Contribution-based energy-trading mechanism: A multi-level energy management approach

Hala Alsalloum, Rana Rahim, Leila Merghem-Boulahia

Contribution-Based Energy-Trading Mechanism: A multi-level Energy management approach

Hala Alsalloum [a,b,*], Rana Rahim[a,c], Leila Merghem-Boulahia[b]

[a] Doctoral school of Science and Technologies, EDST, Lebanese University, Beirut, Lebanon

[b] ERA, University of Technology of Troyes, 12 rue Marie Curie, CS 42060, 10004, Troyes Cedex, France

[c] Faculty of Science, Lebanese University, Tripoli, Lebanon

* Corresponding author. E-mail address: alsalloumhala@gmail.com ; Address: 9 rue colonel rochebrune, 92500, Rueil Malmaison, France; Phone number: +33 (0) 7 54 59 26 08

Declarations of interest: none

Abstract: As dynamic pricing is one of the most recent topics in the energy management system in smart grids, prosumers are invited to participate in the trading mechanism. Unlike the current grid, the bidirectional communication enables the information and energy transfer between the entities. Therefore, the complex dilemma, between selling energy and consuming it, outcomes specifically from the prosumer side. This paper proposes a hierarchical solution based on game theory to identify the optimal local consumption and surplus selling of energy while maintaining an agreement between the sellers, the buyers, and the grid. Our method is composed of three mechanisms: (1) the interactions between the sellers and the grid to define the optimal energy consumption, (2) the interactions between the sellers and the buyers to identify the price that maximizes the prosumers gain, (3) the interactions between the grid and the buyers to afford the rest of the needed energy when the second step is not sufficient. The proposed method based on Stackelberg game, takes into consideration the variety of the prosumers present in the energy market system. Depending on the priority accorded to each one and the spatial constraints, an optimal energy demand is defined using Lagrange multipliers. A distributed algorithm is then proposed to manage the complex interactions while preserving the minimum exchange of information, guarantying the privacy of the participants. Extensive simulations are carried out to verify the performance of the proposed method while maintaining a fair energy distribution. Thus, a unique equilibrium for the proposed game is proved.

Keywords: *demand side management, dynamic pricing, game theory, prosumer, seller, buyer*

1. INTRODUCTION

Nowadays, there is a high energy consumption due to the population increase. In addition, with the evolution of technologies, everything becomes connected to the Internet known as the Internet of Things (IoT) domain [1], which also leads to a higher energy consumption. Thus, the Smart Grid (SG) has become one of the essential topics for scientists to overcome the rise in energy demand. SG refers to the evolution of

a basic transmission infrastructure of energy from provider to consumers towards an intelligent infrastructure. Also, the evolution of information and communication technologies represents a key factor for the implementation of smart grids. That is contributing to the modernization of networks and infrastructures towards a decentralized architecture and autonomous behavior of the current entities [2]. In consequence, compared to the unidirectional centralized power flow, bidirectional communications will considerably enhance the decentralized energy infrastructure by exchanging data and energy for an efficient exploitation of the system. These developments improve the different domains in the SG like the generation, the distribution, the transport and the transmission sectors. Hence, one of the main objectives of SG is to maintain a balance between energy consumption and production. The Virtual Power Plants (VPP) arrive as a new solution to a more efficient and sustainable energy management system. The VPP group multiple energy sources together like the wind and photovoltaics panels, the biomass plants, the batteries and the conventional power plants through a remote software system [3]. The aspect of cooperative agents is presented in the VPP which have a lot of benefits such as minimizing the energy loss and cost, and reducing the CO2 emission while maintaining a real time management for the two essentials energy markets: (1) wholesale and (2) the retail markets. For example, authors in [3] developed a multi-scale economic scheduling strategy for the wholesale market and the reserve market. Authors in [4] developed an optimal power flow for VPP in an integrated active distribution networks in a decentralized manner. Accordingly, Demand Side Management DSM represents an interesting feature in the smart grids. Its main aims are: (1) shaping the load profile by avoiding peak loads, (2) integrating renewable energy sources, and (3) reducing the consumer's energy bills by minimizing the energy cost [5]. The consumer becomes active, henceforward named prosumer. He will be able to produce and sell energy. More specifically, he will be integrated with the energy trading system and will negotiate prices and demands [6]. These improvements turned the energy network world upside. In consequence, the trading energy between the prosumers and the providers turns into complex exchanges. Different issues need to be addressed, such as consuming or selling the stored

energy and defining how best to manage it to maximize the income of prosumers and providers, respectively. Besides, the DSM is a broad term under which we group several measures such as Dynamic Pricing (DP) or incentive-based demand management programs [7]. A DP program aims to find a suitable method to provide a cost-effective incentives to a consumer [8]. DP, as many engineering problems, needs optimization based on multi-criteria methods to find compromised non-dominated solutions.

Game Theory (GT) represents one of the best solutions to model complex interactions between prosumers and providers [9]. It allows a formal analysis of the problems used by a strategic group or individual rational agents pursuing their own goals [10]. This theory is defined by a set of tools capable of analyzing the situations in which the optimal action of an agent depends on the anticipations of other agents. The main objective is to determine an optimal strategy for each agent, to predict the equilibrium of the game and to achieve an optimally distributed situation [11].

Several works based on game theory, regarding the energy management in smart grids, were proposed for different aims. We cite the optimal appliances scheduling, the minimization of energy consumption and prices, or the minimization of energy losses [12]. Nevertheless, our study aims to achieve a trade-off among these diverse goals by proposing a game-theoretical-based approach, which considers the distances between entities to minimize energy losses and prioritizes prosumers in order to achieve a fair distribution of energy.

In this context, our prosumer-centric contribution method is summarized into three aims:

- Define the best local energy to be consumed by the seller side. Each seller will decide his strategy based on local information. A distributed algorithm is proposed, in a real time manner, and allows to optimize the profit of the grid and sellers alongside.
- Outline the best price of traded energy between sellers and buyers and the communication strategy between them. It gives incentives for the prosumers to be integrated in the energy market by sharing the minimum information needed and having each the local autonomous control. So, the privacy concerns are well respected.

- Delimit the energy allocated by the grid side to the buyers by considering their energy consumption preferences. A priority is accorded to each buyer for the dispatching loads process based on their sectors, which models the competitive aspect opposite to the consensus-based cooperative control.

The paper is structured as follows: Section 2 describes the related works. Section 3 is dedicated to our system model. The interactions between sellers and the grid are presented in section 4. Section 5 is related to the interactions between sellers and buyers, and finally, the interactions between buyers and grid are presented in section 6. The proposed distributed algorithm is described in section 7. The existence and the uniqueness of the equilibrium is shown in section 8. Numerical analysis is provided in section 9. And finally, we conclude the paper in section 10.

2. RELATED WORKS

The reviewed studies devoted to energy trading in smart grid show that many research groups are orienting their work toward a decentralized and distributed system [13]. Moreover, the majority of the research works aims to outline a new methodology to model the complex interactions between the prosumers and the grid [14].

Nomenclature

N	Number of the prosumers
N_b	Number of the buyers
N_s	Number of the sellers
T	Number of the time slots
t	Serial number of each time slot
S	Serial number of each seller
B	Serial number of each buyer
G	Serial number of the grid
D	Distance
$P_{s,b,t}$	Price given by the seller s at the time slot t
$P_{g,t}^{a}$	Buying Price of energy for the grid at the time slot t
$P_{g,t}^{v}$	Selling Price of energy for the grid at the time slot t
$EN_{b,k}$	Energy needed by the buyer b at the time slot t

$AS_{s,t}$	Surplus of the energy for the seller s at the time slot t
$E_{s,b,t}$	Energy consumption of the buyer b from the seller s at the time slot t
$E_{b,g,t}$	Energy consumption of the buyer b from the grid g at the time slot t
$E_{s,g,t}$	Energy consumption of the grid g from the seller s at the time slot t
$U_{b,t}^{T}$	Cost function for the buyer b at the time slot t
$U_{s,t}$	Utility function for the seller s at the time slot t
$U_{g,t}$	Utility function for the grid g at the time slot t

In [15], authors proposed a non-cooperative Stackelberg game between residential consumers and a controller to explore their energy exchanges with each other as well as the grid. Based on the properties of the game, they have shown that the maximum benefit, in terms of total cost reduction, is obtained when Nash Equilibrium is attained. However, the proposed approach is complex with centralized decision-making, where no priority for prosumers is taken into consideration.

[16] studied the behavior of buyers and sellers in a non-cooperative game during the energy negotiation process. Two iterative algorithms are proposed for the implementation of games where each of them has a unique equilibrium. The proposed method is applied to a small community microgrid with a photovoltaic system. Nevertheless, the same price is offered to the buyers despite their distance from the sellers or their energy consumption.

In [17], authors proposed a decentralized approach where buyers and sellers communicate with each other. However, a buyer could choose only one seller. The set of sellers is already known by the buyers in each iteration, and the latter' aim is to reduce energy costs.

Authors in [18] proposed a Peer-to-Peer energy transfer between prosumers divided into buyers and sellers. Two competitions exist: (1) the first competition is between sellers and is called Price competition and (2) the second one is between buyers. Price competition is designed as a non-cooperative game. Evolutionary game theory is used to model buyer dynamics for a seller selection who have batteries to store the energy that comes from photovoltaics. In addition, a multi-leader / multi-follower Stackelberg set is used to model

the interactions between buyers and sellers. However, the grid is responsible for setting the energy traded price between sellers and buyers.

Authors in [19] developed a Stackelberg game to model the interactions between sellers and buyers. A non-cooperative game is proposed among prosumers to get the optimal prices using a localized Practical Byzantine Fault Tolerance based-Consortium Blockchain (PBFTCB). They have demonstrated that the profit of sellers increases by 12.61% while the buyers' satisfaction decreases by 4.36%. Though, all buyers purchase energy for the same price for the whole trading mechanism.

In [20], authors developed a Stackelberg Game to model the interactions between the prosumers and the providers. The results show that with the peer-to-peer energy trading, prosumers attain 47% higher benefits. They have also introduced a willingness parameter. Nonetheless, a social welfare function is solved to obtain the optimal price and demand.

In [21], authors used auctions to model the transfer of energy between a seller and multiple buyers of energy, and between suppliers. The buyers proposed a bid and suppliers calculate offers. However, different buyers in the proposed model do not receive their energy demands because the applied method promotes the energy suppliers 'gain.

Authors in [22] developed a cooperative game theory between prosumers for a cost-saving energy bills purpose. They show that their algorithm converges well to an equilibrium. However, prosumers are obliged to stay in the coalition otherwise, they will pay more.

Authors in [23], [24] proposed a peer to peer fair energy trading between buildings to reduce the energy cost based on distributed game theoretical approach. They integrated into their model the renewable energy resources and proved the uniqueness of a generalized Nash Equilibrium. In [24], they developed an energy sharing between buildings to overcome the dependence on the electrical system. However, the objective for [23], [24] of each prosumer is not taken into consideration.

In [25], authors suggested two phase models between clusters of prosumers to reduce global energy cost. The latter share their energy within the same community for real time uncertainties while using energy storage system. However, the notion of seller/buyer is unstudied, and an aggregator is responsible for the decision-making of the community of prosumers.

In [26], [27], authors developed an energy trading between the combined and power market in order to define the energy prices while taking into account the consumers thermal comfort. In [26], a distributed algorithm is developed where a trading center, integrated energy suppliers (IESs) and consumers communicate with each other in multi round auction model to define the energy prices. They prove the existence and the uniqueness of the generalized Nash Equilibrium. In [27], a two stage game model is proposed between the suppliers and the consumers in order to resolve the contradictory profits for both. A unique Nash Equilibrium is solved to guarantee the solvability of the proposed model. Nevertheless, for [26], [27], the residential sector has been taken into consideration.

To this end, related to the existing literature, the originality of our work is summarized into the points below:

- The seller has multiple choices, either to sell or consume locally his energy stored depending on the price offered by the grid. By evidence, each seller is responsible for his strategy without sharing information.
- Prices are discriminated to fit each buyer's priority from the seller's point of view. Subsequently, buyers will pay less, and a minimization of energy cost will be noticed.
- Regarding buyers, depending on the distance that separates them from the sellers and their priority in terms of energy needed, they will have the opportunity to choose the best sellers.
- Energy allocated to the buyers from the grid side takes into consideration their priority also.

The difference between our work and the one cited in [28] is the hierarchical study proposed where: (1) new priorities are added to the system to differentiate between prosumers and (2) a diversity of choices is enlarged to decide the appropriate energy demand while (3) defining the best prices proposed.

Even if the investigations of this study seem to be a buyer-centric model, however, the constraints added to the model guarantee a maximized revenue for the seller and grid, respectively with a unique optimal agreement.

3. SYSTEM MODEL

The main players in our approach are N prosumers and the grid. Based on the amount of the surplus of energy, prosumers are divided into sellers with a total number equal to N_s and buyers with a total number equal to N_b. Therefore, given the importance of dynamic pricing, we consider a scenario in which these prosumers communicate with each other and with the grid to optimize the energy price, as well as to choose the best strategies while considering the distance between them. Our system is divided into t time slots, where each slot is equivalent to one hour. At each time slot, each prosumer is considered either as a seller or as a buyer. Our approach is divided into three steps as illustrated in *Figure 1*:

- The first step, called Seller Grid Energy Trading (SGET), is the interaction between sellers and the grid for the purpose of selling their energy $E_{s,g,t}$. Based on the price given by the grid $P_{g,t}^{a}$, the seller will calculate his local energy consumption.
- The second step, called Seller Buyer Energy Trading (SBET), is the interaction between the seller and the buyer in order to supply the latter with the needed energy $E_{s,b,t}$ first from the sellers side. An optimal price is decided in this step $P_{s,b,t}$.
- The third and final step, called Buyer Grid Energy Trading (BGET), is the interaction between the buyers and the grid. This step only exists in case the buyers have not obtained all the needed

energy from the seller's side. It frequently happens due to the limited energy storage capacity on the seller's side, especially in winter where photovoltaics are not able to store a large amount of energy [29]. The traded energy in this step is denoted by $E_{b,g,t}$.

In the next sub-sections, we will define the utility functions for each of the seller, the grid, and the buyer.

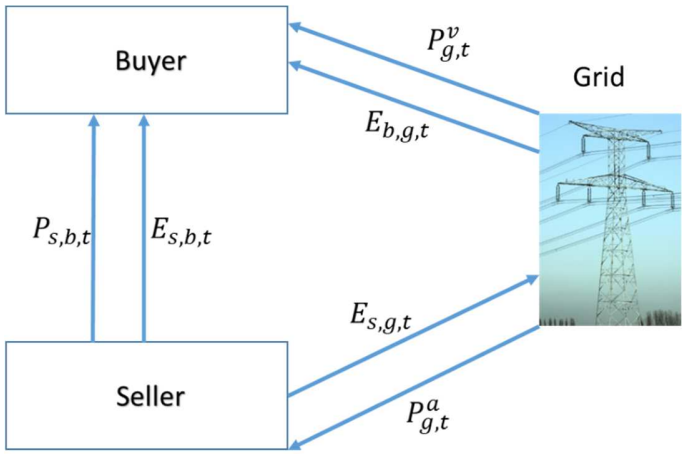

Figure 1: Our proposed scenario (the arrow direction means the data/energy flow direction)

3.1. Seller side

The utility function of energy sellers can take the following form:

$$U_{s,t} = ln(1 + E_{s,t}) + AS_{s,t} * P \quad (1)$$

Where $AS_{s,t}$ is the available surplus for the seller, with:

$$AS_{s,t} = A_{s,t} - E_{s,t}$$

$A_{s,t}$ is the energy produced by the renewable energy sources such as photovoltaic or wind panels, $E_{s,t}$ is the local energy consumption of the seller.

The properties that must be present in a utility function are diverse:

- Property 1: The utility functions are not decreasing. This is why consumers are always interested in consuming more energy, if possible, until they reach their maximum consumption level. Mathematically, this means that $\frac{\partial U_{s,t}}{\partial E_{s,t}} \geqslant 0$.

- Property 2: The marginal advantage of consumers is a non-increasing function $\frac{\partial^2 U_{s,t}}{\partial E_{s,t}} \leq 0$.
- Property 3: We assume that we generally expect zero energy consumption to provide no benefit, so $U_{s,t}(E_{s,t} = 0) = 0$.

To this end, the logarithmic function has been widely used for modeling the behavior of the prosumers for a fair distribution of energy between them as seen in references [30] [31].

Eq. (1) is divided into two parts:

The gain that the prosumer earns from his own consumption $ln(1 + E_{s,t})$.

The gain of trading energy between the seller and the buyer and/or the grid (SBET, SGET).

Regardless of who will buy the energy, P denotes the price at which the seller sells his energy. It can be equal to $P^a_{g,t}$ or $P_{s,b,t}$.

As consequence, the utility function of the seller is:

$$U_{s,t} = P^a_{g,t} * E_{s,g,t} + \sum_{N_b} E_{s,b,t} * P_{s,b,t} + ln(1 + E_{s,t}) \quad (2)$$

Where $AS_{s,t} * P = \sum_{N_b} E_{s,b,t} * P_{s,b,t} + P^a_{g,t} * E_{s,g,t}$

3.2. Grid side

The utility function for the grid is as follows:

$$U_{g,t} = \sum_{N_b} E_{b,g,t} * P^v_{g,t} - \sum_{N_s} E_{s,g,t} * P^a_{g,t} \quad (3)$$

Where $P^v_{g,t}$ is the price fixed by the grid to sell energy.

This function is composed of two parts:

- $\sum_{N_b} E_{b,g,t} * P^v_{g,t}$ is the gain from the trading energy between buyers and the grid (BGET).

- $\sum_{N_s} E_{s,g,t} * P_{g,t}^{a}$ is the cost paid for the sellers from the trading energy between the grid and the sellers (SGET).

3.3. Buyer side

The buyer' cost function could be modeled as follows:

$$U_{b,t}^{T} = \sum_{N_s} P_{s,b,t} * E_{s,b,t} + P_{g,t}^{v} * E_{b,g,t} \quad (4)$$

It is divided into two parts:

- The cost paid for the trading energy $E_{s,b,t}$ with the sellers with $P_{s,b,t}$ price (SBET).
- The cost paid for the trading energy $E_{b,g,t}$ with the grid with $P_{g,t}^{v}$ price (BGET).

Normally, $P_{s,b,t} < P_{g,t}^{v}$. Indeed, one of the main challenges is to develop an appropriate energy management system bringing together the interactions between these entities in the smart grid environment. Therefore, it is necessary to start with the energy exchange mechanism between prosumers for different reasons. The buyer, not having a surplus of energy, must buy all the energy needed from sellers and providers. In typical cases, providers, i.e. the energy suppliers, will sell the energy produced at a higher price than that given by prosumers [32]. To this end, each buyer would be primarily interested in purchasing power from the sellers and the rest of his needs, if any, from the provider which is the grid in our case. In the next sections, each step will be discussed separately.

4. SELLER-GRID ENERGY TRADING

It is essential to mention that the sellers first determine their optimal local demands. Indeed, sellers have an interest in using their excess energy for their own needs for the two following reasons: (1) to minimize dependence on the grid, (2) to minimize their energy bills. Depending on these demands, the excess energy

will then be sold to either the prosumers or the grid. So, we apply the first derivative to the utility function of the seller:

$$\frac{\partial U_{s,t}}{\partial E_{s,t}} = 0$$

$$\frac{1}{1 + E_{s,t}} - P = 0$$

$$E_{s,t} = \frac{1}{P} - 1 \tag{5}$$

Eq. (5) represents the optimal value of energy that the seller should consume. It clearly relates his decision-making process to the fixed price whether the source is the grid or the buyers.

Usually, $P_{g,t}^{a}$ is defined by the government legislations.

For example, in France, EDF must buy the seller surplus of electricity for an amount of 0.082 € from the first to the tenth year and 0.028 € to 0.082 € / kWh from the tenth to the fifteenth year[1]. We notice that the amount of energy chosen to be consumed is inversely proportional to the price. As a result, for a higher price, the seller would be more inclined to sell the excess energy by reducing the local consumption and vice versa to increase his gain. The rest will be shared between the grid and the buyers. The only constraint considered is the amount of energy required from the grid, especially when the number of sellers increases. Thus, the grid, which fixes the price of energy, will meet its need from the two closest sellers. We choose this method to reduce the energy loss on the transmission lines. *Figure 2* shows the activity diagram for SGET.

[1] https://www.quelleenergie.fr/questions/eolienne-tarif-rachat-electricite

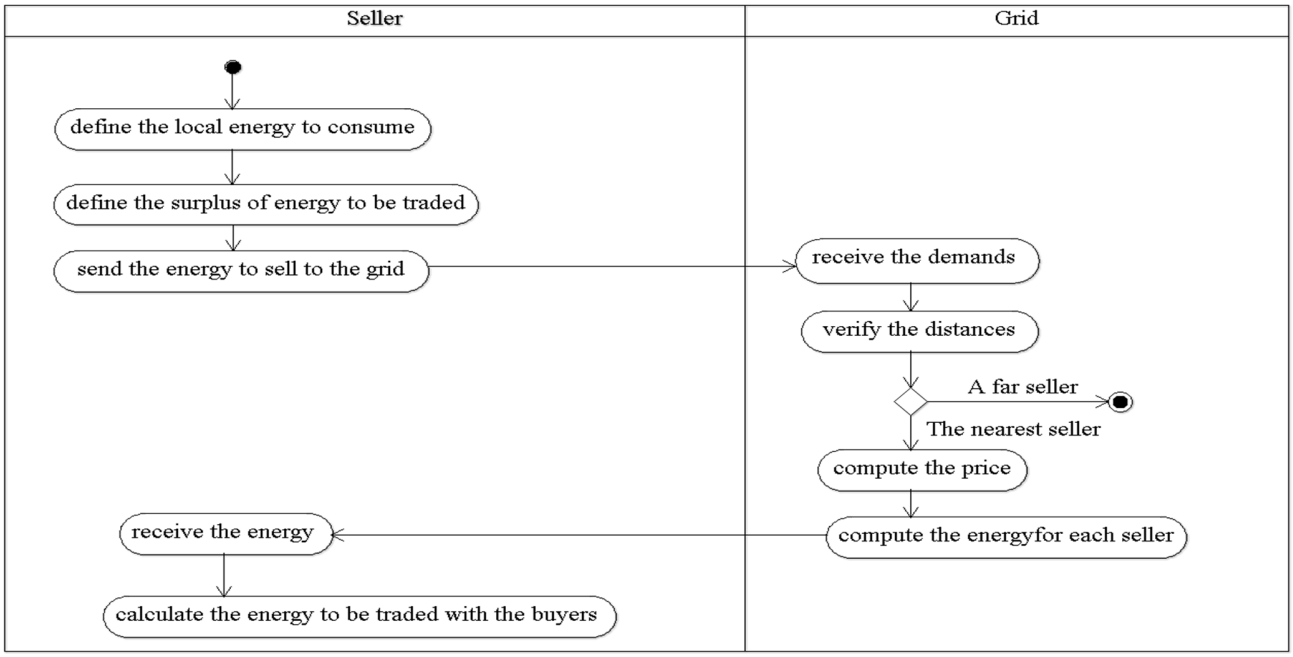

Figure 2: Activity diagram of SGET.

5. SELLER-BUYER ENERGY TRADING

In this section, SBET is discussed. The seller is interested to maximize his profit, contrarily to the buyer who aims to reduce his energy cost.

For the seller side, the optimization problem is formulated as follows:

$$Max\ U_{s,t} \tag{6}$$

$$s.t. E_{s,g,t} + \sum_{N_b} E_{s,b,t} \leq AS_{s,t}$$

$AS_{s,t} > 0, E_{s,b,t} \geqslant 0, E_{s,g,t} \geqslant 0 \ \ \forall t \ \in T, \forall\, s \ \in N_s, , \forall\, b \ \in N_b$

As mentioned above, the objective of each buyer is to minimize his cost function. Hence, the objective function becomes:

$$Min\ U_{b,t} \tag{7}$$

$$s.t. \sum_{N_s} E_{s,b,t} + \ E_{b,g,t} = EN_{b,t}$$

With $EN_{b,t} > 0$, $E_{s,b,t} \geqslant 0$, $E_{b,g,t} \geqslant 0$, $\forall t \in T, \forall s \in N_s, \forall b \in N_b$, where $EN_{b,t}$ is the Energy Needed for a buyer b at time slot t.

However, if the price proposed by the sellers is higher than the one proposed by the grid, the quantity sold will be reduced or equal to zero in the SBET step. And conversely, if the price offered by the sellers is lower than the one proposed by the grid, buyers will be interested to afford their consumption from the sellers. Nevertheless, a compromise between maximizing the seller's income and minimizing the cost of energy should be considered. Therefore, the choice of the price should be within a reasonable range to promote the exchange of energy between prosumers. However, if the energy produced is not sufficient to meet the needs of the buyer, he must purchase the rest of the energy from the main grid (BGET). For the sake of simplicity, we have set the number of sellers to two. Each buyer then communicates with the two closest sellers. An important question could be asked: Why do not buyers buy all the electricity from the cheapest seller? Different reasons are behind this choice: (1) the nature of energy market, where the sellers do not always have surplus of energy to trade because as seen in section Seller-Grid Energy Trading, sellers use their surplus for local consumption and sell energy to grid, (2) when limiting the trading between one seller, buyers found themselves obliged to communicate with the grid and paying more (later discussed in Figure 7), (3) DSM can be divided into two main categories: incentive-based DSM and price-based DSM [27]. Our work approaches the price based DSM. However, to be more realistic, the incentive-based DSM is also an important category. In this consequence, trading with two sellers enlarges the choices for buyers, so they will receive incentives as being new clients for sellers known as sponsorship. Thus, we introduce a parameter k which is defined as follows:

$$k = \begin{cases} 0.7 \\ 0.3 \end{cases}$$

- K=0.7, corresponds to the seller in the same geographical area offering the lowest price.
- K=0.3 corresponds to the seller in the same geographical area offering the second lowest price.

From the buyer side, he chooses the two closest sellers, favoring 70% of the energy demanded from the first cheapest and 30 % from the second lowest energy price. Then he communicates with the grid if there is still a need for energy.

To find the best solution, sellers calculate their prices based on:

$$U_{b,t}^{T} = \sum_{N_s} P_{s,b,t} * k \sum_{N_b} E_{s,b,t} + P_{g,t}^{v} * \left(EN_{b,t} - \sum_{N_s} E_{s,b,t} \right)$$

Substituting $\sum_{N_b} E_{s,b,t}$ by $\sum_{N_b} E_{s,b,t} = AS_{s,t} - E_{s,g,t}$,

$U_{b,t}^{T}$ will take the form:

$$U_{b,t}^{T} = \sum_{N_s} P_{s,b,t} * k \left(AS_{s,t} - E_{s,g,t} \right) + P_{g,t}^{v} * \left(EN_{b,t} - \sum_{N_s} E_{s,b,t} \right)$$

$$= \sum_{N_s} \left(P_{s,b,t} * A_{s,t} - P_{s,b,t} * E_{s,g,t} - P_{s,b,t} * E_{s,t} \right) + P_{g,t}^{v} * EN_{b,t} - kP_{g,t}^{v} \sum_{N_s} A_{s,t} + k\, P_{g,t}^{v} \sum_{N_s} E_{s,g,t} +$$

$$k\, P_{g,t}^{v} \sum_{N_s} E_{s,t}$$

To find the price that each seller offers by comparing it to that proposed by the grid, we derive the equation above with respect to $P_{s,b,t}$:

$$k \sum_{N_s} A_{s,t} - k \sum_{N_s} E_{s,g,t} + k\, N_s - k\, P_{g,t}^{v} \sum_{N_s} \frac{1}{P_{s,b,t}^{2}} = 0$$

$$\sum_{N_s} P_{s,b,t} = \sqrt[2]{\frac{k\, P_{g,t}^{v}}{k \sum_{N_s} A_{s,t} - k \sum_{N_s} E_{s,g,t} + k\, N_s}}$$

$$P_{s,b,t} = \sqrt[2]{\frac{P_{g,t}^{v}}{A_{s,t} - E_{s,g,t} + 1}} \tag{8}$$

$$\forall\ s \in N_s, \forall\ b \in N_b, \forall\ t \in T$$

Thus, we notice that the price and the surplus of energy are inversely proportional. When the amount of surplus is high, the price is low and vice versa. If the seller was not chosen by the grid, then $E_{s,g,t}$ is equal to zero. In the next sections, we will prove that $P_{s,b,t}$ is the best and optimal price.

To validate the model, a non-cooperative game is proposed between the sellers and the buyers. In fact, the reason behind this choice is to be more realistic and take into consideration the selfish behavior of stakeholders. To this end, each buyer will be responsible for his own strategy within an imperfect information game. The leaders are the sellers with their proposed price. The buyers, the followers of the game, respond by choosing the best sellers with the best energy demand. *Figure 3* shows the activity diagram between the seller and the buyer for SBET, illustrating the sequence of interactions.

6. BUYER-GRID ENERGY TRADING

In this section, we define the optimal energy demand from a grid point of view differently from the studies done in the previous sections where the solution is distributed between prosumers. The optimization problem comes down to maximizing the profit of buyers while taking into account that (1) the energy allocated from the grid to each buyer is equal to or less than his demand (eq. 13), (2) the total demands received from the buyers will be less than its maximum production capacity (eq. 12).

Thus, the utility function for the buyers is defined in eq. (9):

$$U_{b,t} = \begin{cases} Imp_b(\omega_b\, E_{b,g,t}) - \frac{\gamma_b}{2}\, E_{b,g,t}^2 & si\ 0 \leq E_{b,g,t} \leq \frac{\omega_b}{\gamma_b} \\ \frac{\omega_b^2}{2\gamma_b} & si\ E_{b,g,t} \geqslant \frac{\omega_b}{\gamma_b} \end{cases} \quad (9)$$

Where Imp_b is the importance parameter added to give each buyer a priority based on his energy consumption. So, industrials come first since, nowadays, Industry 4.0 is evolving, and everything has become connected to the Internet or more precisely to the IoT. Then the commercial sector comes second and last the residential sector which normally has a moderate consumption compared to other sectors:

$$Imp_{bi}(\, industrials) > Imp_{bc}(commercials) > Imp_{br}(residentials)$$

γ_b is a buyer specific parameter.

ω_b is a willingness parameter that influences the buyer seriousness to pay his bills. The considered utility function is a linearly decreasing marginal benefit, an appropriate form for the buyers [33]. From (9), it is easy to show that a buyer with higher willingness and/or preference has a higher utility satisfaction.

Each buyer aim is to maximize his utility function, in other words, affording the maximum amount of the rest of his needed energy, hence, the optimization problem is:

$$Max\ U_{b,t} \tag{10}$$

Yet, in contrast to the existing works, an optimization method is used to define the amount of energy allocated from the grid side, based on the preference of each buyer and his willingness to pay. In consequence, the optimization problem is defined as:

$$Max\ U_{b,t} \tag{11}$$

$$\text{s.t. } \sum_{N_b} E_{b,g,t} \leq AP_{g,t} \tag{12}$$

$$E_{b,g,t} < EN_{b,t} \tag{13}$$

$$E_{b,g,t} \geqslant 0\ \forall t\ \in T, \forall\ b\ \in N_b$$

where $AP_{g,t}$ is the Available Power of the grid at the time slot t.

By applying Lagrange as mathematical tools, the optimization problem turns into:

$$L = Imp_b(\omega_b\ E_{b,g,t}) - \frac{\gamma_b}{2}\ E_{b,g,t}^2 - \mu_1(\sum_{N_b} E_{b,g,t} - AP_{g,t}) - \mu_2\left(E_{b,g,t} - EN_{g,t}\right) + \mu_3\ E_{b,g,t} \tag{14}$$

Where μ are the Lagrange multipliers.

The first order optimality leads to $\frac{\partial L}{\partial\ E_{b,g,t}} = 0$

$\forall$ b $\in N_b, \forall$ t $\in T$,

$$\frac{\partial L}{\partial E_{b,g,t}} = Imp_b\omega_b - \gamma_b\ E_{b,g,t} - \mu_1 - \mu_2\ + \mu_3\ = 0 \tag{15}$$

With

$$\mu_1 \left(\sum_{N_b} E_{b,g,t} - AP_{g,t}\right) = 0 \tag{16}$$

$$\mu_2 \left(E_{b,g,t} - EN_{b,t}\right) = 0 \tag{17}$$

$$\mu_3 \, E_{b,g,t} = 0 \tag{18}$$

$\mu_1 > 0;\ \mu_2 \geqslant 0, \mu_3 \geqslant 0$

It is clear that the objective function and the inequality constraints are differentiable and convex, and the equality constraints are affine. In the following, we formulate the equation to find the optimal energy allocated to each buyer.

With $0 < E_{b,g,t} < EN_{b,t}$, $\mu_2 = \mu_3 = 0$, thus the optimal energy allocated will take the form:

$$E_{b,g,t} = \frac{Imp_b \omega_b - \mu_1}{\gamma_b} \tag{19}$$

By substituting the equation found in (16), we get the formula for:

$$\sum_{N_b} Imp_b * \omega_b - AP_{g,t} \sum_{N_b} \gamma_b = \mu_1 \tag{20}$$

Then, we substitute eq. (20) in (19), and find the optimal formula for energy such as:

$$E_{b,g,t} = \frac{-\sum_{p,p\neq b,p\in N_b} Imp_p * \omega_p + AP_{g,t} \sum_{N_b} \gamma_b}{\gamma_b}$$

$$\forall\ b \in N_b, \forall\ t \in T \tag{21}$$

We notice, from eq. (21), that the grid must know the importance of all its buyers, to decide the allocated energy for each one. The preference of each type of buyers (Imp_b), and the willingness within each category (ω_b) are the essential parameters to maintain a fair energy distribution among them. *Figure 4* represents the activity diagram for BGET step.

7. PROPOSED DISTRIBUTED ALGORITHM

Sellers, buyers and the grid communicate with each other. One of the requirements of the proposed distributed algorithm is synchronization. Nonetheless, with wireless networks today and the evolution of information and communication technologies, we think synchronization will not be an issue. Thus, we use the characteristics of IEEE 802.11b protocol for communication. Each player must send two messages at each step of the game as shown in *Figure 5*. Each seller sends to the grid a request containing the amount of energy he wants to sell, and another one for the buyers containing the price. Each buyer responds in SBET by sending the energy to be traded with sellers, and requests the rest from the grid in BGET. The grid sends two response messages, one in SBET, and another one in BGET. Each player should wait and receive all requests from others first. After that, a response is sent.

The algorithm below represents a distribution of tasks between the prosumers and the grid. *Figure 6* represents the sequence diagram of the distributed algorithm proposed. It summarizes the complex interactions proposed in our approach.

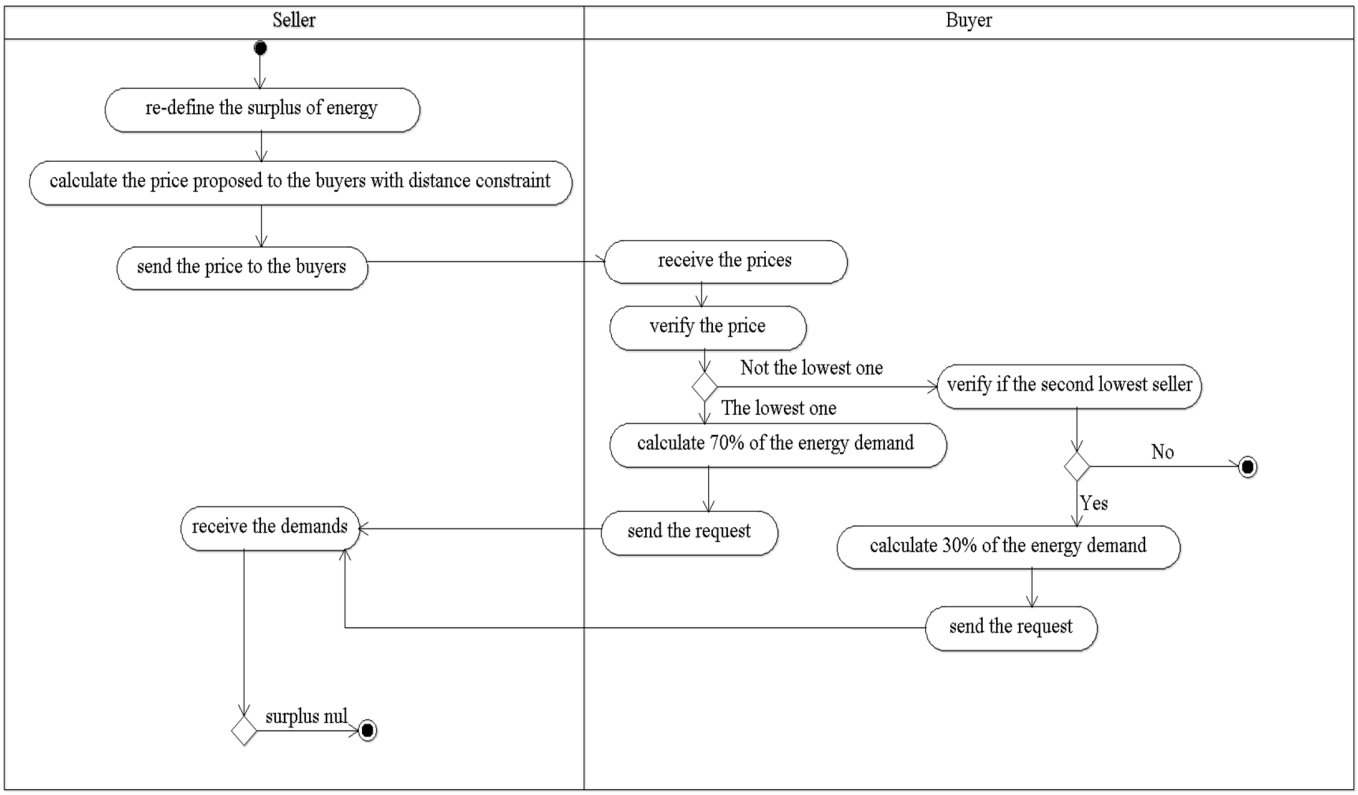

Figure 3: Activity diagram of SBET.

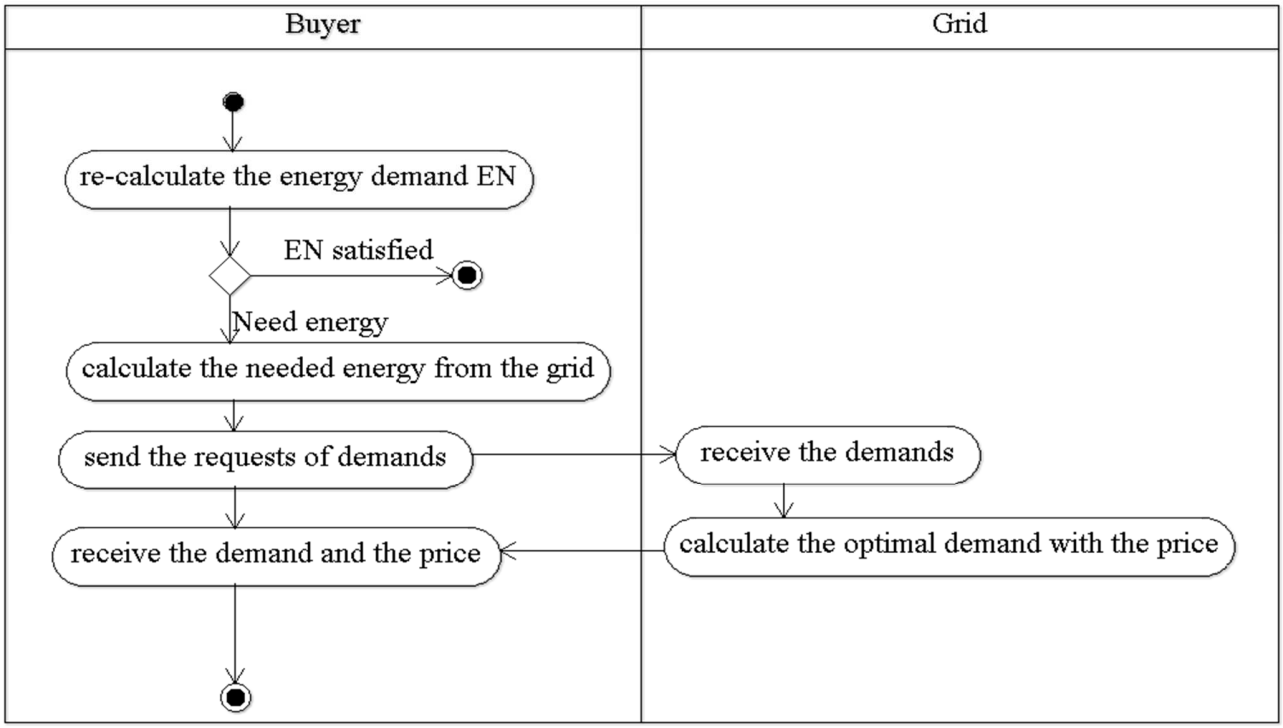

Figure 4: Activity diagram of BGET.

Type (request)	SellerID	Price	SelectionFlag
Type (request)	SellerID	Surplus	SelectionFlag
Type (request)	BuyerID	Energy	SelectionFlag

Type (response)	GridID	Demands	Distance
Type (response)	BuyerID	Demands	Distance
Type (response)	GridID	Energy	Distance

Figure 5: Requests and Reponses messages.

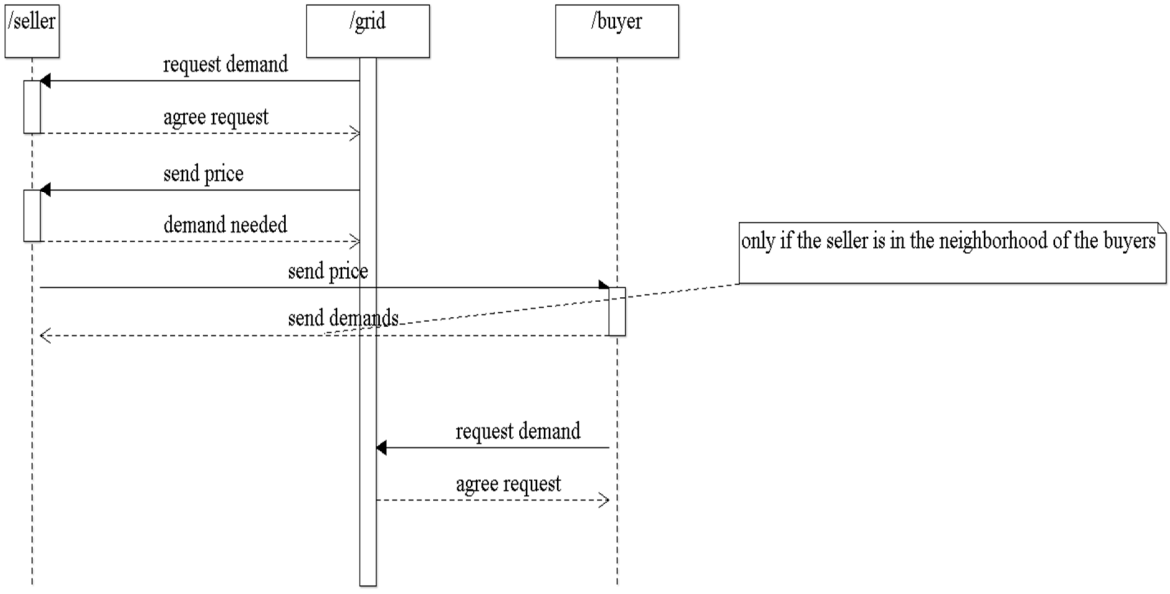

Figure 6: Sequence diagram of the distributed algorithm.

Distributed algorithm between seller, buyer, and the grid

Seller

For t=1… 24

1. Compute $AS_{s,t}$
2. Calculate the optimal local energy to be consumed $E_{s,t}$
3. Diffuse the energy traded with the grid

Grid

1. Define the set of sellers
2. Diffuse the price $P_{g,t}^{a}$
3. Calculate the energy demand from the nearest sellers depending on $AP_{g,t}$

Seller

1. Define the rest of the energy to be traded with the buyers $AS_{s,t} - E_{s,g,t}$
2. Compute the price based on (8)
3. Diffuse the price to the buyers

Buyer

1. Receive the messages with the price $P_{s,b,t}$ of the sellers
2. Define the nearest sellers
3. Calculate 0.7 of the surplus from the seller with the lowest price and 0.3 of the surplus from the seller with second lowest price (after each iteration, sellers should update their surplus of energy)
4. Calculate $EN_{b,t} - \sum_{N_s} E_{s,b,t}$
5. if $EN_{b,t} - \sum_{N_s} E_{s,b,t} = 0$
6. Stop
7. Else
8. Request the rest of needed energy to the grid

Grid

1. Receive the demands from the buyers
2. Calculate the optimal demands

End else

End for

8. EXISTENCE AND UNIQUNESS OF THE NASH EQUILIBRIUM

The three main categories of participants are the sellers, the buyers, and the grid. They play a non-cooperative game with each other. In the first step, the sellers trade their energy with the grid without cooperation. As discussed above, the former responds to the prices and chooses the optimal local energy consumption. Let $\Gamma_{seller,s}$ and $\Gamma_{buyer,b}$ be the strategy sets for the seller and the buyer respectively (the seller

in SGET and the buyer in SBET). The price found in eq. (8) and the local energy consumption found in eq. (5) are a Stackelberg equilibrium strategy if and only if the chosen strategies satisfy the following criteria:

$$U_{s,t}\left(E_{s,t}^{*}, P_{s,b,t}^{*}\right) > U_{s,t}\left(E_{s,t}, P_{s,b,t}^{*}\right) \quad (22)$$

$$\forall\ s \in N_s, \forall\ b \in N_{b,} \forall\ t \in T$$

And

$$U_{b,t}^{T}\left(E_{s,t}^{*}, P_{s,b,t}^{*}\right) < U_{b,t}^{T}(E_{s,t}^{*}, P_{s,b,t}) \quad (23)$$

$$\forall\ s \in N_s, \forall\ b \in N_{b,} \forall\ t \in T$$

To verify the existence and uniqueness of the strategy chosen by a seller, we take the second derivative:

$$\frac{\partial^2 U_{s,b,t}}{\partial E_{s,t}} = \frac{-1}{\left(E_{s,t}+1\right)^2} < 0\ \forall\ n\ \in N_s, \forall\ k\ \in T$$

which is strictly concave. In consequence, we conclude that for any price chosen $P_{s,b,t}$>0, a unique equilibrium exists that satisfies $0 < E_{s,t} < A_{s,t}$.

Similarly, we compute the second derivative for the cost function of the buyer as follows:

$$\frac{\partial^2 U_{b,t}^{T}}{\partial P_{s,b,t}} = k * P_{g,t}^{v} \sum_{N_s} \frac{+2}{P_{s,b,t}^{3}} > 0$$

Then, the cost model is strictly convex. It follows that there is one price (i.e., optimal) to trade energy with from the sellers. In addition, a unique amount of energy that every buyer will buy from seller. Thus, the set of $(E_{s,t}, P_{s,b,t})$ constitutes one and unique equilibrium.

9. NUMERICAL ANALYSIS

This section is dedicated to the numerical analysis validation. We use Matlab as software to investigate the satisfaction of prosumers with respect to the variation of some parameters. We assume that the communication infrastructure between the prosumers and the grid is based on the wireless mesh network.

The sellers, the buyers and the grid are connected to each other. *Table 1* depicts the parameters used in our context. The intervals of the values used are based on the statistics done by "Agence France Electricité"[2].

We consider three sellers with respectively, $AS_{1,t} = 10$ KWh, $AS_{2,t} = 20$ KWh, $AS_{3,t} = 30$KWh, for $t = 1$, and five buyers with $EN_{1,t} = 25$ KWh, $EN_{2,t} = 15$ KWh, $EN_{3,t} = 30$ KWh, $EN_{4,t} = 20$ KWh and $EN_{5,t} = 10$ KWh. The grid has an amount of $AP_{g,t} = 100$ KWh and needs 10 KWh.

We repeat the simulations 10 times using Hp-32 Go RAM and a processor Intel(R) Core(TM) i7-6600U CPU @ 2.60 GHz 2.70 GHz to validate the results.

Table 1: The considered parameters and their corresponding values

	Lower bound	Upper bound
$\boldsymbol{EN_{b,t}}$ (KWh)	10	40
$\boldsymbol{P^{a}_{g,t}}$ (cents/KWh)	6	20
$\boldsymbol{AS_{s,t}}$ (KWh)	10	30
$\boldsymbol{N}$	10	500

Figure 7 shows the cost paid by the prosumers for the three different scenarios: (1) our proposed approach denoted by Energy Trading and Allocating based on Prosumer profit (ETAP), (2) ETAP with one seller and (3) Game ST. Game ST [34] is an energy trading algorithm between sellers, buyers and the grid. The buyer has a full control to choose only one seller based on the cheapest prices. From the results obtained, we can notice that our algorithm is the most efficient in terms of minimizing the cost paid. Different constraints play a key role for the enhancement of our results such as the distance taken into consideration, and the optimal price chosen, i.e. each buyer chooses the two closest sellers and offering the minimum prices. Thus, we minimize losses on the transmission lines, and the price offered.

Figure 8 represents the variation of the total cost in euros, paid by the buyers by varying their number for ETAP and Game ST. We notice that by increasing the number of buyers from 10 to 40, the total sum of the

[2] Agence France Electricité is a site dedicated to the information related to the energy in France.

costs paid increases respectively due to the increase of energy demand. As the geographical distribution becomes narrower, a greater number of sellers will be involved. Comparing our ETAP approach to Game ST, we notice that ETAP is more efficient in terms of minimizing cost than Game ST, which is an essential criterion to affirm the usefulness of our approach. But, in addition, we must assess the time required for the equilibrium. Hence, we have shown in *Figure 9* the number of iterations required to reach the equilibrium state. It is achieved when the buyers choose the suitable sellers and supply their energy demand either from the sellers or from the grid. We note that the number of iterations requested for ETAP is lower than that of Game ST: 10 iterations for ETAP versus 15 for Game ST. This proves that our approach is simple and ensures the diversity of energy sources. *Figure 10* shows the seller satisfaction versus the number of iterations. About 6 iterations are needed for s1 to attain the equilibrium, followed by s2 (8 iterations), and finally s3 (10 iterations).

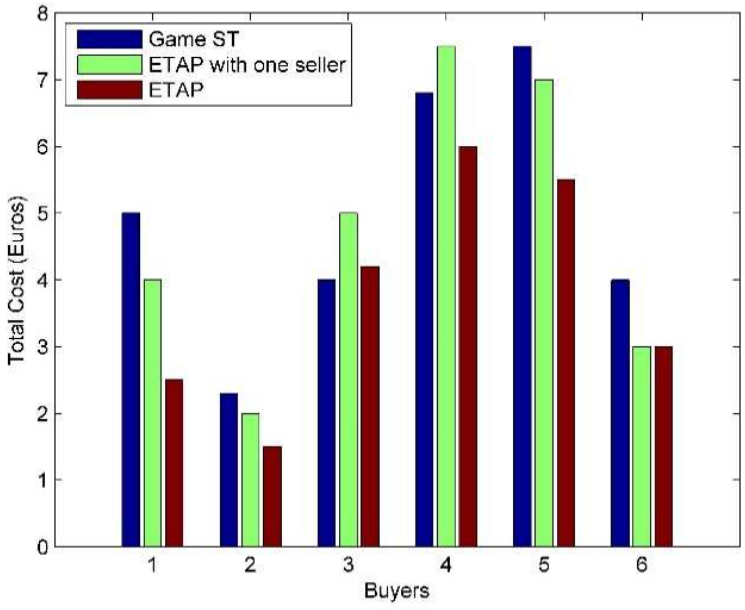

Figure 7: Variation of the total cost in euros for three scenarios: ETAP, ETAP with one seller, and Game. ST

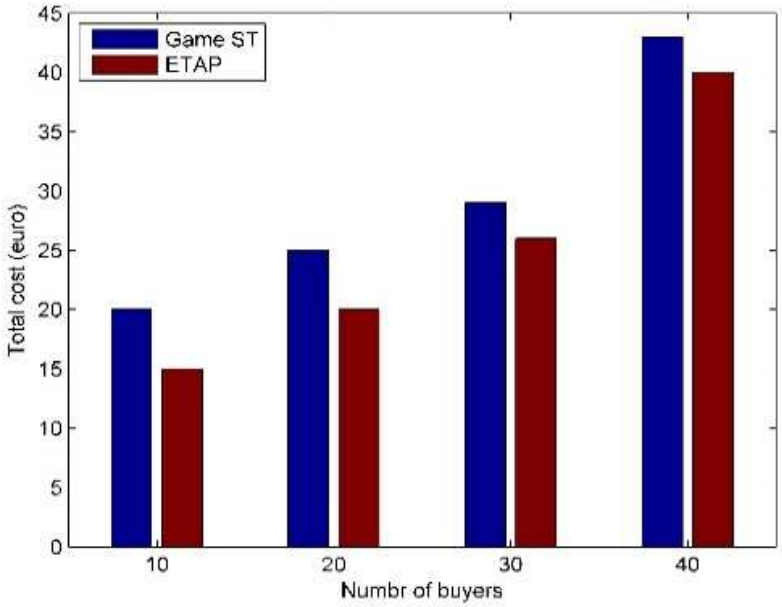

Figure 8: Variation of the total cost versus the number of buyers.

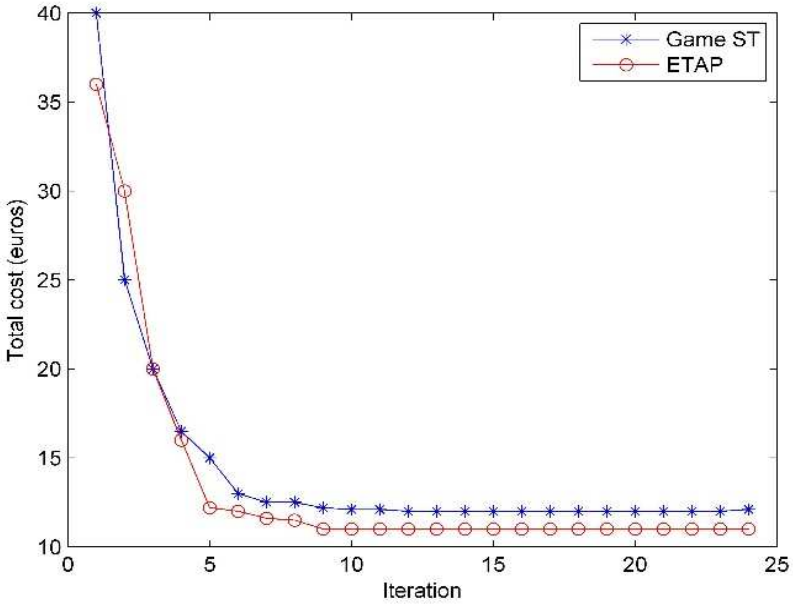

Figure 9: Total cost versus the number of iterations for Game ST, ETAP.

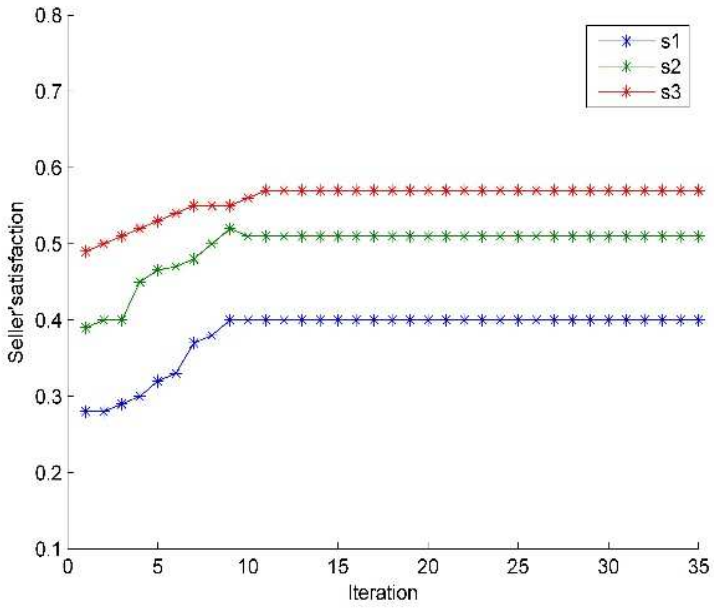

Figure 10: Variation of seller satisfaction versus the number of iterations.

With the geographical distribution and the surplus of energy that each seller has, s3, with the highest surplus of energy and the lowest price, is the best choice for the buyers. Then, he will need more iterations compared to s2, who comes second. The seller s1, with the highest price and the lowest energy produced has the lowest satisfaction.

Figure 11 shows the two prices at equilibrium: (1) the one offered by the grid to the sellers $P_{g,t}^{a}$, and (2) the one proposed by the sellers to the buyers $P_{s,b,t}$ at different time slots. A simple explanation clarifies the results obtained. When the price offered by the grid decreases, the local energy consumption increases as seen in eq. (5), therefore the surplus of energy to be traded with the buyers decreases, and the price $P_{s,b,t}$ will increase accordingly (eq. (8)). In this consequence, *Figure 11* visualizes the strong relation between the prices and the demands at the equilibrium point. As seen in equations (5) and (8), when the surplus of energy decreases, the price proposed to the buyers accordingly increases. The former can decrease for two essential reasons:

- The lack of the energy produced by the photovoltaic or wind panels due to the weather conditions and the season, for example, from time slot 1 p.m. to 8 p.m., the amount of energy produced decreases instantly, in other words, the surplus of energy decreases leading to an increasing in the energy price offered by the sellers.
- The price offered by the grid to buy the energy based on the time of use pricing strategy. As seen in *Figure 11*, from 1 p.m. to 8 p.m., the prices proposed by the grid decreases accordingly because 1 p.m. represents the highest demand of energy compared to 8 p.m.

Figure 12 represents the variation of the total cost in euros in respect to the variation of the number of industrials. Obviously, for the industrial prosumers, the cost will increase when their number increases. However, for the residential prosumers, we notice that the cost decreases and attains a certain threshold. Due to the preference added to our model, industrials have the privilege on other prosumers that is why the grid and the sellers allocate their surplus of energy and generate energy for them. When we exceed 40, the whole energy will be allocated to industrials.

Figure 13 investigates three meaningful values of each buyer: the percentage of importance, measured as $\%\, Imp_b = \frac{Imp_b}{\sum_{N_b} Imp_b} * 100$, the percentage of allocated energy and the energy demand $EN_{b,t}$. Comparing these parameters, the buyer with the highest importance (he can be probably an industrial buyer), will be delivered first (buyers 1 and 3 in Fig. 13). Hence, the percentage of the allocated energy will be equal to the percentage of energy demand. However, for buyers 2 and 4, the allocated energy is lower than the energy demand comparing to the buyers 3 and 1.

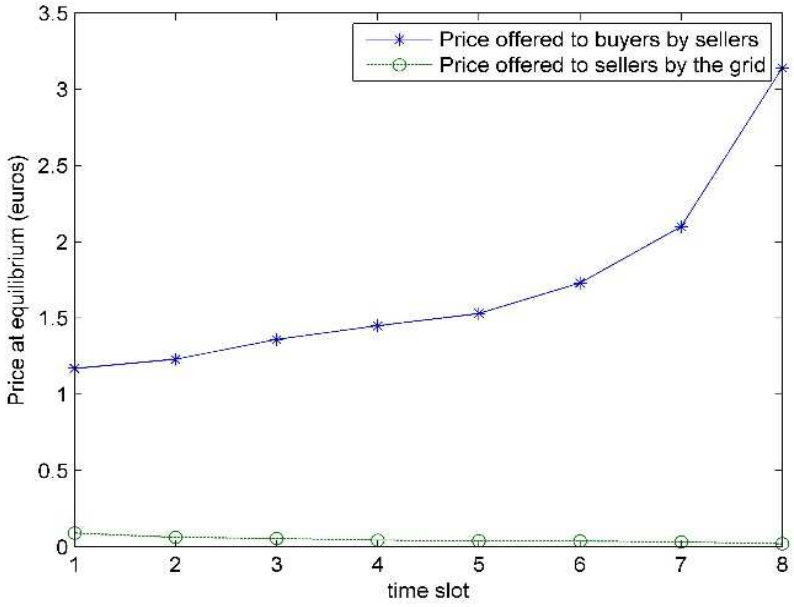

Figure 11: Variation of the prices at equilibrium versus the time slots.

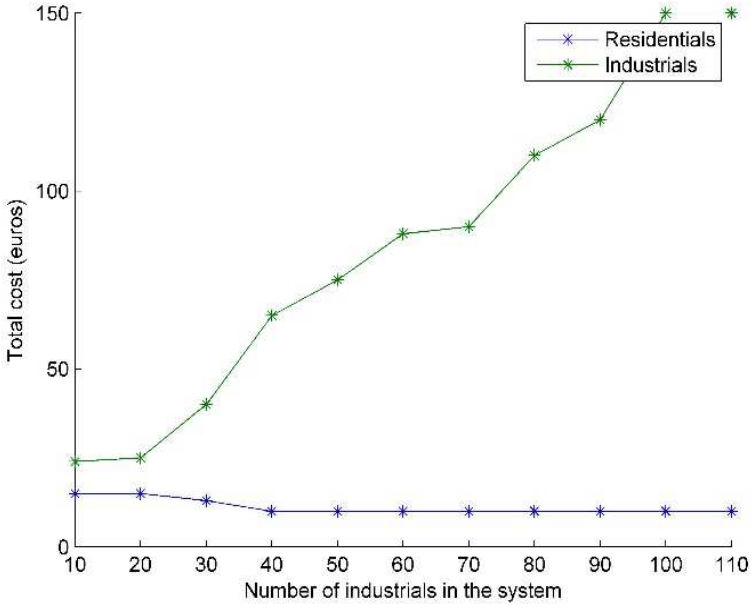

Figure 12: Variation of the total cost versus the number of industrials in the system.

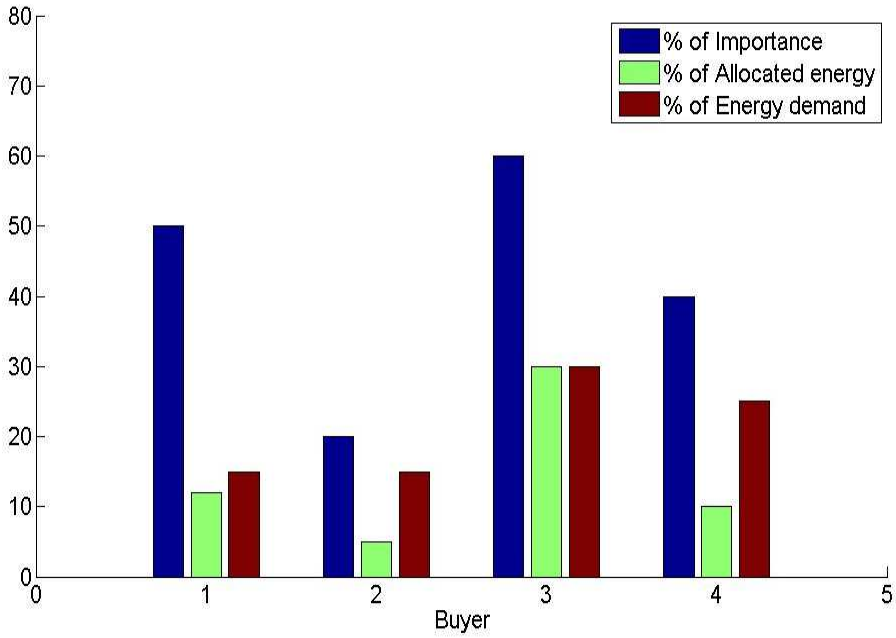

Figure 13: Meaningful values of buyers.

These results can be explained by the percentage of importance. Buyers 2 and 4 have the lowest importance. Other constraints also, play a vital role in the proposed approach for allocating energy such as the available surplus for the seller and the available power of the grid. This is why there is sometimes a difference between the percentage of the energy needed and the energy allocated. *Figure 14* shows the comparison between the centralized and the decentralized proposed solution for 50 up to 500 prosumers. As shown in *Figure 14*, for example, with 200 prosumers, with the decentralized approach, prosumers pay more than with the centralized one. This is due to the fact that each prosumer will tend to maximize his utility or minimize his cost, but with the centralized approach, where only a central unit is responsible for solving the energy distribution, the latter has a full control and knowledge on the energy trading mechanism. As known, the decentralized architecture decreases the computation time as shown in *Figure 15*. It takes hours to converge in the centralized approach. However, even with an important number of prosumers, the decentralized approach overcomes the latter with few seconds.

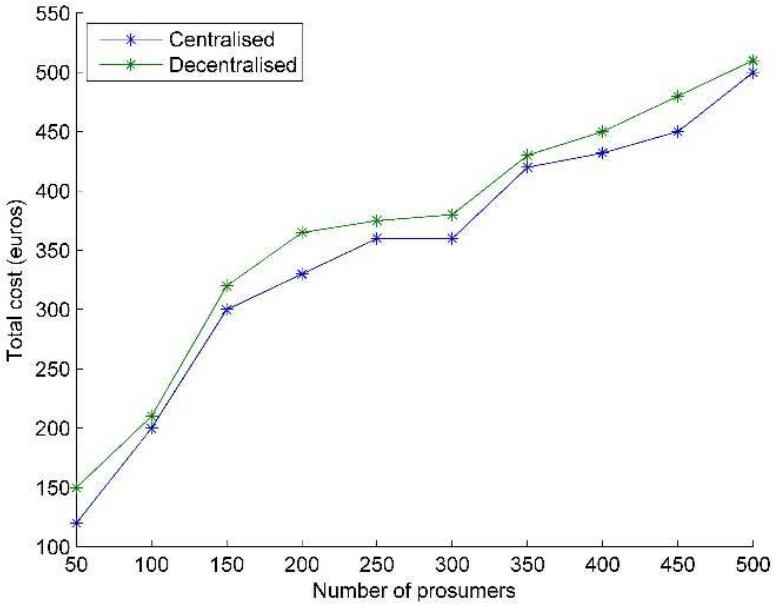

Figure 14: Variation of the total cost in euros versus the number of prosumers for the centralized and the decentralized approach.

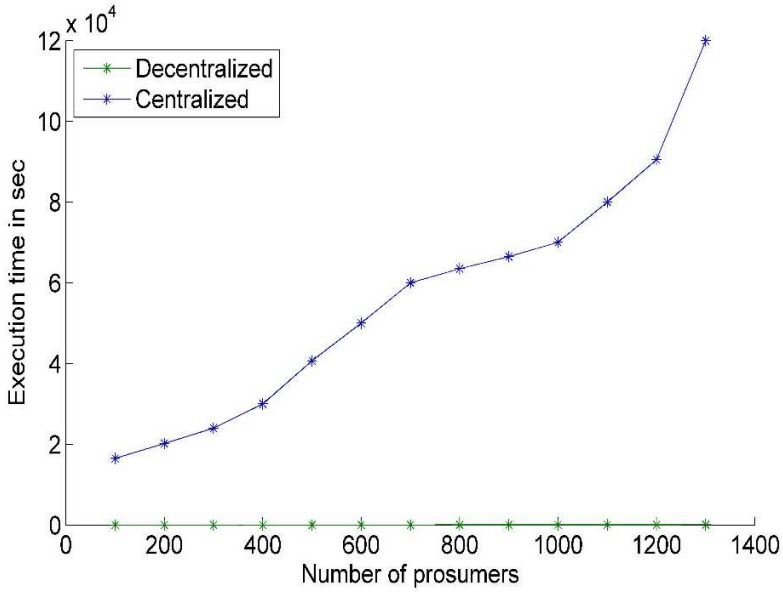

Figure 15: Variation of the execution time in sec versus the number of prosumers for the centralized and the decentralized approach.

10. CONCLUSION

In this paper, a hierarchical approach is proposed to model the complex interactions between the sellers, the buyers and the grid. We adopt a multi-level decision-making for the trading energy mechanism in smart grids. The proposed approach requires minimum interactions. First, we optimize the energy traded between

the grid and the seller to maximize the revenue of both. Second, we define the best price offered by the seller to maximize his revenue and minimize the buyers' bills. Moreover, our proposal assigns a priority to the buyers based on their energy consumption with a fair distribution of energy in the system. The obtained results show that the energy bills are minimized and the algorithm converges well to the equilibrium.

An important extension for our proposed works would be to define a strategy that allows the prosumer to be a buyer and seller in the same iteration and to define new criteria to be considered to prioritize the prosumers. In addition, it would be essential to study the constraints related to the communication network.

ACKNOWLEDGMENT

This work is supported by grants from the Troyes University of Technology and the Lebanese University and is partly supported by the GETCOM project, which is financed by the European Union (FEDER).

REFERENCES

[1] G. Yuan, Y. Gao, B. Ye, and R. Huang, "Real-time pricing for smart grid with multi-energy microgrids and uncertain loads: a bilevel programming method," *Int. J. Electr. Power Energy Syst.*, vol. 123, p. 106206, Dec. 2020.

[2] A. Barbato and A. Capone, "Optimization models and methods for demand-side management of residential users: A survey," *Energies*, vol. 7, no. 9, pp. 5787–5824, 2014.

[3] Z. Yi, Y. Xu, W. Gu, and W. Wu, "A Multi-Time-Scale Economic Scheduling Strategy for Virtual Power Plant Based on Deferrable Loads Aggregation and Disaggregation," *IEEE Trans. Sustain. Energy*, vol. 11, no. 3, pp. 1332–1346, Jul. 2020.

[4] C. Wu, W. Gu, S. Zhou, and X. Chen, "Coordinated Optimal Power Flow for Integrated Active Distribution Network and Virtual Power Plants Using Decentralized Algorithm," *IEEE Trans. Power Syst.*, vol. 36, no. 4, pp. 3541–3551, Jul. 2021.

[5] K. Han, J. Lee, and J. Choi, "Evaluation of Demand-Side Management over Pricing Competition of Multiple Suppliers Having Heterogeneous Energy Sources," *Energies*, vol. 10, no. 9, p. 1342, Sep. 2017.

[6] R. Zafar, A. Mahmood, S. Razzaq, W. Ali, U. Naeem, and K. Shehzad, "Prosumer based energy management and sharing in smart grid," *Renew. Sustain. Energy Rev.*, vol. 82, no. August 2016, pp. 1675–1684, Feb. 2018.

[7] G. Dutta and K. Mitra, "A literature review on dynamic pricing of electricity," *J. Oper. Res. Soc.*, vol. 68, no. 10, pp. 1131–1145, Oct. 2017.

[8] H. Alsalloum, L. Merghem-Boulahia, and R. Rahim, "A systematical analysis on the dynamic pricing strategies and optimization methods for energy trading in smart grids," *Int. Trans. Electr. Energy Syst.*, p. e12404, Mar. 2020.

[9] W. Liu, W. Gu, J. Wang, W. Yu, and X. Xi, "Game Theoretic Non-Cooperative Distributed Coordination Control for Multi-Microgrids," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 6986–6997, Nov. 2018.

[10] W. Saad, Z. Han, H. V. Poor, and T. Başar, "Game Theoretic Methods for the Smart Grid," Feb. 2012.

[11] W. Saad, Z. Han, H. Poor, and T. Basar, "Game-Theoretic Methods for the Smart Grid: An Overview of Microgrid Systems, Demand-Side Management, and Smart Grid Communications," *IEEE Signal Process. Mag.*, vol. 29, no. 5, pp. 86–105, Sep. 2012.

[12] M. K. Sohrabi and H. Azgomi, "A Survey on the Combined Use of Optimization Methods and Game Theory," *Arch. Comput. Methods Eng.*, pp. 1–22, Nov. 2018.

[13] R. Deng, Z. Yang, M.-Y. Chow, and J. Chen, "A Survey on Demand Response in Smart Grids: Mathematical Models and Approaches," *IEEE Trans. Ind. Informatics*, vol. 11, no. 3, pp. 570–582, Jun. 2015.

[14] S. Maharjan, Q. Zhu, Y. Zhang, S. Gjessing, and T. Basar, "Demand Response Management in the Smart Grid in a Large Population Regime," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 189–199, Jan. 2016.

[15] W. Tushar *et al.*, "Three-Party Energy Management With Distributed Energy Resources in Smart Grid," *IEEE Trans. Ind. Electron.*, vol. 62, no. 4, pp. 2487–2498, Apr. 2015.

[16] A. Paudel, K. Chaudhari, C. Long, and H. B. Gooi, "Peer-to-Peer Energy Trading in a Prosumer-Based Community Microgrid: A Game-Theoretic Model," *IEEE Trans. Ind. Electron.*, vol. 66, no. 8, pp. 6087–6097, Aug. 2019.

[17] N. Yaagoubi and H. T. Mouftah, "Energy Trading In the smart grid: A game theoretic approach," in *2015 IEEE International Conference on Smart Energy Grid Engineering (SEGE)*, 2015, pp. 1–6.

[18] N. Liu, X. Yu, C. Wang, and J. Wang, "Energy Sharing Management for Microgrids With PV Prosumers: A Stackelberg Game Approach," *IEEE Trans. Ind. Informatics*, vol. 13, no. 3, pp. 1088–1098, Jun. 2017.

[19] Y. Jiang, K. Zhou, X. Lu, and S. Yang, "Electricity trading pricing among prosumers with game theory-based model in energy blockchain environment," *Appl. Energy*, vol. 271, p. 115239, Aug. 2020.

[20] K. Anoh, S. Maharjan, A. Ikpehai, Y. Zhang, and B. Adebisi, "Energy Peer-to-Peer Trading in Virtual Microgrids in Smart Grids: A Game-Theoretic Approach," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1264–1275, Mar. 2020.

[21] J. S. PankiRaj, A. Yassine, and S. Choudhury, "An Auction Mechanism for Profit Maximization of Peer-to-Peer Energy Trading in Smart Grids," *Procedia Comput. Sci.*, vol. 151, pp. 361–368, 2019.

[22] J. Li, Y. Ye, and G. Strbac, "Stabilizing peer-to-peer energy trading in prosumer coalition through computational efficient pricing," *Electr. Power Syst. Res.*, vol. 189, p. 106764, Dec. 2020.

[23] S. Cui, Y.-W. Wang, Y. Shi, and J.-W. Xiao, "A New and Fair Peer-to-Peer Energy Sharing Framework for Energy Buildings," *IEEE Trans. Smart Grid*, vol. 11, no. 5, pp. 3817–3826, Sep. 2020.

[24] S. Cui, Y.-W. Wang, and J.-W. Xiao, "Peer-to-Peer Energy Sharing Among Smart Energy Buildings by Distributed Transaction," *IEEE Trans. Smart Grid*, vol. 10, no. 6, pp. 6491–6501, Nov. 2019.

[25] S. Cui, Y. W. Wang, Y. Shi, and J. W. Xiao, "An Efficient Peer-to-Peer Energy-Sharing Framework for Numerous Community Prosumers," *IEEE Trans. Ind. Informatics*, vol. 16, no. 12, pp. 7402–7412, Dec. 2020.

[26] C. Wu *et al.*, "Energy Trading and Generalized Nash Equilibrium in Combined Heat and Power Market," *IEEE Trans. Power Syst.*, vol. 35, no. 5, pp. 3378–3387, Sep. 2020.

[27] C. Wu *et al.*, "A Two-Stage Game Model for Combined Heat and Power Trading Market," *IEEE Trans. Power Syst.*, vol. 34, no. 1, pp. 506–517, Jan. 2019.

[28] H. Alsalloum, R. Rahim, and L. Merghem-Boulahia, "Prioritizing Prosumers in the energy trading mechanism: A Game Theoretic approach," in *International Conference on Wireless and Mobile Computing, Networking and Communications*, 2019, vol. 2019-October.

[29] T. Morstyn, N. Farrell, S. J. Darby, and M. D. McCulloch, "Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants," *Nat. Energy*, vol. 3, no. 2, pp. 94–101, Feb. 2018.

[30] S. Maharjan, Q. Zhu, Y. Zhang, S. Gjessing, and T. Basar, "Dependable Demand Response

Management in the Smart Grid: A Stackelberg Game Approach," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 120–132, Mar. 2013.

[31] F. P. Kelly, A. K. Maulloo, and D. K. H. Tan, "Rate control for communication networks: shadow prices, proportional fairness and stability," *J. Oper. Res. Soc.*, vol. 49, no. 3, pp. 237–252, Mar. 1998.

[32] E. Samadi, A. Badri, and R. Ebrahimpour, "Decentralized multi-agent based energy management of microgrid using reinforcement learning," *Int. J. Electr. Power Energy Syst.*, vol. 122, p. 106211, Nov. 2020.

[33] W. Tushar, J. A. Zhang, D. B. Smith, S. Thiebaux, and H. V. Poor, "Prioritizing consumers in smart grid: Energy management using game theory," in *2013 IEEE International Conference on Communications (ICC)*, 2013, pp. 4239–4243.

[34] N. Yaagoubi and H. T. Mouftah, "Energy trading in the smart grid: A distributed game-theoretic approach," *Can. J. Electr. Comput. Eng.*, 2017.