# Energy Trading in the Smart Grid: Poly-sellers Decision based on Game Theory

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Abstract: An essential element in the smart grid is the existence of prosumers, i.e. the consumers who can also produce and sell the energy. They will become one of the stakeholders of the future grid. Their active behavior is helpful on different sides: the environmental, economical and social sides. In fact, integrating the prosumers will result in selling the surplus of energy to the grid or other consumers. However, the interactions between prosumers and the grid need to be defined in order to maximize the profit of each stakeholder. This paper proposes an energy-trading algorithm based on game theory and genetic optimization in order to optimize the satisfaction of prosumers. In our solution, buyers can afford their demands from different sellers taking into consideration the distance, the price and the amount of energy traded and needed. Simulation results indicate the effectiveness of our proposed approach in terms of minimization the total cost and maximization each prosumer satisfaction i.e. minimization the buyer's bills and maximization the seller's revenues.



## 1 INTRODUCTION

In the past, consumers were passive. They pay what they consume without any intelligence in the energy management. Nowadays, the integration of renewable energies in the smart grid and the bidirectional communication give the consumers the ability to participate in their own energy scheduling to store energy for use during peak hours or for sale to the grid or other consumers. Furthermore, the prosumers become environmentally aware and informed about the energy control. Unlike in traditional energy management, they will be able to sell or buy the energy to/from each other or to/from the grid and use storage systems to find optimal strategies and maximize their profits (Mediwaththe *et al.*, 2018). Thus, we emphasize that the consumer transition to prosumer is one of the key features to enhance the reliability of the smart grid. This evolution increases the energy savings and the use of the intermittent green energy. Moreover, it increases the energy cost savings and decreases the peak demands (El Rahi *et al.*, 2016).

Energy trading refers to the sale and purchase of energy between the consumers and the providers/grid (Wu *et al.*, 2015) (Ahmadzadeh and Yang, 2015). However, with the existence of multiple constraints, a multi objective optimization is needed to handle all the constraints. In this manner, many authors have been interested in the energy trading in the smart grid. Looking at the trading capabilities, works are divided into two categories: (1) the centralized energy trading i.e. the surplus of energy is sold/bought between the prosumers and the grid or the aggregator that is a new entity in the electricity market that acts as a mediator / broker between consumers and the grid, (2) the decentralized energy trading between the prosumers themselves. For the first category (the centralized energy trading), (Wu *et al.*, 2015) propose a centralized decision where a local energy-trading controller is responsible for managing the surplus of energy of all the prosumers. For (El Rahi *et al.*, 2016), a double auction mechanism is proposed to solve the energy trading. For (Rahi *et al.*, 2017), the energy is traded between residential prosumers and an energy controller based on Stackelberg game. (Tushar *et al.*, 2013) propose a non-cooperative single leader multiple followers Stackelberg game to trade the energy between prosumers and a central power station CPS. Their aim is to offer an energy unit price



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that matches each prosumers' constraints. (Tushar, Chai, *et al.*, 2015) develop a game theory proposal to model the interactions between prosumers and a shared facility controller. They model the behaviors of the prosumers and predict the benefit that they will gain from the trading energy using cake cutting game. For the second category (the decentralized energy trading), (Yaagoubi and Mouftah, 2017) propose a game theory approach to trade energy between sellers and buyers. The best seller is chosen according to the trading energy price and the traded amount of energy. (Yaagoubi and Mouftah, 2015) propose a fully distributed game theory approach to trade energy among smart grid prosumers with distributed energy generation and storage units. They develop a decentralized optimization decision based on the suitable path among the smart grid infrastructure. (Kumar Nunna and Doolla, 2013) propose a multi agent system in a scenario with two to four micro grids with and without storage. Each agent in a microgrid represents a real seller/buyer by adopting an auction-based algorithm.

However, in the existing centralized and decentralized energy trading schemes, the surplus of each seller is sold to one buyer. It cannot be traded between more than one buyer. It is difficult, in this way, to encourage the prosumers to contribute with their superfluous energy. In this study, we are dividing the surplus of energy between different buyers. Our aim is to share the surplus of energy of each seller between different prosumers according to multi-objective functions in a decentralized way.

Our contribution focuses mainly on the interactions between the prosumers and the grid. Different from all previous works, a hybrid algorithm is proposed to trade energy between the grid and the prosumers based on a game theory approach and a genetic algorithm.

Our solution is poly-sellers. It will offset the lack of energy on the buyer side from different sellers. This will add different constraints that will impact the decision. In addition, a new energy trading context is proposed within the smart grid: Prosumer-Grid Energy Trading (PGET), and Prosumer-Prosumer Energy Trading (PPET). Based on game theory and genetic optimization approaches, we propose a fully distributed algorithm to trade the energy stored between prosumers and the grid. Extensive simulations are done to evaluate our work and to compare it to an existing energy trading algorithm (Tushar, Chai, *et al.*, 2015) (Yaagoubi and Mouftah, 2015).

The rest of this paper is organized as follows. In section II, the proposed algorithm is described with the multi objective restrictions. In section III, we present the results. We conclude our work in section IV.

# 2 SYSTEM MODEL

We consider a system with S sellers and B buyers. Let $A = \{1, 2, 3 \dots S\}$ denotes the set of sellers and $C = \{1, 2, 3 \dots B\}$ denotes the set of buyers. The seller represents the prosumer with an excess of energy to sell. The buyer represents the grid or the prosumer who is not able to meet his energy demands. In this paper, we are considering the case where the grid is only a buyer and not a seller of energy. Our goal is to optimize the satisfaction of prosumers. Thus, in our proposal, the buyer, the one who needs energy, will choose the seller with the lowest energy unit price. On the other side, the seller will sell his excess of energy to the one who will pay the highest energy price. One of the main motivation of our work is to find a solution to this dilemma between satisfying sellers and buyers or even the grid. We study two cases; the first one is between the prosumers and the grid where we suppose that the grid will give the highest energy unit trading price comparing to the energy price given by the prosumers, while the second case is between the prosumers themselves.

Each seller will define his amount of energy to sell, while each buyer will determine his demands. The energy price unit E for each seller n is modeled as (Kohen, 2015):

$$E(n) = y(n) * L(n) \tag{1}$$

Where y is the energy price (cents) and L is the energy to sell (KWh). This cost function is based on thermal generation cost function (Djurovic, ZivicM.Z. Djurovic, A. Milancic, 2012) (Chouikhi, Merghem-Boulahia and Esseghir, 2018) and is used for determining the grid and the prosumers energy price. This type of cost function allows us to calculate different economic dispatch practices like the energy price minute by minute and the total operating cost comparing to other functions (Chouikhi, Merghem-Boulahia and Esseghir, 2018).

## 2.1 Energy Trading Algorithm

We propose an iterative algorithm for energy trading. each iteration is about fifteen minutes. During each iteration, each seller sends to other prosumers the amount of energy to sell, after calculating the energy needed for his local demand, and each buyer defines the quantity of energy that he needs. We suppose that the prosumer is either a buyer or a seller. The main notations are listed in Table 1. Our algorithm is divided into two steps:

- Trading energy between prosumers and the grid.
- Trading energy between prosumers.

In fact, when comparing the grid to the consumer in terms of prices, it is known that the grid offers a higher price to buy energy than the one offered by prosumers as referred in (Tushar, Yuen, *et al.*, 2015). The prosumers, especially residential prosumers, are not able to pay as much as the grid. Hence, the prosumers start by interacting with the grid at first in order to maximize their revenues, as they will sell the surplus with a higher price.

Table 1: Summary of notations.

| Symbols | Description |
|---|---|
| S | The total number of sellers |
| B | The total number of buyers |
| n | The serial number of seller |
| k | The serial number of iteration |
| b | The serial number of the buyer |
| D | The distance constraint |
| g | The index of the grid |
| T | The total number of iterations |

After that, we calculate the amount of energy bought/sold in this interaction. Then, prosumers communicate with each other to trade their energy. Questions then arrive: How can a buyer choose different sellers to maximize his profit? What are the constraints for the energy trading system?

In this respect, we formulate utility functions for sellers and buyers.

The global utility function for a seller n in an iteration K is formulated as:

$$F(n,k)= J(n,k) + U(n,k) \tag{2}$$

$$J(n,k) = \alpha \ln (1+ e(n,k)) \tag{2-a}$$

$$U(n,k)= E(n,k)* ( T(n,k) – D(n,k)) \tag{2-b}$$

It is composed of two parts:

- The first part J(n,k) is the utility function that illustrates the energy consumption from the grid without any energy trading system where we use the logarithmic function, where e(n,k) is the energy bought by a prosumer from the grid and α is an adjustment parameter (Ahmadzadeh and Yang, 2015).
- The second part U(n,k) is the utility function that illustrates the energy traded between the prosumers themselves and the grid. E(n,k) is the energy price offered by seller n in the iteration k, T(n,k) is the surplus of energy for seller n in the current iteration k and D(n,k) is the energy needed by the seller n in the iteration k.

T(n,k) is calculated as following:

$$T(n,k) = T_{n,g,k} + T_{n,b,k} \tag{3}$$

Where $T_{n,g,k}$ is the energy traded between seller n and the grid, and $T_{n,b,k}$ is the energy traded between seller n and the prosumer buyer b at the $K^{th}$ iteration.

In this work, we are focusing on the second part. The utility function used in our work for the seller n in an iteration k is U(n,k). For the first part, our work (Alsalloum *et al.*, 2018) takes into consideration the energy management between the providers and the consumers without any storage systems.

The goal is to maximize the satisfaction of each prosumer in order to maximize the satisfaction of the overall utilities functions $\sum_S \sum_k U(n,k)$. Thus, maximizing each utility function of each prosumer permits to maximize the overall utilities.

The optimization problem is formulated as follows:

$$\text{Max } U(n,k) \tag{4}$$

$$\text{s.t} \quad \text{distance (seller-buyer)} < D \tag{4-a}$$

$$\sum T(n) = Ng,k \tag{4-b}$$

$$\sum G(i) < Tn,k \tag{4-c}$$

$$E(n) < E(g) \tag{4-d}$$

The equation (4-a) ensures that the distance between the prosumers themselves and between them and the grid is below D meters in order to minimize the energy loss. The equation (4-b) ensures that the energy bought from the sellers is equal to the energy that the buyer needs Ng,k in an iteration k. The constraint in (4-c) is based on the amount of energy traded between each seller and the buyers. The sum of the energy bought by the buyers G(i) should be lower than the surplus of the energy traded by the seller n for each iteration k. The equation (4-d) ensures that the seller will sell his surplus of energy to buyers with a lower price comparing to the grid. This makes the energy transition between sellers and buyers acceptable.

To model the buyers' satisfaction, the global utility function for a buyer b at iteration k is formulated as:

$$H(b,k)= U(b,k)+ X(b,k) \tag{5}$$

$$U(b,k)= \sum T(n,k) * E(n,k) \tag{5-a}$$

$$X(b,k)= \sum e(n,k) *E(g,k) \tag{5-b}$$

The equation (5) is divided into two parts:

- The first part U(b,k) is the utility function that illustrates the energy consumption from the surplus of prosumer energy.
- The second part X(b,k) is the utility function that illustrates the energy bought from grid when the energy traded does not afford the prosumers needs, where E(g,k) is the energy grid unit price.

As aforementioned, in this work, we are focusing on the traded energy (part 1). Each buyer aims to maximize his satisfaction.

$$\text{Max } U(b,k) \tag{6}$$

In this paper, we are going to compare our work with the two research works described in (Tushar, Chai, *et al.*, 2015) (Yaagoubi and Mouftah, 2015). Authors (Tushar, Chai, *et al.*, 2015) use the Stackelberg Game theory to model the energy trading between the prosumers and the grid taking into account the storage capabilities for each prosumer. The aim is to maximize the profit of each prosumer and grid. They evaluate their work with and without storage.
(Yaagoubi and Mouftah, 2015) proposed also a Game theory to model the energy trading process between the prosumers. They take into consideration the geographical position to define the energy losses, the price and the energy needed. Their decision is based on the optimal path.

<u>Parameters and Methods Adopted</u>

Having insights into the properties of the optimization methods, the game theory approach is well used in the energy trading mechanism (Sen and Baysal, 2018). Genetic Algorithms (GA) are also helpful in this context. GA represent an appropriate evolutionary algorithm having potential to solve these types of complex problems. GA provide near optimal solution for the given problem. Hence, we use GA based scheduling algorithm to solve our optimization problem. The fitness function is usually the utility function solved in a way to respond to different constraints that we will see in the next sections (Longoria and Shi, 2017).

Therefore, our proposal is defined as:

- The initial step is to define the set of sellers able to sell the surplus of energy to buyers after calculating the energy needed for their own use.
- The second step is to define the sellers with a distance between them and the buyers lower than D meters.
- The third one is to choose the best sellers based on the energy price for the prosumers and the grid.
- At the end, when finding the best sellers, the needed energy will be divided between two sellers based on the lowest price and the nearest distance.

## 2.2 Prosumer Grid Energy Trading (PGET)

In this section, we will describe the algorithm PGET used between each seller n and the grid.
To start, it is essential to determine the set of sellers, the price, the energy needed and traded. In our model, the sellers and the grid are required to set the energy unit price according to the equation (1). In each iteration, the prices will vary according to the available surplus and the needed energy that the sellers and grid have respectively. We solve the optimization problem according to equations (4) and (6) and find the best sellers based on the distance, the price and the energy demands. To make our proposal more realistic, we suppose to work on a small region with 800 meters as an acceptable distance between two prosumers or even the grid and a prosumer. This distance has taken in our simulations.
Input: the amount of surplus T(n) for each seller n, his energy price E(n), his energy demands D(n), the grid energy price E(g).
Output: the best two sellers and the percentage of energy from each one.
We can extend our work to more than two sellers adding more constraints but we choose to evaluate the performance of the proposal with two sellers as a first step.

Table 2: PGET Algorithm.

```
PGET
1:  Select the sellers with the distance <800 meters
2:  Calculate the energy needed for next iteration
3:  Calculate the energy to be traded
4:  Define the set of sellers
5:  Calculate the price E(n) according to (1)
6:  Calculate the price E(g) according to  (1)
7:   For t=1… T
8:      For s=1…S
Table 3: PGET Algorithm.
9:         Solve optimization according to (4) for
prosumer and (6) for grid
10:        Find the best two sellers
11:     End for
12: End for
```

## 2.3 Prosumer-Prosumer (Seller/Buyer) Energy Trading (PPET)

After selling the surplus of energy to the grid, the sellers recalculate if any energy can be sold to other prosumers (the buyers in this part). Like the PGET hierarchical steps, the first step is to calculate the distance between seller/buyer. The threshold for the distance is the same as in PGET as 800 meters. Each buyer fixes the amount of energy that he wants to buy. The originality of our work resides in purchasing the energy from different sellers. The population is the set of sellers and buyers. In addition, we study the case where the surplus of energy from sellers is not sufficient to the buyers. In this case, we add a second step that consists in purchasing the energy needed from the grid. As in our first work, a game theory approach models the interactions between prosumers and providers (multi period multi provider Stackelberg game) (Alsalloum *et al.*, 2018) without taking into consideration the energy stored that each prosumer can trade.

Table 4: PPET Algorithm.

```
1: for i=1: B
2:     for j=1: S
3:     Initialize the population
4:     Compute the fitness function (4)
5:     Choose optimal sellers according to (4) based on the distance constraint
6:     Choose optimal sellers according to (4) based on the price constraint
7:     Find if the crossover will give a good parent for the next generation
8:         Else Choose next generation based on mutation
9:     End for
10: End for
```

## 3 SIMULATIONS RESULTS

We evaluated the performance of our proposals using Matlab. Table 4 depicts the parameters used in our scenario. The interval of these parameters are taken from real data values (Yaagoubi and Mouftah, 2015). These parameters are set to compare our work to the Game ST presented in (Yaagoubi and Mouftah, 2015). We have to notice that in some iterations, few of sellers will exit the algorithm without any energy sold especially when the number of sellers is higher than the number of buyers. In addition, the decision-making depends on the distance between the buyer/seller and the price given by the sellers. The main idea is to find the best two sellers with the nearest distance and the lowest price. In our work, a seller will afford the deficient of energy to two or more buyers. It is essential to mention that our simulations are repeated ten times.

Table 5: Scenario Parameters.

| | Lower bound | Upper bound |
|---|---|---|
| Energy traded (KWh) | 10 | 85 |
| Energy needed (KWh) | 18 | 61 |
| Price (cents) | 1 | 48 |
| Distance (meters) | 600 | 1200 |

PGET Case

We suppose that the grid needs 20 KWh. For example, we evaluate our proposal with 7 sellers and 6 buyers in addition to the grid.

Looking at the distance constraint shown in Table 5, the grid will choose the sellers 1 and 5 with respectively a distance of 30 and 60 meters. Moving to the next constraint, which is the price, to optimize the grid revenue, the grid should choose the sellers 1 and 3 with the lowest prices 3 and 1.5 cents. Alternatively, when combining these two constraints, we find that the best sellers that the grid chooses are 1 and 6 with respectively 15 and 5 KWh. These results vary from one iteration to another according to the price and the demands.

Table 5: The price and the distances between the sellers and the grid.

| Sellers | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|
| Price (cents) | 3 | 5 | 1.5 | 4 | 5.3 | 3.5 | 3.5 |
| Distance (meters) | 30 | 800 | 150 | 200 | 60 | 100 | 300 |
| Energy to be traded (KWh) | 66 | 80 | 20 | 60 | 88 | 15 | 60 |

PPET Case

Our algorithm starts with the buyer who has the highest energy needs to minimize the consumption from the grid and increase the revenue of buyers and sellers. To prove the efficiency of our algorithm, Figure 1 shows the best two sellers chosen by buyers based on the distance and the price limitations. For example, buyer 4 chooses the seller 7 with the highest percentage of energy and seller 4 with the lowest percentage of energy. In addition, our algorithm can tell the percentage taken from each seller. The height of the bar is in parallel with the percentage of the energy traded. We mean that if buyer 4 needs 25 KWh, seller 7 affords 70% of the energy and seller 4 the rest. Sellers 7 and 4 are the nearest sellers to buyer 4. Buyer 6 chooses the seller 2. The buyer 6 and seller 2 are near each other's (75 meters) with the lowest energy price (2 cents), which is the best response also.

To compare our proposal with another approach in which only one seller is chosen, we modify our algorithm to choose only one seller. Figure 2 illustrates the energy cost in euros for buyers with one proposed seller, two sellers and we compare our work to the Game ST (Yaagoubi and Mouftah, 2015), which consists in a game theory algorithm to trade energy between one seller and a buyer. The most impressive performance of our work is that even with one seller, the energy cost is lower than Game ST. Instead, the energy cost when two sellers are chosen is lower and this is what each prosumer wants. The aim is to achieve the two main goals: (1) minimizing the energy consumption, and (2) minimizing the energy cost. When we increase the number of users, the total cost (the sum of the costs paid by grid and prosumers) will increase. In Figure 3, we compare the total cost versus the number of users for PGPET and Game ST. As in PGPET, we have more than one seller, the total cost is lower than the cost in Game ST where only one seller affords the needed energy for the buyer. We recall that the distance constraint plays also an important role in the decision. This leads to minimizing the transmission losses as in (Yaagoubi and Mouftah, 2015).

Figure 4 shows the changes in the system energy cost while our proposed approach converges to the stability. Our proposed algorithm keeps decreasing until reaching the convergence after 20 iterations. It is somehow a big number in comparison with the number of agents, which is only 13 agents. We should work on our algorithm to minimize the needed iterations when increasing the number of agents. However, the convergent total cost in Game St (Yaagoubi and Moufthah, 2015) is reached after 30 iterations.

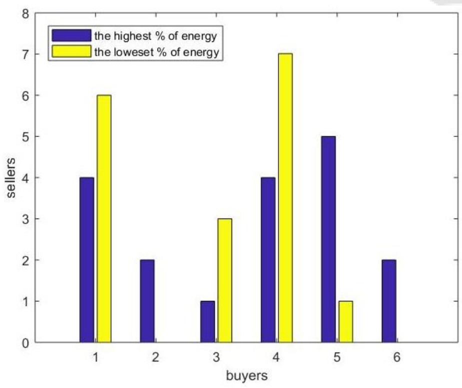


Figure 1: The sellers chosen by each buyer.

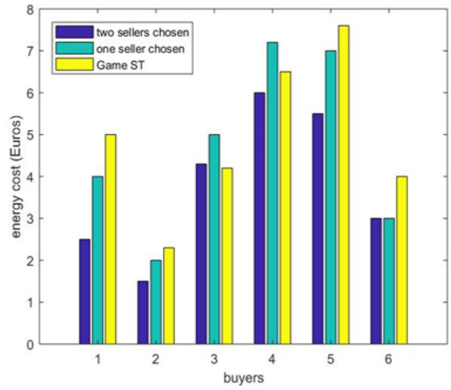


Figure 2: The energy cost versus buyers for one chosen seller, two sellers and the Game ST.

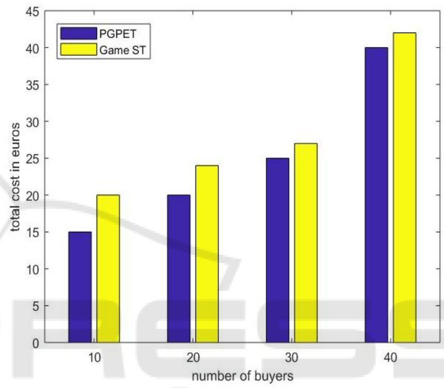


Figure 3: The total cost versus the number of buyers for 10 sellers for PGPET (Prosumer-Grid-Prosumer Energy Trading) and Game ST.

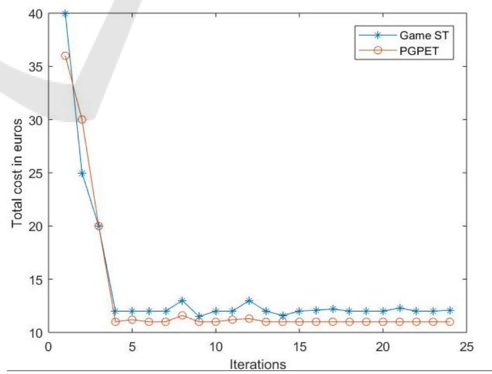


Figure 4: The total cost versus iterations for the Game ST and PGET.

To evaluate the minimization of energy bought from the grid after applying our PGPET algorithm, Figure 5 shows the amount of energy for 10 buyers. We can notice that with the growth of the number of sellers, the energy needed from the grid decreases. It means that the traded energy mechanism can afford the amount of energy without turning back to the grid.

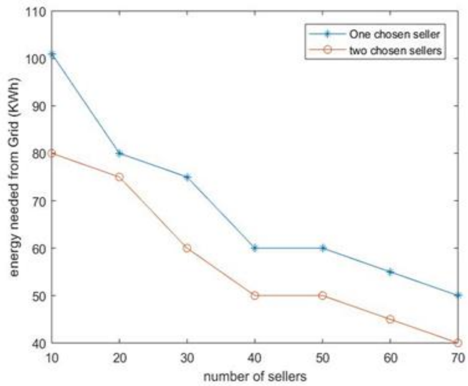


Figure 5: The energy needed from Grid versus the number of sellers with one and two chosen sellers.

In Figure 6, we vary the energy traded to evaluate the satisfaction of 10 buyers. We see that the satisfaction of buyers increases with the increase of the traded energy. When the sellers have more energy to be traded, and as our algorithm chooses the best sellers according to the distance and the price, buyers are able to get their needed energy from the sellers with an optimal price. As seen in Figure 4, they will not require to the grid to get the needed energy. Moreover, with two chosen sellers, the satisfaction is more important than with one chosen seller.

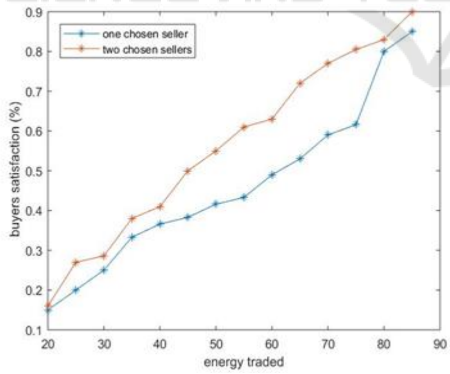


Figure 6: The variation of the buyers' satisfaction versus the energy traded for 10 buyers.

## 4 CONCLUSION

Following the fast development of the smart grid, implementing new pricing schemes is essential to bring more benefits to the overall system. In this paper, we study the complex interactions between the prosumers themselves and with the grid to sell and buy the surplus of energy. We propose a new algorithm based on game theory and genetic optimization to choose the optimal sellers to buy energy from in order to maximize the profits. We notice that getting energy from different sellers is more cost effective than having the deficient of energy from only one. For future work, we will introduce the energy trading between different providers. We will compare our work to other mechanisms like double auction scheme.

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