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Optimal Demand Response Strategies to Mitigate Oligopolistic Behavior of Generation Companies using a Multi Objective Decision Analysis

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***Abstract*—In this paper, an agent-based model is proposed to improve the electricity market efficiency by using different Demand Response Programs (DRPs). In the proposed model, the strategic self-scheduling of each market player in the electricity market and consequent market interactions are considered by using a game theoretic model powered by a security constrained unit commitment. The tariffs of price-based DRPs and the amount of incentive in the incentive-based DRPs are optimized. Furthermore, a market power index and the operation cost are used to evaluate the market efficiency by using a multi-objective decision-making approach. The results show that different types of DRPs differently affect the oligopolistic behavior of market players, and the potential of market power in power systems can be mitigated by employing the proposed model for DRP optimization. Numerical studies reveal that, applying combinational DRPs is more efficient when the regulatory body considers both economic and market power targets.**

***Index Terms*—Demand response programs (DRPs), multi-objective decision-making (MODM), market power, oligopoly electricity market.**

NOMENCLATURE

A. Indexes (Sets)

b, b'	Bus.
c	Customer.
i	Genco.
l	Branch.
$t, t'(T)$	Time.

B. Functions and Operators

Δ	Change in variable amount.
∂	Partial differential.

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C. Parameters

a_i, b_i, c_i	Coefficients of units cost function.
B_l^{sh},B_l^{sr}	Shunt and series admittance of branch l.
B_l^{sr}	Series admittance of branch l.
d_t^{ini}	Initial demand.
$d_t^{Contract}$	Amount of flexibility contracted demand.
$E_{t,t}$	Self-elasticity of demand-price.
$E_{t,t'}$	Cross-elasticity of demand-price.
F_l^{max}	Power flow limit in normal state.
$F_l^{cg,max}$	Power flow limit in contingency state.
G_l^{sh},G_l^{sr}	Shunt and series conductance of branch l.
G_l^{sr}	Series conductance of branch l.
MC_i	Marginal cost.
MD_i	Minimum down time.
MU_i	Minimum up time.
N_c	Number of customers.
N_i	Number of Gencos.
P_i^{max}	Maximum power generation of unit i.
P_i^{min}	Minimum power generation of unit i.
Q_i^{max}	Maximum reactive power of unit i.
Q_i^{min}	Minimum reactive power of unit i.
RD_i	Ramp down constraint.
RU_i	Ramp up constraint.
SD_i	Shut-down cost.
SR_t	Required spinning reserve.
SU_i	Start-up cost.
V_b^{max}	Maximum voltage magnitude limit.
V_b^{min}	Minimum voltage magnitude limit.
$V_b^{cg,max}$	Maximum voltage magnitude after contingency.
$V_b^{cg,min}$	Minimum voltage magnitude after contingency.
δ_b^{max}	Maximum voltage angle limit of bus b.
δ_b^{min}	Minimum voltage angle limit of bus b.
$\delta_b^{cg,max}$	Maximum voltage angle limit after contingency.
$\delta_b^{cg,min}$	Minimum voltage angle limit after contingency.
λ_t^{ini}	Initial price/tariff.

D. Variables

B_t	Customer's benefit function.
d_t	Final demand.
$F_{l,t}$	Power flow in normal state.
$F_{l,t}^{cg}$	Power flow in contingency state.
Inc_t	Rate of incentive of reducing the demand.
OC	Total operation cost.
$P_{l,t}$,$Q_{l,t}$	Active and reactive power flow of branch l.

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$P_{i,t}^{DA}$	Power generation of Genco i in the day-ahead energy market.
$P_{i,t}^{Res}$	Amount of participation of Genco i in the reserve market.
Pen_t	Rate of penalty of not reducing the demand.
$Q_{l,t}$	Reactive power flow of branch l.
$Q_{i,t}$	Reactive power of unit i.
S_i	Share of Genco i of the total generation.
$SWALI$	Share weighted average Lerner index.
$u_{i,t}$	Variable of unit commitment.
Uti_t	Customer's utility function.
$V_{b,t}$,$V_{b,t}^{cg}$	Voltage magnitude before and after contingency.
$V_{b,t}^{cg}$	Voltage magnitude after contingency.
$y_{i,t}, z_{i,t}$	Auxiliary binary variables of unit commitment.
$\delta_{b,t}$,$\delta_{b,t}^{cg}$	Voltage angle before and after contingency.
$\delta_{b,t}^{cg}$	Voltage angle of bus b after contingency.
λ_t	Price/tariff.
$\lambda_{i,t}^{DA}$	Price of day-ahead energy market.
$\lambda_{i,t}^{Res}$	Price of reserve market.
ς_t	Incentive function.
ξ_t	Penalty function.
Δd_t	Change in the demand.

I. Introduction

A. Aims and Motivation

POWER systems have been, on one hand, experiencing a growing concern of environmental pollution because most of the electric power comes from non-renewable energy sources, which are major sources of greenhouse gases. On the other hand, power systems should be able to meet the increasing demand for electricity with an acceptable standard of reliability, quality and security. In order to satisfactorily fulfill the aforementioned conflicting requirements, power systems are evolving towards smart grids relying on new telecommunication and technological advances. In smart grids, demand response (DR) will play a key role in the following years. DR empowers consumers to participate in the electricity markets [1] and contribute their share towards efficient operation of electricity grids. In other words, different Demand Response Programs (DRPs) are effective tools used by electricity market operators and regulatory bodies to operate electricity grids more efficiently.

One of the main objectives of regulatory bodies is to improve the electricity market efficiency. There are many structural and behavioral options for the improvement. Increasing the number of market participants and increasing the price-elasticity of consumers are two main structural options [2]. Changing the rules and the regulation of electricity markets, such as changing the tariffs, are behavioral options of regulatory bodies that enhance market efficiency [3]. In this context, DR plays a crucial role because it can increase the customers elasticity in the long-term as well as the operational impacts on the load shape Therefore, the market operator can employ DRPs to improve market efficiency and mitigate market power.

DRPs can reduce the risk of participation in the electricity markets for small market players, as well as improving the reliability and efficiency of the power system. Although participation of customers in DRPs can be a profitable option from power systems' point of view, it can significantly affect the strategic behavior of generations companies (Gencos), especially in oligopoly environments. On this basis, this paper aims at studying the impacts of different DRPs on the oligopolistic behavior of Gencos in a day-ahead electricity market and finding the optimal DRP in terms of market efficiency.

B. Literature Review and Background

Many reports have analyzed the oligopoly electricity market models [4], [5]. In [6] and [7], two strategic game models, one for studying the electricity markets and another one for assessing the interactions of market participants are reported. In [8], the market clearing prices are achieved by means of a heuristic method, within a hydrothermal power exchange market. But, the power flow formulations in the optimization of oligopolistic market models are rarely reported [9]. This is due to the fact that network constraints determine a complex market clearing mechanism and lead to non-differentiable and non-concave functions. As an example, in [10], the calculations of Nash equilibrium is presented for wholesale electricity markets. The impact of DR has not been addressed in the mentioned electricity market models.

In [11], the interaction among utility companies and responsive demands has been presented in a smart grid by considering the demand response problem as a non-cooperative game. In [12], a linear supply function has been employed for demand response bidding; however, the impact of DRPs on the market power has not been addressed, since the problem has been modeled from the demand side's viewpoint.

In the demand response schemes, the electric utility provides incentives and benefits to consumers in order to compensate their flexibility in DR events or in the timing of energy consumption [13]. In [14], the impact of market structure on the elasticity of the demand for electricity is analyzed and a matrix of self- and cross-elasticities is introduced to describe the consumers behavior. In this paper, the mentioned matrix is employed to model the impact of different DRPs on the customers behavior. The effect of DR on the power system load shape has been investigated by an economic model of price responsive demand in [15]. In [16], a price-based DR has been applied to the power systems. In [17], 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. For implementing DRPs in the electricity markets, usually different objectives are considered; sometimes, these principles contradict each other, hence they cannot be optimized simultaneously. Power system regulatory bodies try to use multi-objective decision analysis to overcome this issue [18], [19]. In [19], a multi-attribute method based on goal programming has been utilized to find the priority of DR programs. However, finding the optimal tariffs as well as incentive and penalty rates has not been addressed.

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C. Contributions

Although many reports 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, an agent-based game-theoretic model is employed and impacts of several DRPs including Real Time Pricing (RTP), Time of Use (TOU), EDRP, I/C and Critical Peak Pricing (CPP) on the 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 of twenty-four hours, in contrary to most of previous studies where the game theoretic model of the electricity market is based on one single hour. Therefore, the proposed model enables to investigate the self-scheduling problem considering the startup and shut down costs, minimum on/off times, and ramp up/down rates.

In addition, the optimal DRP in terms of market efficiency is obtained to increase the level of competition in the electricity market. To this end, the tariffs of the mentioned price-based programs and the amount of incentive and penalty in EDRP and I/C services are optimized. To this end, the proposed model aims at improving the electricity market efficiency by optimizing the mentioned DRPs and selecting the best DRP by means of an MODM approach based on ε-constraint method. The operation cost and a market power index are considered as objectives of the mentioned MODM approach. 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
- Finding the optimal DRP among different DRPs in terms of improving the market efficiency by employing an MODM approach

D. Paper Organization

Section II describes the models of DRPs. Section III devotes to the agent-based model of the electricity market including the MODM approach. Numerical studies are presented in Section IV. In Section V concluding remarks are drawn.

II. Modeling the Demand Response Programs

DRPs aim at making consumers more sensitive to variations of electricity prices over hours. DRPs encourage the 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 have been categorized into two groups, so-called, *price-based*, and *incentive-based* programs.

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:

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

where Δd_t, the change in the demand, is a free variable which can obtain both negative and positive values. d_t^{ini} is the initial amount of demand and d_t denotes the final demand after implementation of DRPs.

The amount of incentive, ς_t, is expressed as:

$$\varsigma_t = Inc_t \left(d_t^{\text{ini}} - d_t\right) \tag{2}$$

where $Inc_t \geq 0$ and $\varsigma_t \geq 0$ are the rate of incentive and the incentive function to reduce the demand, respectively. Similarly, the amount of penalty, ξ_t, can be formulated as:

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

where $Pen_t \geq 0$ and $\xi_t \geq 0$. $d_t^{Contract}$ represents the amount of contracted flexibility. It means that the consumer is obliged to reduce his demand by a certain amount under the risk of being penalized. In other words, if the customer does not reduce its consumption to $d_t^{Contract}$, he is penalized by the rate of Pen_t.

The customer's benefit, *B*, at hour *t* can be as follows [20]:

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

where Uti_t is the customer's utility at hour *t* that is a function of amount of demand, d_t. Uti_t denotes the value of d kWh of electricity for the consumers. Particularly, the customer's utility indicates the production income for industrial customers, while it is the productivity for commercial demands. λ_t denotes the price/tariff at time slot t. The second term in (4) is related to the electricity cost in hour t. Last two terms are related to the amounts of incentive and penalty, respectively.

In order to represent the customer's sensitivity to change in electricity tariffs, incentives or penalties, the current paper uses the concept of elasticity of demand. Elasticity is defined as the load's reaction to the electricity price. As the elasticity increases, the load sensitivity to price increases as well. In fact, the elasticity is used to estimate the load reduction and load recovery by DR participants. The price elasticity of demand in t-th time slot versus t'-th time slot can be defined as (5).

Demand can indeed react to change in electricity tariffs in one of followings. A set of loads is reduced without recovering it later, so-called fixed loads. Such loads have sensitivity just in a single period and it is called *self-elasticity*, i.e., $E(t,t)$. This value is always negative. Some other loads can shift from peak periods to off-peak periods as required, namely shiftable loads. Such behavior is called multi period sensitivity and is evaluated by *cross-elasticity*, i.e., $E(t,t')$. This value is always positive [20]. The correlation of demand in different time slots is modeled by using the concept of the cross-elasticity, in fact multiple time periods are correlated to each other according to the cross-elasticity concept.

$$E(t,t') = \frac{\partial d_t}{\partial \lambda_{t'}} . \frac{\lambda_{t'}^{ini}}{d_t^{ini}} \tag{5}$$

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where λ^{ini} denotes the initial tariff of electricity before implementing the DRPs, $\dfrac{\partial d_t}{\partial \lambda_{t'}} = constant$ and

$$\begin{cases} E(t,t') \leq 0 & if \quad t = t' \\ E(t,t') \geq 0 & if \quad t \neq t' \end{cases} \tag{6}$$

Using the second order Taylor Series expansion of the customer's utility function, the quadratic utility function of consumers based on their demand can be obtained as (7).

$$Uti_t = Uti_t^{ini} + \lambda_t^{ini}\left(\Delta d_t\right)\left(1 + \frac{\Delta d_t}{2E_{t,t} d_t^{ini}}\right) \tag{7}$$

where $E_{t,t}$ is the self-elasticity of demand-price [14].

Ref. [20] showed that the single period price-based economic load model is obtained as shown in (8).

$$d_t = d_t^{\text{ini}} + E_{t,t}\frac{d_t^{\text{ini}}}{\lambda_t^{\text{ini}}}\left(\lambda_t - \lambda_t^{\text{ini}} + Inc_t - Pen_t\right) \tag{8}$$

According to the concept of the cross-elasticity, [20] showed that a change in the electricity price in hour t' might cause the load variation in hour t as represented in (9).

$$d_t = d_t^{\text{ini}} + \sum_{t'=1, t' \neq t}^{T}\left(E_{t,t'}\frac{d_t^{\text{ini}}}{\lambda_{t'}^{\text{ini}}}\left(\lambda_{t'} - \lambda_{t'}^{\text{ini}} + Inc_{t'} - Pen_{t'}\right)\right) \tag{9}$$

As a result of the combination of (8) and (9), the comprehensive DR model will be obtained as (10) [20].

$$\begin{aligned} d_t = d_t^{\text{ini}} + E_{t,t}\frac{d_t^{\text{ini}}}{\lambda_t^{\text{ini}}}\left(\lambda_t - \lambda_t^{\text{ini}} + Inc_t - Pen_t\right) + \\ \sum_{t'=1, t' \neq t}^{T}\left(E_{t,t'}\frac{d_t^{\text{ini}}}{\lambda_{t'}^{\text{ini}}}\left(\lambda_{t'} - \lambda_{t'}^{\text{ini}} + Inc_{t'} - Pen_{t'}\right)\right) \end{aligned} \tag{10}$$

Eq. (10) shows the optimal amount of demand from customers' point of view by participating in DRPs considering given electricity tariffs, λ_t, incentive, Inc_t, and penalty, Pen_t. It should be noted that, the technical and behavioral constraints of customers are reflected in the elasticity, since the calculating methods of elasticity are based on analysis of real data and customers surveys [21]. The tariffs, incentive and penalty rates have been considered as given parameters in the literature. However, in this paper the mentioned parameters are modeled as decision variables and the optimal tariffs, incentive and penalty rates are obtained from the regulatory body's viewpoint. Moreover, in the DRPs, the tariff of each time slot and penalty rate should be limited to a certain interval to avoid the sharp rises of customers electricity purchasing cost and penalty. On this basis, the following constraints are considered for the electricity tariffs and penalty rate.

$$\lambda_t \leq \lambda_t^{max} \tag{11}$$

$$Pen_t \leq Pen^{max} \tag{12}$$

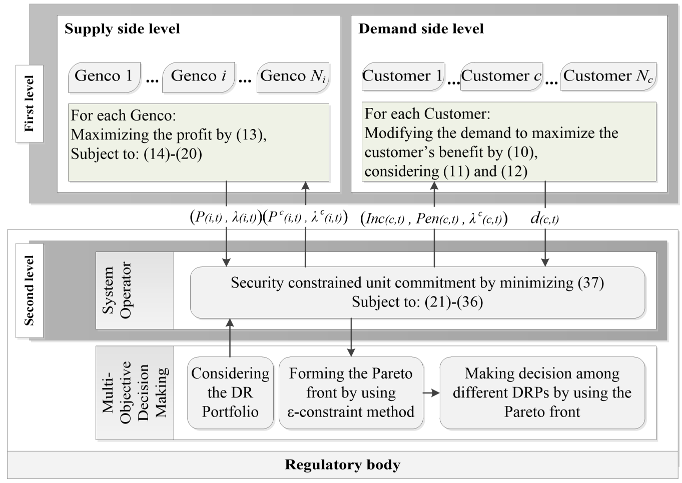

Fig. 1. The proposed electricity market model.

III. Modeling the Electricity Market

In order to consider the reality of market behavior, an oligopoly market model is proposed in this paper. To this end, a multi-agent framework is presented. In the first level of the agent-based model, market players maximize their own profits. The supply function equilibrium (SFE) is employed due to high precision to model the game theory [11], thus each Genco decides on both price and quantity. The Gencos have no information of each other. Hence, from the Gencos' point of view, the market model is an incomplete information game [9]. In addition to the Gencos, in the first level, the behavior of customers participating in a DRP is also modeled as presented in Section II. In the second level, the system operator minimizes its objective function.

The interaction between these two levels is carried out by using an iteration-based game. On this basis, each Genco agent receives the daily price of the energy and reserve markets from the previous iteration. All agents solve their self-scheduling problem to maximize the profit and individually offer their suggestion to electricity markets. The demand is also updated due to the daily prices of the previous iteration. The learning process is based on the hypothesis that each agent can observe the final market loads and prices related to previous iterations, in addition to the results of the auctions. Therefore, the price loop is repeated until the prices of the agents are equal to market clearing ones. It should be noted that using the iteration-based game theory can help the market simulator to find the process of converging to the market equilibrium point. Based on this, the regulation body can observe the dynamic of market participants' strategic behavior. More details of the iteration-based game theory are presented in [22].

A schematic of the proposed model is illustrated in Fig. 1. The details of the proposed electricity market model are expressed as follows.

A. *Genco's model*

The objective function of each Genco corresponds to maximizing its own profit, participating in day-ahead energy and reserve markets. To this end, each Genco considers the nodal prices of the electricity market to determine the optimum strategic behavior in twenty-four hours. The objective function of Genco i is formulated as below:

$$\underset{P_{i,t}^{DA},\lambda_{i,t}^{DA},P_{i,t}^{Res},\lambda_{i,t}^{Res},u_{i,t}}{\text{Max}} \{GencoProfit\} = \text{Max} \sum_{t=1}^{T} \left\{ \begin{array}{l} P_{i,t}^{DA}\lambda_{i,t}^{DA} + P_{i,t}^{Res}\lambda_{i,t}^{Res} \\ -a_i\, P_{i,t}^2 - b_i\, P_{i,t} - c_i\, u_{i,t} \\ -SU_i\, y_{i,t} - SD_i\, z_{i,t} \end{array} \right\} \tag{13}$$

Subject to:

$$P_i^{\min} u_{i,t} \le P_{i,t} \le P_i^{\max} u_{i,t} \tag{14}$$

The first line of (13) denotes the income of Genco from taking part in day-ahead energy and reserve markets. The second line represents the operational costs of the unit. a_i, b_i and c_i are coefficients of cost function of Genco i. $u_{i,t}$ is the binary variable of unit commitment of generator i, and $P_{i,t}{=}P_{i,t}^{DA}{+}P_{i,t}^{Res}$. The last two terms denote start-up and shut-down costs. Constraint (14) presents the limitation of power generation in each hour. $y_{i,t}$ and $z_{i,t}$ are auxiliary variables to determine start-up and shut down times as formulated in (15)-(16).

$$u_{i,t} - u_{i,t-1} = y_{i,t} - z_{i,t} \tag{15}$$

$$y_{i,t} + z_{i,t} \le 1 \tag{16}$$

The unit ramp up and down constraints are formulated by (17)-(18).

$$P_{i,t} - P_{i,t-1} \le RU_i + P_i^{\min}\, y_{i,t} \tag{17}$$

$$P_{i,t-1} - P_{i,t} \le RD_i + P_i^{\min}\, z_{i,t} \tag{18}$$

The minimum on and off time constraints are expressed by (19)-(20).

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

$$z_{i,t} + \sum_{j=1}^{MD_i-1} y_{i,t+j} \le 1 \tag{20}$$

B. Regulatory body model

In order to model the market behavior in twenty-four hours, the market clearing price and quantity are determined by solving a security constrained unit commitment (SCUC) problem. On this basis, once entering the Gencos' offers to the SCUC problem, the most economic solution from the ISO's viewpoint is obtained, considering network and security limits. The solution consists of commitment and generation of Gencos, as well as locational market prices. In [23], it is shown that minimizing the total cost (or maximizing the social welfare) cannot prevent the market players from exercising the market power, and consequently, employing some behavioral market power indexes is crucial.

Instead of minimizing either the operation cost or market power, using the multi-objective problem enables the regulatory body to find a tradeoff between these two important factors. On this basis, in the proposed MODM problem, two objective functions are considered. The first objective function is the total operation cost, while the second one is the Share Weighted Average Lerner Index (SWALI). SWALI is an expanded Lerner index that indicates the market power of the entire power system.

The Lerner index is a well-known operational index of market power that is calculated by the difference between price and marginal cost expressed as a percentage of price [24]. The Lerner index can measure the market power of each single Genco, while in order to measure the market power of all the power system, SWALI is introduced. The introduction of SWALI is based on the concept that if a big Genco has the potential of market power it can deteriorate the power system efficiency more than a small Genco with the same Lerner index. SWALI in completely competitive markets is equal to zero, because the Lerner index of each Genco is equal to zero. In uncompetitive markets, SWALI tends to the number of time slots, because the weighed Lerner index of Gencos is equal to one.

The total operation cost and SWALI are formulated as shown in (21) and (22), respectively.

$$\begin{aligned} &\text{Objective Function I} = OC = \\ &\sum_{t=1}^{T}\sum_{i=1}^{N_i}\left(P_{i,t}^{DA}\lambda_{i,t}^{DA} + P_{i,t}^{Res}\lambda_{i,t}^{Res}\right) \\ &+\sum_{t=1}^{T}\sum_{c=1}^{N_c} Inc_t(d_{c,t}^{\text{ini}} - d_{c,t}) \\ &-\sum_{t=1}^{T}\sum_{c=1}^{N_c} Pen_t\left(d_{c,t}^{contract} - (d_{c,t}^{\text{ini}} - d_{c,t})\right) \end{aligned} \tag{21}$$

$$\text{Objective Function II} = SWALI = \sum_{t=1}^{T}\sum_{i=1}^{N_i} S_i\left(\lambda_{i,t}^{DA} - MC_i\right)/\lambda_{i,t}^{DA} \tag{22}$$

In (21), the first line represents the operation cost resulted from generation and reserve of Gencos. The first term of the second line of (21) denotes the cost of incentive payment to customers who successfully response to incentive-based programs. The second term is the income of penalty received from customers who do not reduce their demand according to the contract.

In (22), MC_i denotes the marginal cost of Genco i, and S_i is the share of Genco i of the total generation as defined in (23).

$$S_i = P_i^{\max} \Big/ \sum_{i=1}^{N_i} P_i^{\max} \tag{23}$$

In (21), the decision variables are $P_{i,t}^{DA}$, $\lambda_{i,t}^{DA}$, $P_{i,t}^{Res}$, $\lambda_{i,t}^{Res}$, Inc_t, Pen_t, while in (22), the decision variable is $\lambda_{i,t}^{DA}$. From the system operator's perspective, some other constraints should be taken into account as presented below:

$$\sum_{\forall i(b)} P_{i,t}^{DA} + \sum_{l} P_{l,t} = \sum_{\forall c(b)} d_{c,t} \tag{24}$$

$$\sum_{\forall i(b)} Q_{i,t} + \sum_{l} Q_{l,t} = \sum_{\forall c(b)} Q_{c,t} \tag{25}$$

$$\sum_{i=1}^{N_i} P_{i,t}^{\max} u_{i,t} \geq \sum_{c=1}^{N_c} d_{c,t} + SR_t \tag{26}$$

$$Q_i^{\min} u_{i,t} \leq Q_{i,t} \leq Q_i^{\max} u_{i,t} \tag{27}$$

$$\begin{aligned} P_{l,t} &= V_{b,t} V_{b',t} (G_l^{sr} + G_l^{sh}) \\ &-V_{b,t} V_{b',t} \left(G_l^{sr} \, cos(\delta_b - \delta_{b'}) + B_l^{sr} \, sin(\delta_b - \delta_{b'})\right) \end{aligned} \tag{28}$$

$$\begin{aligned} Q_{l,t} &= -V_{b,t} V_{b,t} (B_l^{sr} + B_l^{sh}) \\ &+V_{b,t} V_{b',t} \left(B_l^{sr} \, cos(\delta_b - \delta_{b'}) - G_l^{sr} \, sin(\delta_b - \delta_{b'})\right) \end{aligned} \tag{29}$$

$$\delta_b^{\min} \leq \delta_{b,t} \leq \delta_b^{\max} \tag{30}$$

$$\delta_b^{cg,\min} \leq \delta_{b,t}^{cg} \leq \delta_b^{cg,\max} \tag{31}$$

$$V_b^{\min} \leq V_{b,t} \leq V_b^{\max} \tag{32}$$

$$V_b^{cg,\min} \leq V_{b,t}^{cg} \leq V_b^{cg,\max} \tag{33}$$

$$F_{l,t} = \sqrt{P_{l,t}^2 + Q_{l,t}^2} \tag{34}$$

$$F_l^{\min} \leq F_{l,t} \leq F_l^{\max} \tag{35}$$

$$F_l^{cg,\min} \leq F_{l,t}^{cg} \leq F_l^{cg,\max} \tag{36}$$

where $d_{c,t}$ denotes the demand of customer c at time slot t. N_i and N_c are the total number of Gencos and customers, respectively.

The nodal balance on bus b for active and reactive powers is presented in (24) and (25), respectively. Inequality (26) ensures that the committed units can supply the demand and provide the required spinning reserve. Constraint (27) limits the reactive power generation. Equations (28) and (29) represent the active and reactive line flows [25]. Inequalities (30) and (31) limit the bus angle for the normal and contingency states, respectively. Constraints (32) and (33) limit the voltage magnitude in normal and contingency states, respectively. Eq. (34) calculates the power flow trough network branches. Constraints (35) and (36) limit the flows through network branches in normal and contingency states, respectively. The limits of (33) and (36) known as emergency ratings, are not necessarily equal to the pre-contingency limits of (32) and (35) that are the normal ratings.

In order to improve the computational speed of power flow, a hybrid algorithm is employed. Based on the algorithm, in the SCUC problem, a nonlinear AC power flow is solved in normal condition and linearized Jacobian matrices are utilized for contingencies. The applied formulation of power flow calculation has been presented in [26].

It should be noted that proper and practical tariffs should at least cover the expenses for the production of the electricity. Since the expenses of production of electricity are included in the operation cost, the regulator can select a solution (e.g., Tariffs) between the obtained solutions of the Pareto front in such a way to avoid financial losses for Gencos. In other words, the regulatory body can only select solutions for which the operation cost ensures to cover the expenses required for the production of electricity.

C. Multi-objective decision-making

In order to solve the proposed multi-objective problem, the ε-constraint method [27] is employed to transform the problem into a uni-objective problem. Based on ε-constraint method, one objective is optimized while the rest of objectives are considered as new constraints that limit the amount of objectives to parameter ε. In this paper, Operation Cost (Φ_1) is minimized while SWALI (Φ_2) is limited to parameter ε, as presented in (37). This parameter is progressively increased from $SWALI^{min}$ to $SWALI^{max}$, hence one optimal solution is obtained for each value of parameter ε. The obtained solutions form the Pareto front of the multi-objective problem.

$$\begin{aligned} &Objective\,Function = Min(\Phi_1) \\ &Subject\,to : \Phi_2 \leq \varepsilon \end{aligned} \tag{37}$$

In order to select the best compromise solution among Pareto solutions, several methods have been addressed in the literature such as max-min [28] and analytical hierarchy process [29], that can be utilized by the decision maker. On this basis, when Pareto solutions are attained, the regulatory body can employ one of the methods to select the best solution.

It should mention that, the outlook and preference of regulatory body conclude the best compromise solution. In other words, since the regulatory body has concerns about both the operation cost and the market power, it can select the best compromise solution by considering some limits on the operation cost and SWALI.

The proposed method aims at forming the Pareto front for DR portfolio and selecting one or more solutions among the Pareto solutions is only carried out to better analyze the results. On this basis, it is assumed that the regulatory body determines a maximum permitted value for each operation cost and SWALI, and consequently obtains the most effective DRP among DR portfolio. Hence, the decision-aid approach is employed to investigate the solutions, whereas the ultimate decision should be made by the regulatory body, not by the analyst.

IV. Numerical results

In order to examine the performance of the proposed model, three test systems; namely, IEEE six-bus, IEEE 24-bus RTS [30] and IEEE 118-bus are employed; however, only the results

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of the IEEE 24-bus RTS are presented and analyzed in this paper. In the test system, the maximum participation level of customers in DRPs is equal to 20%. Moreover, the values of self and cross price-demand elasticity are extracted from [20].

The platform that has been used to evaluate the proposed model is a 64-bit Workstation with two Xeon E5-2687W 8C 3.10 GHz processors with 256 GB of RAM and an interface of MATLAB R2013b (8.2.0.701) and GAMS 24.0.2 has been utilized. Both levels of the proposed model are formulated as mixed integer nonlinear programing, solved and proven by DICOPT and SBB, respectively.

The hourly load of IEEE 24-bus system corresponds to a weekend day in winter as given in [30] while the peak of the day is assumed 2670 MW. The load curve of the IEEE 24-bus system is divided into four periods: valley (1:00-8:00), off-peak (9:00-16:00), peak (17:00, 20:00-24:00) and critical peak (18:00-19:00). It should be noted that the initial electricity price is assumed to be 15 \$/MWh that equals to the mean value of electricity prices before the DR implementation. The amount of contracted flexibility is considered 10% and 5% of the demand in the critical peak and peak periods, respectively, as presented in (38) and (39).

$$d_{c,t}^{contract} = 0.1 \times d_{c,t}^{ini} \qquad t \in T^{Peak} \tag{38}$$

$$d_{c,t}^{contract} = 0.05 \times d_{c,t}^{ini} \qquad t \in T^{Off-peak} \tag{39}$$

The utilized DR portfolio contains three sets of DRPs. The first set is the price-based DRPs including TOU, RTP and CPP. The second set is EDRP and I/C as incentive-based DRPs. The third set is the combination of the two sets, i.e., TOU+EDRP and TOU+I/C.

In order to evaluate the potential of DRPs on market power, two case studies are considered. In this respect, case 1 deals with economic-driven scheduling, that considers the operation cost as the uni-objective of the electricity market. However, a trade-off between economic and market power objectives is studied in case 2, where SWALI is also considered in the multi-objective function. In case 2, the Pareto front is obtained by using the ε-constraint method.

The obtained tariffs, incentives and penalties for each DRP in both cases are presented in Table I. In RTP, the obtained hourly market prices resulted from clearing the market are used for the tariffs of customers. The off-peak tariff is assumed to be an input parameter and it is considered equal to the electricity price in base case, i.e., 15 \$/MWh.

As it can be seen from Table I, the TOU tariff in case 2 has a higher value in peak period (i.e., 40.5 \$/MWh) compared to case 1 (i.e., 37.5 \$/MWh). This is due to the fact that, when the market power is considered in the objective function, the regulatory body aims to have lower market prices in peak period by using DRPs which reduce the demand in the mentioned period. This can shift more customers' load to the valley and off-peak periods, and consequently the market prices in the peak hours are decreased. This fact can be also observed from the optimal tariffs in CPP program where

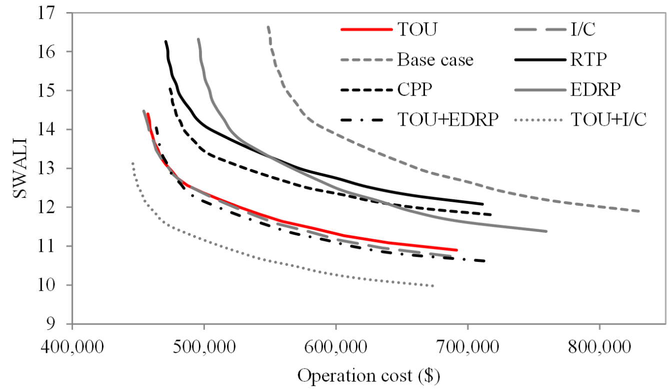

Fig. 2. The obtained Pareto fronts in case 2.

the critical peak tariff in case 2 is 25% higher than case 1. Similarly, higher incentives and penalties in case 2 compared to case 1 reveals that one of the regulatory options for the market power mitigation is to motivate the customers to reduce their level of demand in the peak and critical peak hours, when Gencos have the highest market power. According to Table I, the third set provides a trade-off between price-based and incentive-based programs. On this basis, the tariffs of TOU in combinational DRPs are lower than the tariffs when TOU is individually applied. In contrast, the incentives and penalties in combinational DRPs are higher than those in the second set. Although the incentive and penalty rates in the third set are higher than the ones in the second set, the incentive-based DRPs in the third set have a lower impact on the demand, because some parts of the demand decrease due to the TOU tariffs in the peak and critical peak hours. It can be revealed from the terms of incentive and penalty costs in operation costs for the different DRPs sets as presented in Table II.

According to Table II that, by implementing DRPs, the total operation cost of system is meaningfully decreased in comparison with the base case. Particularly, it can be seen that the DRPs in the third set are more effective in terms of operation cost reduction. Because, these DRPs motivate the customers to change their consumption using both tariff schemes and incentive mechanisms.

It is noteworthy that the penalty costs are negative according to the fact that this term is considered as revenue in the objective function from system operator's viewpoint, i.e., (21).

The obtained Pareto fronts for the considered DR portfolio are illustrated in Fig. 2. The Pareto front of each DRP includes twenty solutions, obtained from applying twenty equal steps for ε parameter. According to Fig. 2, as a result of DR implementation, both the operation costs and SWALI are reduced compared to base case. In the first set of DR portfolio, the minimum values of operation cost and SWALI are related to TOU. In the second set of DR portfolio, I/C is more effective than EDRP in reducing both the operation cost and the market power. This causes that, in the third set, combination of TOU and I/C has better impacts on the market efficiency compared to the combinational TOU and EDRP.

According to Fig. 2, simultaneously implementing TOU and I/C programs is the most effective option to minimize

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TABLE I
OBTAINED OPTIMAL TARIFF, INCENTIVE AND PENALTY

Set	DRPs	Case 1						Case 2					
		Electricity tariffs ($/MWh)				Inc	Pen	Electricity tariffs ($/MWh)				Inc	Pen
		Valley	Off-peak	Peak	Critical peak			Valley	Off-peak	Peak	Critical peak		
Base case	Initial load	15				-	-	15				-	-
1	TOU	6	15	37.5		-	-	5.5	15	40.5		-	-
	RTP	Obtained market prices				-	-	Obtained market prices				-	-
	CPP	15			60	-	-	15			75	-	-
2	EDRP	15				10	-	15				12	-
	I/C	15				6	4	15				7.5	5
3	TOU+EDRP	7.5	15	30		11	-	6	15	37.5		14	-
	TOU+I/C	7.5	15	30		7.5	5	6	15	37.5		9	6

TABLE II
OPERATION COSTS OF DR PORTFOLIO IN CASE 1

	Base-case	Set 1			Set 2		Set 3	
		TOU	RTP	CPP	EDRP	I/C	TOU+EDRP	TOU+I/C
Fuel cost ($)	466800	431410	447700	431630	435380	428100	413190	408090
Reserve cost ($)	22960	23159	23075	23210	23154	23313	23273	23296
Incentive cost ($)	0	0	0	0	21103	19764	15819	19804
Penalty cost ($)	0	0	0	0	0	-6608	0	-3163
Operation cost ($)	489760	454570	470776	454841	479638	464571	452283	448028

both operation cost and market power objective functions. It seems reasonable due to the fact that, TOU is a kind of obligatory DRP implemented by the system operator, so that the customers do not have any choice about it. Moreover, I/C program has a mechanism to penalize the customers, if they do not respond in the required times. Therefore, it seems that the customers are forced to participate in DRP and as a result the maximum benefit is attained from the system operator's perspective.

Comparing case 1 and case 2 reveals that considering market power index in the objective function of the system operator improves the effectiveness of I/C services. In other words, implementation of I/C can be a better option than price-based DRPs, if in addition to the operation cost, the market power is also analyzed. This means that, the incentive-based DRP can play more important roles by considering the market power in the system operator objective.

It is also obvious that implementing incentive-based DRPs is not pleasant for the system operator, because implementation of these programs impose additional costs to the system.

The proposed method enables the regulatory body to select a DR portfolio such a way that a trade-off between operation cost and market power is obtained. For example, based on the regulatory measures, if the operation cost and SWALI respectively less than 500,000 $ and 12.5 are acceptable by the regulatory body, among DR portfolio several compromise solutions can be selected as presented in Table III.

TABLE III
COMPROMISE SOLUTIONS AMONG DR PORTFOLIO

Set	DRPs	Solution	Operation Cost ($)	SWALI
Base case	Initial load	N/A	-	-
1	TOU	#9	499,310	12.37
	RTP	N/A	-	-
	CPP	N/A	-	-
2	EDRP	N/A	-	-
	I/C	#9	495,790	12.42
3	TOU+EDRP	#10-11	490,375*	12.33*
	TOU+I/C	#8-15	469,391**	11.76**

∗ The average value of the two solutions of TOU+EDRP
∗∗ The average value of the eight solutions of TOU+I/C

As it can be seen in Table III, the considered limits for the operation cost and SWALI cause that the list of solutions is shortened. On this basis, RTP, CPP and EDRP are not appropriate options to reduce the operation cost and the market power compared to other DRPs. Each of TOU and I/C has one acceptable solution, while the combination of TOU and EDRP provides two solutions that can indicate this combination works better than each of TOU and EDRP. The most effective option to optimize the objective function is TOU+I/C that obtains eight solutions with the lowest amount of both the operation cost and SWALI. In general, it can be concluded that simultaneous implementation of price-based and incentive-based DRPs is a more favorable option for regulatory bodies to reduce the operation cost while mitigating the market power.

Fig. 3 shows the electricity market price in case 1 for different price-based DRPs. As it can be seen, all the price-based DRPs reduce the electricity prices in the critical peak hours compared to the base case. Among the mentioned DRPs, CPP has more effect on reducing the critical peak price, following by TOU. However, by implementing CPP, the market prices in peak and off-peak periods are higher than the ones in the base case or by implementing other DRPs. It is due to the fact that in CPP, only a very high tariff is applied on the critical peak period and the rest hours of the day have same tariff as the initial fixed-rate tariff. Therefore, for CPP there is no difference between valley, peak and off-peak hours. However, in TOU, the tariffs of valley and peak hours are different, therefore, the demand and consequently the market price in valley hours increase. In addition, since the obtained tariffs of TOU and CPP are higher than the electricity market

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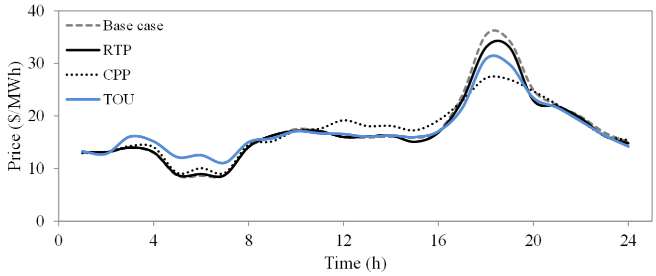

Fig. 3. Market price in case 1 considering different price-based DRPs.

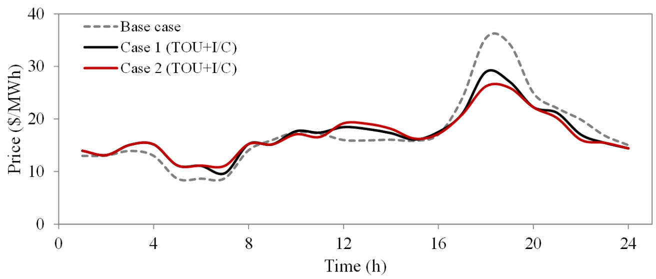

Fig. 4. Market price in different cases.

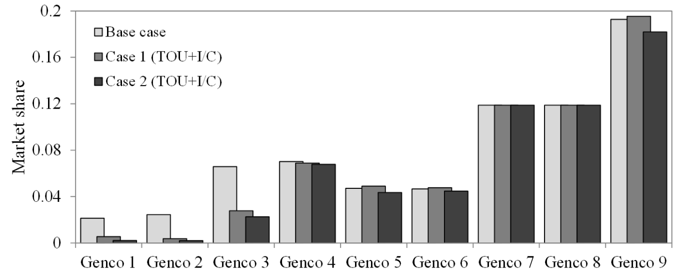

Fig. 5. Gencos' market share in different cases.

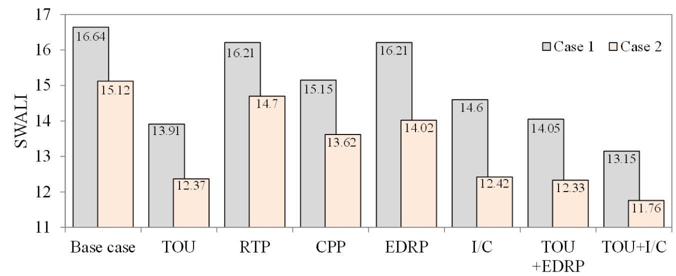

Fig. 6. SWALI in different cases.

prices in critical peak period, these two programs affect the price more than RTP in which the tariff is the same as the electricity market price.

The electricity market prices considering the combination of TOU and I/C in cases 1 and 2 are compared in Fig. 4. In this figure, the solution #10 of the Pareto solutions is utilized for case 2. As it can be seen, case 2 has a better impact on decreasing the electricity market price in both peak an critical peak periods. The market power potential is generally high when the electricity demand increases, therefore considering the market power index (i.e., SWALI) as an objective function of the system operator decreases the market prices in the peak and critical peak hours. By comparing Fig. 4 and Fig. 3, it can be observed that the combination of TOU and I/C in case 2 has the best influence on the market electricity price among different DRPs, since the prices in the valley hours are as high as the ones in TOU in case 1, while the prices are lower than the ones in TOU in peak and critical peak periods.

Fig. 5 indicates the market share of Gencos considering the combination of TOU and I/C in cases 1 and 2. It can be seen that both cases 1 and 2 can significantly mitigate the market share of Gencos 1 to 3. It should be noted that Gencos 1 and 2 are expensive Gencos, and the implementation of TOU and I/C reduces the necessity of their generation. Genco 9 has a high market share in the system. By considering SWALI in the objective function of the system operator (i.e., case 2), the market share of this Genco reduces, while, in case 1, the market share of this Genco increases compared to the base case. Since Genco 9 is not an expensive Genco, by only considering the total cost in the objective function (i.e., case 1), the system operator increases the generation of this Genco that makes a higher market power potential for it.

In Fig. 6, SWALI is illustrated in different DRPs in cases 1 and 2. In this figure, one of the Pareto solutions is used for the initial load, RTP, CPP and EDRP in case 2, while the constraint

TABLE IV
OPTIMIZATION STATISTICS OF THE PROPOSED MODEL

Problem level	No. of constraints	No. of Variables	No. of iterations	Solution time (s)
First level (for one Genco using (13))	358	217	16.4*	0.015*
Second level (minimizing (37))	8016	4832	149729*	9.288*
Total problem (interaction between two levels)	-	-	185	4500

∗ The average of each iteration of the total problem

on SWALI (i.e., SWALI $<$ 12.5) is not considered. TOU and I/C are two most effective individual DRPs on SWALI, therefore the combination of these two programs (TOU+I/C) has the highest impact on the market power index. According to Fig. 6, considering SWALI in the objective function can decrease this index about 2 units in almost all DRPs. However, it has the biggest decrease in SWALI when EDRP and I/C (that are both incentive-based DRPs) are used. Particularly, in EDRP and I/C, SWALI respectively decreases 13.5% and 14.9% from case 1 to case 2. It means that these incentive-based programs have more role when the market power index is considered in the objective function of the system operator. It should be noted that I/C has also a significant impact on the operation of the system when SWALI is considered. Based on Table II, in case 1, I/C program is the third best program in terms of operation cost (that follows TOU and CPP), while in case 2 (according to Table III, I/C is the best individual DRP regarding the operation cost.

In order to clarify the dimension of the mathematical programming problem and convergence performance of the proposed model, the optimization statistics for both levels of the problem are presented in Table IV.

TABLE V
GENCOS' DATA

Genco	Unit cost coefficients			Start-up cost	Pmax (MW)
	a_i	b_i	c_i		
1	0.2917	35.07	3591.39	1460.4	192
2	0.2917	35.07	3591.39	1460.4	192
3	0.0191	14.86	552.8	1725	300
4	0.0322	19.18	1940.98	3056.7	591
5	0.0322	19.18	649.99	749	215
6	0.0628	27.22	1829	312	155
7	0.0086	30	1992.36	0	400
8	0.0086	30	1992.36	0	400
9	0.0112	14.17	927.15	2922	660

V. CONCLUSION

In this paper, a multi-agent model was proposed to improve the market efficiency by using different DRPs. To this end, the oligopolistic electricity market was modeled to consider strategic self-scheduling of each market player. Market interactions were taken into account by game theory and the market transactions were cleared by an SCUC problem. Moreover, different DRPs were investigated to find the optimal tariffs of price-based programs as well as the incentive/penalty rate of incentive-based programs. In the future work, the amount of flexibility contracted demand can be also considered as a decision variable in the model, especially in the long-term studies. SWALI was employed to evaluate the market efficiency and an MODM approach was employed to analyze the solutions. The following results were drawn from the numerical studies:

- 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 periods could decrease the offered prices by the Gencos and consequently it could mitigate the market power.
- The market operator could mitigate the potential of market power in an electricity market by finding an optimal DRP. Therefore, using the proposed model, before implementing the DRPs, can significantly enhance the market efficiency and mitigate market power.
- Applying combinational DRPs including both price-based and incentive-based are more efficient when regulatory body considers both economic and market power targets.

VI. APPENDIX

The cost coefficients of the units, the start-up cost and the maximum power generation are presented in Table V.

REFERENCES

[1] S. Belhaiza and U. Baroudi, "A game theoretic model for smart grids demand management," *IEEE Transactions on Smart Grid*, vol. 6, no. 3, p. 13861393, May 2015.

[2] P. Siano, "Demand response and smart grids - a survey," *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 461–478, 2014.

[3] M. Shafie-Khah, M. P. Moghaddam, and M. K. Sheikh-El-Eslami, "Development of a virtual power market model to investigate strategic and collusive behavior of market players," *Energy Policy*, vol. 61, pp. 717–728, 2013.

[4] A. Foley, B. O. Gallachoir, J. Hur, R. Baldick, and E. McKeogh, "A strategic review of electricity systems models," *Energy*, vol. 35, no. 12, pp. 4522 – 4530, 2010.

[5] T. Sueyoshi, "An agent-based approach equipped with game theory: Strategic collaboration among learning agents during a dynamic market change in the california electricity crisis," *Energy Economics*, vol. 32, no. 5, pp. 1009 – 1024, 2010.

[6] J. Wang, Z. Zhou, and A. Botterud, "An evolutionary game approach to analyzing bidding strategies in electricity markets with elastic demand," *Energy*, vol. 36, no. 5, pp. 3459 – 3467, 2011.

[7] G. Li, J. Shi, and X. Qu, "Modeling methods for genco bidding strategy optimization in the liberalized electricity spot marketa state-of-the-art review," *Energy*, vol. 36, no. 8, pp. 4686 – 4700, 2011.

[8] J. Molina, J. Zolezzi, J. Contreras, H. Rudnick, and M. Reveco, "Nash-cournot equilibria in hydrothermal electricity markets," *Power Systems, IEEE Transactions on*, vol. 26, no. 3, pp. 1089–1101, Aug 2011.

[9] E. Bompard, T. Huang, and W. Lu, "Market power analysis in the oligopoly electricity markets under network constraints," *Generation, Transmission & Distribution, IET*, vol. 4, no. 2, pp. 244–256, 2010.

[10] M. Hesamzadeh and D. Biggar, "Computation of extremal-nash equilibria in a wholesale power market using a single-stage milp," *Power Systems, IEEE Transactions on*, vol. 27, no. 3, pp. 1706–1707, Aug 2012.

[11] F. Kamyab, M. Amini, S. Sheykhha, M. Hasanpour, and M. M. Jalali, "Demand response program in smart grid using supply function bidding mechanism," *IEEE Transactions on Smart Grid*, vol. PP, no. 99, p. 11, 2015.

[12] N. Li, L. Chen, and M. A. Dahleh, "Demand response using linear supply function bidding," *IEEE Transactions on Smart Grid*, vol. 6, no. 4, p. 18271838, Jul 2015.

[13] M. Muratori and G. Rizzoni, "Residential demand response: Dynamic energy management and time-varying electricity pricing," *Power Systems, IEEE Transactions on*, vol. PP, no. 99, pp. 1–10, 2015.

[14] D. Kirschen, G. Strbac, P. Cumperayot, and D. de Paiva Mendes, "Factoring the elasticity of demand in electricity prices," *Power Systems, IEEE Transactions on*, vol. 15, no. 2, pp. 612–617, May 2000.

[15] C.-L. Su and D. Kirschen, "Quantifying the effect of demand response on electricity markets," *Power Systems, IEEE Transactions on*, vol. 24, no. 3, pp. 1199–1207, Aug 2009.

[16] P. Faria, Z. Vale, J. Soares, and J. Ferreira, "Demand response management in power systems using particle swarm optimization," *Intelligent Systems, IEEE*, vol. 28, no. 4, pp. 43–51, July 2013.

[17] M. Sahebi, E. Duki, M. Kia, A. Soroudi, and M. Ehsan, "Simultanous emergency demand response programming and unit commitment programming in comparison with interruptible load contracts," *Generation, Transmission Distribution, IET*, vol. 6, no. 7, pp. 605–611, July 2012.

[18] A. Botterud, *Long Term Planning in Restructured power Systems: Dynamic Modelling of Investments on New Power Generation under Uncertainty*. Fakultet for informasjonsteknologi, matematikk og elektroteknikk, 2003.

[19] M. Shafie-khah et al., "Optimal demand response programs for improving the efficiency of day-ahead electricity markets using a multi attribute decision making approach," in *Energy Conference, IEEE International*, 2016, pp. 1–6.

[20] H. Aalami, M. P. Moghaddam, and G. Yousefi, "Demand response modeling considering interruptible/curtailable loads and capacity market programs," *Applied Energy*, vol. 87, no. 1, pp. 243 – 250, 2010.

[21] P. S. Pricing, "Annual report, april 27, 2010, prepared by summit blue consulting, submitted to ameren illinois utilities," 2009. [Online]. Available: https://www.illinois.gov/sites/ipa/Documents/CUB-Comments-Appendix-D-2009-Navigant-Power-Smart-Pricing-Annual-Report.pdf

[22] M. Shafie-khah and J. P. Catalão, "A stochastic multi-layer agent-based model to study electricity market participants behavior," *Power Systems, IEEE Transactions on*, vol. 30, no. 2, pp. 867–881, 2015.

[23] M. Shafie-khah, M. P. Moghaddam, and M. K. Sheikh-El-Eslami, "Ex-ante evaluation and optimal mitigation of market power in electricity markets including renewable energy resources," *IET Generation, Transmission Distribution*, vol. 10, no. 8, pp. 1842–1852, 2016.

[24] S. Stoft, *Power System Economics: Designing Markets for Electricity*. Wiley-IEEE Press, 2002.

[25] J. Aghaei, A. Nikoobakht, P. Siano, M. Nayeripour, A. Heidari, and M. Mardaneh, "Exploring the reliability effects on the short term ac

security-constrained unit commitment: A stochastic evaluation," *Energy*, vol. 114, pp. 1016–1032, 2016.

[26] M. Shafie-khah, M. Moghaddam, M. Sheikh-El-Eslami, and J. Catalao, "Fast and accurate solution for the scuc problem in large-scale power systems using adapted binary programming and enhanced dual neural network," *Energy Conversion and Management*, vol. 78, pp. 477 – 485, 2014.

[27] S. M. Mohseni-Bonab, A. Rabiee, and B. Mohammadi-Ivatloo, "Voltage stability constrained multi-objective optimal reactive power dispatch under load and wind power uncertainties: A stochastic approach," *Renewable Energy*, vol. 85, pp. 598 – 609, 2016.

[28] X. Wang, Y. Gong, and C. Jiang, "Regional carbon emission management based on probabilistic power flow with correlated stochastic variables," *Power Systems, IEEE Transactions on*, vol. 30, no. 2, pp. 1094–1103, 2015.

[29] W.-H. Chen, "Quantitative decision-making model for distribution system restoration," *Power Systems, IEEE Transactions on*, vol. 25, no. 1, pp. 313–321, 2010.

[30] P. Wong *et al.*, "The ieee reliability test system-1996," *Power Systems, IEEE Transactions on*, vol. 14, no. 3, pp. 1010–1020, 1999.

BIOGRAPHIES

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