Optimizing Nodal Demand Response in the Day-Ahead Electricity Market within a Smart Grid Infrastructure

Neda Hajibandeh, Miadreza Shafie-khah
C-MAST/UBI,
Covilha, Portugal
neda.hajibandeh@ubi.pt;
miadreza@gmail.com

Mehdi Ehsan
Dept. Electrical Engineering
Sharif University of Technology
Tehran, Iran
ehsan@sharif.edu

João P. S. Catalão
INESC TEC and FEUP, Porto,
C-MAST/UBI, Covilha, and
INESC-ID/IST-UL, Lisbon, Portugal
catalao@fe.up.pt

***Abstract*—Developments of the smart grid infrastructure can facilitate the upsurge of Demand Response (DR) share in power system resources. This paper models the effects of Demand Response Programs (DRPs) on the behavior of the electricity market in the Day-Ahead (DA) session. Decision makers look for the best DR tariff to employ it as a tool to obtain a flexible and sustainable energy market. Employing the most effective DRP is of crucial importance. An optimized DR model and the optimum rates for each DRP are found to meet the decision makers' requirements. Optimizing the nodal tariff and incentive values of different DRPs are proposed in the electricity market. In such environment, market interactions are considered by means of a security constrained unit commitment problem. Both types of Price-Based Demand Response (PBDR) and Incentive-Based Demand Response (IBDR) are modeled. The numerical results presented indicate the effectiveness of the proposed model.**

***Index Terms*—Demand Response, Electricity Market, Multi-Attribute Decision Making, Nodal DR.**

I. Nomenclature

A. Sets and Indices

b, b' *(NB)* Index (set) of system buses.

c (NC) Index (set) of customers.

i (NG) Index (set) of generation unit.

j (NJ) Index (set) of load.

m (NM) Index (set) of segments of the piece-wise linear cost functions.

t, t' (NT) Index (set) of hours.

B. Parameters

A_t Incentive payments to customers at hour *t*.

$AS_{m,t}$ Slope of segment *m* in linearized total incentive curve in hour *t*.

$C_{i,m}^{G\_Eng}$ Slope of the cost function for unit *i* in segment *m* of the piece-wise linear cost function.

$C_{i,t}^{G\_DC}$ Down-reserve offered price of unit *i* at hour *t*.

$C_{i,t}^{G\_UC}$ Up-reserve offered price of unit *i* at hour *t*.

$F_{b,b'}^{\max}$ Maximum branch capacity between buses *b* and b'.

MDT_i Minimum down-time of unit *i*.

MUT_i Minimum up-time of unit *i*.

MPC_i Minimum production cost (no-load cost) of unit *i*.

$P_i^{\max}, P_i^{\min}$ Maximum/minimum capacity of unit *i*.

Pl_t Value of loss of load at hour *t*.

RU_i Ramp-up of unit *i*.

RD_i Ramp-down of unit *i*.

SC_i Startup cost of unit *i*.

SUR_i Startup ramp rate of unit *i*.

SDR_i Shutdown ramp rate of unit *i*.

$X_{b,b'}$ Reactance of branch between buses *b* and b'.

ρ^0 Initial electricity price.

C. Variables

C^{EDRP} Cost of customer's participation in EDRP.

$F_{b,b',t}$ Power flow of line *l* at hour *t*.

$P_{i,t,m}^{e}$ Power of unit *i* at hour *t* in segment *m* of the piece-wise linear cost function.

$R_{i,t}^{G\_DC}$ Down-reserve of unit *i* at hour *t*.

$R_{i,t}^{G\_UC}$ Up-reserve of unit *i* at hour *t*.

$SUC_{i,t}$ Startup cost of unit *i* at hour *t*.

$U_{i,t}$ Binary status indicator of unit *i* at hour *t*.

$\delta_{b,t}$ Voltage angle of bus *b* at hour *t*.

$\upsilon_{m,t}$ Award of segment *m* in linearized total incentive curve in hour *t*.

II. Introduction

A. Motivation and Aims

Due to the widespread use of conventional fossil fuels from exhaustive resources and growing environmental concerns, Demand Response Programs (DRPs) will play a significant role to enhance market efficiency in the future smart grid [1]. Developments of the smart grid infrastructure can facilitate the upsurge of Demand Response (DR) share in the power system resources [2]. The electric utilities consider DRPs a progressively effective resource that is enabled more by grid modernizations. For instance, sensors and advanced metering infrastructures expand the range of DRPs. On the other hand, the regulatory body aims to mitigate the market power. This target can be achieved by promoting DR, such as new legislation to support it, set up new markets, e.g., Demand Response eXchange (DRX) market [3], or subsidized payments for DR.

To this end, the electricity market regulatory bodies should change market structures and policies to support employment of DRPs in electricity markets [4]. According to the major impact of DR on the level of market competition and growing attention to demand side resources, many regulatory bodies are dedicated to motivating customers to take part in the electricity market [5]. However, implementation of DR on different nodes can cause negative of side impacts on the operation cost and security of the system. On this basis, this paper proposes a nodal DR optimization considering various types of DRPs.

B. Literature review and contribution

In [6], [7], authors examined the latest DR definition and classification which is used in this paper. An effective management system associated with DRPs is required [8], [9] to play a significant role in mitigating the electricity markets, furthermore improve the reliability and efficiency of the electrical system.

In order to analyze the electricity markets a large number of simulation-based methods have been reported from the regulatory body's perspective (e.g. [10]-[14]). In [10], various Cournot models have been utilized for electricity markets considering network constraints. In [11]-[14], game-based models have been reported to evaluate the electricity markets.

The impacts of DR on social welfare are analyzed in [15] and [16]. In [17], a two-stage Stochastic Programming (SP) approach is introduced for optimal day-ahead power procurement with RER and DR. In [17], the authors focus on reducing the energy cost in demand side. In [18], the concept of online DR is used to minimize the operational cost. Two online DR strategies have been introduced in [18] to minimize the operation cost considering non-deferrable loads.

In [19], a stochastic Security Constrained Unit Commitment (SCUC) is presented considering DRPs under the uncertainty of wind power productions. In [20], the new DRX market is employed to help the operation of energy market in the presence of renewable energy resources.

The authors of [21] have focused on the minimization of end-users electricity bills and maximization of their satisfaction. To motivate the customers to be responsive to price changes, financial incentives are considered in [22]. Moreover, to increase the participation of customers in DRPs, smart appliances for load shifting have been employed in [22].

In these models, the offering strategies are obtained by employing slope of the offering curve. In [23], a game-theoretic method has been presented to analyze the market behavior.

Although many research works have studied the operation of power systems in the presence of DR, a nodal DR optimization has not been addressed. To this end, a comprehensive model including various types of DRPs is developed for the operation scheduling of electricity markets. The proposed model aims at increasing the network security and decreasing the operation cost.

C. Paper organization

The remainder of the current paper is structured as follows. The model of demand response is introduced in Section III, and the proposed model of the electricity market is presented in Section IV. The numerical results of the model are presented in Section V, and the final section is the conclusion.

III. DEMAND RESPONSE MODEL

In this paper, both priced-based and incentive-based categories are considered as DR programs.

A. PBDRs model

Economists believe that informing consumers from real electricity prices will increase efficiency [24]. On the other hand, PBDR or time-varying tariffs applied in the restructured power system improve the demand curve and reduce the load during peak hours. Due to the changes in electricity prices, consumers are encouraged to participate in DRPs. PBDR programs in this paper include Time-of-Use (TOU), Critical Peak Pricing (CPP), and RTP. In these programs, the electricity tariff varies according to the cost of energy in each time slot. Besides, by applying time-varying tariffs with higher rates at peak hours, consumers are encouraged to reduce their electricity consumption during peak hours. The amount of demand-side consumption related to customers participating in PBDR programs in a day-ahead market is given in (1) [25].

$$d_{c,t} = d_{c,t}^{0}\left\{1+\sum_{t'=1}^{24} E_{c,t,t'}\frac{[\rho_{c,t'}-\rho_{c,t'}^{0}]}{\rho_{c,t'}^{0}}\right\} \tag{1}$$

where $d_{c,t}^{0}$ and $d_{c,t}$ are the electricity demand of customer c before and after applying the PBDR program; $\rho_{c,t'}^{0}$ and $\rho_{c,t'}$ are the electricity tariffs of customer c before and after applying the PBDR program; $E_{c,t,t'}$ represents the elasticity of customer c pertaining to hours t and t'. Eq. (1) presents the PBDR model based on "self-elasticity" and "cross-elasticity" concepts of demand to model a plunge in load through the participation of customers in price-based DRPs [25].

B. IBDRs model

In these kinds of programs, an incentive fee is offered to customers participating in DRPs. The incentive amount is separate from the cost paid by customers for electricity consumption. The amount of power consumption incentive may be just credit, payments on preset contracts, or proportional to the amount of reduced load [25].

Customers' participation in IBDR programs is often optional. However, in some DRPs, a fine of some amount will be considered for consumers who state that they will participate in the program but do not reduce their loads at the relevant time. In these programs, a series of incentives are used to encourage consumers to participate in DRPs.

Unlike PBDR programs, the response rates in these programs are not related to the customer reaction to price changes and even other effective parameters such as weather conditions. Therefore, it is not difficult to predict their effectiveness. In order to measure the amount of load reduction to determine the amount of payments to customers, DRPs employ methods for the determination of normal consumption versus their reduced load. These types of programs unlike price-based DRPs (in which predicting and measuring the amount of consumption reduction are difficult), are employed as a useful tool for estimating production costs and also satisfying a target reliability level by Independent System Operators (ISOs). The IBDR in this paper includes Emergency Demand Response Program (EDRP).

These programs are employed as the solutions to avoid increasing the market price. These programs are attractive for many consumers as they keep the electricity prices fixed for customers. These programs are implemented by encouraging large consumers to bid for their purchased energy with self-offers or by encouraging consumers to determine the amount by which they are willing to reduce their consumption in response to the market price.

In the EDRP, participants receive an incentive reward for dropping their load when the system reliability seems to be in doubt. This incentive amount is announced in advance. In such programs, reducing the load is optional, and there is no penalty for consumers who do not participate in the program. So after the announcement of the need to reduce the burden, consumers can ignore the incentive fee and not reduce their consumption.

Equation (2) illustrates how the incentive-based economic load model is obtained [25]:

$$d_{c,t} = d_{c,t}^{0}\left\{1+\sum_{t'=1}^{24} E_{c,t,t'}\frac{\mathrm{A}_{c,t'}}{\rho_{c,t'}^{0}}\right\} \tag{2}$$

Implementation of IBDR pushes some costs up to the ISO. These costs include the incentive payments per hour to customers for reducing their load at peak hours. Equation (3) is formulated to state this cost function.

$$\mathrm{C}_{c,t}^{EDRP} = A_{c,t}(d_{c,t}^{0} - d_{c,t}) \tag{3}$$

Equation (2) is substituted in (3) until the cost of the customer's participation in EDRP from the ISO point of view can be calculated through (4):

$$\mathrm{C}_{c,t}^{EDRP} = -d_{c,t}^{0}\left\{\sum_{t'=1}^{24} E_{c,t,t'}\frac{\mathrm{A}_{c,t'}^{2}}{\rho_{c,t'}^{0}}\right\} \tag{4}$$

From (4), C_{t}^{EDRP} can be accurately approximated by a piecewise linear model, which is as given in (5):

$$\mathrm{C}_{c,t}^{EDRP} = \sum_{m=1}^{NM} \upsilon_{c,m,t}\,\mathrm{AS}_{c,m,t} \tag{5}$$

IV. Modeling the Electricity Market

In this paper, an agent-based model is employed to simulate the electricity market from the regulatory body's point of view. To this end, each market participant (i.e., Gencos) is independently modeled by using an agent that aims to maximize its profit. The objective function of each Genco agent can be formulated as follows:

$$\begin{aligned}&\mathrm{Max}\{Genco\ Profit\} = \\ &\sum_{t=1}^{T}\left\{\begin{aligned}&P_{i,t}\lambda_{t}^{En} + P_{i,t}^{Res}\lambda_{t}^{Res}\\ &-\left(a_i P_{i,t}^{2} + b_i P_{i,t}\right) - c_i I_{i,t} - \lambda_{i}^{up} y_{i,t} - \lambda_{i}^{down} z_{i,t}\end{aligned}\right\}\end{aligned} \tag{6}$$

subject to:

$$P_{i}^{\min} I_{i,t} \le P_{i,t} \le P_{i}^{\max} I_{i,t} \tag{7}$$

where $P_{i,t}$ and $P_{i,t}^{Res}$ represent the offers of Genco i to the day-ahead energy and reserve markets, respectively. λ_{t}^{DA} and λ_{t}^{Res} denote the prices of the mentioned markets. a_i, b_i and c_i represent the cost coefficients of Genco i. $I_{i,t}$ is the commitment binary variable; whereas, $y_{i,t}$ and $z_{i,t}$ are auxiliary variables to determine start-up and shut down times.

$$I_{i,t} - I_{i,t-1} = y_{i,t} - z_{i,t} \tag{8}$$

$$y_{i,t} + z_{i,t} \le 1 \tag{9}$$

$$y_{i,t} + \sum_{j=1}^{MU_i - 1} z_{i,t+j} \le 1 \tag{10}$$

$$z_{i,t} + \sum_{j=1}^{MD_i - 1} y_{i,t+j} \le 1 \tag{11}$$

$$P_{i,t} - P_{i,t-1} \le RU_i + P_{i}^{\min} y_{i,t} \tag{12}$$

$$P_{i,t-1} - P_{i,t} \le RD_i + P_{i}^{\min} z_{i,t} \tag{13}$$

where RU_i and RD_i are the ramp up and down rates, respectively. MU_i and MD_i are minimum up and down times, respectively. Inequality (7) denotes the unit output limits. Constraints of minimum up and down times are linearly expressed in (8)-(11). Constraints of unit ramp up and ramp down are presented in (12) and (13), respectively.

The roles of ISO for clearing the energy and spinning reserve markets and determining the auction winners are played by using an SCUC that aims to maximize social welfare in a certain period. This SCUC method includes ramp rates, minimum up/down time constraints and power flow limits in both normal and contingency conditions. The details of SCUC model including the power flow formulation were presented in [26]. In the market model, each agent solves the self-scheduling problem to maximize its profit and then defines its offering strategy to participate in the market using the SFE model. In this study, SFE is employed to model the offering strategy of agents. Due to market players' simultaneous decisions on their price and quantity, SFE model with two degrees of freedom is the most accurate model for simulation of game theory. So, in this paper, each market player uses the SFE vector (price-quantity) to submit its hourly offers to the day-ahead energy and spinning reserve markets. Once the agents' offers are entered into the SCUC program, the economical solution for the participant agents in the energy and spinning reserve markets is obtained considering security constraints of the system.

Here, the objective function of the SCUC problem is expressed as (14):

Minimize

$$\begin{aligned}&\sum_{t=1}^{NT}\sum_{i=1}^{NG}\underbrace{\begin{pmatrix}SUC_{i,t} + MPC_i U_{i,t} + \\ \sum_{m=1}^{NM}(P_{i,t,m}^{e} C_{i,m}^{G\_Eng})\end{pmatrix}}_{\text{Thermal unit generation cost}}\\ &+\sum_{t=1}^{NT}\sum_{i=1}^{NG}\left(\underbrace{C_{i,t}^{G\_UC} R_{i,t}^{G\_UC}}_{\text{Scheduled up reserve cost}} + \underbrace{C_{i,t}^{G\_DC} R_{i,t}^{G\_DC}}_{\text{Scheduled down reserve cost}}\right)\\ &+\sum_{t=1}^{NT}\sum_{c\in customers}\underbrace{C_{c,t}^{EDRP}}_{\text{EDRP cost}}\end{aligned} \tag{14}$$

In (14), the first summation is power generation cost by thermal units. The offered prices of units for up/down reserve capacities are given in the second summation of (14). The third summation is respect to EDRP cost. The objective function is satisfying the following equality or inequality constraints.

The balance between demand and supply is guaranteed through (15). The branch flow based on DC network modeling is given in (16). Branch flow limitations are formulated in (17).

Equation (18) represents the power of a thermal unit based on the powers of the segments of the linearized cost function. Inequalities (19) and (20) restrict the power generation of thermal units. The up- and down-reserve limits are defined in (21)-(22). The inequality (23) represents the startup constraint of thermal plants. The minimum up/down times for thermal power plants are modeled in (24) and (25), respectively.

$$\sum_{i\in NG_b} P_{i,t} - \sum_{j\in NJ_b} L_{j,t} = \sum_{b,b'\in NB} F_{b,b',t} \quad \forall b,t \tag{15}$$

$$F_{b,b',t} = \left(\delta_{b,t} - \delta_{b',t}\right) / X_{b,b'} \quad \forall (b,b'),t \tag{16}$$

$$-F_{b,b'}^{\max} \le F_{b,b',t} \le F_{b,b'}^{\max} \quad \forall (b,b'),t \tag{17}$$

$$P_{i,t} = \sum_{m=1}^{NM} P_{i,t,m}^{e} \ , \ 0 \le P_{i,t,m}^{e} \le P_{i,m}^{\max} \quad \forall i,t \tag{18}$$

$$P_{i,t} + R_{i,t}^{G\_UC} \le P_i^{\max} \quad \forall i,t \tag{19}$$

$$P_{i,t} - R_{i,t}^{G\_DC} \ge 0 \quad \forall i,t \tag{20}$$

$$0 \le R_{i,t}^{G\_UC} \le RU_i\, \tau \quad \forall i,t \tag{21}$$

$$0 \le R_{i,t}^{G\_DC} \le RD_i\, \tau \quad \forall i,t \tag{22}$$

$$SUC_{i,t} \ge SC_i (U_{i,t} - U_{i,t-1}) \quad \forall i,t \tag{23}$$

$$\sum_{t'=t+1}^{t+MUT_i-1} \left(1 - U_{i,t'}\right) + MUT_i \left(U_{i,t} - U_{i,t-1}\right) \le MUT_i \quad \forall i,t \tag{24}$$

$$\sum_{t'=t+1}^{t+MDT_i-1} U_{i,t'} + MDT_i \left(U_{i,t-1} - U_{i,t}\right) \le MDT_i \quad \forall i,t \tag{25}$$

Fig. 1 indicated the proposed electricity market model. It should be noted that, unlike the traditional game-theoretic models that simulate the power market for an hour, the proposed model has been developed for a certain period. Based on this, the agents predict the day-ahead nodal prices and then submit their 24-hour offers to the day-ahead energy and spinning reserve markets. This important feature of the proposed model can significantly improve the accuracy of the market simulation because the start-up/shut-down costs, constraints of minimum up/down times and ramp up/down rates are properly considered can be modeled.

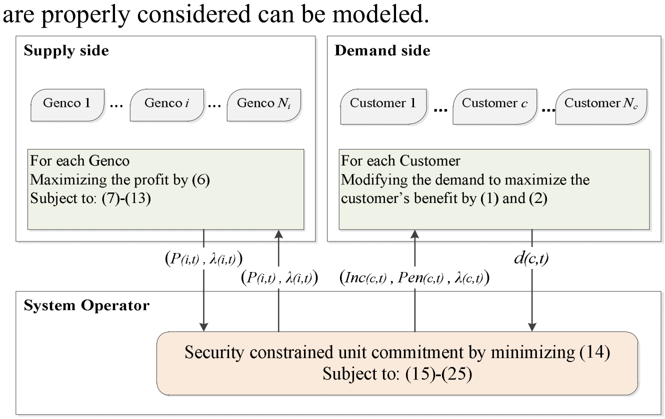

Fig. 1. The electricity market model.

V. Numerical Studies

The proposed model has been tested on the IEEE six-bus test system. The mixed-integer linear programming has been modeled in GAMS 24.0 and solved by CPLEX 12.0.

In order to investigate the effectiveness of the proposed model, two main cases have been analyzed. In case 1, various types of DRPs have been considered for all the demand nodes of the system. In other words, in case 1, it is assumed that the tariffs and incentives are the same for all the nodes. In case 2, the tariffs and incentives can be changed for different nodes.

In case 1, in addition to different types of TOU programs, RTP, CPP, and EDRP are studied. These programs are illustrated in detail in Table I and Table II. In this case, it is assumed that 20% of consumers are responsive demand. The RTP program prices are received according to the simulation of the energy market without considering the DRPs. The average of market prices is defined as energy tariff in all hours for the base case. For TOU and CPP programs, the mentioned tariff is defined as the tariff in the off-peak period.

According to Table I, TOU-1 and TOU-2 have three steps of tariffs, while TOU-3 has four steps. While an incentive fee equal to 30% of the tariff is defined in term of the amount of demand reduction, the tariffs of EDRP are the same as the base case prices. The self and cross elasticities are presented in Table III.

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	189.56	189.56
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

TABLE III
SELF AND CROSS ELASTICITIES

	Critical peak	**Peak**	**Off-peak**	**Valley**
Critical peak	-0.1	0.014	0.015	0.016
Peak	0.014	-0.1	0.013	0.012
Off-peak	0.015	0.013	-0.1	0.010
Valley	0.016	0.012	0.010	-0.1

To explore the impacts of different types of DR programs on the behavior of market players, Fig. 2 illustrates the influence of the implementation of DRP variants on the prices offered by Genco 1. As can be seen, different types of DRPs lead to differences in the prices offered by Genco 1 to the power system. On this basis, the offers of Genco 1 in the CPP-1 program, in this case, are lower in the peak period compared to the other programs.

Fig. 3 illustrates the tremendous influence of a variety of DRPs tariffs on the final demand load curve in the peak hours due to the implementation of these kinds of programs in the system. As shown in Fig. 3, the application of different types of DRPs brings down the load curve of customers on the demand side. It can be found in Fig. 3 that the CPP-1 has the most impact on the curve. TOU-1 and EDRP have the second and third largest impacts, respectively.

The impacts of different kinds of TOU programs on the efficiency of the energy market are presented in Fig. 4. This figure depicts the market clearing price of the power system.

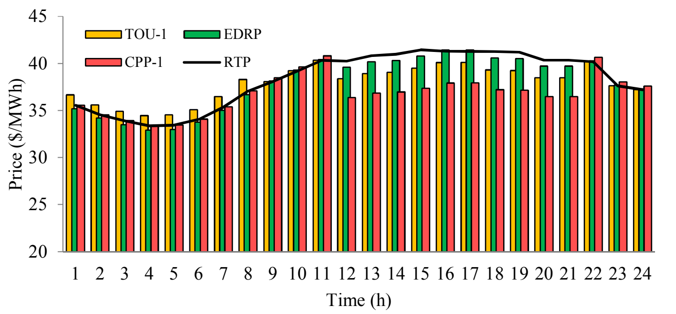

Fig. 2. The impact of different types of DR programs on the offers of Genco 1 (case 1).

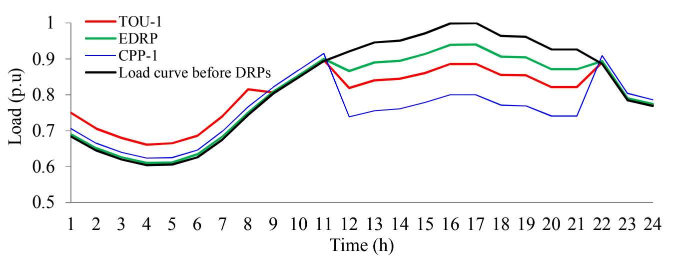

Fig. 3. The impact of different types of DR programs on the final load curve (case 1).

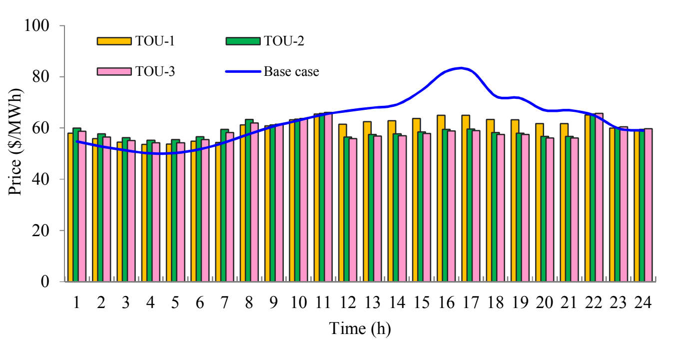

Fig. 4. The impact of different types of DR programs on the market clearing price (case 1).

These results demonstrate that the variant tariffs of the TOU program can have a greater influence on pushing down the market clearing prices principally in the peak period.

The impact of the proposed nodal DR optimization (case 2) on the offers of Genco 1 is shown in Figs. 5-7. As it can be seen, the proposed model can reduce the offering of Gencos better than the traditional uniform DR tariffs (case 1).

Therefore, the market prices are lower than the prices in case 1 in the peak and critical peak periods that shows the proposed DR is more effective than the uniform DR.

According to Fig. 5, the proposed nodal DR optimization in TOU program reduces the offers of thermal units in the critical peak, peak and off-peak periods, due to a reduction in the electricity consumption in these periods. However, the offers in valley hours increase compared to the conventional uniform DR. As it can be seen, the offers in critical peak hours in case 2 is much lower than the ones in case 1, that shows different tariffs for different nodes can have a better impact on the critical peak period when the system should overcome the network congestion.

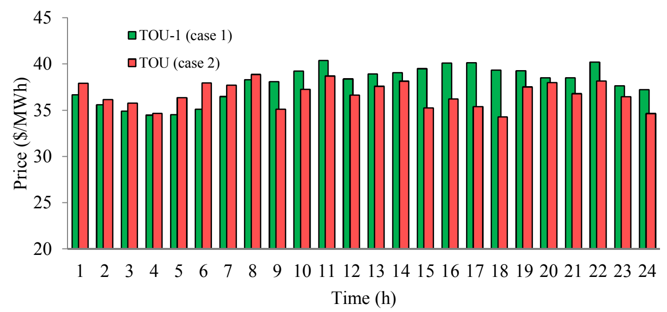

Fig. 5. The impact of the proposed nodal DR on the offers of Genco 1 (TOU).

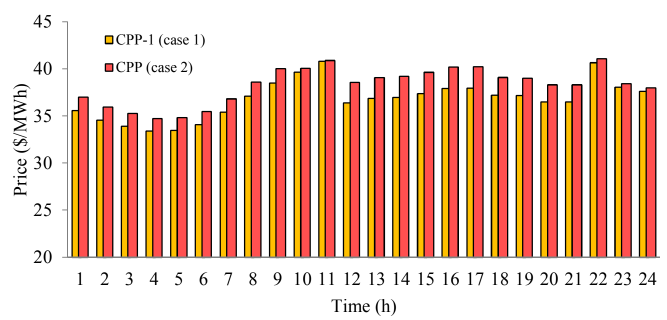

Fig. 6. The impact of the proposed nodal DR on the offers of Genco 1 (CPP).

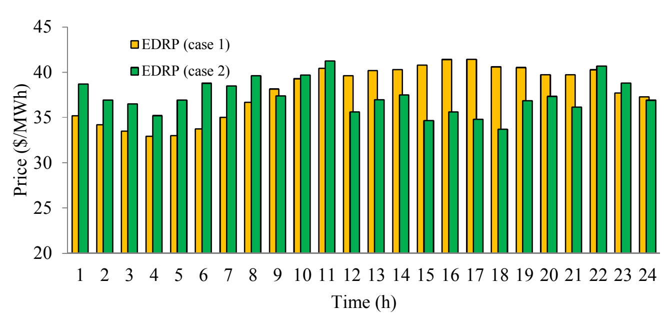

Fig. 7. The impact of the proposed nodal DR on the offers of Genco 1 (EDRP).

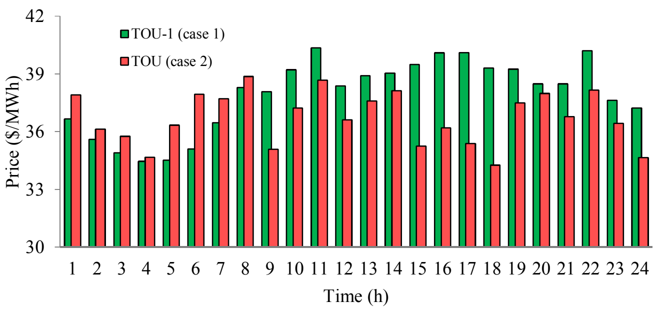

Fig. 8. The impact of the proposed nodal DR on the market clearing price in TOU program.

According to Fig. 6, the implementation of nodal CPP (case 2) can make the price profile flatter compared to the uniform CPP (case 1). It is because the final demand curve in case 2 is smoother than the one in case 1.

As it can be seen in Fig. 7, nodal EDRP can also reduce the offers of Genco 1 in the peak and critical peak periods, because of its impact on reducing the load in these periods. Fig. 8 illustrates the effect of nodal DR on the electricity market price. The proposed model can decrease the price of peak and critical peak hours up to 12%, although the average of the price decreases about 3% compared to uniform DR implementation.

VI. CONCLUSION

In this paper, an agent-based model was developed to investigate the effects of Demand Response Programs (DRPs) on the behavior of the electricity market in the Day-Ahead (DA) session. An optimized nodal DR model and the optimum rates for each DRP were found. Optimizing the nodal tariff and incentive values of different DRPs were proposed in the electricity market. In order to prove the effectiveness of the proposed model, several numerical studies were carried out. The impacts of employing both IBDR and PBDR were thoroughly investigated. The numerical results showed that the presence of nodal DRP led to lower prices and higher market efficiency. The results of this model proved that employing appropriate types of DRPs made it possible to maximize operator benefits, while inappropriate types of DRPs might increase the operation cost.

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