A MAS based energy-coordination by game theory to apply a new incentive-based demand response in the electrical market

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Abstract: - In this work, a multi-agent system implementing a new incentive-based demand response model (MAS-IBDR) is designed to help the Grid Manager (GM) to find a balance between energy produced and demand during peak hours. The proposed approach adopts the negotiation model of the game theory, where a stackelberg game with two interaction loops is formulated to capture interactions between the actors of this hierarchical market (Generator, Grid Manager (GM), Charge Aggregators (CA) and end Users (Us)) having an oligopolistic structure in order to reduce costs required to compensate the resource deficiency. The Grid Manager launches an incentive offer to sell a demand reduction from the Charge Aggregators, which trigger a trading routine with their registered Users to encourage them to reduce their consumption and receive in return an award. From this negotiation process based on game theory, an optimal solution of stackelberg equilibrium is obtained. The simulation results confirm that the proposed approach is effective in offsetting the deficiency of system resources at minimum cost during peak hours.

Key-Words: - Multi Agent System; Game theory; Stackelberg duopoly; Oligopolistic Market; Demand Response; Incentive-Based Demand Response.

1 Introduction

The growing demand for electricity has put a heavy load on the power grids. Conventionally, power generation is usually forced to follow varying loads in its systems [1]. To compensate for capacity shortage during peak times, grid manager (GMs) needs to build more backup in generation capacity. However, this conventional approach has faced criticism for a range of reasons, including heavy investment, due to the use of generators during rush hours, and carbon emission issues [2].

With the appearance of the smart grid [3], demand response (DR) is now playing a more active role in improving the efficiency and reliability of the network [4], to respond positively to inadequate demand.

There are two possible DR models: the incentive-based demand response (IBDR) model and the price-based demand response (PBDR) model [5]. In the IBDR model, also known as the reward-based model, customers receive financial incentives in return for reducing energy consumption. In the PBDR model, the price is controlled to induce customers to decrease demands when necessary.

In this paper, we are interested in the incentive-based model, because it is more common and wide spread in the real system. IBDR is based on contractual arrangements designed by decision-makers (GMs or utilities) to achieve reductions in customer demand during the " events " program [3], which could be triggered in response to a price increase or a contingency system that threatens the reliability of the power system. IBDR provides registered users with incentives to reduce their charges [4].

Lot of work relies on incentive mechanisms. In [6], a decentralized framework has been developed in which the aggregator seeks to maximize profits while its users (consumers) aim to minimize their respective costs; the interaction between them is coordinated by monetary incentives. the work on [7] used the concept of price elasticity of demand and the function of customer profit to improve an economical model for two incentive DR programs that are interruptible / Curtailable service and capacity market program, the model proposed can help the GM to identify and use relevant DR program. The incentive mechanism between energy suppliers and users for demand management uses auction theory studied in [6].

Most of the existing IBDR models [8–10] were designed from the viewpoint of a mediator (e.g., utility company, electricity retailer or service provider), to push end users to participate in the provided sub-programs.

Recently, game theory has attracted a lot of attention in the modeling of hierarchical decision problems. The Stackelberg game model was proposed in [11], between the retailer of electricity and its users, where the retailer aims to maximize his profits by adjusting the retail price according to the users who have to manage their devices to minimize their electricity bill. Moreover, eventhough Stackelberg game theory has been widely acknowledged as a useful means to model smart grid related issues with hierarchical structure, the recent studies [11, 12], focused mainly on modeling the interactive process between mediator(s) and end users. In other words, the demand response resources were gathered and brought to the aggregation level only, causing the value of DR to be underestimated.

This paper opens the way for the shift of DR resources from utility programs to programs controlled by the GM. Besides, GM sets up a threshold of minimum load reduction before a DR resource is allowed to have access to the wholesale market. One solution to this issue is to enroll small-scale users in sub-programs of charge aggregators (CAs) who play spectacular role on behalf of their subscribed users and participate in the wholesale electricity market to sell aggregated load reduction [13], thus hedging small-load users from being exposed to the risks by competing with large-load users. Some work has been done to aggregate small loads of the demand side. [14] proposed a phased auction mechanism by proxy that can be used by an aggregator to plan small loads and calculate the final price via two phase’s auction. In [15], a bidding strategy was designed to permit small scale users to submit power offers and load balancing to the charge aggregators (demand response service provider), in return for a potential monetary compensation.

By thoroughly analyzing and understanding past literature, authors typically focus on the aggregation level by employing small load users into sub-programs or encouraging them to take part in retail markets, whereas the discussion about DR outside the aggregation level is absent.

Following this work, this paper presents the idea of a new negotiating process of DR resources to help the GM to obtain the resources necessary at minimal cost and solve the problem of imbalance between supply and demand energy during peak hours. The proposed approach is divided into four steps:

Firstly, design the architecture of the multi-agent system implementing the proposed IBDR model, determine the coordination mechanisms and the communication protocol between the actors of this hierarchical market: Generators, Grid Manager, Charge Aggregators and end-Users.

Secondly, find out the objective of the control strategy and the agent model of each actor.

Thirdly, formulate a stackelberg game with two interaction loops, which takes into account asymmetric behavior of the actors of this oligopolistic market, formulate a coordination control algorithm to calculate the optimal solutions from Stackelberg Equilibrium.

Finally, check the benefit and the functioning of the economic stability of the different actors based on the case study.

The paper is organized as follows: Section 2 presents the structure of the MAS-IBDR market, objective of the control startegy and the agent model of actors. A stackelberg game with two interaction loops is formulated in section 3, to allow the negotiation of ressources between market actors and achieve a balance. The case study, simulation results and their interpretation are given in section 4, and finally the study is concluded in section 5.

2 Structure of the proposed MAS-IBDR market, objective of the control startegy and the agent model of actors.

2.1 Structure of the proposed MAS-IBDR.

The electricity market fig 1, has an oligopolistic structure, consisting essentially of three main actors: producers, Grid Manager and end-users (consumers); the role of GM actor is to anticipate the lack of operating resources and try to compensate it by exploiting flexible generators, or buying a reduction on the demand (encouraging users to participate in DR programs). For this, we introduced a fourth actor named Charge Aggregator (demand response service provider).

Fig 1. Structure of electrical market

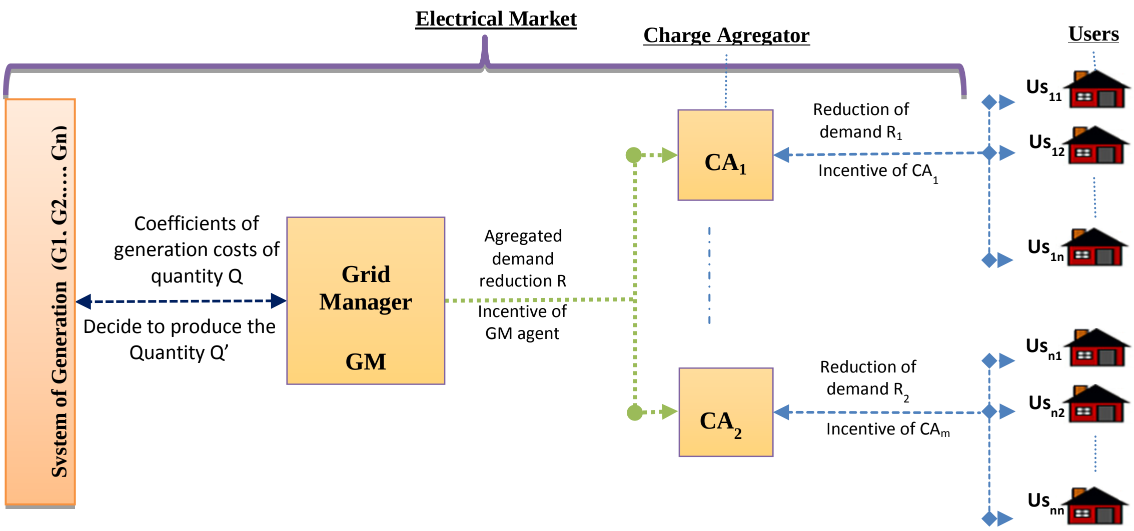
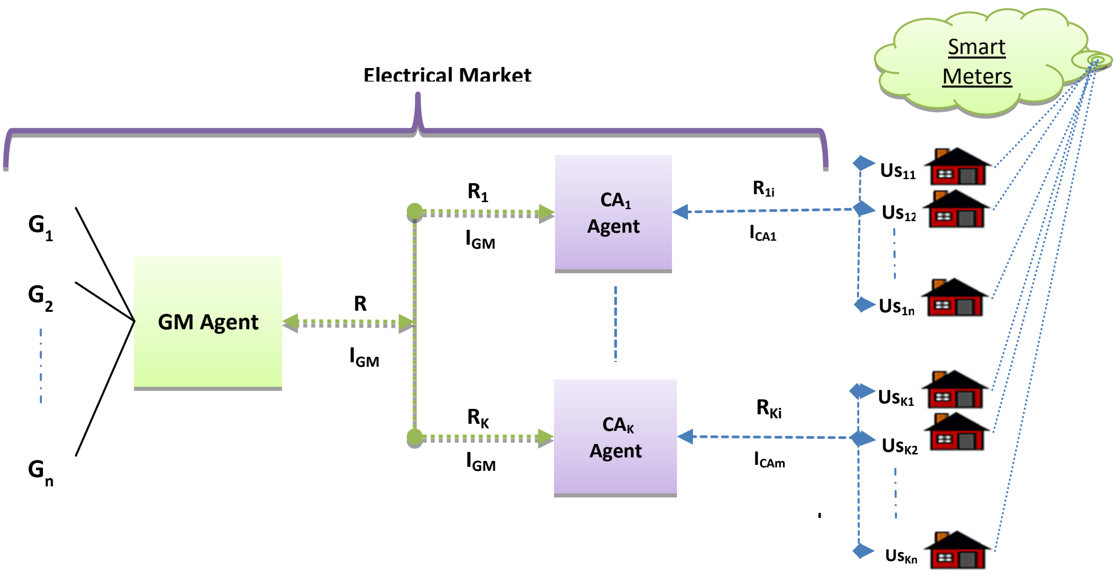


Fig 2. Structure of MAS-IBDR.



In order to allow DR in this market, to better meet the specific objectives and to take into account the coordination between these actors (producers, grid managers, charge aggregators and end-users), a multi-agent system is designed in this paper, where each actor is modeled by an agent (Fig 2). Three agents are designed in this document, including the Grid Management Agent (GM), the Charge Aggregator Agent (CA_K), and the User Agent (Us_{ki}).

The time interval of valley, off-peak, and peak periods are determined using equation (1a) [16].

$$\text{Period} = \begin{cases} \text{Valley} & \text{if } \delta_1 < D^{Ini}(t) \le \delta_1 + \frac{1}{3}\times(\delta_2-\delta_1) \\ \text{off-peak} & \text{if } \delta_1 + \frac{1}{3}\times(\delta_2-\delta_1) < D^{Ini}(t) \le \delta_1 + \frac{2}{3}\times(\delta_2-\delta_1) \\ \text{peak} & \text{if } \delta_1 + \frac{2}{3}\times(\delta_2-\delta_1) < D^{Ini}(t) \le \delta_2 \end{cases} \quad (1)$$

2.2. Objective of the control startegy and the agent model of actors.

2.2.1. GM Agent

The objective of the control strategy of GM Agent is to maximize his profit while minimizing the cost of purchase. GM costs are composed of two parts: the production cost caused by the current generators and Incentive payments to CA_k Agents. The profit function of GM Agent is formulated in (2a).

$$\prod_{GM} = P \times G - \sum Cost_{GM}$$
$$\text{with } Cost_{GM} = C_{Gen}(G) + I_{GM} \sum_{k \in K} R_k \quad (2a)$$

Under the following constraints:

$$I_{GM}^{min} \leq I_{GM} \leq I_{GM}^{max} \quad (2b)$$

$$G + \sum_{k \in K} R_k = D_{req} \quad (2c)$$

In (1a), G denotes amount of energy produced; P is the selling price of electricity in the market, $C_{Gen}(G)$ is the cost of producing the quantity of energy G; I_{GM} is the incentive offered by the GM Agent, which is limited by I_{GM}^{min} and I_{GM}^{max} (2b). R_k is the corresponding load reduction submitted by the k^th Charge Aggregator Agents. In addition, the sum of the generating amount (G) and the load reduction submitted by all CA_k Agents must be equal to D_{req} (2c).

Generational costs $C_{Gen}(G)$ are strictly convex and assumed to be an increasing monotonic function [17], equation (3).

$$C_{Gen}(G) = a.(G)^2 + b.(G) + c \quad (3)$$

Where a, b, and c are the generation coefficients that are available to the GM Agent in advance

2.2.2. CA_k Agent

CA_k Agent is located between the GM Agent and end-users (Figure 2). This leads a negotiation routine based on game theory with its users to encourage them to sell their load reduction in exchange for incentive payments. On the other hand, this agent also participates in the wholesale electricity market to sell the load reduction (aggregated with its subscribing users) to the GM Agent for the incentive I_{GM} provided. The objective of the control strategy of CA_k Agent ($k \in K$) is to maximize his profit from trading with the GM Agent on the wholesale market, while minimizing incentive payments to registered users. Therefore, his function profit is expressed in (4a).

$$\prod_{CA_k} = \sum_{i \in N_k} R_{ki}.I_{GM} - \sum_{i \in N_k} R_{ki}.I_{CA_k} \quad (4a)$$

Under the following constraint:

$$I_{CA_k}^{min} \leq I_{CA_k} \leq I_{CA_k}^{max} \quad (4b)$$

In (4a), R_{ki} represents the reduction of the demand provided by the ith user (Us_{ki}; $i = 1, 2, \ldots, N_k$) of the k^{th} aggregator agent (CA_k), and N_k denotes all users who are subscribed to the CA_k Agent. I_{CA_k} is the incentive provided by the kth charge aggregator agent to encourage users to reduce their demand and $I_{CA_k}^{min}$ and $I_{CA_k}^{max}$ are the lower and upper bounds respectively.

The demand reduction R_{CA_k}, for the kth aggregator, is the given by:

$$R_{CA_k} = \sum_{i \in N_k} R_{ki} \quad (5)$$

2.2.3. Us_{ki} Agent.

All Us_{ki} Agents ($i = 1, 2, ..., N_k$) are assumed to have smart meters, incorporating a home energy management system (HEMS), to offer load reductions by controlling the charges. Each Us_{ki} Agent is expected to register in a CA_k Agent sub-program, as shown in Figure 2; When the Us_{ki} Agents are informed of the incentives offered by the CA_k Agent, they try to maximize their income incentives while considering the cost of dissatisfaction and determine their optimal amounts of demand reductions. Here, when an Us_{ki} Agent reduces his load, he experiences discomfort which is often modeled as the cost of dissatisfaction [18].

After receiving the incentives, the goal of the control strategy of each Us_{ki} Agent is to maximize his function profit (6a):

$$\prod_{Us_{ki}} = R_{ki}.I_{CA_k} - \mu_{ki}.\varphi_{ki}(R_{ki}) \quad (6a)$$

Under the following constraint:

$$0 \le R_{ki} \le R_{ki}^{tar} - R_{ki}^{min}$$
(6b)

In (6a), the first term represents the incentive income of the Us_{ki} Agent, offered by the CA_k Agent by providing a reduction in demand R_{ki}; the second term is the cost of dissatisfaction incurred φ_{ki}, where $\mu_{ki} > 0$ is defined as the weighting factor with respect to φ_{ki}. The constraint (6b) regulates R_{ki} so that it does not exceed the available quantity, i.e. the difference between the target demand R_{ki}^{tar} and the minimum demand R_{ki}^{min}. The energy consumption level, named the user reference (CB), from which the reduction of demand is given by [19]. In practice, the CB should be determined by the CA_K Agent using a specific method (for example, using historical data on energy consumption or signing contracts with users) [8].
In addition, R_{ki}^{min} should be determined by each Us_{ki} Agent according to his own characteristic or requirement. The dissatisfaction cost function in (6a) models the degree of discomfort a user may experience in reducing demand, defined convex, i.e., dissatisfaction will increase significantly with a greater reduction in demand [20]:

$$\varphi_{ki}(R_{ki}) = \frac{\theta_{ki}}{2}(R_{ki})^2 + \lambda_{ki}.R_{ki} \qquad (7)$$

With

$$\lambda_{ki} > 0 \quad \theta_{ki} > 0$$

In (7), φ_{ki} and θ_{ki} are user-dependent parameters, where φ_{ki} reflects a user's attitude towards demand reduction: φ_{ki} greater value implies that the Us_{ki} Agent has an attitude of more conservative towards demand reduction, and vice versa.

2.2.4. Ways of communication between Agents.

The objectives of the three agents mentioned above differ from each other. The coordination between them is reactive (stimulus-response) as shown in fig 2, it is ensured by two types of incentives: the GM Agent incentive I_{GM} and the CA_k Agent incentive I_{CA_k}. Once GM Agent announces the I_{GM} incentive, each CA_k Agent triggers a sub-program with the registered Us_{ki} Agents, to encourage them to reduce their charges R_{ki}, and then respond with demand reduction R_k, that's why the negotiation based on the game theory is adopted to be the way of communication between agents.

3 Game theory, demand response modeling and startegy of coordination.

3.1 Motivation of using game theory in the proposed MAS-IBDR.

The aim behind the use of negotiation based on game theory is the comprehension of communication between the actors of this electricity market with oligopolistic structure. By analyzing the profits functions of each agent (2a), (4a) and (6a), it can be seen that the optimization of each function will lead to a compromise between two terms, for example: maximizing (2a), comes from minimizing production costs that's why the GM Agent must incentivize more CA_k Agents that will lead to increased payments to CA_k Agents.
Similarly, to maximize (4a), each CA_k Agent must make a trade-off between the revenue from the wholesale market trading with the GM Agent and the Us_{ki} Agent payments. In addition, the maximizing of (6a) will translate also by a compromise between "incentive income" and "cost of dissatisfaction", since more demand reduction will increase "incentive income" but exacerbate dissatisfaction. In this regard, the incentive provided by the GM Agent will affect the amount of aggregated demand reductions (R_k)of a CA_k Agent, and the incentive I_{CA_k} provided by a CA_k Agent will also affect how Us_{ki} Agents determine their demand reductions R_{ki}. In contrast, user-adjusted demand reductions will have an inverse impact on how a CA_k Agent regulates a new incentive, and will also have an impact on the total purchase cost of the GM Agent since the aggregate load reduction of CA_k Agents is changed. These factors naturally lead to interactions between these agents, which are coordinated through two types of incentives: the GM Agent incentive I_{GM} and the CA_k Agents incentive I_{CA_k}. The Stackelberg duopoly is adapted to illustrate such a hierarchical decision framework. In this work, the Stackelberg duopoly with two interaction loops is proposed to capture the concept behind the presented model.

3.2 Formulation of two-loop Stackelberg Game.

As shown in Fig 2, this electrical market consists of two duopoly:

- First is formed by GM Agent and CA_k Agent.
- Second is formed by CA_k Agent and Us_{ki} Agent.

Both duopoly are asymmetrical, one speaks of the concept of leader and follower, where the CA_k Agents plays a dual role in this game, leader Us_{ki} agents side and follower GM Agent side.

For this two-loop Stackelberg duopoly with a hierarchical decision-making structure, the desired results take the form of a Stackelberg Equilibrium (SE), which is defined as follows: **Definition**: For the two-loop Stackelberg game above, a set of strategies $(R^*, I^*_{CA}, I^*_{GM})$ constitutes a Stackelberg Equilibrium of this game, if and only if the following set of inequalities is satisfied:

$$\prod_{ki}(R^*_k, I^*_{CA_k}) \geq \prod_{ki}(R_{ki}, I^*_{CA_k}) \quad \forall i \in N_k \tag{8}$$

$$\prod_{CA_k}(R^*_k, I^*_{CA_k}, I^*_{GM}) \geq \prod_{CA_k}(R^*_k, I_{CA_k}, I^*_{GM}) \quad \forall k \in K \tag{9}$$

As well as:

$$Cost_{GM}(R^*, I^*_{CA}, I^*_{GM}) \leq Cost_{GM}(R^*, I^*_{CA}, I_{GM}) \tag{10}$$

Where $R^*_{ki} = \lfloor R^*_{k1}, R^*_{k2}, ..., R^*_{kN_k} \rfloor$ with (i=1, 2, …, N_k) denotes the strategies of all the Us_{ki} Agent registered under CA_k Agent and $R^* = \lfloor R^*_1, R^*_2, ..., R^*_k \rfloor$, represents the union of the strategies of the Us_{ki} Agent of all the CA_k Agent (k=1, 2, …, K). In addition $I^*_{CA} = \lfloor I^*_{CA_1}, I^*_{CA_2}, ..., I^*_{CA_k} \rfloor$, denotes the strategies of all CA_k Agent.

The inequalities in (8) - (10) mean that, when all agents (players) are at an SE, no Us_{ki} Agent can increase its profile by choosing a strategy other than R_{ki}, and no CA_k Agent can improve its utility by deviating to other strategies; In addition, the GM Agent cannot further reduce costs by choosing other incentives.

3.3 Calculates stackelberg equilibrium.

There is a unique Stackelberg equilibrium of this game to find it; we must use the backward induction, as in any sequential game. That is, start analyzing the decision of the follower. On the basis of this equilibrium the optimal solutions for GM agent, CA_k agents and respective Us_{ki} agents are determined; and those by following these steps:

- The first step is to identify the "best response" of the users in response to the CA_k Agent strategy (i.e., I_{CA_k}) in the bottom loop of the game; given the "best response" of each user.
- The second step is to find the best strategy for a CA_k Agent. On the basis of the information revealed by all the CA_k Agents.
- The third step is to check for a better strategy for GM Agent.

Demonstration:

First step: Identify the "best answer" of Us_{ki} Agents in the response to the strategy I_{CA_k}, of the CA_k Agent .

Given the strategy I_{CA_k} of the leader, the best response function R_{ki} of Us_{ki} Agent under CA_k Agent can be obtained by setting the derivative of the first order of $\Pi_{ki}(R_k, I_{CA_k})$ in (6a) with respect to R_{ki}, equal to zero : $\Pi_{ki}(R_k, I_{CA_k})$:

$$\frac{\partial \prod_{ki}(R_k, I_{CA,k})}{\partial R_{ki}} = 0 \quad \Rightarrow \quad R_{ki} = \frac{I_{CA_k} - \mu_{ki}\lambda_{ki}}{\mu_{ki}\theta_{ki}} \tag{11}$$

In order to ensure that the strategy of the best response in terms of (11) is optimal and unique, the second order derivative of $\Pi_{ki}(R_k, I_{CA_k})$ in (11) is computed with respect to R_{ki}:

$$\frac{\partial^2 \prod_{ki}(R_k, I_{CA_k})}{\partial R^2_{ki}} = -\mu_{ki}\theta_{ki} \tag{12}$$

The value of (12) is negative which means that $\Pi_{ki}(R_k, I_{CA_k})$ is strictly concave. So the best answer obtained in (11) is optimal and unique.

Second step: Found best strategy I_{CA_k} to the CA_k Agent, since the response of Us_{ki} Agents is anticipated.

By replacing the best response (11), obtained by the follower (Us_{ki} Agent), in the equation of the objective function of the CA_k Agent (4a), I_{CA_k} becomes:

$$\prod_{CA_k}(R_k, I_{CA_k}, I_{GM}) = -I_{CA_k}^2 \sum_{i\in N_k} \frac{1}{\mu_{ki}\theta_{ki}} +$$
$$I_{CA_k}\left(I_{GM}\sum_{i\in N_k}\frac{1}{\mu_{ki}\theta_{ki}} + \sum_{i\in N_k}\frac{\mu_{ki}}{\theta_{ki}}\right) - I_{GM}\sum_{i\in N_k}\frac{\mu_{ki}}{\theta_{ki}} \quad (13)$$

By following the same method as that of the first step, putting the result obtained by the first-order derivative to zero, of (13) with respect to I_{CA_k}, we obtain:

$$\frac{\partial \prod_{CA}(R_k, I_{CA_k}, I_{GM})}{\partial I_{CA_k}} = 0 \quad \Rightarrow$$
$$I_{CA_K} = \frac{1}{2} I_{GM} + \frac{1}{2}\frac{\sum_{i\in N_k}\frac{\lambda_{ki}}{\theta_{ki}}}{\sum_{i\in N_k}\frac{1}{\lambda_{ki}\theta_{ki}}} \quad (14)$$

In order to ensure that the strategy of the best response in terms of (14) is optimal and unique, the second order derivative of $\prod_{CA}(R_k, I_{CA_k}, I_{GM})$ in (13) is computed with respect to I_{CA_k}:

$$\frac{\partial^2 \prod_{CA_k}(R_k, I_{CA_k}, I_{GM})}{\partial I_{CA_k}^2} = -\sum_{i\in N_k}\frac{2}{\mu_{ki}\lambda_{ki}} < 0 \quad (15)$$

The result of the second derivative (15) is negative, which means that $\prod_{CA_k}(R_k, I_{CA_k}, I_{GM})$ is strictly concave. So the best answer obtained in (14) is optimal and unique.

Third step: Check for a better strategy for the GM Agent using the information revealed by all CA_k Agents.

Substituting (14) into the best answers of Us_{ki} Agent in (11), the optimum demand reduction R_{ki} of Us_{ki} Agent, register under the CA_k Agent can be expressed as follows:

$$R_{ki}^* = \frac{1}{2}\frac{I_{GM}}{\mu_{ki}\theta_{ki}} + \frac{1}{2}\frac{\sum_{i\in N_k}\frac{\lambda_{ki}}{\theta_{ki}}}{\sum_{i\in N_k}\frac{1}{\mu_{ki}\theta_{ki}}}\cdot\frac{1}{\mu_{ki}\theta_{ki}} - \frac{\lambda_{ki}}{\theta_{ki}} \quad (16)$$

As a result, the aggregated reduction in demand for CA_k Agents with $k \in N_k$, can be achieved:

$$R_{CA_k}^* = \sum_{i\in N_k} R_{ki}^* = \frac{I_{GM}}{2}\sum_{i\in N_k}\frac{1}{\mu_{ki}\lambda_{ki}} - \frac{1}{2}\sum_{i\in N_k}\frac{\lambda_{ki}}{\theta_{ki}} \quad (17)$$

Then, the total reduction of demand is:

$$\begin{aligned}\sum_{k\in K} R_{CA_k}^* &= \sum_{k\in K}\sum_{i\in N_k} R_{ki}^* \\ &= \frac{I_{GM}}{2}\sum_{k\in K}\sum_{i\in N_k}\frac{1}{\mu_{ki}\lambda_{ki}} - \frac{1}{2}\sum_{k\in K}\sum_{i\in N_k}\frac{\lambda_{ki}}{\theta_{ki}} \\ &= \frac{I_{GM}}{2}\alpha - \frac{1}{2}\beta\end{aligned} \quad (18)$$

With:

$$\alpha = \sum_{K\in K}\sum_{i\in N_k}\frac{1}{\mu_{ki}\lambda_{ki}} > 0, \quad \beta = \frac{1}{2}\sum_{K\in K}\sum_{i\in N_k}\frac{\lambda_{ki}}{\theta_{ki}} > 0 \quad (19)$$

Substituting equations (2c), (3) and (18) in (2a), the objective function of GM Agent becomes as follows:

$$Cost_{GM}(D, I_{CA}, I_{GM}) = \begin{pmatrix} a.\left(D_{req} - \left(\frac{I_{GM}}{2}\alpha - \frac{1}{2}\beta\right)\right)^2 \\ +b.\left(D_{req} - \left(\frac{I_{GM}}{2}\alpha - \frac{1}{2}\beta\right)\right) \\ +c + I_{GM}\cdot\left(\frac{I_{GM}}{2}\alpha - \frac{1}{2}\beta\right) \end{pmatrix} \quad (20)$$

Then it is necessary to check the convexity of the costs of the GM Agent, the reformulated $Cost_{GM}$. By putting the first derivative of (20) with respect to I_{GM} equal to zero, we can obtain the optimal value of I_{GM}, as described below:

$$\frac{\partial Cost_{GM}(R, I_{CA}, I_{GM})}{\partial I_{GM}} = 0$$
$$\Downarrow$$
$$I_{GM}^* = \frac{a\alpha(2D_{req} + \beta) + b\alpha + \beta}{\alpha(a\alpha + 2)} \quad (21)$$

The second derivative of (20) with respect to I_{GM} is:

$$\frac{\partial^2 Cost_{GM}\left(D, I_{CA}, I_{GM}\right)}{\partial I_{GM}^2} = \left(\frac{a\alpha^2}{2} + \alpha\right) > 0 \quad (22)$$

Since the outcome (22) is strictly positive if $a > 0$, then the objective function is convex GM Agent according to I_{GM}. With α and β are defined in (19).

Once the unique and optimal I_{GM}, is determined for the GM Agent, the best strategies for all CA_k Agents are also verified according to (14). Subsequently, all Us_{ki} Agents enrolled under different CA_k Agents will determine their best $\left(R^* = [R_1^*, R_2^*, ..., R_k^*]\right)$ response strategies based on (11). Finally, the strategy profile $\left(R^*, I_{CA}^*, I_{GM}^*\right)$ is the unique Stackelberg Equilibrium (SE) of the proposed two-loop Stackelberg game.

3.4. Algorithm and coordination control process.

A distributed iterative algorithm is developed in order to obtain the unique stackelberg equilibrium; the procedures of this algorithm are defined as follows:

Distributed iterative algorithm to achieve stackelberg equilibrium

1. For t ranging from t=1h to 24 h.
2. Hourly prediction of production and demand.
3. Period determination equation (1)
4. While (t ϵ {peak hour}) do

4.1 GM Agent initializes $I_{GM}^* = 0, Cost_{GM}^* = C_{Gen} D_{req}$

4.2. While ($I_{GM} < I_{GM}^{max}$) do

4.3. For each CA_k Agents, launch sub-program with enrolled Us_{ki} Agent

- By using (13) and (15) respectively:
  - CA_k Agent calculates the optimal $I_{CA_k}^*$.
  - The aggregated demand reduction $R_{CA_k}^*$.

4.4 End for

- GM Agent calculate $Cost_{GM} = C_{Gen}(D_{req} - \sum_{k \in K} R_{CA_k}^*) + I_{GM} . \sum_{k \in K} R_{CA_k}^*$

4.5 If $(Cost_{GM} \le Cost_{GM}^*)$

- The GM Agent records the optimal incentive and minimal cost: $(I_{CA_k}^* = I_{CA_k})$ and $(Cost_{GM}^* = Cost_{GM})$

4.6 Else ($I_{GM} = I_{GM} + I_{GM}^{min} < I_{GM}^{max}$)

4.7 End For

4.8 End While

- The stackelberg equilibrium $(R^*, I_{GM}^*, I_{CA_k}^*)$ has been obtained.

5. End While
6. End for.

Remark 1: It should be noted that the cost function $Cost_{GM}$ of the GM Agent is essentially strictly convex with respect to I_{GM} (see section 2.2.1); thus, the I_{GM} enumeration of the GM Agent varies from I_{GM}^{min} to I_{GM}^{max}, will naturally lead to the minimal cost for the GM Agent, which means that the proposed algorithm is always guaranteed to converge to the unique stackelberg equilibrium.

The process of the coordination control mainly comprises the following steps:

Step 1: Inform the GM Agent of the generation cost coefficients.
Step 2: initialize the incentive I_{GM} of GM Agent and procurement cost.
Step 3: send I_{GM} to CA_k Agent
Step 4: CA_k Agent launch of negotiation program with enrolled Us_{ki} Agent.
Step 5: CA_k Agent calculate the optimal incentive I_{CA_k} using (13) and load reduction using (15).
Step 6: CA_k Agent send respond aggregated reduction R_{CA_k} to GM Agent
Step 7: GM Agent calculates the total procurement cost using (20).
Step 8: GM Agent record the current incentive I_{GM} if it results in lower cost.
Step 9: Repeat the above process until the enumeration of GM Agent incentive I_{GM} can be ascertained.
Step 10: GM Agent announce the optimal incentive I_{GM} and decide generation quantity.
Step 11: CA_k Agent announce the final I_{CA_k} incentive.

4 Case study.

This paper designs MAS with Java Agent Development (JADE), which is a FIPA (The

Foundation for Intelligent Physical Agents) standard-based multi-Agent software development.

4.1 Basic data

The structure of MAS-IBDR studied in this paper is constituted of one GM Agent representing the Grid Manager, three CA_k Agents $(k=1, ..., 3)$ representing Charge Aggregators (demand response service provider) and six Us_{ki} Agents $(i=1, ..., 6)$ representing residential customers equipped with smart meters integrating home energy management system (HEMS).

The parameters of the Us_{ki} Agents, representing their individual attitudes $\theta_{i,k}$ towards the reduction of the load and the weighting factor μ_{ki} of the dissatisfaction cost are reported in table 1.

Renewable Energy production and demand profile studied are taken as shown in figure 3, for this demand profile the valleys time intervals, the off-peak and peak periods are calculated using (1a) and the results obtained are reported in table 2.

The simulations are carried out according to two scenarios:

- **The first scenario (S1):** does not apply the proposed IBDR model (in this scenario the resource deficiency is compensated only by running generators, in which case the cost was calculated using (3)).
- **The second scenario (S2):** applies the proposed IBDR model where the GM Agent will try to compensate for the resource deficiency by applying this scenario.

4.1 Results and analysis.

2.1.1 Performance of the proposed algorithm.

During each peak hour, the GM Agent predicts the resource deficiency that is equal to the gap between the demand and the supply that's why he offers an incentive to CAk Agents, in return for the reduction of demand.

For the first peak hours (Table 2) of the load profile studied (figure 3), the proposed algorithm converges to the stackelberg equilibrium at the 8th iteration as shown in fig 4a and 4b: in (4a) the total cost of the GM Agent cannot decrease under 2205 $/MWH and the corresponding optimal incentive (3.5135 $ / MWH) is shown in fig (4b). By Comparing the optimal value of GM Agent incentive (3.514 $ / MWH), obtained by using equation (21), with the value obtained by the proposed algorithm (3.5135 $ / MWH), it is clear that these two values of incentives are very close which shows the effectiveness of this algorithm.

Table 1. Us_{ki} Agent parameters.

CA_1 Agent						
Us_{ki} Agents	Us_{11}	Us_{12}	Us_{13}	Us_{14}	Us_{15}	Us_{16}
θ	3.2	3.6	3.8	3.6	3.8	4
λ	0.6	0.8	1	0.6	0.8	1
μ	5	5	5	5	5	5
CA_2 Agents						
Us_{ki} Agents	Us_{21}	Us_{22}	Us_{23}	Us_{24}	Us_{25}	Us_{26}
θ	3.3	3.6	3.9	3.7	3.8	4
λ	0.6	0.8	1	0.6	0.8	1
μ	5	5	5	5	5	5
CA_3 Agents						
Us_{ki} Agents	Us_{31}	Us_{32}	Us_{33}	Us_{34}	Us_{35}	Us_{36}
θ	4	4.2	4.3	3.6	4.8	5
λ	0.6	0.8	1	0.6	0.8	1
μ	5	5	5	5	5	5

Table 2. Time intervals of different periods for demand profile studied.

Time interval	**Valley**	**Off-peak**	**Peak**
Profile of demand figure 3	Hours: 1- 8, 24	Hours: 9- 16	Hours: 17- 21

Fig 3. Demand profile and production curve studied.

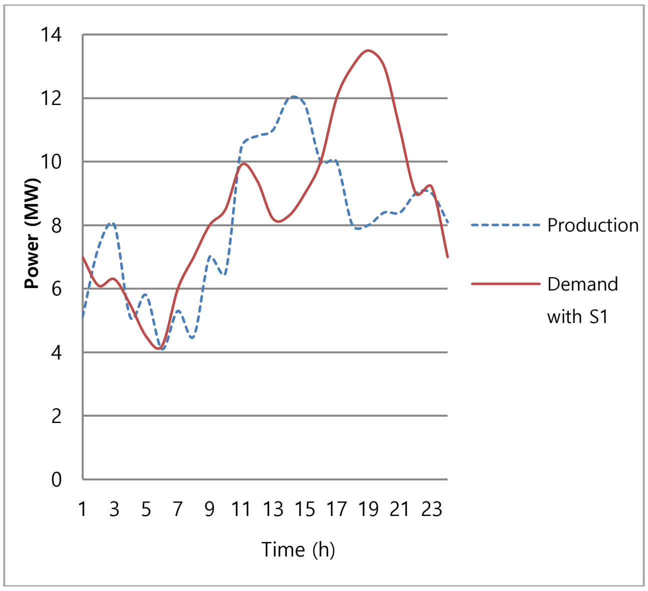


Fig 4a. Iteration of proposed algorithm to converge to the optimal cost of GM Agent.

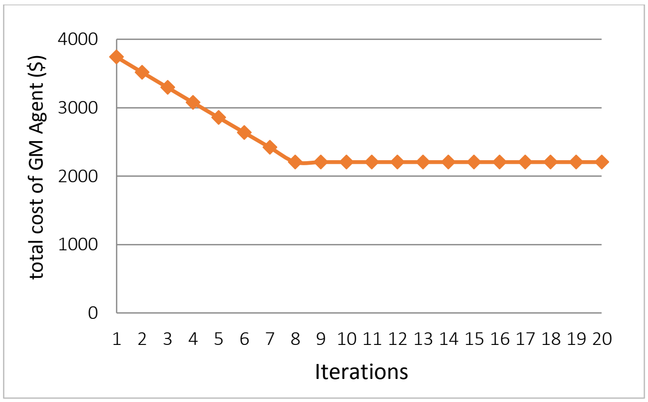
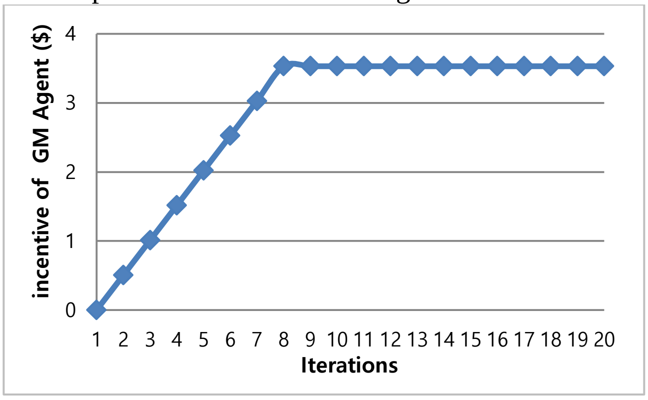


Fig 4b. Iteration of proposed algorithm to converge to the optimal incentive of GM Agent**.**



4.2.1 Comparison of costs against a benchmark.

Figure 5 shows a real-time illustration of the evolution of the production system and the consumption with and without the application of the proposed IBDR model. This figure also shows that the consumption is adapted to the production: the consumption curve follows the production curve when the proposed IBDR model is applied (Scenario 2). This adaptation is due to the DR strategy adapted during peak times, where GM Agent encourages charge aggregators to reduce the demand of users in exchange for rewards.

Figure 6 shows a real-time illustration of the optimal demand reductions during peak hours shown in scenario S2 obtained using the presented algorithm in section 3.4.

Figure 7 shows the total costs of GM Agent for scenarios (S1 and S2) during each hour of the day. Comparing the total costs obtained for the two scenarios, we find that during peak hours, the costs of (S1) are very high compared to (S2). Concerning the other periods (Off-peak and valley), the costs are equal. This leads to the conclusion that the proposed IBDR model applied in scenario 2 has reduced the overall costs of the GM Agent.

By comparing the total costs of one day for both scenarios represented in fig 8, we find that the total costs of S2 are down by 5% compared to those of S1.

Fig 5. Real time function of each scenario (S1 and S2).

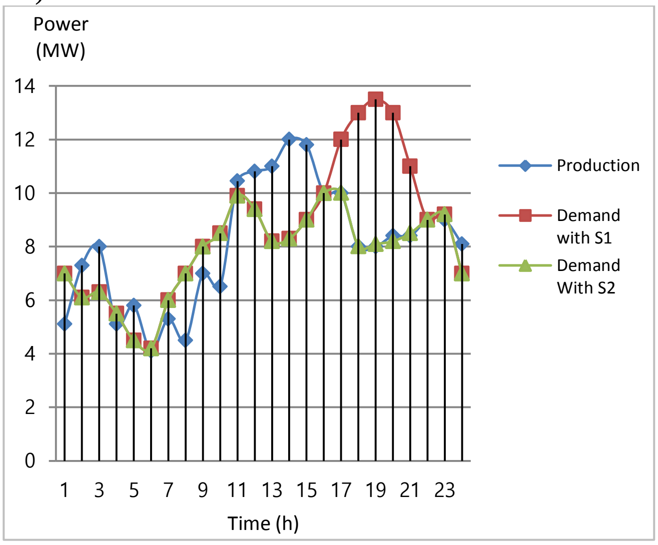
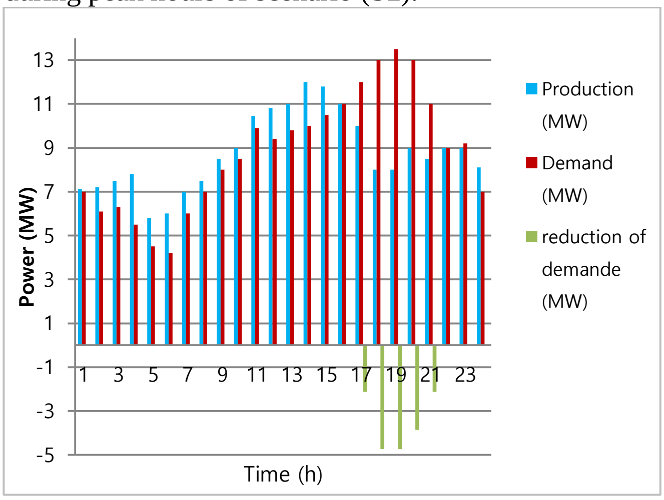


Fig 6. Real-time illustration of demand reductions during peak hours of scenario (S2).



performance with and without application of the proposed IBDR model. More than 24 605, 10283$ is the total daily costs to meet users demand when the proposed IBDR model is not applied. Once MAS-IBDR is applied, the costs are reduced to less than 23 374, 13191 $. The application of the proposed MAS-IBDR has saved approximately 5 155,485 $ in one day (24 hours). From the economic point of view, the proposed MAS-IBDR model applied to the load profile in Fig 3 has resulted in earnings greater than 5155,485 $ per day, or more than 188 175,025 $ per year.

Fig 7. Totals costs of the GM Agent for both scenarios (S1 and S2) for each hour of the day.

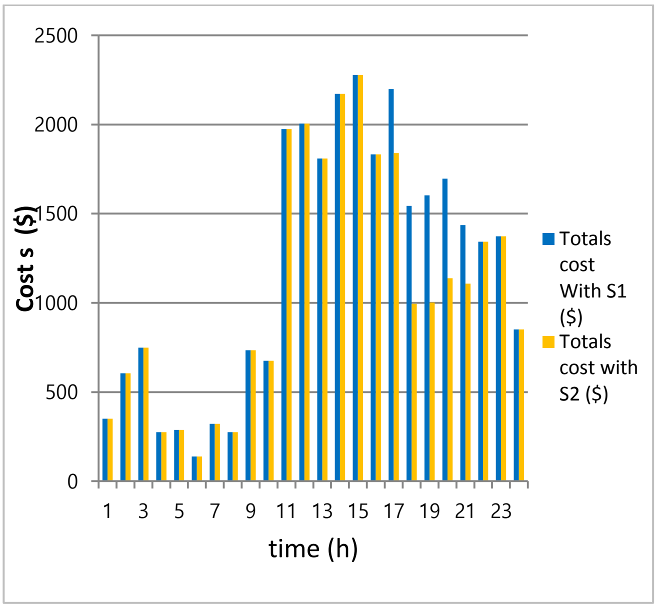


Table 3 also presents a comparison of the system

Fig 8. Total costs of both scenarios (S1 and S2) for one day.

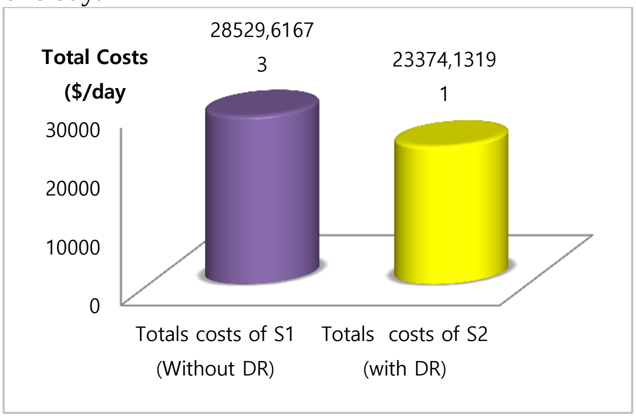


Table 4 successively provides the financial analysis of the GM Agent, namely the optimal incentives I_{GM}, I_{CAk} (payments of GM Agent to CA_k Agents and payments of CA_k Agent to Us_{ki} Agents) the costs of the generation and the optimal demand reduction of each CA_k Agent are also provided to help interpret the following analyses.

Tables 5, shows the benefit of each CA_k Agent as speculator, which is actually the profit of the CA_k Agent (equation 4a) acquired by differences in price negotiation with the GM Agents and Us_{ki} Agent. Table 5 also provides the optimal incentives I_{CAk} offered by the CA_k Agent to the Us_{ki} Agents and payments of each CA_k Agent to the Us_{ki} Agents. For each respective Us_{ki} Agent, the optimal demand reduction and the corresponding income are also provided successively in Tables 6 and 7, where the income was calculated on the basis of the first term of (equation 6a).

Note:

- The payments of the GM Agent to CA_k Agents were calculated according to the first term of (4a) and the generation costs were calculated using (equation 3).
- CA_k Agents payments to Uski Agents were calculated by multiplying the incentives I_{CAk} by aggregate demand reduction.

Table 3. Benefit of the application of proposed approach.

Scenario	Earnings of a day ($)	Earnings of a Year ($)
S2	5155,485	188.175,025

Table 4. Financial analysis of the GM Agent.

Time (h)	Optimal incentive of GM Agent ($/MWh)	Demand reduction (MWh)	Payments to CA_k Agent ($)	Generation cost ($)
1	0	0	0	43,095
2	0	0	0	85,775
3	0	0	0	102,4
4	0	0	0	43,256
5	0	0	0	55,1
6	0	0	0	28,5
7	0	0	0	46,375
8	0	0	0	33,975
9	0	0	0	79,1
10	0	0	0	68,557
11	0	0	0	171,84
12	0	0	0	183,93
13	0	0	0	190,3
14	0	0	0	225,6
15	0	0	0	244,375
16	0	0	0	128,7
17	3,549	-1,99	7,06251	158
18	8,8992512	-4,99	44,407263	102,4
19	9,6304522	-5,4	52,004442	128,7
20	8,5604020	-4,8	41,089929	128,7
21	4,4585427	-2,5	11,146356	115,17
22	0	0	0	128,7
23	0	0	0	128,7
24	0	0	0	104,89

Table 5. Financial analysis of the CA_k Agents.

Time (h)	Incentive of CA_k Agent ($/MWh)		
	CA_1	**CA_2**	**CA_3**
1-16	0	0	0
17	3,475	3,4843	3,4657
18	8,7137	8,737	8,6904
19	9,4296	9,4549	9,4044
20	8,3819	8,4043	8,3595
21	4,3656	4,3773	4,3539
22-24	0	0	0
Time (h)	**Optimal demand reduction of CA_k Agent ($/MWh)**		
	CA_1	**CA_2**	**CA_3**
1-16	0	0	0
17	-0,69	-0,59	-0,67
18	-1,69	-1,59	-1,67
19	-1,81	-1,71	-1,79
20	-1,61	-1,51	-1,59
21	-0,856	-0,756	-0,836
22-24	0	0	0
Time (h)	**Income of CA_k Agent ($)**		
	CA_1	**CA_2**	**CA_3**
1-16	0	0	0
17	2,44881	2,09391	2,37783
18	15,0397346	14,1498095	14,8617496
19	17,4311186	16,4680734	17,2385095
20	13,7822472	12,926207	13,6110392
21	3,81651256	3,37065829	3,72734171
22-24	2,44881	2,09391	2,37783
Time (h)	**CAk payment to Us_{ki} Agent ($)**		
	CA_1	**CA_2**	**CA_3**
1-16	0	0	0
17	2,39775	2,055737	2,322019
18	14,726153	13,89183	14,512968
19	17,067576	16,167879	16,833876
20	13,494859	12,690493	13,291605
21	3,7369536	3,3092388	3,6398604
22-24	0	0	0
Time (h)	**Profit of CA_k Agent ($)**		
	CA_1	**CA_2**	**CA_3**
1-16	0	0	0
17	0,05106	0,038173	0,055811
18	0,31358161	0,25797949	0,34878159
19	0,36354259	0,30019436	0,40463355
20	0,28738824	0,23571404	0,3194342
21	0,07955896	0,06141949	0,08748131
22-24	0	0	0

Table 6. The optimal demand reduction, of each Us_{ki} Agent during peak hours.

Time (h)	Optimal demand reduction of each Us_{ki} Agent (MWh)					
	CA_1 Agent					
	Us_{11}	**Us_{12}**	**Us_{13}**	**Us_{14}**	**Us_{15}**	**Us_{16}**
1-16	0	0	0	0	0	0
17	-0,114	-0,096	-0,2	-0,09	-0,073	-0,18
18	-0,253	-0,2131	-0,4439	-0,2507	-0,2034	-0,5014
19	-0,2697	-0,2271	-0,4732	-0,27	-0,219	-0,54
20	-0,2419	-0,2037	-0,4244	-0,2379	-0,1929	-0,4757
21	-0,1371	-0,1154	-0,2405	-0,1167	-0,0946	-0,2334
22-24	0	0	0	0	0	0
Time (h)	**CA_2 Agent**					
	Us_{21}	**Us_{22}**	**Us_{23}**	**Us_{24}**	**Us_{25}**	**Us_{26}**
1-16	0	0	0	0	0	0
17	-0,084	-0,077	-0,185	-0,075	-0,073	-0,18
18	-0,2007	-0,1839	-0,4419	-0,238	-0,2317	-0,5713
19	-0,2147	-0,1968	-0,4728	-0,2576	-0,2507	-0,6183
20	-0,1913	-0,1754	-0,4214	-0,225	-0,219	-0,54
21	-0,1034	-0,0948	-0,2277	-0,1021	-0,0993	-0,245
22-24	0	0	0	0	0	0
Time (h)	**CA_3 Agent**					
	Us_{31}	**Us_{32}**	**Us_{33}**	**Us_{34}**	**Us_{35}**	**Us_{36}**
1-16	0	0	0	0	0	0
17	-0,069	-0,066	-0,0168	-0,077	-0,058	-0,144
18	-0,1768	-0,1691	-0,0431	-0,187	-0,1409	-0,3497
19	-0,1898	-0,1815	-0,0462	-0,2002	-0,1508	-0,3744
20	-0,1682	-0,1609	-0,041	-0,1782	-0,1342	-0,3333
21	-0,0869	-0,0831	-0,0212	-0,0953	-0,0718	-0,1781
22-24	0	0	0	0	0	0

Table 7. Income of each Uski Agent.

Time (h)	Income of each Uski Agent ($)					
	CA_1 Agent					
	Us_{11}	**Us_{12}**	**Us_{13}**	**Us_{14}**	**Us_{15}**	**Us_{16}**
1-16	0	0	0	0	0	0
17	0,396	0,333	0,695	0,3135	0,25435	0,62717
18	2,204	1,856	3,8680	2,1904	1,77673	4,38098
19	2,543	2,141	4,4618	2,5528	2,07062	5,10563
20	2,0276	1,7075	3,557	1,9990	1,62143	3,99806
21	0,5984	0,5039	1,049	0,5107	0,4142	1,0214
22-24	0	0	0	0	0	0
Time (h)	**CA_2 Agent**					
	Us_{11}	**Us_{12}**	**Us_{13}**	**Us_{14}**	**Us_{15}**	**Us_{16}**
1-16	0	0	0	0	0	0
17	0,29111	0,26685	0,6411	0,2605	0,25360	0,64269

18	1,74386	1,59854	3,8406	2,0736	2,01834	3,84986
19	2,01881	1,85057	4,446	2,4284	2,36370	4,45684
20	1,59944	1,46615	3,522	1,8853	1,83511	3,53102
21	0,45004	0,41254	0,9911	0,4454	0,43356	0,99355
22-24	0	0	0	0	0	0
Time (h)	**CA_3 Agent**					
	Us_{11}	**Us_{12}**	**Us_{13}**	**Us_{14}**	**Us_{15}**	**Us_{16}**
1-16	0	0	0	0	0	0
17	0,24023	0,22978	0,058	0,267	0,20180	0,501
18	1,54361	1,47650	0,375	1,631	1,2289	3,051
19	1,79267	1,71473	0,436	1,890	1,4237	3,534
20	1,41241	1,35100	0,343	1,495	1,1265	2,796
21	0,380076	0,363551	0,0925	0,416	0,3136	0,778
22-24	0	0	0	0	0	0

5. Conclusion

A multi-agent system, implementing a new incentive-based demand response model, was presented in this work to help the Grid Manager to find a balance between energy produced and demand during peak hours. The proposed approach adopts the negotiation model of the game theory, where a stackelberg game with two interaction loops is formulated to capture interactions between the actors of this hierarchical market (System Production, Grid Manager, Charge Aggregators and end Users) having an oligopolistic structure. In addition, we have proven the existence of a unique Stackelberg balance that provides optimal system solutions. In addition, we have proved the existence of a single Stackelberg balance that provides optimal system solutions. Finally, it was verified that the proposed incentive-based DR approach was able to compensate for system resource deficiencies at minimal cost.

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