Optimal Demand Response Programs for Improving the Efficiency of Day-Ahead Electricity Markets using a Multi Attribute Decision Making Approach

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***Abstract*—In this paper, an agent-based model is proposed to improve market efficiency by using different Demand Response Programs (DRPs) in the day-ahead electricity market. To this end, both incentive-based and price-based DRPs are considered. On this basis, time of use, real time pricing, emergency demand response program, interruptible/curtailable services and critical peak pricing are investigated. The tariffs of the considered price-based programs and the amount of incentive in the incentive-based programs are optimized through the proposed model. Furthermore, a market power index, i.e., Share Weighted Average Lerner Index (SWALI) and the operation cost are used to evaluate the market efficiency and the market power. The proposed model optimizes the DRPs to improve the electricity market efficiency by using a multi-attribute decision-making approach. The results show that the market operator can mitigate the potential occurrence of market power in a power system by finding the optimal DRP.**

***Index Terms*—Demand response programs (DRPs), Electricity market, Multi-attribute decision-making (MADM), Market power.**

I. INTRODUCTION

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 years to come. DR, upon laying the necessary framework, empowers consumers to participate in the electricity markets [1] and contribute their fair share towards efficient operation of electricity grids.

In other words, different Demand Response Programs (DRPs) are one of the 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 [4]. Therefore, the market operator can employ DRPs to improve market efficiency and mitigate market power.

In [5], the interaction among utility companies and responsive demands has been presented in smart grid by considering the demand response problem as a non-cooperative game. In [6], a linear supply function has been employed for demand response bidding; however, the impact of DRPs on the market power has not been addressed.

Many reports have analyzed the oligopoly electricity market models [7], [8]. In [9] and [10], two strategic game models, one for studying the electricity markets and another one for assessing the interactions of market participants are reported. In [11], 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 [12]. This is due to the fact that network constraints make a complex market clearing mechanism and leads to non-differentiable and non-concave functions [13]. As an example, in [14], the calculations of Nash equilibrium is presented for wholesale electricity markets.

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In demand side management schemes, system operators provide consumers incentives and profits in order to persuade them to be more flexible in DR programs or in the timing of their power consumption [15]. The impact of DR on the power system's load shape has been studied and reported in [16] by defining an economic model of price responsive loads. In [17], a model is reported to improve aggregation agents' offering/bidding strategy by means of DR resources.

In [18], a price-based DR is utilized in the power systems. For implementing DR programs in the electricity markets, usually different criteria are considered; sometimes, these principles contradict each other in which they cannot be optimized simultaneously. Power system regulators try to use multi-attribute decision making (MADM) to overcome these issues.

In [19], an MADM method is being utilized for extracting the priority of DR programs. This method is also used in other reports, like in [20], for evaluating components restoration schemes in power systems, multiple types of attributes like fuzzy numbers, interval numbers or linguistic terms are taken into consideration. In [21], in order to find optimal place for photovoltaic power plants in the electricity network, various aspects of the problem are assessed and different relative weights are assigned to them by means of the MADM method.

This paper develops a multi-agent model to improve the efficiency of electricity market by incorporating different DRPs. To do so, both types of incentive-based and price-based DRPs are considered. On this basis, various types of price-based DR including Time of Use (ToU), Real Time Pricing (RTP), and Critical Peak Pricing (CPP); as well as two incentive-based DRPs, i.e., Interruptible/Curtailable services (I/C) and Emergency Demand Response Program (EDRP) are investigated. In the proposed model, the tariffs of the mentioned price-based programs and the amount of incentive and penalty in EDRP and I/C services are optimized.

In order to assess the efficiency of electricity market and to evaluate the market power, different electricity market indices are employed. To this end, the proposed model aims to improve the electricity market efficiency by optimizing the mentioned DRPs by means of an MADM approach. Several market power and market efficiency indices are considered in the mentioned MADM approach.

The remainder of this paper is organized as follows: in Section II, DRPs are described. Section III devotes to power market model including the MADM approach. Numerical studies are presented in Section IV. Finally, Section V concludes the paper.

II. DEMAND RESPONSE PROGRAMS

DRPs aim to make consumers more sensitive to variations of electricity prices at different hours. Moreover, DRPs encourage electricity consumers to change their electricity use in response to fluctuations of price over time, or to offer incentives, or to charge penalties that are considered to provide lower electricity consumption during hours with high electricity prices or when the power system reliability is threatened. In this sense, DRPs can be categorized into two major groups: price-based and incentive-based programs. Each group can also be categorized into some subsets as discussed in [22].

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 either price changes, an incentive payment or a penalty consideration, the impacts of DRPs on a customer's consumption can be formulated as:

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

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:

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

where $d_t^{contract}$ represents the amount of flexibility contracted. The customer's benefit, B_t, at hour t can be as follows [23]:

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

where Rev_t is the customer's revenue at hour t that is a function of the demand, d_t. In order to optimize the customers' benefit by implementing DRPs, we have [24]:

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

where

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

By considering a quadratic revenue function for customers [25] and by using Taylor Series expansion, the customer's revenue function is formulated as (7)

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

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

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

In Eq. (8), λ_t^{ini} denotes the initial price/tariff of electricity before implementing the DRPs (i.e., the fixed-rate tariff). E_t is a self-elasticity of demand-price [25].

Substituting (8) in (6), we get:

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

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

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

Expanding (10) for a multi period consumption, the economic model of DR is obtained as in Eq. (11).

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

Eq. (11) shows the optimal amount of demand from customers' point of view by participating in DRPs. Note that $E_{t,t'}$ in Eq. (11) is a cross elasticity of demand-price [25].

III. Modelling the Power Market

In this paper, aiming to improve the reality of the studies, the electricity market is modeled as an oligopoly market instead of being perfectly competitive. For this purpose, a multi-agent environment based on bi-level optimization has been developed. In the first level of the model, agents of market players maximize their own profits. The agents do not have any information about their competitors. Hence, the aforementioned environment is a game with incomplete information [26]. In the second level, the system operator minimizes its objective function. The interaction between these two optimization levels is carried out by using an iteration-based model presented in [27]. The details of the proposed electricity market model are expressed as follows:

A. Market players' model

In the proposed agent-based model, each market player (e.g., Gencos and retailers) is independently modeled using agents, so that their objective functions correspond to maximizing their profit, participating in day-ahead and balancing markets. The objective function of each Genco agent can be formulated as follows:

$$\text{Max}\{Genco\ Profit\} = \sum_{t=1}^{T}\left\{\begin{aligned} &P_{i,t}\lambda_t^{DA} + P_{i,t}^{Res}\lambda_t^{Res} \\ &-\left(a_i P_{i,t}^2 + b_i P_{i,t}\right) - c_i I_{i,t} - \lambda_i^{up} y_{i,t} - \lambda_i^{down} z_{i,t} \end{aligned}\right\} \tag{12}$$

Subject to:

$$P_i^{\min} I_{i,t} \le P_{i,t} \le P_i^{\max} I_{i,t} \tag{13}$$

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.

$$I_{i,t} - I_{i,t-1} = y_{i,t} - z_{i,t} \tag{14}$$

$$y_{i,t} + z_{i,t} \le 1 \tag{15}$$

$$y_{i,t} + \sum_{j=1}^{MU_i - 1} z_{i,t+j} \le 1 \tag{16}$$

$$z_{i,t} + \sum_{j=1}^{MD_i - 1} y_{i,t+j} \le 1 \tag{17}$$

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

$$P_{i,t-1} - P_{i,t} \le RD_i + P_i^{\min} z_{i,t} \tag{19}$$

where RU_i and RD_i are ramp up and down rates, respectively. MU_i and MD_i are minimum up and down times, respectively.

Inequality (13) denotes the unit output limits. Constraints of minimum up and down times are linearly expressed in (14)-(17). Constraints of unit ramp up and ramp down are presented in (18) and (19), respectively.

B. System operator model

In order to model the behavior of market players in a specific period, in this paper, instead of optimal power flow (OPF), the role of ISO in day-ahead horizon in clearing the electricity market and determining auction winners has been defined using a security constrained unit commitment (SCUC) problem [28]. The objective function of the system operator has two main terms, which minimizes the total operation cost and Share Weighted Average Lerner Index (SWALI). SWALI is an expanded Lerner index [29] that indicates the market power of the entire power system. In (20), weighting factors W_{OC} and W_{SWALI} represent the significance of operation cost and SWALI from the ISO's point of view in the decision-making problem. Therefore, different weights can be considered to assign different share of market efficiency and market power in the objective function. Moreover, the total operation cost and SWALI are formulated as shown in (21) and (22), respectively.

$$\begin{aligned} &Objective\ Function = \\ &\qquad Min\left(W_{OC}OC + W_{SWALI}SWALI\right) \end{aligned} \tag{20}$$

$$\begin{aligned} OC = &\sum_{t=1}^{T}\sum_{i\in Gencos}\left(P_{i,t}\lambda_t^{DA} + P_{i,t}^{Res}\lambda_t^{Res}\right) \\ &+ \sum_{t=1}^{T}\left\{Inc_t \Delta d_t - Pen_t\left(d_t^{contract} - \Delta d_t\right)\right\} \end{aligned} \tag{21}$$

$$\begin{aligned} &SWALI = \\ &\qquad \sum_{t=1}^{T}\sum_{i\in Gencos} S_i\left(\lambda_{t,i}^{DA} - MC_i\right)\Big/\lambda_{t,i}^{DA} \end{aligned} \tag{22}$$

In Eq. (22), MC_i denotes the marginal cost of Genco *i*, and S_i is the share of Genco *i* of the total generation.

From the ISO's point of view, some other constraints should be considered as presented below:

$$\sum_{i \in Gencos} P_{i,t} = d_t \tag{23}$$

$$\sum_{i \in Gencos} P_{i,t}^{\max} I_{i,t} = d_t + SR_t \tag{24}$$

$$-F_k^{\max} \le F_{t,k} \le F_k^{\max} \tag{25}$$

$$-F_k^{\max} \le F_{t,k}^{cg} \le F_k^{\max} \tag{26}$$

where Eq. (23) ensures the balance between supply and demand. The required spinning reserve is expressed in (24). Inequalities (25) and (26) consider the network limits in normal and contingency states, respectively. The applied formulation of power flow calculation has been presented in [28].

C. Multi-attribute decision-making

Various DRPs have different impacts on the oligopolistic behavior of market players; and consequently on the electricity market efficiency. In this context, it is crucial for the regulatory body to select and implement an appropriate DR program which yields the most efficient market with the lowest market power.

In order to compare the effectiveness of different DRPs, a DR portfolio is utilized by the Geometric Average Utility Function (GAUF) as one of the methods of Goal Programming (GP) that can be employed for engineering applications [30]. On this basis, the Strategy Index (SI) and Strategy Success Index (SSI) are used as it can be seen in Eqs. (27) and (28) [31].

$$SI = \sum_{t=1}^{24} \left\{ \left(St_1(t)\right)^{w_1} \left(St_2(t)\right)^{w_2} \cdots \left(St_k(t)\right)^{w_k} \right\} \tag{27}$$

$$SSI = \sum_{t=1}^{M} SI(t) \Big/ \sum_{t=1}^{M} SI(\max) \tag{28}$$

In Eq. (27), $St_k(t)$ indicates the performance value of k^{th} attribute for each alternative in the t^{th} period; and M represents the time horizon of study which is one day here. In Eq. (27), W_k shows the weight of k^{th} attribute. The SSI which is represented by (28) is the normalized value of the SI factor. In short, the higher SSI shows the better performance of a DR program. On this basis, the regulatory body can prioritize different DR programs due to its preferences which can include indices of market efficiency and potential occurrence of market power.

IV. Numerical Studies

In order to examine the performance of the proposed model, IEEE 24-bus RTS [32] is used.

The hourly load corresponds to a weekend day in winter as given in [32] while the peak of the day is assumed 2670 MW. The load curve is divided into three periods: low-load period (1:00-8:00), off-peak period (9:00-16:00), and peak period (17:00-24:00). Moreover, the maximum participation level of customers in DR programs is considered 20%. 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 values of self and cross price-demand elasticity are extracted from [23].

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 as it can be seen in Table I.

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 objective of the electricity market. However, a trade-off between economic and market power objectives is studied in case 2, where SWALI is considered in the objective function.

In the first case, W_{OC} and W_{SWALI} coefficients are set to be 1 and 0, respectively. Operation costs for the different DRPs sets are presented in Table II.

It can be observed from 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. Moreover, the start-up cost of generating units is relatively diminished after DR implementation which can potentially decrease the maintenance cost of generating units and increase their expected lifetime.

TABLE I. THE PORTFOLIO OF DRPs

Set	DRPs	Electricity price (\$/MWh)	Incentive (\$/MWh)	Penalty (\$/MWh)
Base case	Initial load	15 flat rate	-	-
1	TOU	7.5 at low-load, 15 at off-peak, 30 at peak	-	-
	RTP	Obtaining from market transactions	-	-
	CPP	60 at hours 18 and 19	-	-
2	EDRP	15 flat rate	10	-
	I/C	15 flat rate	7.5	5
3	TOU+EDRP	7.5 at low-load, 15 at off-peak, 30 at peak	10	-
	TOU+I/C	7.5 at low-load, 15 at off-peak, 30 at peak	7.5	5

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**
Start-up cost ($)	3691	2803	2803	2803	2803	2803	2891	2803
Fuel cost ($)	466800	432270	449040	432060	436250	428530	414020	408500
Reserve cost ($)	22960	23205	23144	23256	23223	23360	23320	23343
Incentive cost ($)	0	0	0	0	21124	19784	15866	19844
Penalty cost ($)	0	0	0	0	0	-6621	0	-3166
Operation cost ($)	493451	458278	474987	458119	483401	467855	456097	451323

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 ISO's point of view, i.e., (21).

In the second case, W_{OC} and W_{SWALI} coefficients are assumed to be 0.5 and 0.5, respectively to include both cost and market power in the objective function with a similar weight. The optimal values of operation cost and SWALI are reported for different scenarios in Table III. According to the results in Table III, the operation costs as well as SWALI are reduced as a result of DR implementation. In the first set, the minimum values of operation cost (527,107$) and SWALI (0.52) are related to ToU.

The same procedure can also be applied for DRPs of the second and the third sets. Since determination of the most efficient DRP is crucial from the regulatory body's viewpoint, this paper utilizes SSI coefficient to compare the performance of DRP portfolios in market power mitigation. On this basis, the predefined DRP portfolios are prioritized in different case studies as presented in Table IV.

It is noteworthy that, here, the operating cost and the market power index are considered as the attributes. In addition, the different DRPs of Table I are considered as the alternatives. As can be seen in Table IV, the highest priority has been achieved by simultaneously implementing ToU and I/C programs. It seems reasonable due to the fact that, ToU is an obligatory DRP implemented by ISO, so that the customers do not have any choice about it.

TABLE III. COMPARISON OF DIFFERENT DR PORTFOLIOS IN CASE 2

Set	DRP	Operation Cost ($)	SWALI
Base-case	-	599,810	0.58
1	ToU	527,107	0.52
	RTP	542,122	0.56
	CPP	531,730	0.54
2	EDRP	558,109	0.55
	I/C	523,064	0.51
3	ToU+EDRP	537,022	0.49
	ToU+I/C	511,671	0.46

TABLE IV. PRIORITIZING OF DRPS PORTFOLIO

Case 1 Operation cost		**Case 2** Operation cost – Market Power	
DRP	SSI (%)	DRP	SSI (%)
ToU+I/C	100	ToU+I/C	100
ToU+EDRP	99.11	ToU+EDRP	99.73
CPP	98.54	I/C	97.12
ToU	98.10	ToU	96.61
I/C	96.41	CPP	94.52
RTP	95.38	EDRP	94.49
EDRP	94.14	RTP	93.78
Base-case	91.01	Base-case	89.32

Moreover, I/C program also have 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 ISO perspective. 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 market power. It is also obvious that implementing incentive-based DRPs is not pleasant for the ISO because implementation of these programs impose additional costs to ISO.

V. CONCLUSIONS

In this paper, an agent-based model was proposed to improve the market efficiency by using different DRPs. On this basis, different DRPs were investigated to find the optimal tariffs of price-based programs as well as the incentive rate of EDRP. Different electricity market indices were employed to evaluate the market power by using the MADM approach. Several numerical studies were carried out to show the effectiveness of the proposed model. On this basis, the impact of different types of DRPs on the considered indices was investigated. Furthermore, a comprehensive DRP portfolio was designed using the price-demand elasticity concept.

The results showed that the market operator could mitigate the potential occurrence of market power in a power system by finding an optimal DRP. The results revealed that, before implementing the programs, using the proposed model could significantly enhance the market efficiency and mitigate market power. Moreover, the results showed that applying combinational DRPs including both price-based and incentive-based are more efficient when regulatory body considers both economic and market power targets.

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