Demand Response based Trading Framework in the Presence of Fuel Cells Using Information-Gap Decision Theory

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***Abstract*—Nowadays demand response (DR) is known as one of the main parts of the power system especially in the smart grid infrastructure. Furthermore, to enhance the participation of the consumers in the DR programs, the Independent System Operators (ISOs) have introduced a new entity, i.e. Demand Response Aggregator (DRA). The main contribution of this paper is to investigate a novel framework to increase the profits of the DRA participating in the day-ahead electricity market, i.e. employment of an axillary generation system in the DRA entity. It is supposed that the DRA in this paper has an axillary generation system and it would lead to an increase in the profit of the DRA through avoiding the economic loss in the process of trading DR obtained by the active participation of prosumers in the electricity market. The fuel cell is introduced as the axillary generation unit to the DRA unit. In the framework proposed in this paper, the DR is acquired from end-users during peak periods and will be offered to the day-ahead electricity market. The power flow during the off-peak hours is in another direction, i.e. from the grid to the consumers. In this model, the information-gap decision theory (IGDT) is chosen as the risk measure. The uncertain parameter is the day-ahead electricity market price. The optimization problem's objective is to maximize the profit of the DRA. The behavior of the risk-seeker decision-maker is analyzed and investigated. The feasibility of the program is demonstrated by applying it to realistic data.**

Keywords—Demand response (DR), demand response aggregator (DRA), fuel cell, information-gap decision theory (IGDT), risk management, uncertainty.

I. NOMENCLATURE

A. Sets

t	The time set
j	The level of the DR reduction

B. Parameters, Variables and Functions

B_0	The deterministic profit of the DRA
B^*	The opportunistic profit of the DRA
B_ω	The targeted profit of the DRA
P_t^{DA}	The amount of the available DR
λ_t^{DA}	The price of power in the market
C_t^{FC}	The cost of fuel cell unit
PR_t	The consumers' participation rate in DRP
P_t^{DR}	The obtained power value of available DR
P_t^{FC}	The fuel cell power
C_{OM}	The maintenance cost of the fuel cell unit
$P^{FC,\ max}$	The maximum capacity of the fuel cell unit
η_t	The efficiency of the fuel cell
$R_{t,j}^{DR}$	The amount of the reward in DRP
$P^{DA,\ Max}$	The maximum capacity of the DRA
$P^{DA,\ min}$	The minimum capacity of the DRA
$\tilde{\beta}$	The optimum value of the opportunity function
α	The horizon of the uncertainty
$\tilde{\lambda}_t^{DA}$	The expected price of the market price
ρ	The deviation amount of the risk factor

II. INTRODUCTION

A. Motivation and Background

Independent system operators (ISOs) are developing different demand response (DR) programs to encourage active participation of the demand side resources in the electricity markets. The aggregation of DR programs has been known as an appropriate solution to enhance offering participation of consumers in electricity markets. A Demand Response Aggregator (DRA) plays an intermediary role in the electricity markets which is between consumers and ISOs as new market entities [1].

These entities carry out the DR programs on consumers to resell their outcomes through various electricity markets [2]. In addition, the use of an energy storage system by the DRA could lead to an increase in the profit of the DRA. One of the popular axillary generation systems is the fuel cell. Some research works have addressed the impacts of the energy storages on optimal operation of electricity markets [3]–[6] and among them, a comprehensive study has been investigated on the implementation and operation of the fuel cell on DRA [5].

B. Relevant Literature

There are a set of works related to the problem present in the literature using different models and points of view. In [7], the uncertainty of the DR had been modelled based on the consumers' behavior. Moreover, a battery was employed as a deterministic response recourse to decrease the risk of the system as the storage unit of the system.

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This problem is formulated as a profit maximization optimization problem. A framework of a DRA for heavy industries was introduced in [8]. In this work, the main idea was to give the power system more operational flexibility through the capacities of the storage of the studied heavy industries. To acquire energy, the DRA trades in the electricity market while on the other side, the consumption behavior of the studied cases was optimized. The uncertainty of the wholesale electricity market price is studied through a robust self-scheduling approach. While heavy consumers were studied in the previous model, small and medium-sized consumers are considered in [9]. As stated in [9], in a microgrid the effects of a DRA had been analyzed. The results of this model indicate that DRA has this capability to both reduce the cost to the prosumer and for the energy storage owners to achieve some benefits from the energy usage self-management. However, this could affect the amount of available grid-balancing resource that causes higher microgrid costs. Golmohamadi et al. [10] present a model to manage the demand of the residential and industrial consumers' flexibility through the multi-agent structure. In this work, each type of consumer has their specific aggregators, i.e. residential DRA and industrial DRA.

Moreover, these aggregators are managed and are controlled through a central DR provider. Electric and thermal storage of the appliances which are being controlled thermostatically are used by the residential DRA. Rooftop photovoltaic (PV) sites have also been considered in this model to link between the storage units through the home energy management system in the residential section. Moreover, [11] provided flexibility in the reductions of the load during critical demand hours by the application of the storage units in the system. Besides, a bi-level DR optimization approach is modeled where the operation goals of the distribution system operator are being meet in the upper level and the consumer's discomfort level is minimized in the lower level of the problem. A hierarchical model of energy management in the presence of DR and energy storage is presented in [12] in a microgrid which is connected to the network.

Two uncertainties had been taken into account in this study of which one of them is the load of the microgrid and the other one is the renewable energy resources. Three types of scheduling are assumed in this model including day-ahead, hour-ahead and real-time scheduling. In order to minimize the operation cost of the microgrid, a stochastic programming model was employed. A game theoretical model had been developed in [13] for optimal bidding strategies in the DRA in deregulated electricity markets. Price elasticity and consumer benefit functions are considered in this work where the cooperation between the ISOs and the DRA in the deregulated electricity markets is proposed. The bids are being collected from the DRA through the ISO and the ISO decides about the amount of DR share in a revenue maximization optimization problem. Rewards are offered to the DRA in order to encourage them to participate in the DR share. There is also a competition among the DRAs in offering their services to the ISO and this competition is solved by the Nash equilibrium idea.

The storage unit and the DR programs (DRP) are employed in [14] with the aim of coping with the fluctuations of the power generation in wind turbines. A time-of-use program was utilized in the model of a disconnected microgrid from the network. This DRP is based on customer benefit function and the price elasticity in several levels of participation in the program. An economic dispatch and unit commitment of the model is solved through AC power flow considering minimizing the operational cost.

C. *Contributions and Paper Organization*

In the proposed model, the behavior of a risk-seeker decision maker is investigated through an IGDT-based approach. In this model, the aggregator owns a fuel cell and uses it if the amount of the obtained DR is lower than the trading amount of energy in the day-ahead market in order to gain additional profits. In this work, a fuel cell unit is employed as the auxiliary generation unit of the DRA.

The paper is organized as follows: In section III, the proposed model and the problem formulation is introduced and explained. Then, the simulation results and discussion are presented in section IV. In this section, both deterministic and probabilistic behavior of the decision maker have been seen. Finally, section V presents the conclusions.

III. THE PROPOSED MODEL

In the proposed DR framework, there are three sources of DR providers. The aggregator has three kinds of clients, residential, commercial and industrial. The aggregator can trade the available power in the day-ahead electricity market. The DRP that is employed by the aggregator is an incentive-based program. In this program, the aggregator offers different amounts of incentives (rewards) for each level of load reduction by the consumers at each hour. The complete description of the employed DRP is given in [15]. It is noteworthy that the electricity tariff has two tiers, peak and off-peak. The peak period starts start at 9:00 and end at 22:00. The flow of energy is from the consumers to the day-ahead market during the peak period. In other words, the obtained DR from the consumers during peak period is being offered to the day-ahead market. While during the off-peak hours the power flow direction is from consumers to the grid.

A. *The DR framework without considering uncertainty:*

The problem formulation is introduced in two parts. In the first part, the deterministic mathematical problem formulation is given. In this stage, it is assumed that there is no uncertain parameter and the aggregator as the decision-maker can perfectly forecast the electricity prices in the day-ahead market. This problem is formulated as the profit maximization model and it is as follows:

Objective Function:

$$B_0 = Max \sum_{t=1}^{T} \left[P_t^{DA} \lambda_t^{DA} - C_t^{FC} - \sum_{j=1}^{N_J} PR_t P_{t,j}^{DR} R_{t,j}^{DR} \right] \quad (1)$$

Constraints:

$$P_t^{DA} = P_t^{DR} + P_t^{FC} \ ,\forall t \in \Omega^T \quad (2)$$

$$C_t^{FC} = \left[\lambda_g \left(\frac{P_t^{FC} + P_a}{\eta_t} \right) + P^{FC,\ max} C_{OM} \right] \eta_t \quad (3)$$

$$0 \leq P_t^{FC} \leq P^{FC,\ Max} \ ,\forall t \in \Omega^T \quad (4)$$

$$P_t^{DR} = \sum_{j=1}^{N_J} PR_t\, \bar{P}_{t,j}^{DR}\, v_{t,j}^{DR} \quad ,\forall t \in \Omega^T, \forall j \in \Omega^J \tag{5}$$

$$R_t^{DR} = \sum_{j=1}^{N_J} R_{t,j}^{DR} \quad ,\forall t \in \Omega^T, \forall j \in \Omega^J \tag{6}$$

$$\bar{R}_{t,(j-1)}^{DR} v_{t,j}^{DR} \le R_{t,j}^{DR} \le \bar{R}_{t,j}^{DR}\, v_{t,j}^{DR} \quad ,\forall t \in \Omega^T, \forall j \in \Omega^J \tag{7}$$

$$\sum_{j=1}^{N_J} v_{t,j}^{DR} = 1 \quad ,\forall t \in \Omega^T, \forall j \in \Omega^J \tag{8}$$

$$P^{DA,\ min} \le P_t^{DA} \le P^{DA,\ Max} \quad ,\forall t \in \Omega^T \tag{9}$$

$$P_t^{DA} \ge P_t^{DR} \quad ,\forall t \in \Omega^T \tag{10}$$

$$v_{t,j}^{DR} \in \{0,1\} \tag{11}$$

The objective function of the model is given in Eq. (1). In this equation, B_0 is the deterministic profit of the aggregator which is going to be maximized. The first term of the maximization function is related to the revenue of the traded power in the day-ahead market multiplied by the day-ahead market price ($P_t^{DA}\ \lambda_t^{DA}$). The second term is the operating cost of the fuel cell unit in each studied hour. The last term indicates the cost of implementing the DRP ($\sum_{j=1}^{N_J} PR_t\ P_{t,j}^{DR}\ R_{t,j}^{DR}$). The first element of this term is the considering rate of the consumers in the DRP (PR_t). The second one is the amount of reduced power at hour *t* and step *j* ($P_{t,j}^{DR}$)and the last element is the corresponding reward of that amount of power reduction ($R_{t,j}^{DR}$). The constraints of this problem are given in (2) – (11). Equation (2) deals with the power balance constraint. This constraint confirms that in every hour of the studied period, the amount of the traded power in the day-ahead market must be equal to the available amount of the aggregator which is the power that is acquired from the consumers through the DRP and the power of running the storage if needed. Equation (3) indicates the cost of the hourly operation of the fuel cell. In this equation, the first term refers to the price of purchased natural gas and P_t^{FC} is the electrical power produced by the fuel cell unit and P_a is the amount of the power for auxiliary devices and η_t is the fuel cell efficiency at each hour t. Then, $P^{FC,\ max}$ is the maximum capacity of the fuel cell and C_{OM} is the maintenance cost of the fuel cell unit. In (4), the minimum and maximum capacities of the fuel cell unit are presented. Equations (5) – (8) are related to the DRP. In this DRP framework, (5) determines the amount of reduced power at each hour P_t^{DR}. The corresponding reward allocated to the hourly load reduction is addressed in (6). In the next constraint, i.e. (7), the amount of the reward in every step is determined.

According to [16], the amount of hourly power reduction is limited to the previous step and the current step. Eq. (8) shows that the reduced amount of energy in each hour can only occur in one j step. The amount of the traded power in the day-ahead market (P_t^{DA}) is limited to a maximum and minimum amount of power that is given in (9). As stated in (10), the amount of the traded power in the day-ahead market has to be greater or equal to the obtained power from the consumers through employing the hourly DRP. Finally, the last equation confirms that $v_{t,j}^{DR}$ is a set of binary variables.

B. The Proposed IGDT-based DR framework considering uncertainty:

In this stage, the uncertain parameter is taken into account. The electricity price in the day-ahead market is considered as the uncertain parameter in this study (λ_t^{DA}). The decision variable in this model is the amount of power which will be traded in the day-ahead market. To manage the risk of the uncertain parameter, the IGDT opportunity function has been implemented in this paper. First, it is considered that the decision-maker has perfect information about the uncertain parameter and can forecast it perfectly in every hour. These perfectly forecasted values are considered as $\tilde{\lambda}_t^{DA}$. In our proposed model, the fractional IGDT model is utilized to address the uncertainty. The problem formulation of this stage is written as follows:

Objective Function:

$$\tilde{\beta} = min\, \beta \tag{12}$$

Constraints:

$$B^* \ge B_\omega = (1+\rho)\, B_0 \tag{13}$$

$$B^* = Max \left\{ \sum_{t=1}^{T} \left[P_t^{DA}\, \lambda_t^{DA} - C_t^{FC} - \sum_{j=1}^{N_J} PR_t\, P_{t,j}^{DR}\ R_{t,j}^{DR} \right] \right\} \tag{14}$$

$$\tilde{\lambda}_t^{DA}\,(1-\beta) \le \lambda_t^{DA} \le \tilde{\lambda}_t^{DA}\,(1+\beta) \quad ,\forall t \in \Omega^T \tag{15}$$

$$(2) - (11) \tag{16}$$

As explained in [17], there are reasonable probabilities of high price spikes in the day-ahead market prices. A risk-seeker aggregator is willing to gain some extra profits by considering these favorable deviations of the market prices. To this end, the opportunity model from the IGDT approach is being employed. In (12), the objective function is introduced. The optimum opportunity function value $\tilde{\beta}$ is equal to the minimum amount of β that the aggregator can endure and achieve a higher profit. β is the horizon of the uncertain parameter from the forecasted values. The maximum profit is gained by the aggregator if the greatest day-ahead market price that is allowed by the IGDT model denoted here by $\tilde{\lambda}_t^{DA}(1+\beta)$. Thus, the above bi-level opportunity model can be simplified if $\lambda_t^{DA} = \tilde{\lambda}_t^{DA}(1+\beta)$. The opportunity model is rewritten by considering this equation as follows:

Objective Function:

$$\tilde{\beta} = min\, \beta \tag{17}$$

Constraints:

$$(13) \tag{18}$$

$$B^* = \sum_{t=1}^{T} \left[P_t^{DA}\, \tilde{\lambda}_t^{DA}\,(1+\beta) - C_t^{FC} - \sum_{j=1}^{N_J} PR_t\, P_{t,j}^{DR}\ R_{t,j}^{DR} \right] \tag{19}$$

TABLE I THE FUEL CELL RUNNING AND STOP MODE IN 24 HOURS IN DETERMINISTIC MODE

Time (h)		Working Period
1	Off-Peak Period	0
2		0
3		0
4		0
5		0
6		0
7	Peak Period	1
8		1
9		1
10		1
11		1
12		1
13		1
14		0
15		1
16		1
17		1
18		1
19		1
20		1
21		1
22	Off-Peak Period	0
23		0
24		0

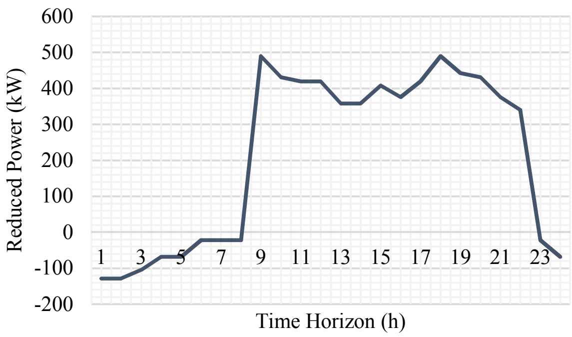

Fig. 1. The amount of the available energy for the DRA in deterministic mode.

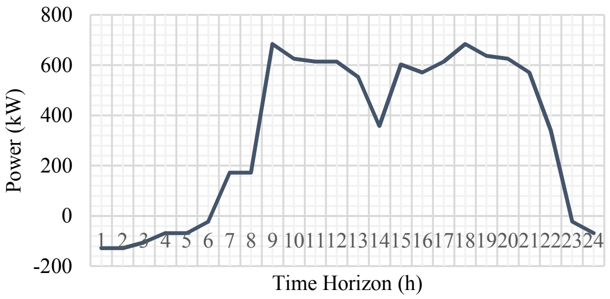

Fig. 2. The scheduling of the traded power in the day-ahead market through the DRA in deterministic mode.

$$(2) - (11) \qquad (20)$$

Hence, in order to achieve the possibility of gaining greater profits than the target one (B_ω), it is required that favorable deviations of the day-ahead market prices from the forecasted values occur.

It should be noted that $\tilde{\beta}$ indicates the minimum required favorable price deviations that makes the aggregator certain that it will gain at least the targeted profit.

IV. SIMULATION RESULTS AND DISCUSSIONS

This model is formulated as a mixed integer non-linear programming (MINLP) problem. The GAMS software is used in order to solve the problem through the commercial solver Standard Branch and Bound (SBB) [18]. The specification of the fuel cell is given in [5]. The whole simulation process has been done with a personal PC with a CPU with a 2.43 GHz speed and 6 GB RAM.

A. The scheduling without considering any uncertainty:

First, it is supposed that the day-ahead market price is forecasted perfectly for the aggregator. In other words, the decision maker considers that there is no uncertain parameter in this stage. In this condition, the model is simulated and the objective function which is the profit of the DRA is equal to 137834.67$.

In Fig. 1, the amount of the energy that is available for the aggregator through implementing DRP to the consumers to trade this amount in the day-ahead market is shown. As depicted, in the on-peak periods, the flow of energy is from the consumers to the day-ahead market and in the off-peak period, the flow is in the opposite direction. In other words, by deploying this DR program, the consumers are encouraged to reduce their energy usage during on-the peak periods and offer it to the day-ahead market through the aggregator and increase it during the off-peak periods. It can be seen that in the figure, the maximum reduction occurs at 9 and 18 o'clock, i.e. 490 kW. And during the off-peak periods, the maximum amount occurs at 1:00 and 2:00 h, that is 128 kW.

Table I shows the hours that the storage unit, i.e. fuel cell is utilized through the aggregator or not. As mentioned before, the fuel cell is utilized through the aggregator just when the amount of the power to be traded in the day-ahead market is lower than the obtained amount of power through implementing the DRP. According to this table, the running hours during the studied day is indicated by number 1. According to these results, the fuel cell is working both in off-peak, i.e. {7, 8} and on-peak periods, i.e. {9, 10, 11, 12, 13, 15, 16, 17, 18, 19, 20, 21}.

In Fig. 2, the scheduling of the power to be traded in the day-ahead market is illustrated. As can be seen in the figure, the maximum amount of power to be offered in the on-peak period through the aggregator is 684 kW. Likewise, the maximum amount of power to be purchased from the market during off-peak is 128 kW.

The optimization problem shows that at 14:00 h there is a sharp drop in the schedule. And the main reason for this drop is that at 14:00 h the fuel cell unit is not used by the aggregator. According to the formulation, it is defined that the storage will be run through the aggregator if the amount of the P_t^{DA} would be greater than or equal to P_t^{DR}. Hence, the amount of DR at 14:00h is greater than it; therefore, there is no need to run the fuel cell unit. Since employing the storage unit would incur cost to the aggregator, it would only be utilized if the aggregator finds it necessary.

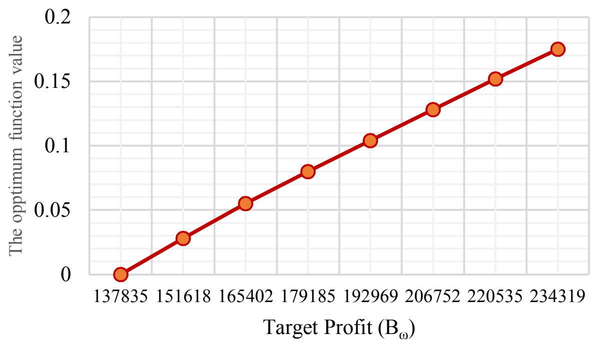

Fig. 3. Optimal opportunity function values for various target profits

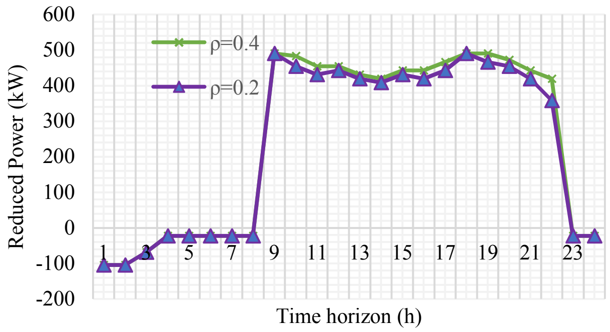

Fig. 4. The amount of the available energy for the DRA in a IGDT-based method

B. The scheduling with uncertainty in the day-ahead market price:

In this case, the uncertain parameter is taken into account. Therefore, the decision-maker is seeking to determine the minimum value of the uncertain parameter, i.e. the day-ahead market price, while the aggregator can still obtain the targeted higher profit. To this end, the opportunity optimization function is being run and the profit deviation factor i.e. ρ is changing from 0 to 0.7 to study the profit of aggregator in this condition. Figure 3. depicts the opportunity parameter $\breve{\beta}$ over the various target profits of the DRA.

As depicted in Fig. 3, if the aggregator desires to achieve higher profits than the targeted value, the uncertain parameter, which is the day-ahead market price, is required to deviate more in the favorable direction from the forecasted values. In other words, higher profits will result in higher positive day-ahead market prices. To provide more detailed information, ρ=0.2 is chosen. In this case, the targeted profit will be as follows: $B_{\omega} = B_0(1+\rho) = 137834.67\$(1+0.2) = 165402\$$. If the aggregator desires to achieve 165402\$, which is 20 percent higher than the B_0, the observed day-ahead market prices has to be at least 5.5% higher than the forecasted rates.

The amount of consumed energy reduced by implementing DRP is shown in Fig. 4. These amounts have been achieved for the opportunistic model where the targeted profit equals to $B_{\omega 1} = B_0(1+0.2) = 165402\$$ and $B_{\omega 2} = B_0(1+0.4) = 192969\$$. This figure indicates the impact of the target profit over the participation rate of the consumers in the DRP.

According to this figure, it is obvious that the participation of the consumers for a higher profit of the aggregator ($B_{\omega 2}$) are greater or equal to lower target profit of the aggregator ($B_{\omega 1}$). In other words, reaching higher targeted profits require higher deviations of the uncertain parameter in a favorable direction which in this case is DA electricity market prices.

The hours which the storage unit has been utilized by the aggregator when the optimum opportunistic value $\tilde{\beta}(B_{\omega 1}) = 0.045$ for $\rho = 0.2$ is given in Table II. As it is observed, the fuel cell unit is being run continuously by the DRA from 7:00 h until 23:00 h. The main reason is that since the aggregator desires to achieve the targeted profits, the aggregator is willing to increase the amount of the power that is trading in the day-ahead market. Thus, the fuel cell unit being used non-stop to meet the aggregator's expectations. Therefore, it is running in the whole peak period, i.e. $\{9, 10, \dots 21, 22\}$ and also in some hours in off-peak period, i.e. $\{7, 8, 23\}$.

Figure 5 provides a figure that indicates the amount of available power that the aggregator can trade in the day-ahead market in an opportunistic model. Similar to the previous results, the deviation factor is considered to be $\rho = 0.2$.

TABLE II THE FUEL CELL RUNNING AND STOP MODE IN 24 HOURS IN PROBABILISTIC MODE

Time (h)	Period	Working Period
1	Off-Peak Period	0
2		0
3		0
4		0
5		0
6		0
7		**1**
8		**1**
9	Peak Period	**1**
10		**1**
11		**1**
12		**1**
13		**1**
14		**1**
15		**1**
16		**1**
17		**1**
18		**1**
19		**1**
20		**1**
21		**1**
22		**1**
23	Off-Peak Period	**1**
24		0

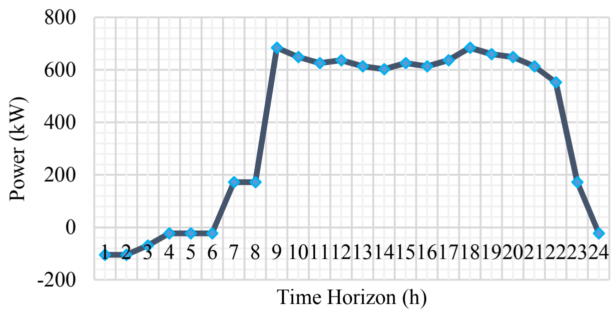

Fig. 5. The scheduling of the traded power in the day-ahead market through the DRA in a IGDT-based method

According to this figure, it can be shown that the aggregator in this case that uses the opportunity model, trades more power in the day-ahead market. Therefore, in order to meet the targeted profit which is $B_{\omega 1} = B_0(1 + 0.2) = 165402\$$, the scheduling of the traded power is increased, which is completely expected.

V. Conclusions

The proposed DR framework utilized a storage unit in the system to maximize the profit of the DRA. In this model, the uncertainty of the day-ahead market prices was managed through the IGDT method. In this problem, the behavior of the risk-taker DRA was analyzed through the opportunity function. In this regard, if the observed prices of the day-ahead market fluctuate more in a favorable direction than the forecasted values, the aggregator could be sure that its profit would be equal or greater than the target profit. The optimization problem aimed at finding the minimum amount of the uncertain horizon of the day-ahead market prices. The problem formulation was presented in two stages. In the first stage, it was supposed that there was no uncertainty and, in the second stage, the day-ahead market price uncertainty was studied. The results revealed that higher profits (e.g. 165400$ which is 20 percent higher than the B_0) of the DRA would result in higher observed positive day-ahead market prices than the forecasted values (e.g. 5.5%.). Moreover, the results in the opportunity IGDT-based approach also indicated that, by employing the storage unit by the DRA, since the risk-seeker aggregator desired to gain more profit, the fuel cell unit was run to increase the amount of DR offered in the day-ahead electricity market. For future work, the behavior of the risk-averse aggregator can also be investigated through the robust-based IGDT model. Other markets like balancing market can also be added to the model to study the short-term electricity market more comprehensively.

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