# Energy Management Framework for Transactive Energy Communities

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2024 IEEE 22nd Mediterranean Electrotechnical Conference (MELECON) | 979-8-3503-8702-5/24/$31.00 ©2024 IEEE | DOI: 10.1109/MELECON56669.2024.10608690

***Abstract*—Transactive Energy Communities (TECs) are in a crescent evolution, being one of the most promising solutions for integrating renewable generation and managing energy flexibility in communities. Renewable energy solutions, like photovoltaic, are very important to the planet but bring new problems to the grid, since they are variable, non-dispatchable and present a strong mismatch with the demand in most buildings. Therefore, the management of flexible resources at the community level, namely using energy storage, is crucial to ensure the matching between local generation and demand in such communities. This work proposes a framework that optimizes the energy selling prices to the community and the use of an energy storage unit by the buildings. Such a framework optimizes the energy transactions of a transactive energy community composed of four buildings, and an energy storage unit at the community level. To ensure, three different algorithms are used: (i) fuzzy logic, (ii) reinforcement learning, and (iii) a management system with the gurobi optimizer. The fuzzy logic algorithm computes the energy tariff price between a building and the community. Using such a price, the management system will optimize the use of an energy storage unit to minimize the total energy cost of the community. The reinforcement learning will ensure the connection between the management and fuzzy logic systems. The results showed that by assembling a dynamic tariff system, using a fuzzy algorithm, it is possible to potentiate the transactions between buildings. In future transactive communities, with energy storage units, this system will potentiate collaboration between buildings, which can consequently represent economic benefits for the buildings.**

***Index Terms*—transactive energy, energy management, fuzzy systems, reinforcement learning, optimization.**

## NOMENCLATURE

| | |
|---|---|
| $\Delta h$ | Time step (hour) |
| $\mathcal{B}$ | Buildings belonging to TEC (dimensionless) |
| $\mathcal{C}_{BD}$ | Cost associated with battery degradation (€) |
| $\mathcal{C}_E^b(h)$ | Electricity cost of building $b$ at time step $h$ (€) |
| $\mathcal{C}_{EC}(h)$ | Tariff for power exported to the community at time step $h$ (€$/kWh$) |
| $\mathcal{C}_{EG}(h)$ | Tariff for power exported to the grid at time step $h$ (€$/kWh$) |
| $\mathcal{C}_{IC}(h)$ | Tariff for power imported from the community at time step $h$ (€$/kWh$) |
| $\mathcal{C}_{IG}$ | Tariff for power imported from the grid at time step $h$ (€$/kWh$) |
| $\mathcal{C}_P$ | Cost of contracted power (€) |
| $\mathcal{H}$ | Maximum period assessed by the minimization function (minute) |
| $\mathcal{L}^{b+}(h)$ | Positive net electricity load in building $b$ at time step $h$ $(kW)$ |
| $\mathcal{L}^{b-}(h)$ | Negative net electricity load in building $b$ at time step $h$ $(kW)$ |
| $\mathcal{P}^{b,C}$ | Contracted power in building $b$ $(kW)$ |
| $\mathcal{P}_{BS}^{b+}(h)$ | Charging power of batteries in building $b$ at time step $h$ $(kW)$ |
| $\mathcal{P}_{BS}^{b-}(h)$ | Discharging power of batteries in building $b$ at time step $h$ $(kW)$ |
| $\mathcal{P}_{C}^{b+}(h)$ | Export power flow in the time step $h$ between building $b$ and the community $c$ $(kW)$ |
| $\mathcal{P}_{C}^{b-}(h)$ | Import power flow in the time step $h$ between building $b$ and the community $c$ $(kW)$ |

## I. INTRODUCTION

### A. Motivation

Implementing a local market in a renewable energy community allows the democratization of energy transactions, enabling electrical energy transactions between final users. This type of community is usually called the Transactive Energy Community (TEC). Since renewable energy sources are mostly non-dispatchable, other flexibility options are needed to ensure the matching between generation and demand. Therefore, energy management systems aim to incentivize users to schedule their demand according to power availability. To do it, they can use a local market, and with dynamic tariffs, can influence the users' behavior. TECs that use a management system with dynamic tariffs to achieve technical objectives can be considered [1]. In such a context, the objective is to maximize the matching between the local generation and local demand, not only in each building but in the set of all buildings that form the TEC. Since the tariffs paid by the energy injected into the grid are usually low, ensuring that the global maximization of demand and generation is equivalent to minimizing the energy costs for each user. Therefore, a management system that aims to minimize the total electricity cost of a given TEC achieves the main proposed goal.

The tariffs are defined in order to ensure that TEC members using their local or available surplus of the community have lower costs in comparison to acquiring the energy from the grid [2]. However, the hours with higher generation levels are the same for all members, and it is necessary to promote the use of energy storage to ensure the needed flexibility. The storage units can be, for example, electrical vehicles, stationary batteries in each building, or a large-scale unit of storage that can be used by all TEC members. Therefore, to implement such a system, it is necessary to stimulate local transactions to influence both energy profiles, the demand with lower or higher prices, and the profile of the use of the surplus energy, to maximize the matching between the available generation and demand.

### B. Related Works

In the past decade, the field related to transactive energy has become more important due to the increasing need for flexibility options at the community level, which resulted in a significant increment of papers about it [3]. T. Saha et al [4] made a systemic review of energy management systems. This work concluded that in future energy communities, advanced optimization algorithms and control strategies can be developed to enhance energy management systems. Management systems are, most of the time, implemented by using demand response techniques. More recently, in [5] an overview of the path followed in the scientific field of demand response is presented. This work concluded that the load shifting strategy is the most used, and black-box models are the main implementation approach. For example, in [6], it is implemented a scheduling strategy for controlling home appliances, where the main goal is to minimize the peak demand and reduce operation costs without affecting the thermal inertia of the building. Demand Response techniques can affect user habits or influence their comfort. In [7], it was used the predicted mean vote index to measure the thermal confront, and it was concluded that an energy storage system can reduce curtailment power to prosumers by 602.98 kW. In [8] two novel transactive control schemes are proposed for energy communities to solve the energy scheduling problem in a community with prosumers and providers' groups with energy storage units.

Strategies for the management of energy flexibility can also be implemented for the energy community itself, by implementing a market strategy, it is possible to influence the buildings to move their loads according to what is intended by the community management system [9]. In [10], a transactive system for energy communities is proposed. Such work evaluates three possible solutions: no market access, wholesale market, and a collaborative combination between wholesale and local market. Energy storage units, such as local batteries or electric vehicles, are promising ways to address more flexibility to non-dispatchable generation. In this context, in [11], a stochastic model was developed for predictive control that uses forecasted data to manage the use of energy storage units. With the integration of new loads, power quality issues are becoming more common. To address such issues, [12] developed a transactive energy framework through the implementation of a local market system. Moura et al. in [2] proposed a transactive energy market where the main goal is the minimization of total costs at the community level. This market has the capability of establishing transactions between electric vehicles and buildings. In [13], the approach used the Gurobi optimizer to minimize the energy bill. With pre-established tariffs, the defined decision variables are the imported/exported power flow and batteries' charging/discharging power.

### C. Contribution

The objective of this paper is to solve the problem of maximizing the matching between demand and generation, by splitting it into three phases: (i) computation of the tariffs between TEC members and the community using a fuzzy system; (ii) management of energy storage usage to minimize energy costs [13]; (iii) Use a Reinforcement Learning (RL) to improve the system iteratively. This approach optimizes the use of energy storage units, as well as the tariffs, to minimize electricity costs. The tariffs algorithm and the minimization system are connected with an RL strategy to ensure a continued and collaborative learning process to allow both processes to converge for a good solution that can satisfy both conditions inherent to each system. To the best of our knowledge, this is the first framework that assembles the computational of tariffs, in the same framework of the management system, connected through an RL algorithm. The results showed that this framework with dynamic tariffs can lead to lower energy costs, in comparison with a management system where the tariffs are pre-established.

### D. Paper Organization

The remainder of the paper is structured as follows. The methodology is presented in Section II. The developed framework is described in Section III, and the achieved results are presented in Section IV. Finally, the main conclusions are highlighted in Section V.

## II. Framework

The developed framework is designed to be used by a transactive energy community, which has a server-client architecture. However, the developed framework will also use a peer-to-peer (p2p) approach. The dynamic tariff calculation system is implemented in the server, the management system uses a p2p scheme to connect all buildings in the community, and both systems are supported by a third system. This third system makes the connection between the previous two using a Reinforcement Learning System (RLS), and the defined architecture for it is a client-server. Figure 1 presents a diagram of the workflow of the implemented framework.

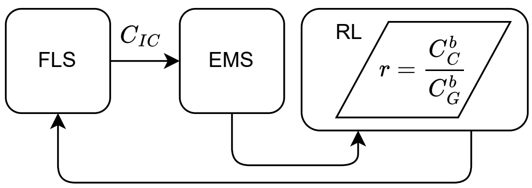



Fig. 1: Diagram representing the workflow of the implemented framework.

A Fuzzy Logic System (FLS) is implemented to calculate the energy tariff, for a building $b$, purchased energy from the community $C_{IC}$ based on the net demand profile of $b$. After calculating the energy tariff, the building community will run the local energy management system (EMS) to optimize the use of the energy storage battery unit. Finished, is activated the RLS to infer the results back in the FLS, creating a cycle where the main goal is to reduce the total cost of the energy in the community.

## III. Methodology

### A. Energy Management System

In [13], a framework for optimizing energy storage in the TECs is proposed. Such a work developed an algorithm, based on tariffs, to minimize the total costs at the community level, Equation (1) presents the objective function. Equation (1) can be described as the minimization of the sum for all buildings $\mathcal{B}$ of their total energy bill. For building $b$, the total energy bill for a period $\mathcal{H}$ is the sum of the electricity cost, $C_E^b(h)$, less the multiplication between the discharging power of the batteries, $P_{BS}^{b-}(h)$, the time step $\Delta h$, and the cost associated with battery degradation, $C_{BD}$. At this sum is added the multiplication between the contracted power in building $b$, $P^{b,C}$, and their cost $C_P$.

$$min \sum_{b=1}^{B} \left( \sum_{h=1}^{H} \left( C_E^b(h) - P_{BS}^{b-}(h) \cdot \Delta h \cdot C_{BD} \right) + P^{b,C} \cdot C_P \right) \quad (1)$$

The electricity cost, $C_E^b(h)$, is computed by Equation (2). $P_c^{b-}(h)$ / $P_c^{b+}(h)$ are the imported (or exported) power flows, $C_{IC}(h)$ / $C_{EC}(h)$ are the tariff for power imported (or exported) from (or to) the community, $C_{IG}(h)$ / $C_{EG}(h)$ are the tariff for power imported (or exported) from (or to) the grid, $L^{b+}(h)$ / $L^{b-}(h)$ are the positive (or negative) net electricity load, and $P_{BS}^{b+}$ / $P_{BS}^{b-}$ are the charging (or discharging) power of the batteries.

$$\begin{aligned} C_E^b(h) = \Delta h \cdot \big[ & P_c^{b-}(h) \cdot C_{IC}(h) + P_c^{b+}(h) \cdot C_{EC}(h) + \\ & \left( L^{b+}(h) - P_c^{b-}(h) - P_{BS}^{b-}(h) \right) \cdot C_{IG}(h) + \\ & \left( L^{b-}(h) - P_c^{b+}(h) - P_{BS}^{b+}(h) \right) \cdot C_{EG}(h) \big] \end{aligned} \quad (2)$$

### B. Fuzzy Logic System

This section presents the Fuzzy Logic System (FLS) that is used in this work to compute the energy tariff $C_{IC}$. The FLS is composed of a knowledge-base element which is defined by a set of IF-THEN fuzzy rules [14] that can be designed using people's common sense and experience. In this work, the FLS is represented by a set of $\mathcal{N}$ fuzzy rules $\mathcal{R}_i$ ($i = 1, \ldots, \mathcal{N}$) in the form of Equation (3).

$$\mathcal{R}_i: \text{ IF } \hat{\mathbf{P}}_{nd}^b(h) \text{ is } A^i \text{ THEN } C_{IG}(h) \text{ is } b_i \,. \quad (3)$$

The developed FLS computes the tariff for power imported from the community $C_{IG}(h)$ at time step $h$, based on the importance of selling energy at the same time step. $b_i$ are scalar values that represent the consequent parameter. In the antecedent part (IF part) of the fuzzy rules, $\hat{\mathbf{P}}_{nd}^b(h)$ is the net demand represented by three linguist terms: $\mathcal{A} = \{yellow, orange, red\} \equiv \{\mathcal{A}^1, \mathcal{A}^2, \mathcal{A}^3\}$. The linguistic terms are characterized by fuzzy membership functions $\mu_{\mathcal{A}^i}(h) = U \to [0,1]$; $i = 1, \ldots, \mathcal{N}$. Two membership functions' types are used: right-angled trapezoidal for the linguist terms *yellow* and *red*, and triangular for *orange*. Figure 2 illustrates the defined membership functions for $\hat{\mathbf{P}}_{nd}^b(h)$. Figure 2 beyond presenting the membership functions also has represented the boxplot to allow analyzing the variation of the data. The boxplot has represented the median ($\mathbf{Q_2}$ or $50^{th}$ percentile) representing the middle value of the dataset, the first quartile ($\mathbf{Q_1}$ or $25^{th}$ percentile) is the middle number between the smallest number and $\mathbf{Q_2}$, analogously the third quartile ($\mathbf{Q_3}$ or $75^{th}$ percentile) is the median of the upper half. Equation (4) computes the $\mathbf{Q_2}$ for a dataset with $n$ values. If $n$ is odd ($mod(,n,2) \neq 0$) $\mathbf{Q_2}$ it is equal to the middle observation (obs.), the case if it is even is done an average with both of the middle. To compute $\mathbf{Q_1}$ and $\mathbf{Q_3}$ the same equation is used, but only the lower or the upper half of the dataset is considered. It should be noticed that such operations needed to be preceded by the arrangement of the data in ascending order.

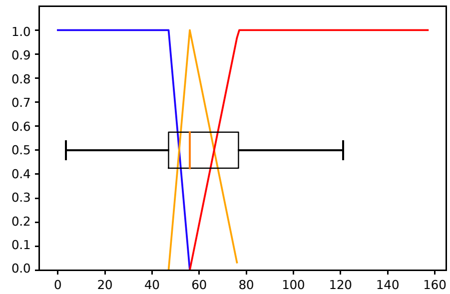



Fig. 2: Membership functions of $\hat{\mathbf{P}}_{nd}^b(h)$ variable.

$$\mathbf{Q_2} = \begin{cases} \left( \dfrac{n+1}{2} \right)^{th} obs., & \text{if } \mathbf{mod}(n,2) \neq 0; \\ \dfrac{\dfrac{n}{2}^{th} obs. + \left( \dfrac{n}{2} + 1 \right)^{th} obs.}{2}, & \text{if } \mathbf{mod}(n,2) = 0; \end{cases} \quad (4)$$

The upper and lower limits represent the "maximum" and the "minimum" respectively, which can be different from the highest and smallest numbers. To compute such boundaries the inter-quartile range **IQR**, Equation (5) is used. **IQR** is a statistical concept that describes the spread of the dataset using the middle 50% range. The "maximum" is equal to the highest number and the "minimum" is equal to the smallest number, when no outliers were identified. For example, in list $x_j$ to identify a data point as an outlier Equation (6) is used.

$$\begin{cases} \text{"maximum"} = & \mathbf{Q_3} + 1.5 \cdot \mathbf{IQR} \\ \text{"minimum"} = & \mathbf{Q_1} - 1.5 \cdot \mathbf{IQR} \end{cases}, \mathbf{IQR} = \mathbf{Q_3} - \mathbf{Q_1} \quad (5)$$

$$\text{outliers} \to x \notin [\mathbf{Q_1} - 1.5 \cdot \mathbf{IQR}, \mathbf{Q_3} + 1.5 \cdot \mathbf{IQR}]\,; \forall x \in x_j \quad (6)$$

From Figure 2, it is possible to observe the correlation between the membership functions and the boxplot. The function of the linguistic term *yellow* is correlated to the "minimum" boundary, $\mathbf{Q_1}$, and with $\mathbf{Q_1}$, *orange* term is correlated to $\mathbf{Q_1}$, $\mathbf{Q_2}$, and with $\mathbf{Q_3}$. The last linguist term, *red*, is correlated with $\mathbf{Q_2}$, $\mathbf{Q_3}$, and the "maximum" boundary.

In the presented work, the FLS is obtained considering a singleton fuzzifier, center-average defuzzifier, and product inference engine [15]. Therefore, the output of the FLS $C^*_{IG}(h)$ is computed through Equation (7). Where $b_i$ will be obtained by the return matrix of the implemented Reinforcement Learning System.

$$C^*_{IG}(h) = \frac{\sum_{i=1}^{\mathcal{N}} \mu_{\mathcal{A}^i}(h) \cdot b_i}{\sum_{i=1}^{\mathcal{N}} \mu_{\mathcal{A}^i}(h)} \tag{7}$$

### C. Reinforcement Learning System

This section introduces the Reinforcement Learning system [16], and how this is used in the proposed methodology.

RL can be used to solve problems that are intended to trigger actions depending on the environment, where the evaluation process is done by accumulating the maximum rewards that result from those decisions. RL can be mathematically represented by the problem of Markov Decision Processes (MDP). For discrete time steps $h = 1, 2, \cdots$, an *agent* has the goal of maximizing the *rewards* given by a certain *environment*. The objective is that the agent learns to make better decisions. An *action*, $A_t \in \mathcal{A}(s)$, is the agent response at the environment's *state*, $S_t \in \mathcal{S}$. $A_t$ will trigger a numerical *reward*, $R_{h+1} \in \mathcal{R} \subset \mathbb{R}$, and also a transition to a new environment state, $S_{h+1}$. MDP sequence is represented mathematically in Equation (8).

The main system is the RLS, which is implemented by using the Q-learning algorithm. The first layer is iterated over a defined number of episodes $\mathcal{E}$ where, in each episode, also iterates over a certain number of steps $\mathcal{S}$. In short, the algorithm for each step will select an action using the "Exploration vs Exploitation" approach, previously explained in III-C. Selected the given action, the agent applies it in the environment, resulting in a new state, being this selection also evaluated receiving a certain reward $r$.

$$S_0, A_0, \quad R_1, S_1, A_1, \quad R_2, S_2, A_2, \quad \cdots \tag{8}$$

The agent's goal is to collect the maximum rewards in the defined $T$ periods of the energy management system. Therefore, when the management system finishes its process, the RLS will iterate for each time step $t$ and compute the return $G_t$ using Equation (9).

$$G_t \doteq R_{t+1} + \cdots + R_T \tag{9}$$

In time step $t$, Equation (9) treats future time intervals considering them to be of equal importance, i.e., future rewards account for as much as immediate rewards. To reinforce the importance of maximizing immediate rewards, the parameter $\gamma$ is introduced, the *discount rate*, $0 \leq \gamma \leq 1$. Therefore, the return $G_t$ can be reformulated to Equation (10). With this reformulation, when $\gamma$ approximates the value 1, the future rewards are being considered more strongly. On the other hand, when approximates zero, the agent becomes more and more "myopic", i.e., in the scenario where $\gamma = 0$ means that the objective is to maximize the immediate reward.

$$G_t \doteq R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots + \gamma^{T-1} R_{t+T} \tag{10}$$

Before taking the decision to perform a given action in a given state, the agent needs to know the quality of the decision. To ensure it, an agent follows a *policy* $\pi(a|s)$ to compute the probability, at time $t$, of choosing to do the action $a$ under state $s$. Following a certain policy $\pi$, the agent uses the *value function* to know the quality of an action or a specific state for him. To evaluate the quality of a state, the *state-value function* is used, $v_\pi(s)$, mathematically defined by Equation (11), which computes, at time $t$, the expected return if it starts with the state $s$. Analogously, to evaluate the quality of an action, the *action-value function* is used, $q_{s,a}$, also known as $\mathbf{Q}$-function, mathematically defined by Equation (12), which computes, at time $t$, how good is to choose action $a$ in state $s$. In other words, the $\mathbf{Q}$-function is the expected reward that is possible to be achieved under policy $\pi$ when choosing action $a$ in state $s$. The result of the $\mathbf{Q}$-function is called $\mathbf{Q}$-value, where $\mathbf{Q}$ means the **Q**uality of taking a given action in a given state.

$$v_\pi(s) = \mathrm{E}\left(G_t | S_t = s\right) \tag{11}$$

$$q_\pi(s, a) = \mathrm{E}\left(G_t | S_t = s, A_t = a\right) \tag{12}$$

An agent can follow different policies, and the RL's algorithms' main goal is to find the most promising policy. This most promising policy needs to ensure that in all states the expected return is greater or equal than any other possible policy, and is defined as *optimal policy*. Therefore, the optimal policy can be mathematically defined by Equation (13), where $\pi$ is considered better than $\pi'$ if and only if the expected return of state-value function $v_\pi(s)$ is greater or equal to $v_{\pi'}(s)$.

$$\pi \geq \pi' \Leftrightarrow v_\pi(s) \geq v_{\pi'}(s) \forall s \in S \tag{13}$$

Just as there are optimal policies, there are optimal value functions associated. Equation (14) is the definition of the *optimal state-value* function, $v_*(s)$, computed as the maximum expected return achievable by any policy $\pi$ starting from state $s$ at time $t$. Analogously, the *optimal action-value*, $q_*(s, a)$, the function computes the maximum expected return for the sate-action pair $(s, a)$, and is defined by Equation (15).

$$v_*(s) = \max_\pi v_\pi(s) \tag{14}$$

$$q_*(s) = \max_\pi q_\pi(s, a) \tag{15}$$

$$\text{s.t.} \quad q_*(s, a) = E\left[R_{t+1} + \gamma \max_{a'} q_*(s', a')\right] \tag{16}$$

*Bellman Optimality Equation*, Equation (16), is the Q-function of the state-action pair $(s, a)$ at time $t$ following the optimal policy thereafter. Therefore, the Q-value is equal to the received reward, $R_{t+1}$, plus the highest possible projected discounted return from any potential future state-action pair $(s', a')$.

To solve the optimal policy, one of the techniques is *Q-learning*, in which the objective is to learn the optimal Q-values for each state-action pair. By using Equation (17c) and since the objective is to minimize the tariffs $C_{IC}$, the objective is the minimization of the collected rewards. With this approach Eqs.(15) and (16) need to be changed, selecting the maximum argument instead of selecting the minimum argument. The reward is now computed using Equation (17c), which measures the percentage of the cost of buying at the community cost relative to the energy cost of buying at the grid. Equation (17a) and Equation (17b) computed the cost of the imported energy at the community level, considering the community tariff and the grid tariff, respectively.

$$C_C^b = \sum_h^{\mathcal{H}} \frac{1}{\mathcal{B}} \mathcal{P}_C^{b-}(h) \cdot \mathcal{C}_{IC}(h) \tag{17a}$$

$$C_G^b = \sum_h^{\mathcal{H}} \frac{1}{\mathcal{B}} \mathcal{P}_C^{b-}(h) \cdot \mathcal{C}_{IG}(h) \tag{17b}$$

$$r = \frac{C_C^b}{C_G^b} \tag{17c}$$

## IV. Experiments and Results

To test the implemented framework, a dataset of a University Campus at the University of Coimbra was used. The buildings have an annual average consumption of around 500MWh/year, and they have installed a PV system that can meet 50% of the demand.

To study the performance of the developed framework Figure 3 presents the net demand achieved by Building 4 during one week. The red line refers to the scenario where an Energy Storage Unit (ESU) is managed at the community level and the blue line represents the net demand without the ESU. When the net demand is positive, it means that the demand is higher than the self-generation in Building 4, and as opposed to when it is negative, it means that the building consumption is lower than what is generated locally. Therefore, when the blue line is negative and the red line is zero it means that the generation surplus was stored in the ESU. Additionally, when the red line is zero, but the blue line is positive, it means that energy was bought from the ESU. Figure 3 shows that for several periods, it is possible to guarantee the needed energy by using the ESU of the community, avoiding buying energy from the grid, which is more expensive, leaving higher energy costs.

The FLS computes the energy tariff based on one specific building, and in this scenario of study, the selected building was Building 1. Figure 4 presents the net demand achieved by Building 1 for one week. Since the red line (a scenario where EMS manages an ESU) and the blue line (system without ESU) are almost similar, in comparison with Building 4, the periods where the ESU is used are lower. Building 1 net demand is used by the dynamic tariff system to compute the $C_{IC}$ where, consequently, the $|C_{IC}| = |C_{EC}|$ so if $C_{IC}$ it is smaller the $C_{EC}$ becomes more appealing. Due to this reason, Building 4 has more advantages in buying energy from the ESU in some moments, and Building 1 has no advantage in selling it because the price is too low. For example, in the last part of Figure 4, there exists a surplus of generation triggering the dynamic tariff system to infer a lower price to sell the energy. Thus, that period is a good period to buy energy from the community through the ESU. By observing Figure 3, in the same period, it is possible to observe the expected behavior. However, in that instant when the price was lower in Building 1, by observing Figure 4, it can be noticed that red values are lower than the blue line. Therefore, some of that energy is being purchased by the ESU. Existing this way is a trade-off between all community members collaborating to achieve a lower final community energy cost.

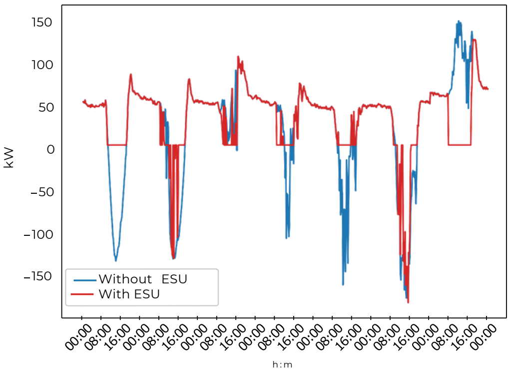



Fig. 3: Net energy demand of one week at Building 4.

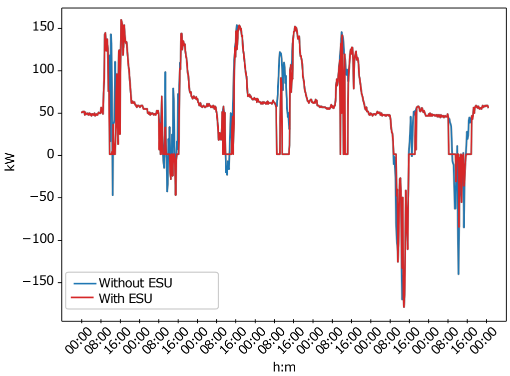
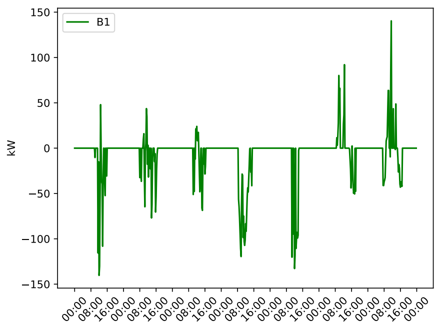


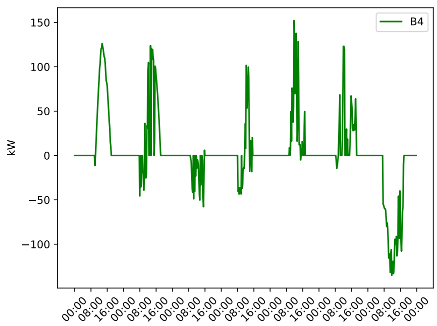

Fig. 4: Net energy demand of one week at Building 1.

Figure 5 emphasizes the impact of the FLS in the framework. This figure represents the Power flow between buildings and the community ESU. Where it is possible to observe that Building 1 is selling its surplus of energy and Building 4 is purchasing at the ESU. Such an approach creates a win-win environment, where Building 1 is winning because $C_{IC}$ is higher than $C_{IG}$, and Building 4 is buying at a minimum price, saving money.

The dynamic tariff system, compared with pre-defined tariffs, was able to reduce 14%, on average, the price of the tariff for the power exported to the community. Figure 6 represents one day of Building 1, where it is possible to infer the behavior of the dynamic tariff system. For example, at 11:30 a.m., the tariff increases because the net demand also increases. In other periods of the day, when the net demand decreases it is possible to decrease the tariff, with this approach is possible to incentivize other users to buy at that period.




(a) Building 1.




(b) Building 4.

Fig. 5: Power flow between buildings and the community energy storage unit.

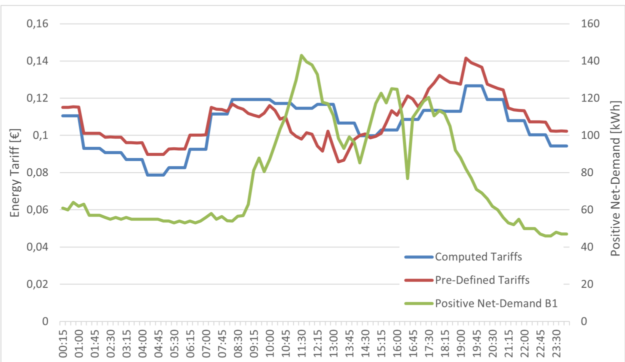



Fig. 6: Tariffs of power exported to the community, and net-demand of Building 1.

## V. Conclusions

This work implemented a framework for transactive energy communities to achieve lower electricity costs by adding extra optimized parameters at the management system developed in [13]. To ensure it, a fuzzy logic system was implemented to infer the values of the tariff for power imported from the community, being this a variable that is not optimized in the original framework. A Q-learning algorithm was implemented to connect both systems creating a close loop, where all the systems are improving to achieve the final objective. The results showed that by optimizing the energy tariff coupled with the energy management system, it is possible to enhance the transactions between buildings. This is possible because the buildings make use of an ESU, and their availability to sell or buy energy, taking advantage of the variations of the tariff, being the energy costs reduced by an average of 14%. Therefore, with this system of collaboration, it is possible to increase the effectiveness of energy transactions between community members.

In future work, it is intended to implement the dynamic tariff system for all tariffs and adapt it to all buildings' net demand. Additionally, the objective is to develop a complete study of the economic advantages that the implemented approach can bring to future transactive energy communities.

## Acknowledgment

This research was supported by the Portuguese Foundation for Science and Technology (FCT) through the projects UIDB/00285/2020, LA/P/0112/2020, UTAP-EXPL/CA/0065/2021 and UIDP/00048/2020.

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