t \theta_t^{\uparrow} = \sum_t \theta_t^{\downarrow} \tag{14}$$

$$\lambda_1^{EC} = \lambda_{|\mathcal{T}|}^{EC} \tag{15}$$

<u>Happy hours tariff</u>

Happy hours is a relatively novel pricing mechanism in which the energy price is null during $H$ hours over a day (known as happy hours) [41]. To model null prices, we introduce the auxiliary binary variable $\zeta_t$, which is equal to zero at happy hours slots. Thus, the energy price is finally modelled, as follows

$$\lambda_t^{EC} = \zeta_t \lambda^{EC}; \forall t \in \mathcal{T} \tag{16}$$

As seen, (16) enforces the energy price to be constant except during happy hours, as customary in currently offered happy hours tariffs [45]. On the other hand, (17) ensures that the total number of happy hours over a day is equal to $H$, as established in the pricing mechanism.

$$\sum_t \zeta_t = |\mathcal{T}| - H/\Delta\tau \tag{17}$$

Typically, happy hours must be consecutive, which is modelled by (18) and (19), where binary variables $\vartheta_t^{\uparrow}$ and $\vartheta_t^{\downarrow}$ are declared to model variation in prices. Finally, binary variables are duly declared in (20).

$$\zeta_t - \zeta_{t-1} = \vartheta_t^{\uparrow} - \vartheta_t^{\downarrow}; \forall t \in \mathcal{T} \backslash t = 1 \tag{18}$$

$$\sum_t \vartheta_t^{\uparrow} = 1 \tag{19}$$

$$\zeta_t, \vartheta_t^{\uparrow}, \vartheta_t^{\downarrow} \in \{0,1\}; \forall t \in \mathcal{T} \tag{20}$$

## 4 – The Proposed Tariff Design Framework

### *4.1 – Foundations*

As commented in Section 1, we understand that a tariff mechanism is user-friendly when the number of pricing signals remains within reasonable margins and results economically attractive for users. The first condition is met by imposing the tariff models described in Section 3.3, which are conceived to reduce the effects of response fatigue, while the second condition was partially solved by including (3f), which ensures that prosumers gain by partaking in the community.

Moreover, the resulting tariff mechanism should seek for maximizing the collective welfare. Broadly speaking, although the manager is the unique responsible on designing the tariff strategy, this decision should be taken collectively, bearing in mind the reaction of prosumers to any pricing decision.

In order to include the reaction of prosumers into the tariff design methodology, we propose a bi-level Stackelberg-based model. Stackelberg games are defined by a leader and various followers [46]. Essentially, the leader takes a decision trying to anticipate the reaction of followers. This way, the model prevents that any decision affecting followers is taken without considering their preferences.

As seen, the foundations of Stackelberg games match perfectly with the premises of our methodology. In Stackelberg optimization models, the leader's problem is constrained by the followers' problems, resulting in a bi-level optimization framework. For our particular problem, we consider the community manager as the leader (upper level), being responsible on designing the community tariff, while the prosumers act as followers (lower level), thus resulting in the following bi-level structure.

$$g(\lambda^{EC}) \in \underset{\substack{\Theta^{M}\cup\text{Aux.}\\ \text{variables}}}{\operatorname{argmin}} F^{M} \tag{21a}$$

Subject to:

(3b)-(3f) (21b)

Tariff modelling (21c)

$$\begin{cases}\min_{\Theta_i} F_i\big(g(\lambda^{EC})\big) \end{cases} \tag{21d}$$

Subject to:

$$(2\text{b}) - (2\text{i})\}; \forall i \in \mathcal{I} \tag{21e}$$

The bi-level framework (21) designs the community tariff $g(\lambda^{EC})$ aiming at minimizing the community cost in (21a), including the constraints of the upper level in (21b) and the tariff modelling in (21c). On the other hand, (21d) and (21e) include the prosumers' objectives and constraints, respectively.

Bi-level optimization problems are difficult to solve [47]. To make (21) tractable in practise, it is transformed into a single-level Mathematical Problem with Complementarity Constraints (MPCC) in the following sub-section.

*4.2 – MPCC*

Bi-level problems can be transformed into tractable single-level models by reducing the lower-level problem to its Karush-Kuhn-Tucker (KKT) conditions. Note that KKT conditions are sufficient condition for optimality in convex problems. In our particular model (21), the lower-level problem is linear and therefore convertible to its KKT conditions, which are given below

$$\frac{\partial \mathcal{L}_i}{\partial p_{i,r,t}^{EC,b}} = \Delta\tau\omega_r g(\lambda^{EC}) + \phi_{i,r,t} - \underline{\mu}_{i,r,t}^{EC,b} + \overline{\mu}_{i,r,t}^{EC,b} = 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{22a}$$

$$\frac{\partial \mathcal{L}_i}{\partial p_{i,r,t}^{EC,s}} = -\Delta\tau\omega_r g(\lambda^{EC}) - \phi_{i,r,t} - \underline{\mu}_{i,r,t}^{EC,s} + \overline{\mu}_{i,r,t}^{EC,s} = 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{22b}$$

$$\frac{\partial \mathcal{L}_i}{\partial p_{i,r,t}^{S,c}} = -\phi_{i,r,t} - \phi_{i,r,t}^{S}\Delta\tau\eta_i^{S} - \underline{\mu}_{i,r,t}^{S,c} + \overline{\mu}_{i,r,t}^{S,c} = 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{22c}$$

$$\frac{\partial \mathcal{L}_i}{\partial p_{i,r,t}^{S,d}} = \phi_{i,r,t} + \phi_{i,r,t}^{S}\Delta\tau/\eta_i^{S} - \underline{\mu}_{i,r,t}^{S,d} + \overline{\mu}_{i,r,t}^{S,d} = 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{22d}$$

$$\frac{\partial \mathcal{L}_i}{\partial p_{i,r,t}^{F}} = -\phi_{i,r,t} + \Delta\tau\phi_{i,r}^{F} - \underline{\mu}_{i,r,t}^{F} + \overline{\mu}_{i,r,t}^{F} = 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{22e}$$

$$\frac{\partial \mathcal{L}_i}{\partial \epsilon_{i,r,t}^{S}} = \phi_{i,r,t}^{S} - \phi_{i,r,t-1}^{S} - \underline{\mu}_{i,r,t}^{\epsilon} + \overline{\mu}_{i,r,t}^{\epsilon} = 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T}\backslash\{t = 1 \wedge t = |\mathcal{T}|\} \tag{22f}$$

$$\frac{\partial \mathcal{L}_i}{\partial \epsilon_{i,r,1}^{S}} = \phi_{i,r}^{S\_Cycle} - \underline{\mu}_{i,r,1}^{\epsilon} + \overline{\mu}_{i,r,1}^{\epsilon} = 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \tag{22g}$$

$$\frac{\partial \mathcal{L}_i}{\partial \epsilon_{i,r,|\mathcal{T}|}^{S}} = \phi_{i,r,|\mathcal{T}|}^{S} - \phi_{i,r,|\mathcal{T}|-1}^{S} - \phi_{i,r}^{S\_Cycle} - \underline{\mu}_{i,r,|\mathcal{T}|}^{\epsilon} + \overline{\mu}_{i,r,|\mathcal{T}|}^{\epsilon} = 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \tag{22h}$$

$$0 \leq p_{i,r,t}^{EC,x} \perp \underline{\mu}_{i,r,t}^{EC,x} \geq 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \wedge x \in \{b,s\} \tag{22i}$$

$$0 \leq \overline{p}^{EC} - p_{i,r,t}^{EC,x} \perp \overline{\mu}_{i,r,t}^{EC,x} \geq 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \wedge x \in \{b,s\} \tag{22j}$$

$$0 \leq p_{i,r,t}^{S,x} \perp \underline{\mu}_{i,r,t}^{S,x} \geq 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \wedge x \in \{c,d\} \tag{22k}$$

$$0 \leq \overline{p}_i^{S} - p_{i,r,t}^{S,x} \perp \overline{\mu}_{i,r,t}^{S,x} \geq 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \wedge x \in \{c,d\} \tag{22l}$$

$$0 \le \epsilon_{i,r,t}^{S} - \underline{\epsilon}_{i}^{S} \perp \underline{\mu}_{i,r,t}^{\epsilon} \ge 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{22m}$$

$$0 \le \overline{\epsilon}_{i}^{S} - \epsilon_{i,r,t}^{S} \perp \overline{\mu}_{i,r,t}^{\epsilon} \ge 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{22n}$$

$$0 \le p_{i,r,t}^{F} \perp \underline{\mu}_{i,r,t}^{F} \ge 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{22o}$$

$$0 \le \overline{p}_{i}^{F} - p_{i,r,t}^{F} \perp \overline{\mu}_{i,r,t}^{F} \ge 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{22p}$$

$$\phi_{i,r,t}, \phi_{i,r,t}^{S}, \phi_{i,r}^{S\_Cycle}, \phi_{i,r}^{F}: \text{free}; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{22q}$$

$$\begin{matrix} \underline{\mu}_{i,r,t}^{EC,b}, \overline{\mu}_{i,r,t}^{EC,b}, \underline{\mu}_{i,r,t}^{EC,s}, \overline{\mu}_{i,r,t}^{EC,s}, \underline{\mu}_{i,r,t}^{S,c}, \overline{\mu}_{i,r,t}^{S,c}, \\ \underline{\mu}_{i,r,t}^{S,d}, \overline{\mu}_{i,r,t}^{S,d}, \underline{\mu}_{i,r,t}^{\epsilon}, \overline{\mu}_{i,r,t}^{\epsilon}, \underline{\mu}_{i,r,t}^{F}, \overline{\mu}_{i,r,t}^{F} \end{matrix} \ge 0; \forall i \in \mathcal{I} \wedge r \in \mathcal{R} \wedge t \in \mathcal{T} \tag{22r}$$

where $\perp$ stands for complementarity.

KKT conditions of prosumers' problems are formed by stationary conditions (22a)-(22h), complementarity conditions (22i)-(22p), and dual feasibility constraints (22q) and (22r). In particular, stationary conditions result after deriving the Lagrangian function (i.e. $\mathcal{L}$) of (2) w.r.t. $\Theta_i$, while complementarity conditions are linked to inequality constraints of (2). Finally, dual feasibility includes the $\phi$'s free variables and positive $\mu$'s.

Due to (22) supposes sufficient optimality conditions for the prosumers' problems, the lower-level in (21) can be passed to the upper-level by its KKT conditions, and thus reducing (21) into the following tractable single-level framework

$$g(\lambda^{EC}) \in \underset{\substack{\Theta^M \cup \Theta_i \cup \breve{\Theta}_i \cup \\ \text{Aux.variables}}}{\text{argmin}} \; F^M \tag{23a}$$

Subject to:

(3b)-(3f) (23b)
Tariff modelling (23c)
(2b)-(2i); $\forall i \in \mathcal{I}$ (23d)
(22a)-(22r) (23e)

where $\breve{\Theta}_i$ encompasses the dual variables (i.e. the $\phi$'s and $\mu$'s) for the $i^{th}$ prosumer partaking in the community. The single-level model (23) includes the upper-level objective (23a) and feasibility (23b), as well as tariff modelling (23c), lower-level feasibility (23d) and KKT conditions of the lower-level (23e).

Although more tractable than (21), the single-level framework (23) is still hardly solvable due to nonlinear terms in (23b) and complementarity conditions in (22). In order to convert (23) into an easily solvable MILP, several linearization tricks are used in the following sub-section.

*4.3 – MILP*

To linearize the nonlinear terms in (23b) (more specifically in (3f)), we apply the Strong Duality Theorem (SDT). SDT establishes that primal and dual objectives have the same value at the optimum if the Slater's conditions hold [48]. As seen, nonlinearities arise in (3f) due to the presence of bi-linear terms in the objective function of prosumers. Due to the prosumers' model (2) is linear, we can assert that the Slater's conditions hold and therefore the primal objective $F_i$ can be replaced by its linear dual counterpart, which is given below

$$\breve{F}_i = -\sum_r \omega_r \left\{ \sum_t \Delta\tau \left\{ \begin{matrix} \overline{p}^{EC}\left(\overline{\mu}_{i,r,t}^{EC,b} + \overline{\mu}_{i,r,t}^{EC,s}\right) + \overline{p}_{i}^{S}\left(\overline{\mu}_{i,r,t}^{S,c} + \overline{\mu}_{i,r,t}^{S,d}\right) - \\ \underline{\epsilon}_{i}^{S} \underline{\mu}_{i,r,t}^{\epsilon} + \overline{\epsilon}_{i}^{S} \overline{\mu}_{i,r,t}^{\epsilon} + \overline{p}_{i}^{F} \overline{\mu}_{i,r,t}^{F} + \\ \phi_{i,r,t}\left(p_{i,r,t}^{D} - p_{i,r,t}^{PV}\right) \end{matrix} \right\} + \phi_{i,r}^{F} \mathrm{Z}_i \right\} \tag{24}$$

On the other hand, complementarity constraints can be linearized using the well-known big-M method [49]. However, selecting proper values for the $M$'s can be challenging in practise [50].

To circumvent this issue, we use the linearization trick proposed in [51], which is based on special ordered set (SOS) variables. Given two continuous variables, namely $y_1$ and $y_2$, its complementarity operator can be linearized by imposing the following constraints

$$y_1 \geq 0, y_2 \geq 0 \tag{25a}$$
$$\psi^{\uparrow} - \psi^{\downarrow} = (y_1 - y_2)/2 \tag{25b}$$
$$(y_1 - y_2)/2 - \left(\psi^{\uparrow} + \psi^{\downarrow}\right) = 0 \tag{25c}$$
$$\left\{\psi^{\uparrow}, \psi^{\downarrow}\right\} \in \mathbb{SOS}1 \tag{25d}$$

In (25), $\psi^{\uparrow}$ and $\psi^{\downarrow}$ are declared SOS1 variables, which indicates that at most one of them is equal to zero. Currently, commercial solvers are able to handle with SOS1 variables efficiently (e.g. Gurobi [52]), thus avoiding the use of big-M values. Hence, the resulting final MILP model for optimal tariff design reads as

$$g(\lambda^{EC}) \in \underset{\substack{\Theta^M \cup \Theta_i \cup \check{\Theta}_i \cup \\ \text{Aux.variables}}}{\operatorname{argmin}} \; F^M \tag{26a}$$

Subject to:

$$\text{(3b)-(3e)} \tag{26b}$$
$$\check{F}_i \leq \Delta\tau \sum_r \left\{\omega_r \sum_t \left\{\lambda_t^{G,b} p_{r,t}^{EC,b} - \lambda_t^{G,s} p_{r,t}^{EC,s}\right\}\right\}; \forall i \in \mathcal{I} \tag{26c}$$
$$\text{Tariff modelling} \tag{26d}$$
$$\text{(2b)-(2i)}; \forall i \in \mathcal{I} \tag{26e}$$
$$\text{(22a)-(22h)} \tag{26f}$$
$$\text{(22q), (22r)} \tag{26g}$$
$$\text{(25)}; \forall \text{ (22i)-(22p)} \tag{26h}$$

## 5 – Case Study

In this section, we present a case study with results. To this end, the developed methodology is applied to a four-prosumers community, whose characteristics are detailed below. The developed optimization problems were coded under Matlab R2021a and solved using Gurobi [52]. All the simulations were run on an Intel® Core™ i5-9400 F @ 2.90 GHz and 8.00 GB RAM taking $\Delta\tau = 1$ over a 24-h time horizon.

### *5.1 – Representative Days*

The developed methodology requires a set of representative days for retailer prices, non-flexible demand and PV generation as inputs. To build up the representative scenario-space, we take real measurements from public databases. More specifically, we consider household demand from [53] and RTP prices from the PJM FE Ohio in [54]. In simulations, selling prices were considered 0.7 times the purchasing ones, thus simulating a typical scenario with generation excess in the power grid [55].

It is worth noting that PV generation was generated from weather data in the city of Madrid (Spain) in 2018 from [56]. In particular, ambient temperature and solar irradiance serve to estimate PV generation considering the panel model described in [57], and peak powers of 3, 2.5, 0.5 and 4 kW, for each prosumer, respectively.

Considering such raw data leads to a year-basis database, which was represented by means of representative days following the methodology described in Section 2.3. Thus, the original set of profiles was reduced to 10 representative scenarios, which are plotted in Fig. 4 and used in simulations reported in this section.

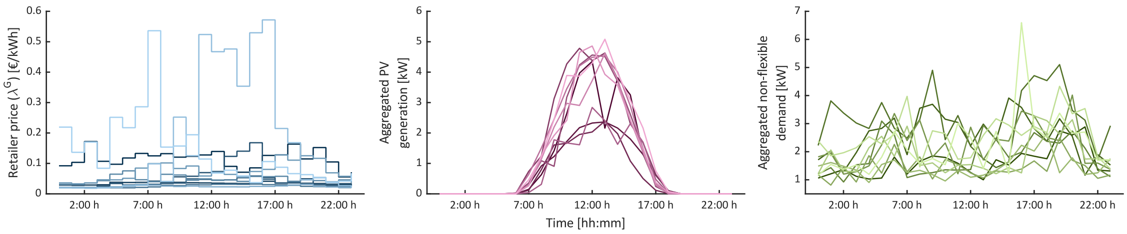


Fig. 4 – Representative days considered in simulations

*5.2 – Other Parameters*

Besides representative days, other parameters regarding components and demand are required as inputs. In this sense, we consider that each prosumer can exchange up to 10 kW with the community whereas the connection with the distribution network is limited to 50 kW. Data regarding local storage are reported in Table 1 and correspond to conventional features of Li-ion batteries [43], while Table 2 collects data regarding flexible loads. Finally, $\underline{\lambda}^{EC} = 0.05\ €/kWh$ and $\overline{\lambda}^{EC} = 0.15\ €/kWh$ at least other values were specified.

Table 1 – BES data

| **Prosumer #** | $\overline{\epsilon}_i^S$ **[kWh]** | $\underline{\epsilon}_i^S$ **[kWh]** | $\overline{p}_i^S$ **[kW]** | $\eta_i^S$ **[pu]** |
|---|---|---|---|---|
| 1 | 5 | $0.2\overline{\epsilon}_i^S$ | $\overline{\epsilon}_i^S/2$ | 0.95 |
| 2 | 7 | | | |
| 3 | 8 | | | |
| 4 | 4 | | | |

Table 2 – Flexible loads data

| **Prosumer #** | $Z_i$ **[kWh]** | $\overline{p}_i^F$ **[kW]** |
|---|---|---|
| 1 | 9 | 3 |
| 2 | 9 | 4 |
| 3 | 7 | 3 |
| 4 | 6 | 2 |

*5.3 – Flat tariff*

Firstly, we consider a flat tariff for our case study. To validate the developed methodology for this tariff strategy, we consider different values for the parameter $\underline{\lambda}^{EC}$, i.e. the minimum value allowed for the community prices. Thus, we run different simulations for $\underline{\lambda}^{EC} \in [0.05,0.15]$ and some interesting results are plotted in Fig. 5.

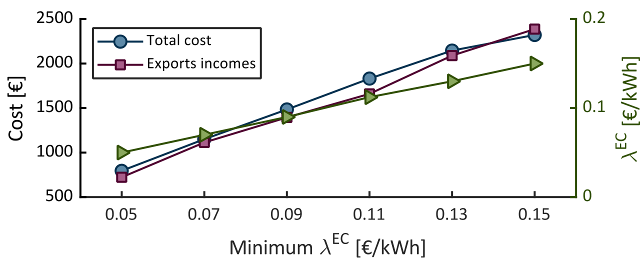


Fig. 5 – Some economic results obtained with a flat tariff and various values of the parameter $\underline{\lambda}^{EC}$

In Fig. 5, it is important to note that the resulting community price always equalled the considered lower bound, in other words, our methodology always prioritized the lowest energy price in the community. This adoption has a double effect: on the one hand, it allows prosumers to purchase energy from the community at low prices. In contrast, exporting power to other prosumers results in turn few profitable. This point is clearly observed in the incomes from exporting energy, which grow with the value of $\underline{\lambda}^{EC}$, indicating that prosumers receive more money for exporting energy. Furthermore, the total energy cost of prosumers increases with $\underline{\lambda}^{EC}$, which is owing to prosumers demand more energy than they are capable to export. Note that this is a typical behaviour of residential installations, where self-generation through PV arrays normally just cover a portion of the total demand.

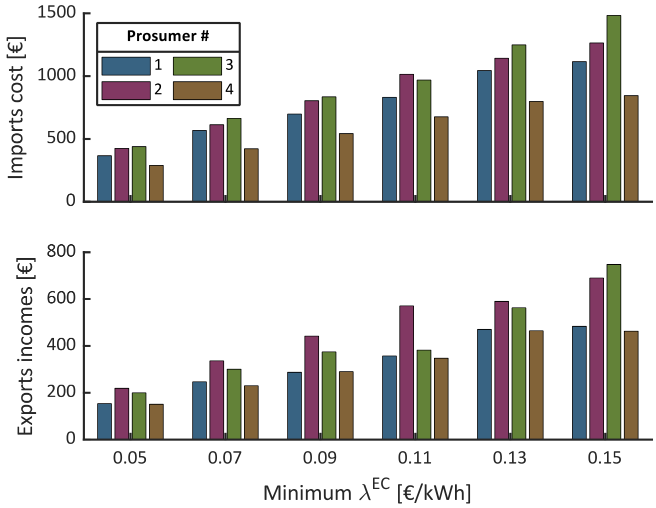


Fig. 6 – Expenditures/Incomes from importing/exporting energy considering a flat tariff and various values of the parameter $\underline{\lambda}^{EC}$

To get a better overview on the results in Fig. 5, Fig. 6 compares the expenditures/incomes from importing/exporting energy individually (i.e. for each prosumer). As seen, the prosumers 2 and 3 fairly gain more than the others prosumers by exporting energy. This result may be surprising, since the prosumers 1 and 4 install more PV power. However, the importance of batteries for incrementing exportable in domestic installations is critical, as remarked in [58]. This way, those prosumers who install large batteries (i.e. the prosumers 2 and 3), are able to increment their exportable capacity and thus obtaining a monetary profit by trading energy with the community.

In this sense, it is interesting to note that the use of a flat tariff does not discourage to export power. In contrast, prosumers can leverage of low demand periods to discharge batteries and thus improving their economy. Also, it is worth noting that prices fixed by the retailer are dynamic yet, involving peak and valley periods, thus, the manager can still incentive exporting energy to reduce the net demand of the community during peak periods.

To show how the proposed tariff mechanism helps to alleviate the effects of response fatigue, Fig. 7 compares the resulting pricing when adopting a flat tariff or a daily clearing market mechanism (both with $\underline{\lambda}^{EC} = 0.05$ €/kWh). As seen, clearing prices daily leads to different prices each day which present high volatility over the day. This pattern may discourage prosumers to partake in the community due to the excessive number of pricing signals received. As seen in Fig. 7, this negative effect can be diminished by adopting user-friendly pricing strategies, as those proposed in this paper. Moreover, adopting a flat tariff keeps prices low, while dynamic strategies frequently fixes high prices.

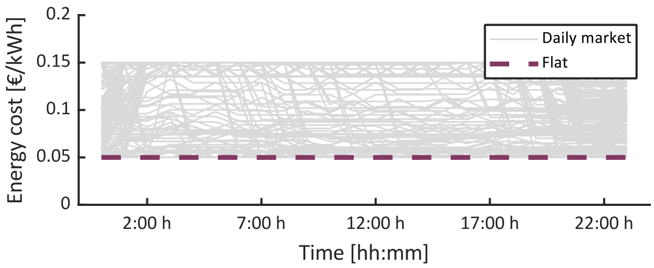


Fig. 7 – Resulting community price with daily market and flat pricing strategies ($\underline{\lambda}^{EC} = 0.05$ €/kWh)

*5.4 – TOU Tariff*

Next, we consider a TOU tariff with $K = 3$ and $k = 2\ h$, and the designed tariff considering different number of periods is shown in Fig. 8. Firstly, it is worth noting that $\lambda_t^{EC} = 0.05\ €/kWh\ \forall t$ for $T = 1$, which is coherent since a TOU tariff with only 1 period is equivalent to a flat tariff. On the other hand, the results in Fig. 8 validates the model developed for TOU tariffs in Section 3, meeting the design premises imposed on this kind of tariff.

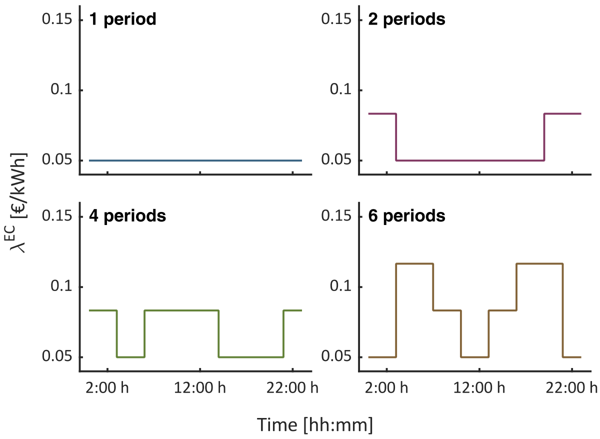


Fig. 8 – Designed TOU tariffs considering different number of periods

Furthermore, it is clear that the number of periods impacts on the final community price. Indeed, the 2-, and 6-periods tariffs fix low prices at midday, whereas the 4-periods tariff shifts valley periods to morning and evening. This particular behaviour seeks for promoting exchanging PV generation at low cost. Indeed, the 2-, and 6-periods tariffs reduce prices at midday when the PV potential is high. This way, prosumers can purchase energy in the community, leveraging surplus PV generation from those prosumers who install large PV arrays. Note that under this particular mechanism, some prosumers gain less for exporting energy. However, the developed Stackelberg game approach seeks for the equilibrium in the community and, in this regard, the optimization model prioritizes trading energy internally, instead of exporting energy to the external grid.

TOU tariffs also promote the efficient use of flexible loads, as seen in Fig. 9 where the power demanded by flexible loads is shown. As seen, prosumers are capable to shift demand to valley periods. This way, unlike to flat tariffs, TOU strategies allow leveraging flexible demand in order to improve the economy of the system.

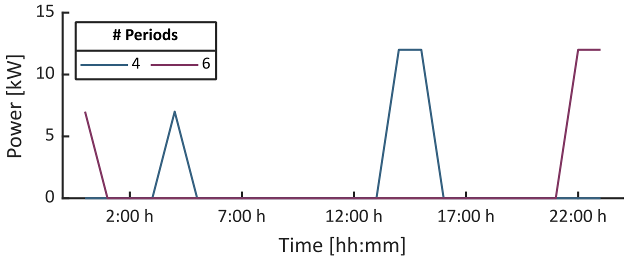


Fig. 9 – Aggregated flexible demand under a TOU tariff considering different number of periods

*5.5 – Happy Hours Tariff*

Lastly, we investigate the Happy Hours tariff, for which the total number of happy hours has been varied within the range $H \in [1,4]$. The resulting tariff scheme in each case is plotted in Fig. 10. As seen, in all cases happy hours were set at night. This behaviour has a twofold aim: on the one hand, motivates shifting flexible demand at night, similar to TOU tariffs. On the other hand, happy hours can be leveraged to charge batteries without cost, as seen in Fig. 11, where it is clear that prosumers demand much energy during night and evening to charge batteries, thus jointly exploiting happy hours and PV generation.

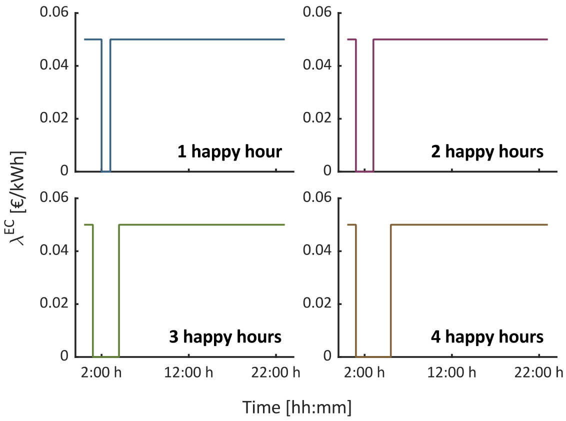


Fig. 10 – Designed Happy Hours tariffs considering different number of happy hours

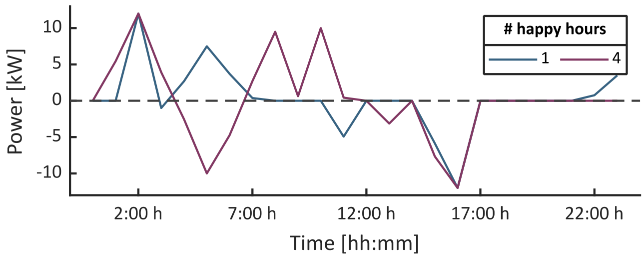


Fig. 11 – Charging-discharging power of batteries under a Happy Hours tariff considering different number of happy hours. In this figure, negative values imply discharging mode

Optimal exploitation of batteries results very profitable for prosumers. Actually, as seen in Fig. 11, batteries are discharged after being charged to either self-supplying or exporting energy. These two practises benefit prosumers, who obtain a net economy income by discharging batteries, which is further checked in Section 5.6. This particular behaviour of happy hour tariffs can be questioned in the presence of high demand at night (e.g. electric vehicles charging), which will be further investigated in future works. It is also worth noting that, for the rest of the day, the energy price is fixed at the lowest allowable bound. In this way, the happy hours tariff results very profitable for prosumers, combining the advantages of flat tariffs with a certain number of hours when the energy can be purchased by free.

*5.6 – Tariff Comparison*

Table 3 reports some interesting results to compare the different pricing strategies considered in this paper. As seen, the happy hours tariff results the most profitable option for prosumers. This result was expected due to prosumers can leverage happy hours not only to cover a portion of the flexible demand, but also to charge batteries and enable energy arbitrage. Actually, the prosumers could eventually obtain a monetary benefit under this tariff for an arbitrary high number of happy hours. On the other hand, flat tariff also shows good economy for prosumers, allowing to set prices at the lowest allowable price during the whole day. TOU tariffs are also attractive from an economic point of view, however, adding periods seem counterproductive as some time periods have peak prices thus impacting on the economy of users. In contrast, daily market clearly impacts on the economy of the prosumers. This is due to, under these tariff strategies, community price is eventually higher in comparison with the other pricing mechanisms.

Table 3 – Comparison of the different tariffs considered in this paper

| **Tariff strategy** | | **Prosumers cost (€)** | **Energy imported (kWh)** | **Energy exported (kWh)** |
|---|---|---|---|---|
| Daily market | $\underline{\lambda}^{EC} = 0.05$ €/kWh | 1318 | 20,756 | 102,9 |
| | $\underline{\lambda}^{EC} = 0.07$ €/kWh | 1591 | 20,975 | 295,6 |
| | $\underline{\lambda}^{EC} = 0.09$ €/kWh | 2179 | 21,753 | 797,1 |
| | $\underline{\lambda}^{EC} = 0.11$ €/kWh | 2532 | 21,809 | 899,2 |
| | $\underline{\lambda}^{EC} = 0.13$ €/kWh | 2807 | 21,514 | 625,8 |
| | $\underline{\lambda}^{EC} = 0.15$ €/kWh | 3130 | 21,718 | 850,3 |
| Flat | $\underline{\lambda}^{EC} = 0.05$ €/kWh | 795 | 27,000 | 11,099 |
| | $\underline{\lambda}^{EC} = 0.07$ €/kWh | 1151 | 27,841 | 11,401 |
| | $\underline{\lambda}^{EC} = 0.09$ €/kWh | 1484 | 28,180 | 11,691 |
| | $\underline{\lambda}^{EC} = 0.11$ €/kWh | 1830 | 27,915 | 11,605 |
| | $\underline{\lambda}^{EC} = 0.13$ €/kWh | 2145 | 28,857 | 12,358 |
| | $\underline{\lambda}^{EC} = 0.15$ €/kWh | 2320 | 27,519 | 12,050 |
| TOU | 1 period | 795 | 27,000 | 11,099 |
| | 2 periods | 989 | 30,364 | 13,862 |
| | 4 periods | 939 | 36,194 | 18,904 |
| | 6 periods | 1660 | 37,191 | 21,116 |
| Happy hours | 1 happy hour | 379 | 29,030 | 13,515 |
| | 2 happy hours | 125 | 29,310 | 13,689 |
| | 3 happy hours | 2.16 | 31,563 | 16,322 |
| | 4 happy hours | -121 | 25,580 | 17,354 |

In Table 3, one can also compare the total energy imported/exported by the entire community under each tariff strategy. Although the happy hours tariff is the most profitable pricing mechanism for prosumers, the total energy imported typically increases in comparison with other tariffs. This is due to this tariff encourages shifting demand to night, which has to be covered entirely from the distribution network since PV potential at this time slots is null. To compensate this point, the community seeks for exporting energy and thus obtaining a monetary counterpart. Indeed, one can check that typically energy exported by the community is higher under this tariff. Nevertheless, it is worth noting that energy exported under a TOU tariff was notably high with 4-, and 6-periods. This is due to the presence of eventually high price periods when prosumers are encouraged to export power rather than import. By the same reasons, energy imported from the community under a TOU tariff was higher in comparison with a flat tariff, owing to the necessity of imported more energy to be exported later. Focusing on the flat tariff, it is interesting to see how energy imported and exported grow with the value of $\underline{\lambda}^{EC}$. Indeed, as already explained, high community prices encourage trading energy within the community, for which the prosumers purchase more energy that has to be eventually satisfied from the external grid. In this regard, storage assets play a vital role enabling energy arbitrage, as previously discussed.

## 6 – Conclusions & Future Works

In this work, a novel tariff design methodology for ECs has been developed. In particular, the new proposal has been focused on local markets environments, where a local coordinator is responsible on setting prices for the prosumers partaking in the community. Different tariffs modelling have been included in the model. Such models consider the undesirable effects of response fatigue. In this regard, the total number of pricing signals (e.g. price variations) sent to consumers within a time window are limited by an external parameter, which can be properly tuned up by the designer.

Following the local market idea, the developed framework has been raised as a bi-level Stackelberg-based problem, in which the reaction of prosumers to any pricing decision is implicitly considered. In this sense, the tariff modelling was implicitly included in the problem, thus ensuring that the resulting pricing strategy meets the premises stablished by the designer.

The new proposal has been tested on a benchmark EC. Results obtained have validated the developed tool as well as serve of valuable interest for understanding the impact of different tariff strategies in ECs. Different tariffs strategies were compared with conventional local market mechanisms based on clearing prices daily. The result obtained show that the conventional strategy results in real-time pricing mechanisms that might provoke response fatigue in consumers. On the other hand, the different pricing strategies have been compared in order to discern the pros and cons of each one. In this regard, it has been observed that flat tariffs are still able to promote self-generation through local storage assets, while dynamic tariffs further leverage flexible loads.

In future works, we will further investigate complementary financial products that may be applicable in ECs. In particular, specific pricing strategies for incentivizing flexibility and the use of electric vehicles as local storage assets will be explored in the near future.

## References


[1] European Parliament and Council. Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources. *Official Journal of European Union* 2018; 328: 82-209.

[2] H. Nagpal, I.-I. Avramidis, F. Capitanescu, A.G. Madureira. Local Energy Communities in Service of Sustainability and Grid Flexibility Provision: Hierarchical Management of Shared Energy Storage. *IEEE Transactions on Sustainable Energy* 2022; 13(3): 1523-35. 10.1109/TSTE.2022.3157193.

[3] European Parliament and Council. Directive (EU) 2019/944 of the European Parliament and of the Council of 5 June 2019 on common rules for the internal market for electricity and amending Directive2012/27/EU. *Official Journal of European Union* 2019; 158: 125-99.

[4] M. Tostado-Véliz, S. Kamel, H.M. Hasanien, R.A. Turky, F. Jurado. Uncertainty-aware day-ahead scheduling of microgrids considering response fatigue: An IGDT approach. *Applied Energy* 2022; 310: 118611. 10.1016/j.apenergy.2022.118611.

[5] Red de Comunidades Energéticas. Online, available at: https://comunidadesenergeticas.org/, (accessed on 26 Sep. 2023).

[6] S. Lilla, C. Orozco, A. Borghetti, F. Napolitano, F. Tossani. Day-Ahead Scheduling of a Local Energy Community: An Alternating Direction Method of Multipliers Approach. *IEEE Transactions on Power Systems* 2020; 35(2): 1132-42. 10.1109/TPWRS.2019.2944541.

[7] C. Orozco, A. Borghetti, B.D. Schutter, F. Napolitano, G. Pulazza, F. Tossani. Intra-day scheduling of a local energy community coordinated with day-ahead multistage decisions. *Sustainable Energy, Grids and Networks* 2022; 29: 100573. 10.1016/j.segan.2021.100573.

[8] W. Guedes, L. Deotti, B. Dias, T. Soares, L.W. de Oliveira. Community Energy Markets with Battery Energy Storage Systems: A General Modeling with Applications. *Energies* 2022; 15: 7714. 10.3390/en15207714.

[9] W. Guedes, C. Oliveira, T. Soares, B. Dias, M. Matos. Collective asset sharing mechanisms for PV and BESS in renewable energy communities. *IEEE Transactions on Smart Grid*. 10.1109/TSG.2023.3288533.

[10] M. Tostado-Véliz, S.A. Mansouri, A.R. Jordehi, D. Icaza-Alvarez, F. Jurado. Information Gap Decision Theory-based day-ahead scheduling of energy communities with collective hydrogen chain. *International Journal of Hydrogen Energy* 2023; 48(20): 7154-69. 10.1016/j.ijhydene.2022.11.183.

[11] W. Feng, C. Ruiz. Risk management of energy communities with hydrogen production and storage technologies. *Applied Energy* 2023; 348: 121494. 10.1016/j.apenergy.2023.121494.

[12] M. Tostado-Véliz, A.R. Jordehi, S.A. Mansouri, F. Jurado. A two-stage IGDT-stochastic model for optimal scheduling of energy communities with intelligent parking lots. *Energy* 2023; 263(D): 126018. 10.1016/j.energy.2022.126018.

[13] MegaWattPuur Cooperative. Online, available at: https://www.megawattpuur.be/, (accessed on 26 Sep. 2023).

[14] SIMRIS – A 100 % Renewable Energy Community Village. Online, available at: https://www.housingevolutions.eu/project/simris-a-100-renewable-energy-community-village/, (accessed on 26 Sep. 2023).

[15] Comunidad Energética de Esparza. Online, available at: https://www.youtube.com/watch?v=pah54XwAiZI, (accessed on 11 Dec. 2023).

[16] M. Mikolajková, H. Saxén, F. Petterson. Mixed Integer Linear Programming Optimization of Gas Supply to a Local Market. *Industrial & Engineering Chemistry Research* 2018; 57(17): 5951-65. 10.1021/acs.iecr.7b04197.

[17] X. Wang, F. Li, Q. Zhang, Q. Shi, J. Wang. Profit-Oriented BESS Siting and Sizing in Deregulated Distribution Systems. *IEEE Transactions on Smart Grid* 2023; 14(2): 1528-40. 10.1109/TSG.2022.3150768.

[18] M. Tostado-Véliz, Y. Liang, H.M. Hasanien, R.A. Turky, J. Martínez-Moreno, F. Jurado. Robust optimal coordination of active distribution networks and energy communities with high penetration of renewables. *Renewable Energy* 2023; 218: 119286. 10.1016/j.renene.2023.119286.

[19] A. Naebi, S.J.S. Shenava, J. Contreras, C. Ruiz, A. Akbarimajd. E PEC approach for finding optimal day-ahead bidding strategy equilibria of multi-microgrids in active distribution networks. *International Journal of Electrical Power & Energy Systems* 2020; 117: 105702. 10.1016/j.ijepes.2019.105702.

[20] M. Tostado-Véliz, H.M. Hasanien, A.R. Jordehi, R.A. Turky, M. Gómez-González, F. Jurado. An Interval-based privacy – Aware optimization framework for electricity price setting in isolated microgrid clusters. *Applied Energy* 2023; 340: 121041. 10.1016/j.apenergy.2023.121041.

[21] J. Vuelvas, F. Ruiz, G. Gruosso. A time-of-use pricing strategy for managing electric vehicle clusters. *Sustainable Energy, Grids and Networks* 2021; 25: 100411. 10.1016/j.segan.2020.100411.

[22] Z. Moghaddam, I. Ahmad, D. Habibi, M.A.S. Masoum. A Coordinated Dynamic Pricing Model for Electric Vehicle Charging Stations. *IEEE Transactions on Transportation Electrification* 2019; 5(1): 226-38. 10.1109/TTE.2019.2897087.

[23] P.A. Gade, T. Skjøtskift, H.W. Bindner, J. Kazempour. Ecosystem for Demand-side Flexibility Revisited: The Danish Solution. *The Electricity Journal* 2022; 35(9): 107206. 10.1016/j.tej.2022.107206.

[24] Piclo-The UK's leading independent market place for flexibility services. Online, available at: https://www.piclo.energy/, (accessed on 26 Sep. 2023).

[25] D. Stølsbotn, A. Staude. NODES White Paper: Trading in NorFlex 2020-23. DNV, Tech. Rep., 6. 2023.

[26] A.D. Mustika, R. Rigo-Mariani, V. Debusschere, A. Pachurka. A two-stage management strategy for the optimal operation and billing in an energy community with collective self-consumption. *Applied Energy* 2022; 310: 118484. 10.1016/j.apenergy.2021.118484.

[27] Y. Li, B. Wang, Z. Yang, J. Li, C. Chen. Hierarchical stochastic scheduling of multi-community integrated energy systems in uncertain environments via Stackelberg game. *Applied Energy* 2022; 308: 118392. 10.1016/j.apenergy.2021.118392.

[28] M. Tostado-Véliz, Y. Liang, A.R. Jordehi, S.A. Mansouri, F. Jurado. An interval-based bi-level day-ahead scheduling strategy for active distribution networks in the presence of energy communities. *Sustainable Energy, Grids and Networks* 2023; 35: 101088. 10.1016/j.segan.2023.101088.

[29] M. Gough et al. Blockchain-Based Transactive Energy Framework for Connected Virtual Power Plants. *IEEE Transactions on Industry Applications* 2022; 58(1): 986-95. 10.1109/TIA.2021.3131537.

[30] M. Tostado-Véliz, A.R. Jordehi, D. Icaza, S.A. Mansouri, F. Jurado. Optimal participation of prosumers in energy communities through a novel stochastic-robust day-ahead scheduling model. *International Journal of Electrical Power & Energy Systems* 2023; 147: 108854. 10.1016/j.ijepes.2022.108854.

[31] N. Vespermann, T. Hamacher, J. Kazempour. Risk Trading in Energy Communities. *IEEE Transactions on Smart Grid* 2021; 12(2): 1249-63. 10.1109/TSG.2020.3030319.

[32] B. Crowley, J. Kazempour, L. Mitridati. Dynamic Pricing in an Energy Community Providing Capacity Limitation Services. *arXiv 2309.05363 v1*. Online, available at: https://arxiv.org/pdf/2309.05363, (accessed on 26 Sep. 2023).

[33] D. Thomas, J. Kazempour, A. Papakonstantinou, P. Pinson, O. Deblecker, C.S. Ioakimidis. A Local Market Mechanism for Physical Storage Rights. *IEEE Transactions on Power Systems* 2020; 35(4): 3087-99. 10.1109/TPWRS.2020.2967998.

[34] N. Vespermann, T. Hamacher, J. Kazempour. Access Economy for Storage in Energy Communities. *IEEE Transactions on Power Systems* 2021; 36(3): 2234-50. 10.1109/TPWRS.2020.3033999.

[35] X. Wu, A.J. Conejo. Distribution Market Including Prosumers: An Equilibrium Analysis. *IEEE Transactions on Smart Grid* 2023; 14(2): 1495-504. 10.1109/TSG.2022.3151338.

[36] M.S. Javadi et al. Self-scheduling model for home energy management systems considering the end-users discomfort index within price-based demand response programs. *Sustainable Cities & Society* 2021; 68: 102792. 10.1016/j.scs.2021.102792.

[37] M. Shafie-Khah, P. Siano. A Stochastic Home Energy Management System Considering Satisfaction Cost and Response Fatigue. *IEEE Transactions on Industrial Informatics* 2018; 14(2): 629-38. 10.1109/TII.2017.2728803.

[38] L. Kotzur, P. Markewitz, M. Robinius, D. Stolten. Impact of different time series aggregation methods on optimal energy system design. *Renewable Energy* 2018; 117: 474-87. 10.1016/j.renene.2017.10.017.

[39] K. Poncelet, H. Höschle, E. Delarue, A. Virag, W. D'haeseleer. Selecting Representative Days for Capturing the Implications of Integrating Intermittent Renewables in Generation Expansion Planning Problems. *IEEE Transactions on Power Systems* 2017; 32(3): 1936-48. 10.1109/TPWRS.2016.2596803.

[40] E.S. Pinto, L.M. Serra, A. Lázaro. Evaluation of methods to select representative days for the optimization of polygeneration systems. *Renewable Energy* 2020; 151: 488-502. 10.1016/j.renene.2019.11.048.

[41] M. Tostado-Véliz, S. Mouassa, F. Jurado. A MILP framework for electricity tariff-choosing decision process in smart homes considering 'Happy Hours' tariffs. *International Journal of Electrical Power & Energy Systems* 2021; 131: 107139. 10.1016/j.ijepes.2021.107139.

[42] M. Tostado-Véliz, H.M. Hasanien, A.R. Jordehi, R.A. Turky, F. Jurado. Risk-averse optimal participation of a DR-intensive microgrid in competitive clusters considering response fatigue. *Applied Energy* 2023; 339: 120960. 10.1016/j.apenergy.2023.120960.

[43] C. Feng, F. Wen, S. You, Z. Li, F. Shahnia, M. Shahidehpour. Coalitional Game-Based Transactive Energy Management in Local Energy Communities. *IEEE Transactions on Power Systems* 2020; 35(3): 1729-40. 10.1109/TPWRS.2019.2957537.

[44] I. Alsaidan, A. Khodaei, W. Gao. A Comprehensive Battery Energy Storage Optimal Sizing Model for Microgrid Applications. *IEEE Transactions on Power Systems* 2018; 33(4): 3968-80. 10.1109/TPWRS.2017.2769639.

[45] Endesa. Tempo Happy time discrimation tariffs. Online, available at: https://www.endesa.com/en/catalog/light/tempo-happy-tariff, (accessed on 28 Sep. 2023).

[46] Z. Shen, M. Liu, L. Xu, W. Lu. An accelerated Stackelberg game approach for distributed energy resource aggregator participating in energy and reserve markets considering security check. *International Journal of Electrical Power & Energy Systems* 2022; 142(B): 108376. 10.1016/j.ijepes.2022.108376.

[47] A. J. Conejo, C. Ruiz. Complementarity, Not Optimization, is the Language of Markets. *IEEE Open Access Journal of Power and Energy* 2020; 7: 344-53. 10.1109/OAJPE.2020.3029134.

[48] J. Kazempour. Advanced Optimization and Game Theory for Energy Systems. Online, available at: https://www.jalalkazempour.com/teaching, (accessed on 28 Sep. 2023).

[49] J. Fortuny-Amat, B. McCarl. A representation and economic interpretation of a two-level programming problem. *The Journal of the Operational Research Society* 1981; 32(9): 783-92. 10.2307/2581394.

[50] S. Pineda and J. M. Morales. Solving Linear Bilevel Problems Using Big-Ms: Not All That Glitters Is Gold. *IEEE Transactions on Power Systems* 2019; 34(3): 2469-71. 10.1109/TPWRS.2019.2892607.

[51] S. Siddiqui and S.A. Gabriel. An SOS1-Based Approach for Solving MPECs with a Natural Gas Market Application. *Networks and Spatial Economics* 2013; 13(2): 205-27. 10.1007/s11067-012-9178-y.

[52] Gurobi Optimization L.L.C. Gurobi Optimizer Reference Manual, 2021. Online, available at: https://www.gurobi.com, (accessed on 28 Sep. 2023).

[53] T. Singh. Smart home dataset with weather information. 2019. Online, available at: https://www.kaggle.com/taranvee/smart-home-dataset-with-weather-information, (accessed on 28 Sep. 2023).

[54] Engie. Historical data reports. Online, available at: https://www.engieresources.com/historical-data#reports_anchor, (accessed on 28 Sep. 2023).

[55] M.S. Javadi, M. Lotfi, A.E. Nezhad, A. Anvari-Moghaddam, J.M. Guerrero, J.P.S. Catalão. Optimal Operation of Energy Hubs Considering Uncertainties and Different Time Resolutions. *IEEE Transactions on Industry Applications* 2020; 56(5): 5543-52. 10.1109/TIA.2020.3000707.

[56] European Comission. Photovoltaic Geographical Information System. Online, available at: https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html, (accessed on 28 Sep. 2023).

[57] S. Mandal, B.K. Das, N. Hoque. Optimum sizing of a stand-alone hybrid energy system for rural electrification in Bangladesh. *Journal of Cleaner Production* 2018; 200: 12-27. 10.1016/j.jclepro.2018.07.257.

[58] M. Tostado-Véliz, A.R. Jordehi, H.M. Hasanien, R.A. Turky, F. Jurado. A novel stochastic home energy management system considering negawatt trading. *Sustainable Cities and Society* 2023; 97: 104757. 10.1016/j.scs.2023.104757.