Impacts of Demand Response on Oligopolistic Behavior of Electricity Market Players in the Day-Ahead Energy Market

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***Abstract*—This paper investigates the effects of Demand Response Programs (DRPs) on the behavior of electricity market players in the day-ahead energy market. To this end, an electricity market environment is proposed based on the multi-agent systems in order to model the strategic self-scheduling of each market player as an individual agent. In such oligopolistic environment, market interactions are considered by using a game theoretic model and the market transactions are cleared by means of a security constrained unit commitment problem. Different types of DRPs are also considered consisting of Time Of Use (TOU), Real Time Pricing (RTP), Critical Peak Pricing (CPP), and Emergency Demand Response Program (EDRP). The proposed model is applied on a modified IEEE six-bus test system. The numerical results indicate that different types of DRPs differently affect the oligopolistic behavior of market players that should be studied by the system operators before their implementation.**

NOMENCLATURE

A. Superscripts

ini	Initial value.

B. Indices (Sets)

c	Customer.
i	Genco.
$t, t'(T)$	Time.

C. Parameters and Variables

a, b, c	Coefficients of units cost function.
B	Customer's benefit function.
d	Demand.
E	Elasticity of demand-price.
Inc	Rate of incentive of reducing the demand.
MD	Minimum down time of unit.
MU	Minimum up time of unit.
N	Number of agents.
P	Power.
Pen	Rate of penalty of not reducing the demand.
Rev	Customer's revenue function.
RD	Ramp down constraint.
RU	Ramp up constraint.
SD	Shut-down cost.
SR	Spinning reserve.
SU	Start-up cost.
u	Variable of unit commitment.
y, z	Auxiliary variables of unit commitment.
λ	Price.
ς	Incentive function.
ξ	Penalty function.

I. INTRODUCTION

A. Aims and Motivation

Developing information and communication technologies on one hand, and growing the environmental concerns on the other hand cause that Demand Response (DR) provides various opportunities for future systems. Due to benefits of DR to attain reliable and efficient electricity markets, Demand Response Programs (DRPs) are a key element on the smart grid path [1]. Although participation of customers in DRPs can be a profitable option from power system's points of view, it can significantly affect the strategic behavior of generations companies (Gencos), especially in oligopoly environments. On this basis, this paper aims to study the impacts of different DRPs on the oligopolistic behavior of Gencos in a day-ahead electricity market.

B. Literature Review and Background

Many models have been reported to analyze the oligopoly electricity markets [2], [3]. In [4], a strategic gaming model for analyzing the electricity markets has been presented. In [5], a game model is used to study the interactions of market participants. In [6], a method has been presented to obtain the market clearance prices within a hydrothermal power exchange market. However, considering the power flow in optimization formulations of oligopolistic market models has been rarely reported [7], because network constraints complicate the market clearing mechanism and cause the income functions to be non-differentiable and non-concave [8]. For instance, in [9], the computation of extremal-Nash equilibria has been reported for wholesale electricity markets considering network constraints.

In the demand response schemes, electric utilities provide incentives and benefits to consumers in order to compensate their flexibility in DR events or in the timing of their electricity consumption [10]. The effect of DR on the power system load shape has been investigated by an economic model of price responsive loads in [11]. In [12], a model has been reported for implementation of Emergency Demand Response Program (EDRP) and Interruptible/Curtailabe (I/C) services in the unit commitment (UC) problem. In [13], a price-based demand response has been applied to the power systems.

C. Contributions

Although many works in the literature have studied the oligopolistic power market, impact of both incentive-based and price-based DRPs on the self-scheduling of market players in an oligopoly electricity market has not been addressed. This paper models the strategic behavior of Gencos in an oligopoly day-ahead electricity market where a part of customers participates in incentive-based and price-based DRPs. To this end, a game-theoretic agent-based model is employed and impacts of several DRPs such as Real Time Pricing (RTP), Time of Use (TOU), EDRP and Critical Peak Pricing (CPP) on strategic behavior of market players are investigated. Since the implementation of DRPs can affect the operational behavior of market players in different hours of a day, in this paper, the electricity market is modeled in a period, in contrary to most of previous works that simulate the equilibrium of the market in only one hour. Therefore, the proposed model enables to investigate the self-scheduling problem with considering the startup and shut down costs, minimum on/off times, and ramp up/down rates. In addition, the optimal DRP is obtained to improve the market efficiency and to increase the level of competition in the electricity market. According to the mentioned expression, the contributions of this paper can be summarized as below:

- Modeling the oligopolistic electricity market by considering the participation of customers in both incentive-based and price-based DRPs
- Investigating the impact of different DRPs on the electricity market behavior and evaluating these programs in terms of market efficiency

D. Paper Organization

Section II describes the models of DRPs. In section III, the agent-based model of electricity market is expressed. Section IV devotes the numerical results. Finally, section V concludes the paper.

II. Modeling the Demand Response Programs

DRPs aim to make consumers more sensitive to variations of electricity prices in different hours. DRPs encourage electricity consumers to change their electricity use in response to fluctuations of price over the time, or to offer incentives, or to charge penalties that are considered to provide lower use during high electricity prices or when the power system reliability is threatened. DRPs can be categorized into two major groups, namely, price-based programs, and incentive-based programs. Each mentioned group can also be categorized into some subsets as discussed in [14].

Assuming that the customer's electricity demand at hour *t* is changed from d_t^{ini}, initial amount of demand, to d_t, due to price changes or an incentive payment or a penalty consideration, the impacts of DRPs on a customer's consumption can be formulated as below:

$$\Delta d_t = d_t^{\text{ini}} - d_t \tag{1}$$

The amount of incentive, ς_t, is expressed as:

$$\varsigma_t = Inc_t \, \Delta d_t \tag{2}$$

Similarly, the amount of penalty, ξ_t, can be formulated as:

$$\xi_t = Pen_t \left(d_t^{Contract} - \Delta d_t \right) \tag{3}$$

The customer's benefit, *B*, at hour *t* can be as follows [15]:

$$B_t = Rev_t - d_t \, \lambda_t + \varsigma_t - \xi_t \tag{4}$$

where $Rev_t$is the customer's revenue at hour *t* that is a function of amount of demand, d_t.

In order to optimize the customers' benefit by implementing of DRPs we have [16]:

$$\frac{\partial B}{\partial d_t} = \frac{\partial Rev}{\partial d_t} - \lambda_t + \frac{\partial \varsigma}{\partial d_t} - \frac{\partial \xi}{\partial d_t} = 0 \tag{5}$$

Therefore, we have

$$\frac{\partial Rev}{\partial d_t} = \lambda_t + Inc_t - Pen_t \tag{6}$$

By considering a quadratic revenue function for customers [17] and by using Taylor Series expansion, the customer's revenue function is formulated as (7)

$$Rev_t = Rev_t^{ini} + \frac{\partial Rev}{\partial d_t} \Delta d_t + 0.5 \frac{\partial^2 Rev}{\partial d_t^2} (\Delta d_t)^2 \tag{7}$$

By using the definition of elasticity, the revenue function can be formulated as (8).

$$Rev_t = Rev_t^{ini} + \lambda_t^{ini} \left(\Delta d_t \right) \left(1 + \frac{\Delta d_t}{2 E_t d_t^{ini}} \right) \tag{8}$$

where E_t is self elasticity of demand-price [17]. By substituting (8) in (6) we have

$$\lambda_t + Inc_t - Pen_t = \lambda_t^{ini} \left(1 + \frac{\Delta d_t}{E_t d_t^{ini}} \right) \tag{9}$$

Hence, the customer's consumption can be formulated as (10).

$$d_t = d_t^{\text{ini}} + E_t \, \frac{d_t^{\text{ini}}}{\lambda_t^{\text{ini}}} \left(\lambda_t - \lambda_t^{\text{ini}} + Inc_t - Pen_t \right) \tag{10}$$

By expanding (10) for a multi period consumption, the economic model of DR is obtained by Eq. (11).

$$\begin{aligned} d_t = d_t^{\text{ini}} + E_t \, \frac{d_t^{\text{ini}}}{\lambda_t^{\text{ini}}} \left(\lambda_t - \lambda_t^{\text{ini}} + Inc_t - Pen_t \right) \\ + \sum_{t'=1, t' \neq t}^{T} \left(E_{t,t'} \, \frac{d_t^{\text{ini}}}{\lambda_{t'}^{\text{ini}}} \left(\lambda_{t'} - \lambda_{t'}^{\text{ini}} + Inc_{t'} - Pen_{t'} \right) \right) \end{aligned} \tag{11}$$

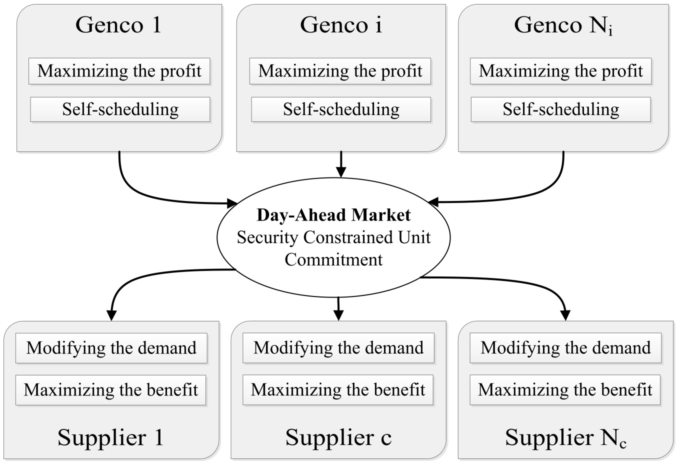

Fig. 1: The proposed agent-based electricity market model.

where $E_{t,t'}$ is cross elasticity of demand-price [17]. Eq. (11) shows the optimal amount of demand from customers' point of view by participating in DRPs.

III. Electricity market model

In this paper, an agent-based system is employed to model the electricity market. On this basis, each market participant is modeled as an agent whose objective maximizes the profit. Therefore, each GenCo utilizes the nodal prices of the energy market to determine the optimum strategic behavior. The behavior of demand side is also modeled as presented in Section II. On the other hand, ISO clears the day-ahead electricity market by using a Security Constrained Unit Commitment (SCUC) maximizing the social welfare by considering security constraints of the power system. A schematic of the proposed model is illustrated in Fig. 1.

Each agent optimizes its self-scheduling problem, aiming of maximizing the profit in the next 24 hours. The model of the self-scheduling problem of each Genco is presented in (12)-(19):

$$\text{Max} \sum_{t=1}^{T} \left\{ \begin{array}{l} P_{i,t}\lambda_t - a_i\, P_{i,t}^2 - b_i\, P_{i,t} - c_i\, u_{i,t} \\ -SU_i\, y_{i,t} - SD_i\, z_{i,t} \end{array} \right\} \tag{12}$$

where

$$u_{i,t} - u_{i,t-1} = y_{i,t} - z_{i,t} \tag{13}$$

$$y_{i,t} + z_{i,t} \leq 1 \tag{14}$$

The first term of (12) denotes the income of Genco from participating in day-ahead market. The next three terms represent the operational costs of unit. The last two terms denote start-up and shut-down costs. The limitation of power generation in each hour is presented in (15).

$$P_i^{\min} u_{i,t} \leq P_{i,t} \leq P_i^{\max} u_{i,t} \tag{15}$$

The unit ramp up and down constraints are formulated by (16)-(14).

$$P_{i,t} - P_{i,t-1} \leq RU_i\,(1 - y_{i,t}) + y_{i,t}\, P_i^{\min} \tag{16}$$

$$P_{i,t-1} - P_{i,t} \leq RD_i\,(1 - z_{i,t}) + z_{i,t}\, P_i^{\min} \tag{17}$$

The minimum on and off time constraints are expressed by (18)-(19).

$$y_{i,t} + \sum_{j=1}^{MU_i-1} z_{i,t+j} \leq 1 \tag{18}$$

$$z_{i,t} + \sum_{j=1}^{MD_i-1} y_{i,t+j} \leq 1 \tag{19}$$

In order to model the role of ISO, an SCUC program is solved. On this basis, once entering the offers to the SCUC program, the economic solution is obtained for participation of Gencos in the day-ahead market, considering security constraints of system. The solution consists of commitment and generation of Gencos, as well as day-ahead market prices. Here, the objective of the problem is to maximize the social welfare as presented in (20).

$$\text{Max} \sum_{t=1}^{T} \left(\sum_{c=1}^{N_c} d_{c,t}\, \lambda_t - \sum_{i=1}^{N_i} P_{i,t}\, \lambda_t \right) \tag{20}$$

where

$$\sum_{i=1}^{N_i} P_{i,t}^{\max} u_{i,t} \geq \sum_{c=1}^{N_c} d_{c,t} + SR_t \tag{21}$$

One of the most challenging parts of a practical model in real-world markets is the consideration of the AC power flow constraints. In order to increase the speed of power flow calculation with high accuracy, a nonlinear/linear AC power flow algorithm is employed. Based on the algorithm, a nonlinear AC power flow is solved in normal condition and linearized Jacobian matrices are utilized for contingencies. Details of this power flow algorithm have been presented in [18].

IV. Numerical results

In order to indicate the impact of DRPs on the oligopolistic behavior of electricity market, the IEEE six-bus test system is employed. Detailed data of the test system is expressed in [19]. It should be noted that, in real-world markets, most of regulatory bodies cannot access to the accurate information of market participants cost function, but some estimation can be carried out. In addition to RTP and EDRP, different types of TOU and three types of CPP programs are studied. It is assumed that 20% of consumers are responsive demand. Details of these programs are presented in Table I and II. It should be noted that the prices in RTP program is obtained from the simulation of the electricity market without implementation of DRPs. In the base case, the average of market prices is considered as electricity tariff in all hours. In TOU and CPP programs, the mentioned tariff is considered as the tariff in off-peak period. As it can be seen, TOU-1 and TOU-2 have three steps of tariffs, while TOU-3 has four steps. It should be noted that the tariffs of EDRP are the same as base case, while an incentive equal to 30% of the tariff is considered for

TABLE I: Tariffs/incentives of considered DRPs ($/MWh)

Case	Valley (1 to 8)	Off-peak (9-11, 22-24)	Peak (12-14, 19-21)	Critical peak (15 to 18)
Base case (fixed-rate)	63.2	63.2	63.2	63.2
TOU-1	31.6	63.2	94.8	94.8
TOU-2	15.8	63.2	126.4	126.4
TOU-3	31.6	63.2	94.8	189.6
CPP-1	63.2	63.2	126.4	126.4
CPP-2	63.2	63.2	252.7	252.7
EDRP	63.2	63.2	63.2	63.2: tariff 18.9: incentive

TABLE II: Real time prices ($/MWh)

Hour	**1**	**2**	**3**	**4**	**5**	**6**
Price	54.7	52.8	51.2	50.1	50.2	51.7
Hour	**7**	**8**	**9**	**10**	**11**	**12**
Price	54.4	57.7	60.7	63.0	65.2	66.7
Hour	**13**	**14**	**15**	**16**	**17**	**18**
Price	67.9	69.2	74.7	82.1	82.4	72.5
Hour	**19**	**20**	**21**	**22**	**23**	**24**
Price	71.6	66.9	66.9	64.9	59.8	59.0

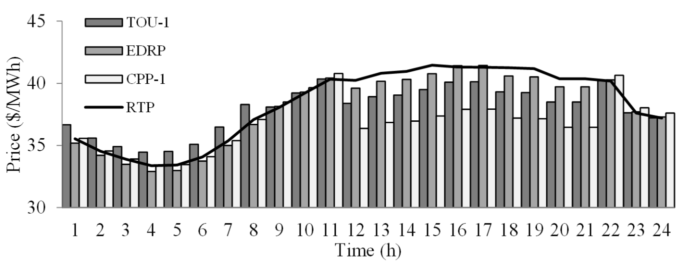

Fig. 2: Impact of different DRPs on the offers of Genco 1.

demand reduction. The self and cross elasticities are extracted from [15].

Fig. 2 shows the effect of implementation of different DRPs on the offered prices by Genco 1. As can be seen, different types of DRPs cause Genco 1 to offer differently to the day-ahead energy market. On this basis, the offers of Genco 1 in CPP-1 program is lower in peak period compared to the other programs. The reason is the lower amount of demand in this period by implementing CPP program. In order to indicate the bahavior of other market players, offers of Genco 2 in two types of CPP are presented in Fig. 3. As it can be observed, by increasing the peak tariff, the electricity demand is decreased and consequently, Genco 2 decreases its offered price to be able to win the auction in the peak period.

Impact of different types of TOU program on the generation of Genco 1 is compared with the generation in base case in Fig. 4. According to Fig. 4, Genco 1 is affected by the load shifting arisen from TOU tariffs. On this basis, the generation in valley period is increased based on the low tariff, while the generation reduces in the peak period.

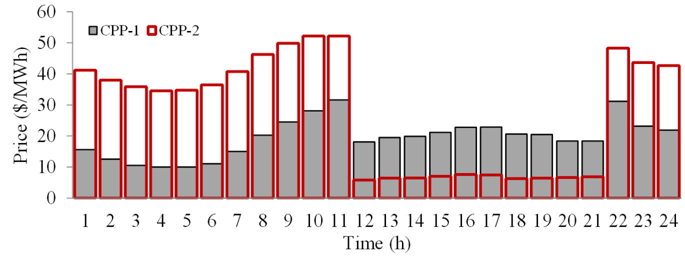

Fig. 3: Impact of different types of CPP program on the offers of Genco 2.

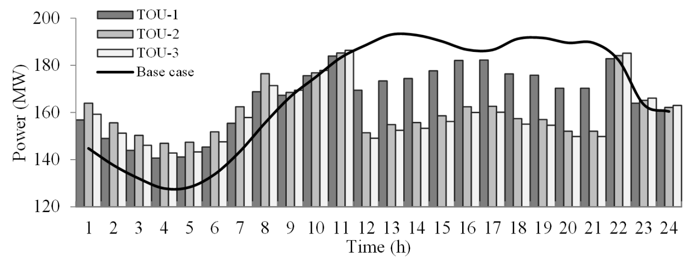

Fig. 4: Impact of different types of TOU program on the generation of Genco 1.

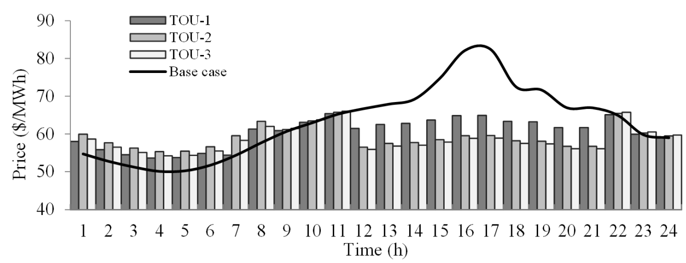

Fig. 5: Impact of different types of TOU program on the market clearing price.

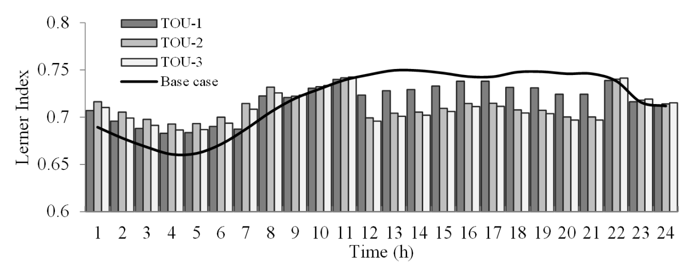

Fig. 6: Impact of different types of TOU program on Lerner Index of Genco 1.

Fig. 5 shows the significant impact of TOU programs on the electricity market prices in the peak period, because of the reduction of offered prices of the system's Cencos. The hourly market power indices, Lerner and SWALI, are illustrated in 6 and 7, respectively. As can be seen, TOU can mitigate the market power in peak hours when the Gencos become critical suppliers.

Table III presents the impact of considered DRPs on Lerner

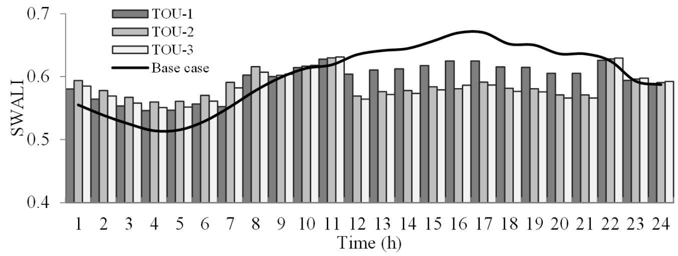

Fig. 7: Impact of different types of TOU program on SWALI.

TABLE III: Market power indices for different DRPs

Case	Lerner Index			SWALI
	Genco 1	Genco 2	Genco 3	
Base case	0.72	0.33	0.61	0.60
TOU-1	0.70	0.31	0.62	0.58
TOU-2	0.69	0.31	0.62	0.57
TOU-3	0.69	0.30	0.62	0.56
CPP-1	0.70	0.30	0.61	0.56
CPP-2	0.63	0.11	0.51	0.47
EDRP	0.71	0.32	0.63	0.58

and SWALI indices. By comparing the obtained indices with the ones of base case can be concluded that, the considered DRPs are able to mitigate the market power and improve the market efficiency. Among the DRPs, the second type of CPP (that has a very high peak tariff) has the highest potential to mitigate the market power. The third type of TOU and the fisrt type of CPP are also effective programs in this context.

V. Conclusion

The impact of different types of DRPs on the oligopolistic behavior of electricity market in the day-ahead energy market was studied by using an agent-based system. Market interactions were taken into account by game theory and the market transactions were cleared by an SCUC problem. Several numerical results indicated that different types of DRPs had significant effect on the oligopolistic behavior of market players. Based on the obtained results, implementation of price-based DRPs with a high tariff in peak and critical peak period could decrease the offered prices by the Gencos and consequently it could mitigate the market power. The results revealed that these kind of studies should have carried out by the system operators before selecting and implementing a DRP. The future work would focus on employing the optimal DR strategies on realistic electricity markets. To this end, an estimation for cost function of market players would be required. Due to uncertainty of coefficients of cost function from competitors' viewpoint, the problem would be solved by a stochastic programing approach.

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