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Demand Response Based Operation Model in Electricity Markets with High Wind Power Penetration

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***Abstract*—The issue of climate change has received considerable attention in recent decades. Therefore, renewable energies and especially wind units have become a central point of attention. The stochastic nature of wind power production is modeled by means of a scenario-based method to show the possible events in the real-time. Based on the Monte-Carlo Simulation (MCS) method and employing constructed Rayleigh probability distribution function (PDF), several scenarios that demonstrate the behavior of wind farms in real time are generated. To this end, a uniform random variable is generated and assigned to the mentioned PDF. Afterwards, a wind speed with a probability is achieved followed by the amount of wind power generation. Also, with a scenario reduction method (forward method), the desired number of scenarios can be obtained. To cope with the uncertainties of wind power generation, resulting from the intermittent nature of this kind of energy, this paper proposes a Demand Response (DR) based operation approach. In other words, unlike the previous models in the literature that considered a supplementary role for the DR, this paper introduces the main role for the DR in the operation of future electricity markets. This approach focuses on a comprehensive modeling of the Demand Response Programs (DRPs) for the operational scheduling of electricity markets, considering the uncertainties of the generation of wind turbines, aiming at increasing the network security and decreasing the operation cost. The incorporation of market-based DRPs such as Demand Bidding (DB) and Ancillary Service Demand Response (ASDR) is also considered. Two novel quantitative indices are introduced to analyze the success of DRPs regarding efficiency and wind integration. Numerical results obtained on two IEEE test systems indicate the effectiveness of the proposed model.**

***Index Terms*—Demand response, DR-based operation model, electricity market, quantitative index, renewable energy, stochastic programming.**

NOMENCLATURE

A. Sets and Indices

b, b' (NB)	Index (set) of system buses.
d (ND)	Index (set) of stepwise demand bidding.
K(NK)	Index (set) of stepwise for ASDR.
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.
w (NW)	Index (set) of wind scenario.
wf (WF)	Index (set) of wind farm.

B. Parameters

A_t	Incentive payments to customers at hour t [\$/MWh].
$AS_{m,t}$	Slope of segment m in linearized total incentive curve in hour t [MWh].
$C_{i,m}^{G\_Eng}$	Slope of cost function for unit i in segment m of the piece-wise linear cost function [\$/MWh].
$C_{i,t}^{G\_DC}$	Down-reserve offered price of unit i at hour t [\$/MWh].
$C_{i,t}^{G\_UC}$	Up-reserve offered price of unit i at hour t [\$/MWh].
$C_{i,t}^{G\_DE}$	Offered price for down-employed reserves of unit i at hour t [\$/MWh].
$C_{i,t}^{G\_UE}$	Offered price for up-employed reserves of unit i at hour t [\$/MWh].
$F_{b,b'}^{\max}$	Maximum capacity of branch between buses b and b' [MVA].
MDT_i	Minimum down-time of unit i [h].
MUT_i	Minimum up-time of unit i [h].
MPC_i	Minimum production cost (no-load cost) of unit i [\$].
$P_i^{\max}, P_i^{\min}$	Maximum/minimum capacity of unit i [MW].
Pl_t	Value of loss of load at hour t [\$/MWh].
RU_i	Ramp-up of unit i [MW/h].
RD_i	Ramp-down of unit i [MW/h].
SC_i	Startup cost of unit i [\$/each switching].
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' [Ω].
ρ^0	Initial electricity price [\$/MWh].
ρ_w	Probability of wind power scenario w.

C. Variables

C^{EDRP}	Cost of customer's participation in EDRP [\$].
$F_{b,b',t}^0$	Expected power flow of line l at hour t [MVA].
$F_{b,b',w,t}$	Power flow of line l at hour t in scenario w [MVA].
$LShed_{b,t,w}$	Load shedding of bus b at hour t in scenario w [MWh].
$P_{i,t,m}^e$	Power of unit i at hour t in segment m of the piece-wise linear cost function [MWh].
$P_{wf,t}^{WP,S}$	Scheduled generation of wind farm wf at hour t for day-ahead market [MWh].
$P_{wf,t}^{WP,\max}$	Expected wind generation of wind farm wf at hour t [MWh].
$P_{wf,w,t}^{W}$	Realized wind generation of wind farm wf at hour t in scenario w [MWh].
$r_{i,t,w}^{G\_dn}$	Real-time down-used reserves of unit i at hour t in scenario w [MWh].
$r_{i,t,w}^{G\_up}$	Real-time up-used reserves of unit i at hour t in scenario w [MWh].
$R_{i,t}^{G\_DC}$	Scheduled down-reserve of unit i at hour t [MWh].
$R_{i,t}^{G\_UC}$	Scheduled up-reserve of unit i at hour t [MWh].
$SUC_{i,t}$	Startup cost of unit i at hour t [\$].
$U_{i,t}$	Binary status indicator of unit i at hour t.
$\delta_{b,t}^0$	Expected voltage angle of bus b at hour t [rad].
$\delta_{b,w,t}$	Voltage angle of bus b at hour t in scenario w [rad].
$\upsilon_{m,t}$	Award of segment m in linearized total incentive curve in hour t [\$/MWh].

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I. INTRODUCTION

A. Motivations

RENEWABLE energies are boosting substantially to resolve the environmental issues such as the global emission of carbon dioxide and the high consumption of fossil fuels [1]. However, the balancing between supply and demand in power system runs into one of the serious and major difficulties due to expanding renewable energies. Demand Response Programs (DRPs) are a worthy and suitable choice to cope with the intermittent nature of renewable energies [2]. This paper proposes a Demand Response (DR) based operation model of the electricity market considering various types of DRPs, such as Demand Bidding (DB), which is one of the most efficient mechanisms to smooth the demand side curve and to compensate the renewable energy fluctuations in the power system [3], [4].

B. Literature Review

In [1], the offering strategy of a wind power producer is studied in the presence of DR, while, the objective function is to maximize the profit of the wind power unit. In [2], the role of retailing entity in the wholesale and retail markets is modeled. A robust DC optimal power flow has been presented in [5] for power systems with high penetration of wind power which is able to mitigate the potential variability of wind generation. In [6], a self-decision making method has been developed for load management using the multi-agent system considering distributed generation and DR resources. The location and capacity of renewable generations and electric vehicle charging stations are simultaneously determined using a multi-objective model in [7]. The implementation of DRPs in a power system considering renewable energy is proposed in [8] and [9] to illustrate the need for these kinds of economic models of responsive loads to provide protection against an inflexible load profile. Nevertheless, these references only focused on one DR program. The Incentive-Based Demand Response (IBDR) model is introduced and utilized in [8] while the Real-Time Pricing (RTP) model is presented and used in [9]. On the contrary, both categories of DRPs are formulated in this paper.

In [10] and [11], a planning tool has been presented to determine the optimal location and size of Renewable Energy Resources (RERs) and Energy Storage Systems (ESS) under Price-Based Demand Response (PBDR) programs. Also, the impacts of DR and ESS on social welfare are analyzed in [10] and [11]. Moreover, a robust optimization scheduling framework to derive an optimal unit commitment decision in systems with high penetration of wind power incorporating DRPs as well as bulk ESS in co-optimized energy and reserve markets has been proposed in [12]. In [13], a two-stage Stochastic Programming (SP) approach is introduced for optimal day-ahead power procurement with RER and DR. In [13], the authors focus on reducing the energy cost in demand side. In [14], a bi-level distribution expansion planning model considering RERs and a time-varying DR model is presented. In [15], the concept of online DR is used to minimize the operational cost and two online DR strategies have been introduced to minimize the operation cost considering non-deferrable loads. In [16], a stochastic Security Constrained Unit Commitment (SCUC) is presented considering DRPs under the uncertainty of wind power productions. In [17], the new Demand Response eXchange (DRX) market is employed to help the operation of energy market in the presence of RERs. The authors of [18] have focused on the minimization of end-users electricity bills and maximization of their satisfaction, enabling the problem to become a convex problem. To obtain the optimal results. To motivate the customers to be responsive to price changes, financial incentives are considered in [19]. This publication also employed smart appliances for load shifting to increase the participation of customers in DRPs. The day-ahead electricity market condition would be more complicated in the presence of renewable generation and DRPs.

C. Aims and Contributions

Although many research works have studied the operation of power systems in the presence of DR and renewable resources, a DR-based operation of energy and reserve markets in the wind integrated systems has not been addressed. In other words, the previous works in the literature have focused on the supplementary role for DR in the energy and reserve markets, while this paper aims at introducing the main role for DR in the operation of future electricity markets. Particularly, the presented models of ISO in the literature do not consider that some DR programs such as Time-of-Use (TOU) and Critical Peak Pricing (CPP) should be designed for a day-ahead market, while some other DR programs such as ancillary service demand response (ASDR) should be provided for real-time markets. This important issue has not been addressed in the models of ISO in the presence of DR; hence, in those models, DR programs have not been categorized in terms of the market session. Therefore, in those ISO's models, different DR programs have not been placed in a multi-stage model. The contribution of this work is not only to include all possible DR programs in a comprehensive model, but also to design the model to consider the inherent feature of each DR program in terms of the market session.

To this end, a comprehensive model including various types of DRPs is developed for the operational scheduling of electricity markets, considering the uncertainties of the generation of wind turbines through a two-stage SP model. The proposed DR-based operation approach aims at increasing the network security and decreasing the operation cost. Unlike the previous works, the incorporation of market-based DRPs such as Demand Bidding (DB) and ASDR is considered in the proposed model to enhance the substantial role of active customers in the power exchanges of the electricity markets. In order to quantify the effectiveness of the proposed approach, two new indices have also been proposed.

The contributions of this paper can be summarized as follows.

- Developing a DR-based operation model in the electricity markets with high penetration of RERs.
- Proposing a comprehensive operation model to incorporate different types of DRPs including DB and ASDR in day-ahead and real-time market sessions.
- Introducing two new indices to quantify the impact of DR on the wind integrated power systems.

D. Paper Organization

The remainder of the current paper is structured as follows. The proposed model is introduced in Section II, and its mathematical equations and constraints in Section III. Novel indices for calculating the value of the implemented DR programs with wind integration are introduced in Section IV. The numerical results of the model are presented in Section V, and the final section is the conclusion.

II. MODELING OF THE PROBLEM

In this paper, both priced-based and incentive-based categories are considered as DR programs. The colored boxes in Fig. 1 [20] refer to the DR programs included in the proposed model.

A. PBDRs model

Economists believe that informing consumers from real electricity prices will increase efficiency [21]. 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. It should be mentioned that the considered electricity market is based on the uniform pricing due to two main reasons. Firstly, most of the well-known electricity markets such as PJM, NYISO, ISO-NE and MISO have uniform price auctions. Secondly, it has been proven that the uniform price auctions achieve the most efficient results in both the short run and long run [22]. As indicated in Fig. 1, PBDR programs in this paper include TOU, 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. More details about these DR programs can be found in [23]. The amount of demand-side consumption related to customers participating in PBDR programs in a day-ahead market is given in (1) [23].

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

where d_t^0 and d_t are the electricity demand before and after applying the PBDR program; $\rho_{t'}^0$ and $\rho_{t'}$ are the electricity tariffs before and after applying the PBDR program; $E_{t,t'}$ represents the elasticity of demand pertaining to hours t and t'. It should be noted that the elasticity of demand can be calculated by various methods based on the analysis of real data and customers' surveys [24]. Equation (1) presents an exhaustive PBDR model based on the "self-elasticity" and "cross-elasticity" concepts of demand to model a plunge in load through the participation of customers in price-based DRPs [23]. Note that, the load reduction and load recovery processes in DRPs implementation have been modeled through price elasticity of demand concept, simultaneously.

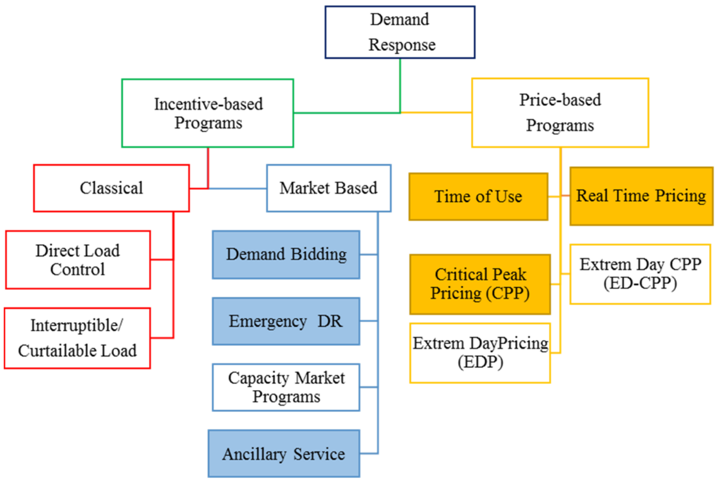

Fig. 1. The highlighted boxes refer to our model DRPs implemented to cover the uncertainty of wind power generation.

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 [23]. 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 in the relevant time. In these programs, a series of incentives is 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) [25].

The IBDRs in this paper include DB, ASDR, and Emergency Demand Response Program (EDRP). In the DR method (also called Buyback), the major customers submit a load reduction bid to the ISO. If the bid is accepted after-market clearing, the customer will be obliged to execute the contract; otherwise, penalties will be imposed. 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.

1) EDRP Model

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 [23]:

$$d_t = d_t^0 \left\{ 1 + \sum_{t'=1}^{24} E_{t,t'} \frac{A_{t'}}{\rho_{t'}^0} \right\} \tag{2}$$

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.

$$C_t^{EDRP} = A_t (d_t^0 - d_t) \tag{3}$$

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):

$$C_t^{EDRP} = -d_t^0 \left\{ \sum_{t'=1}^{24} E_{t,t'} \frac{A_{t'}^2}{\rho_{t'}^0} \right\} \tag{4}$$

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

$$C_t^{EDRP} = \sum_{m=1}^{NM} \upsilon_{m,t} \, AS_{m,t} \tag{5}$$

2) ASDR Model

The ASDR model works as a reserve source. The customer can submit a bid for load curtailment to the ISO as an operating reserve, and if accepted, ISO will pay the customer for committing as a standby reserve capacity.

If the costumer's reserve capacity is needed, the ISO calls them with the spot market price.

The ASDR model is shown in Fig. 2 as a stepwise curve at bus *b* at hour *t* as given in (6).

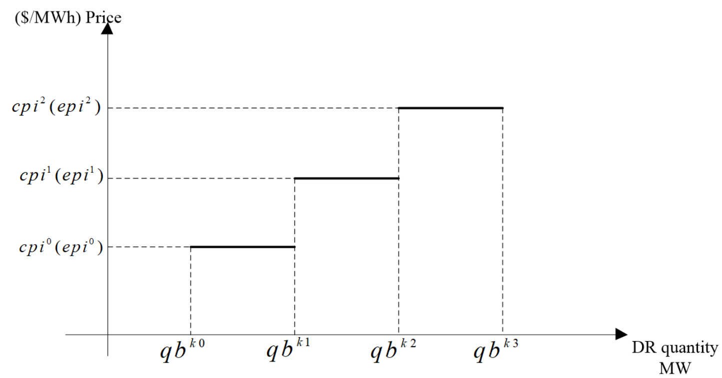

Fig. 2. ASDR demand price.

$$ASDR_{t,b} = qb_{t,b}^0 u_{t,b}^0 + \sum_{k=1}^{K} \lambda d_{t,b}^k u_{t,b}^k \tag{6-a}$$

$$C_{t,b}^{ASDR} = cpi_{t,b}^0 qb_{t,b}^0 u_{t,b}^0 + \sum_{k=1}^{K} cpi_{t,b}^k \lambda d_{t,b}^k u_{t,b}^k \tag{6-b}$$

$$\lambda d_{t,b}^k = qb_{t,b}^k - qb_{t,b}^{k-1} \tag{6-c}$$

In this model, $qb_{b,t}^k$ and $cpi_{t,b}^k$ denotes the DR quantity and DR price respectively at bus *b* at hour *t* in block *k*; $\lambda d_{t,b}^k$ denotes the difference between the DR quantity in two adjacent blocks; and $u_{t,b}^k$ is a binary variable indicating the selection status of each block by the program. $ASDR_{t,b}$ is total amount of DR reserve in day-ahead market and $C_{t,b}^{ASDR}$ is the capacity cost of ASDR deployment in day-ahead market.

3) DB model

The bidding strategy in DRPs could have the same formulation as in day-ahead and real-time markets. In the day-ahead market, participants in these DRPs can bid the amount of energy reduction on the preceding day and can be involved in optimum operational planning. If their bids are accepted in this market, the participants are obliged to reduce their daily consumption. If they do not reduce their consumption, they will be charged by heavy penalties. A similar DB program is running in the New York Independent System Operator (NYISO). In another approach, the participants are asked to reduce their consumption, and if they drop their electricity usage, they will be paid at the market clearing price as in the model used in NYISO [26]. In the DB method, customers identify how much and at what price they would like to curtail their load. To deal with the DB program, a new modeling technique is proposed in this paper. In fact,

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in this model, customers submit bids for the desired demand to be served and accordingly the ISO will decide how much load should not be served. Based on this, the formulation below is introduced to deal with the DB.

$$Demand\ bidding = \sum_{t=1}^{NT}\sum_{b=1}^{NB}\sum_{d=1}^{ND}(Bid_{b,t,d} Loadsch_{b,t,d}) \tag{7}$$

where $Bid_{b,t,d}$ is a parameter which indicates proposed price steps (d) for demand by customers and $Loadsch_{b,t,d}$ is a variable which represents the accepted amount of demand for each step by ISO. $Bid_{b,t}$ has a stepwise curve which dedicates, for example, 4 price steps for demand. Based on the proposed price steps, $Loadsch_{b,t,d}$ is scheduled in the program for the accepted amount of load that should be supplied at each bus and hour. Meanwhile, $Loadsch_{b,t,d}$ should be lower than a percentage of total forecasted loads. Additionally, $DisL_{b,t}$ is the summation of load steps, which should be lower than total forecasted load demand. The bidding mechanism for customers in this method is illustrated in Fig. 3. The unserved load in the proposed DB model is calculated through (8):

$$\sum_{d=1}^{ND}(Loadsch_{b,t,d}) = L_{b,t} - DBP_{b,t} \quad \forall t, b \in NJ_b \tag{8}$$

where $DBP_{b,t}$ indicates the loads that are not supplied at bus b and hour t based on the price that customers proposed for their loads. $L_{b,t}$ denotes the load at bus b and hour t.

The customers' bidding is effective on choosing which hours customers should be supplied or curtailed. In other words, customers' bidding in peak hours and off-peak hours determines that some consumptions in peak hours should be shifted and covered in off-peak hours to reduce the operation cost.

It should be noted that there are several obstacles that prevent full DR implementation in real-life. The main obstacles to effective DR implementation are recognized to be the inelasticity of demand and low level of participation due to asymmetries in information. In addition, slow deployment of the technical infrastructures, such as smart metering and required telecommunication platforms, is another difficulty in full DR implementation.

III. Mathematical Equations and Formulation

In the proposed model, the objective function maximizes the Social Welfare (SW) which is the customers' surplus minus the suppliers' cost (presented in (9)), subject to relative constraints from the ISO's point of view.

$$\begin{aligned}
&Maximize\ SW = \\
&\underbrace{\sum_{t=1}^{NT}\sum_{b=1}^{NB}(Bid_{b,t} DisL_{b,t})}_{\text{Customer surplus}} - \Bigg\{ \sum_{t=1}^{NT}\sum_{i=1}^{NG}\underbrace{\left(SUC_{i,t} + MPC_i U_{i,t} + \sum_{m=1}^{NM}(P^{e}_{i,t,m} C^{G_Eng}_{i,m})\right)}_{\text{Thermal unit generation cost}} \\
&+\sum_{t=1}^{NT}\sum_{i=1}^{NG}\left(\underbrace{C^{G_UC}_{i,t} R^{G_UC}_{i,t}}_{\text{Scheduled up reserve cost}} + \underbrace{C^{G_DC}_{i,t} R^{G_DC}_{i,t}}_{\text{Scheduled down reserve cost}}\right) \\
&+\sum_{t=1}^{NT}\sum_{b=1}^{NB}\underbrace{C^{ASDR}_{b,t}}_{\text{ASDR cost}} + \sum_{t=1}^{NT}\underbrace{C^{EDRP}_{t}}_{\text{EDRP cost}} \\
&+\sum_{t=1}^{NT}\sum_{w=1}^{NW}\rho_w \Bigg(\sum_{i=1}^{NG}\Big(\underbrace{C^{G_UE}_{i,t} r^{G_up}_{i,t,w}}_{\text{Deployed up reserve cost}} - \underbrace{C^{G_DE}_{i,t} r^{G_dn}_{i,t,w}}_{\text{Deployed down reserve cost}} \Big) \\
&+\sum_{b=1}^{NB}\underbrace{E^{ASDR}_{t,w,b}}_{\text{ASDR cost}} + \underbrace{(Pl_t\, LShed_{t,w,b})}_{\text{Load shedding cost}} \Bigg) \Bigg\}
\end{aligned} \tag{9}$$

Indeed, in (9), the first term is the customers' surplus declared by the demand bidding and all other parts are the operation cost presented by the two-stage stochastic model. In the two-stage stochastic model, the first stage represents the day-ahead session and the second stage represents the real-time session. The schematic diagram of the proposed strategy is illustrated in Fig 4. In fact, a conceptual diagram besides an appropriate flowchart to state the solution method and decision variables are presented in Fig. 4.

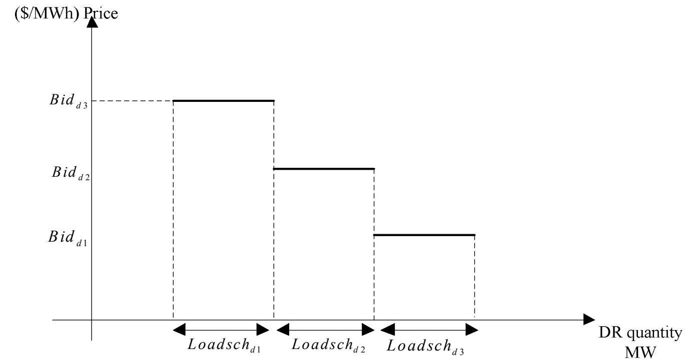
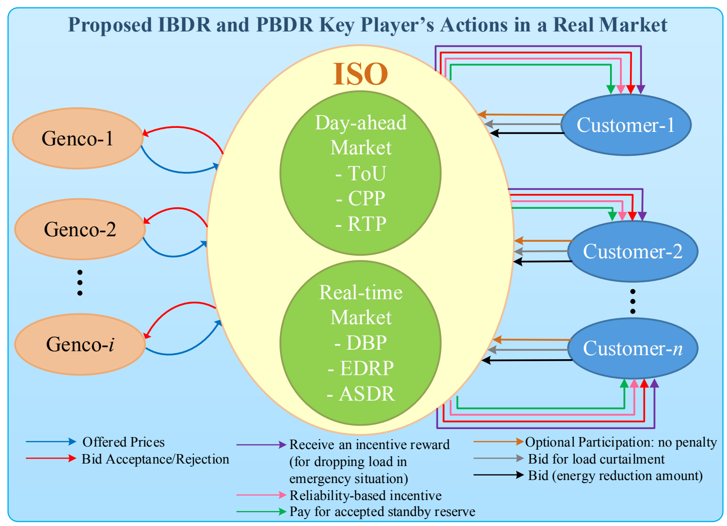
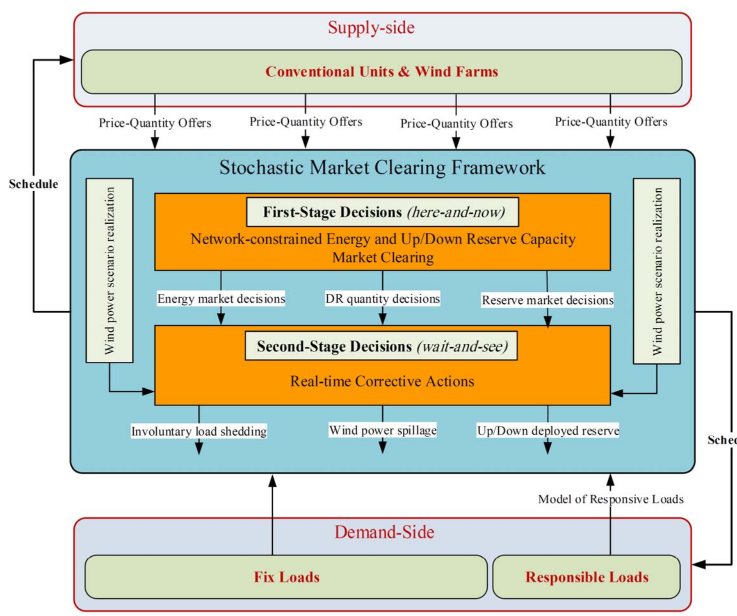


Fig. 3. Demand bidding curve.



(a) Conceptual diagram



(b) Solution method flowchart

Fig. 4. Schematic diagram of the proposed strategy.

In (9), the first summation represents the total surplus for customers for serving their loads by ISO. In fact, the operators decide which load bids should be selected by proposed prices. In this program, $Bid_{b,t}$ is fixed and $DisL_{b,t}$ is decision variable. The second summation is the generation cost of thermal units.

Decision variables of the second summation are $SUC_{i,t}$, $U_{i,t}$ and $P^{e}_{i,t,m}$. The offered prices of units for up/down reserve capacities are given in the third summation of (9) where $R^{G\_UC}_{i,t}$ and $R^{G\_DC}_{i,t}$ are decision variables. The fourth summation is related to the capacity cost of ASDR deployment in day-ahead market which is variable and obtained from (6-b). The fifth summation corresponds to EDRP cost which is a decision variable and obtained from (5). The sixth summation is associated with the scenarios consideration which includes prices relative to the pre-planned delivered up/down reserves through generating units, energy cost of ASDR deployment in balancing market, and load shedding cost. In this summation, decision variables include $r^{G\_up}_{i,t,w}$, $r^{G\_dn}_{i,t,w}$, $E^{ASDR}_{t,w,b}$ and $LShed_{t,w,b}$. The objective function is maximized subject to the following equality and inequality constraints.

A. Day-ahead equations

The balance between demand and supply is guaranteed through (10). The branch flow based on DC network modeling is given in (11). Besides, branch flow limitations are formulated in (12). The scheduled generations of wind farms in day-ahead market are limited between zero and their expected available generations in (13). Equation (14) represents the power of a thermal unit based on the powers of the segments of the linearized cost function.

$$\sum_{i\in NG_b} P_{i,t} + \sum_{wf\in WF_b} P^{WP,S}_{wf,t} - \sum_{j\in NJ_b} L_{j,t} = \sum_{b,b'\in NB} F^{0}_{b,b',t} \quad \forall b,t \tag{10}$$

$$F^{0}_{b,b',t} = \left(\delta^{0}_{b,t} - \delta^{0}_{b',t}\right) / X_{b,b'} \quad \forall (b,b'),t \tag{11}$$

$$-F^{\max}_{b,b'} \le F^{0}_{b,b',t} \le F^{\max}_{b,b'} \quad \forall (b,b'),t \tag{12}$$

$$0 \le P^{WP,S}_{wf,t} \le P^{WP,\max}_{wf,t} \quad \forall wf,t \tag{13}$$

$$P_{i,t} = \sum_{m=1}^{NM} P^{e}_{i,t,m},\ 0 \le P^{e}_{i,t,m} \le P^{\max}_{i,m} \quad \forall i,t \tag{14}$$

The rest of day-ahead constraints are presented in Appendix.

B. Real-time equations

The second-stage constraints pertaining to the scenarios are presented in this section. In this paper, since there are wind generators, the uncertain nature of their generations has been modeled through a scenario-based method to represent the possible events in the real-time operation. Wind speed profile in one area is conformed approximately to the Rayleigh PDF [27]. The parameters of the relative PDF would be calculated from processing of the given historical data [28], [29]. To convert wind speed to electric power a linear equation extracted from [29] is employed. Using MCS and constructed Rayleigh PDF, a sufficient number of scenarios are generated. Afterward, through applying a scenario reduction method (forward method), the desired amount of scenarios can be obtained. Constraints and equations for ASDR in the second stage are indicated in the equations (15) where $epi^{k}_{t,b}$ is the energy price for each DR block and $uk^{k}_{t,b}$ is the selection state of each block by the program in the second stage. $E^{ASDR}_{t,w,b}$ is the energy cost of ASDR and $asdr_{t,b,w}$ is the total amount of ASDR, both in the real-time market.

$$0 \le asdr_{t,b,w} \le ASDR_{t,b} \tag{15-a}$$

$$asdr_{t,b,w} = qb^{0}_{t,b} uk^{0}_{t,b,w} + \sum_{k=1}^{K} \lambda d^{k}_{t,b} uk^{k}_{t,b,w} \tag{15-b}$$

$$E^{ASDR}_{t,w,b} = epi^{0}_{t,b} qb^{0}_{t,b} uk^{0}_{t,b,w} + \sum_{k=1}^{K} epi^{k}_{t,b} \lambda d^{k}_{t,b} uk^{k}_{t,b,w} \tag{15-c}$$

The rest of real-time constraints are presented in Appendix.

IV. The Proposed Indices

Uncertainties are the key elements that can affect the expected schedules and system regulation. To verify the implemented model and investigate the impacts of different DR programs on promoting grid integration of wind power, this paper introduces some novel metrics and measures based on load changes. To represent the impact of DRPs, the rate of wind generation is considered constant in its total power production capacity while different kinds of DRPs are implemented. The average Demand Response Program Benefit (DRPB) shows how much the social welfare increases due to participation of 1 MW load in a specific DR program. For an ISO that aims at maximizing the social welfare, it is very important to know the value of this index, since it can be a good measure of the effectiveness of different DR programs and consequently to make a decision on the investment in the useful DR programs.

The results are illustrated in the following section. This index illustrates a more useful program to overcome the uncertainty of the wind. The index is represented by (16).

$$DRPB = \frac{1}{24}\sum_{t=1}^{24} \frac{SW^{DR}_{t} - SW^{NoDR}_{t}}{MAX^{DR} \times Load_{t}} \tag{16}$$

where MAX^{DR} is the percentage of consumers who are responsive demand and in this current paper it is assumed to be 20%.

It is noteworthy that besides implementation of DR, there are many other options for an ISO to improve the system social welfare, such as making new rules and regulations, changing the market structure and adding new market players. On this basis, the ISO must select the best option among the different options; hence, a measure to reveal the effectiveness of DR implementation is crucial.

Load changes resulting from the implementation of DR programs critically affect wind power activities; thus, introducing an index is necessary to investigate the effect of different DR programs on the grid integration of wind power. This index, which is called Demand Response Benefits for Social Welfare (DRSW), indicates the impact of the proposed DR scheduling model on social welfare in the presence of wind power generation. In other words, it presents an increase in social welfare as a result of the integration of 1 MWh of extra wind power. In fact, the DRSW index is introduced to measure the effectiveness of implementing a specific DR program as a result of the injection of an extra 1 MW wind power on the average increase of social welfare. This index is formulated by (17).

$$DRSW = \frac{1}{24}\sum_{t=1}^{24} \frac{SW^{DR}_{t} - SW^{NoDR}_{t}}{\sum_{w} \rho_{w} . P^{W}_{wf,w,t}} \tag{17}$$

DRSW is created to analyze the impact on the social welfare as a result of the penetration of wind units when implementing a variety range of DRPs when the amount of power generated by the system is increased by the injection of an additional 1 MWh of wind power. In the numerical result section, the effect of the different percentages of wind penetration associated with the wide range of variant DRPs is investigated. In the next section, the quoted indices are employed to evaluate the results more accurately and precisely.

The main purpose of this paper is to investigate the impact of the variety of IBDR and PBDR programs in a market-based power system in detail through an SCUC. To comprehensively assess the model, it is implemented on two different power systems, and the results are illustrated and discussed. Numerical results have been obtained to demonstrate the abilities of the presented model.

V. Results and Discussions

In this paper, two case studies are taken into account. In case study 1, IEEE 6-bus test system is used to analyze the proposed model, while in case study 2, more investigations are carried out by using the IEEE 14-bus test system. All the case studies have been solved using CPLEX solver 12.5.0 under General Algebraic Modeling System (GAMS) software. It is notable that, as our model is an MILP optimization, the CPLEX is a good choice for solving the large-scale MILP problems.

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A. Case Study 1

1) Data Sets

The proposed model and indices formulations have been tested on the IEEE six-bus test system, with the presence of wind units.

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. 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 the 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 based on [23], [30].

2) Numerical Results

To explore the impacts of different types of DR programs on the behavior of market players, Figs. 5 and 6 respectively illustrate the influence of the implementation of DRP variants on the prices offered by Genco 1 in comparison with the effect of implementation of the same DRPs on Genco 1's offered prices in the presence of wind units. As can be seen, different types of DRPs lead to differences in the prices offered by Genco 1 to the power system associated with the renewable energy. The presence of renewable energy in the electricity system has a profound effect on the prices offered by Genco 1, particularly during peak hours. On this basis, the offers of Genco 1 in the CPP-1 program in both cases are lower in the peak period compared to the other programs, but the presence of wind units causes the prices to plunge dramatically during peak hours. The reason for the lower amount of demand in this period is the injection of wind production into the power system. In fact, the impacts of different types of DRPs on bids submitted by Genco 1 with and without the presence of wind farm units are compared. According to Fig. 6, the prices offered by Genco 1 are affected by the load shift that arises from four types of DRPs tariffs in the presence of wind units. On this basis, the injection of wind electric power brings the prices down. Implementation of these four DRPs' tariffs while taking into account the role of the wind power plants leads to a sharp drop in prices during peak hours specifically through the CPP program. From the perspective of clustering the DRPs, the implementation of the IBDR program, as shown in Fig. 6, leads to the same great effect but with more considerable and beneficial changes in the PBDR programs in the presence of wind units. Besides, a far-reaching reform in the curve and chart is depicted in Fig. 6.

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

Fig. 7 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. 7, the application of different types of DRPs brings down the load curve of customers on the demand side. It can be found in Fig. 7 that the CPP-1 has the most impact on the curve. TOU-1 and EDRP have the second and third largest impacts, respectively.

As it can be observed in Fig. 7, the CPP-1 has a significant impact on peak reduction whilst the TOU-1 mainly has led to load shifting from peak to valley period. For instance, CPP-1 and TOU-1 reduce the total daily energy consumption by 8.2% and 2.8%, separately.

The impacts of different kinds of TOU programs on the efficiency of the energy market are presented in Figs. 8 and 9. These figures depict the market clearing price of the power system without and with the presence of wind farm units, respectively. These results demonstrate that the variant tariffs of the TOU program in the presence of wind farm units can have a greater influence on pushing down the market clearing prices principally in the peak period. Fig. 9 shows the significant impact of TOU programs on the electricity market prices in the peak period, because of the decrease in the prices offered by the Gencos in the system while considering the role of wind power plants.

Note that the presence of wind generation in the generation mixture can reduce the maximum market clearing price at peak hour (18:00), significantly. For instance, the market clearing price without the presence of wind generation at 18:00 in the base case is 82 $/MWh, whilst it will be reduced by wind integration to 73$/MWh in a similar case study.

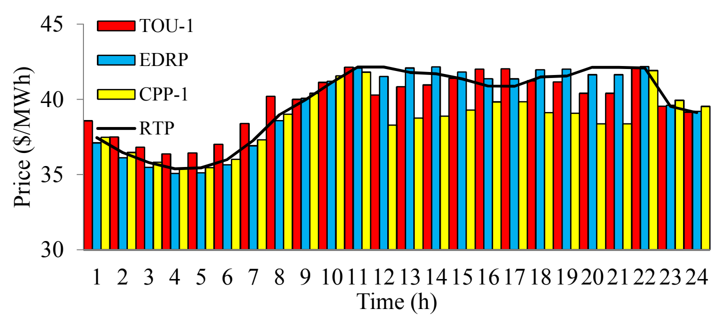

Fig. 5. The impact of different types of DR programs on the offers of Genco 1 without the presence of wind farm.

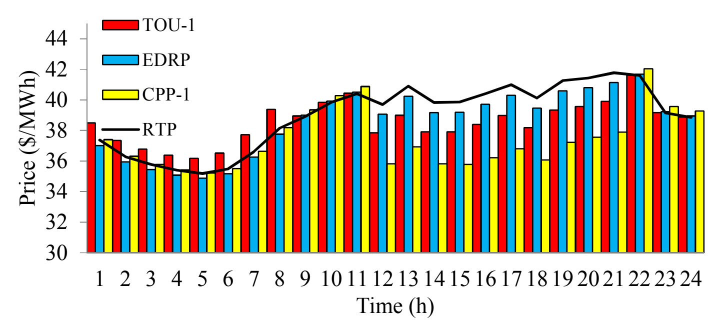

Fig. 6. The impact of different types of DR programs on the offers of Genco 1 with the presence of wind farm.

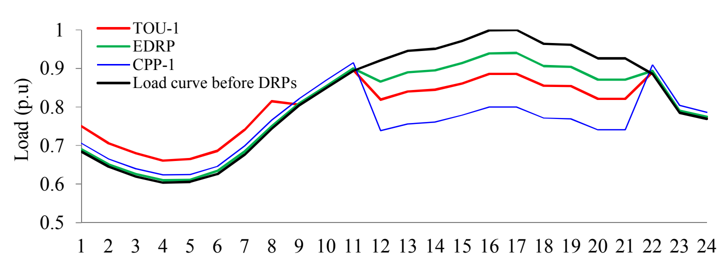

Fig. 7. The impact of different types of DR programs after implementation on the final load curve.

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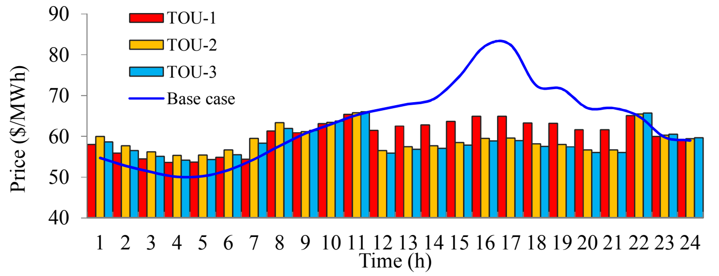

Fig. 8. The impact of different types of DR programs on the market clearing price without the presence of wind farm.

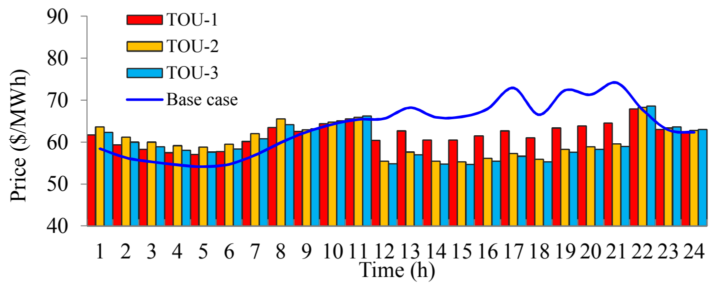

Fig. 9. The impact of different types of DR programs on the market clearing price with the presence of wind farm.

As depicted in Fig. 9, the presence of renewable energy smoothed the base case price curve and shifted it downwards.

By comparing Figs. 8 and 9, it can be found that there is no crucial difference between the implementation of TOU2 and TOU3 on the clearing price of the market.

In the following, the variant DRPs have been compared by employing the proposed indices. Fig. 10 illustrates the impact of the varied amount of wind production along with the implementation of various DRPs tariffs. As can be observed, the more substantial the percentage of wind power production, the higher the DRSW index for all kinds of DRPs, in general. With the same amount of wind power in the power system, the DRSW index indicates that EDRP has the most profound effect on the efficiency of the market. Implementing the EDRP program with the same rate of wind power can have more influence on reducing the system operation cost. Similarly, TOU1 is one of the most effective DRPs. Furthermore, CPP1 and TOU2 have approximately identical impacts on the social welfare of power systems associated with renewable units. In Fig. 11, the second type of CPP program has the highest DRPB. Hence the program has the most effect on increasing the social welfare with a constant rate of wind power generation. The TOU3 program is followed by TOU2, and then TOU1 to have the higher DRPB index. The DRPB index illustrates that the EDRP program has the least impact on driving down the market price or pushing up the social welfare with a constant rate of the wind power generation compared with other DRPs. The other DR resources can be considered in future works.

B. Case Study 2

1) Data Sets

The 14-bus IEEE power system is used as a second case study to investigate the ASDR and DB. The slack bus of the system is Node 1. Two wind farms are connected to the power system at Node 5 and Node 8. The capacity of each one is equal to 100 MW. Here are several scenarios that each trajectory is the sum of power production of two nodes. Accordingly, three states are considered for this case study including base case without DR, second with considering ASDR and third with considering DB. For base case and ASDR, the load bidding $Bid_{b,t}$ is supposed to be a constant value of 60 \$/MWh. However, for DB, load bidding is divided into 4 blocks (d) as $Bid_{b,t,d}$ which are as Table III. The width of each load block for each bus will be 38% of total bus load demand. For ASDR, price steps for capacity and energy reserve proposed by ISO are demonstrated in the Table IV. Based on this demonstration, 25 percent of each load can be eligible to participate in ASDR, and this percentage is divided into 4 equal blocks as Table IV.

2) Numerical Results

Accordingly, the social welfare is supposed to be maximized, and comparisons between results are performed. First of all, the effect of ASDR and DB on load profile is demonstrated in Fig. 12. By running the proposed DB program, loads in peak and critical peak hours are declined, and the consumption is shifted automatically to the valley and off-peak night hours to increase the social welfare. Therefore, the proposed DB program helps to not only shave the peak load but also shift the demand to off-peak hours. The load curve for ASDR is total load minus the scheduled capacity of loads as a reserve for ASDR. In other words, this decrease may not happen unless it needs. As can be seen, most of these decreases for ASDR are taken place in peak hours. Hourly social welfare for each program is illustrated in Fig. 13. As can be expected, the hourly social welfare of ASDR and DB programs is higher than base case social welfare except for two hours of ASDR. In this term, DB program has a better situation to provide social welfare. To present a better vision what is happening inside these programs, total social security, total operation cost, security cost and reserve cost are listed in Table V. Based on Table V, it is clear that DB has placed in the best situation in terms of social welfare and total operation cost compared with ASDR and base case.

Therefore, proposed DB algorithm can provide a better economic condition for both ISO and customers. For extracting the effect of wind power on this program, DRSW index is calculated, and the results for DB and ASDR are demonstrated in Fig. 14. In Fig. 14, the ASDR and DB have been compared using proposed DRSW index. DB program has the highest DRSW; therefore, the program has the most impact on increasing social welfare due to wind power generation.

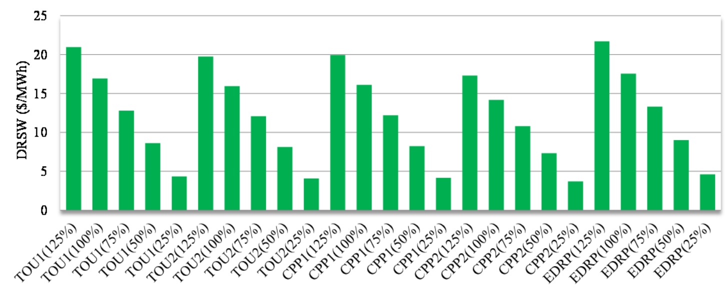

Fig. 10. The impact of variant types of DR programs considering the different percentage of the wind penetration on the proposed DRSW index.

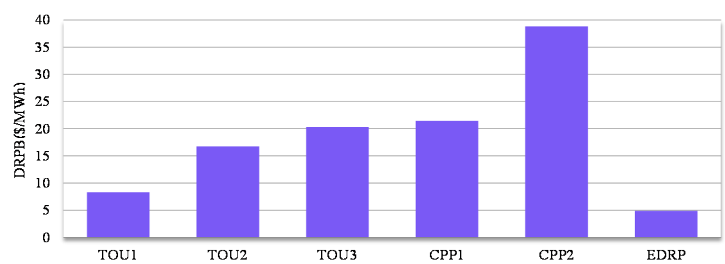

Fig. 11. The impact of variant types of DR programs on the proposed DRPB index.

TABLE III
PROPOSAL PRICES BY CUSTOMERS FOR DB PROGRAM

d	1	2	3	4
$Bid_{b,t,d}$ (\$/MWh)	70	60	50	30

TABLE IV
PROPOSED PRICE STEPS FOR ASDR BY ISO

k	0	1	2	3
$q_t^k\,(MW)$	25% of eligible loads	25% of eligible loads	25% of eligible loads	25% of eligible loads
$cpi_t^k\,(\$/MWh)$	8	10	12	14
$epi_t^k\,(\$/MWh)$	12	15	18	21

TABLE V
DIFFERENT TOTAL COSTS FOR DIFFERENT PROGRAMS (BASE CASE, ASDR, DB)

	Total social welfare ($)	Total operation cost ($)	Security cost ($)
ASDR	231750,804	349529,20	5678,340
DB	245011,748	341175,08	27167,464
Base case	228440,572	352839,42	28243,072

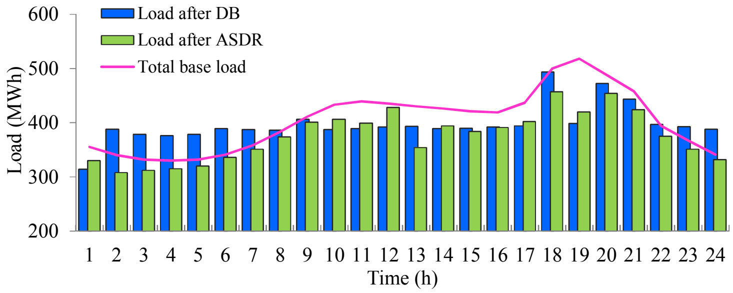

Fig. 12. Load profiles in three states including base case, with DB and with ASDR.

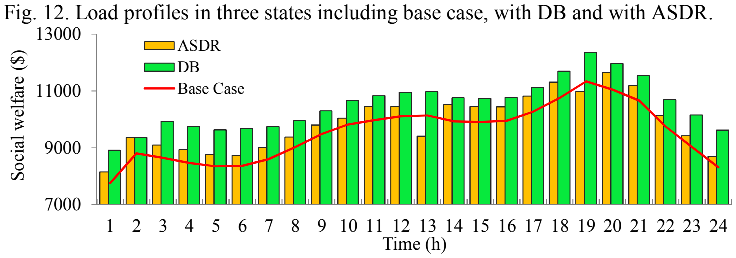

Fig. 13. Hourly social welfare for the base case, ASDR, and DB.

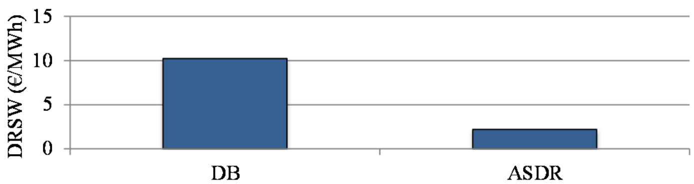

Fig. 14. Effect of different DR programs on the proposed index DRSW.

Since considering DB in different buses leads to different impacts on social welfare and load profile, a comparison is performed to assess DB in different buses. In one case, DB is considered only in six buses 2, 5, 6, 9, 12, and 13. In another case, five other buses, which were not taken into account for DB in the previous case, including buses 3, 4, 10, 11, and 14, are considered for DB. The results of load profile after DR and social welfare are demonstrated in Fig. 15 and 16, respectively. Based on Fig. 15, considering five nodes causes a flat load profile and more load reductions in peak hours, although the number of shifted loads is not remarkable compared with considering all nodes and 6 nodes. On the other hand, the load pattern with considering six buses is almost similar to the case when all nodes are considered for DB; however, the number of shifted loads is still not comparable with considering all nodes. Moreover, hourly social welfare with considering five nodes is less than two other DB cases in peak hours. Nevertheless, at off-peak hours, including 3, 4 and 5, it is a bit more than even considering all nodes for DB. At other hours, hourly social welfare is the same for these three DB cases.

C. Results' Implications for the Future Practice

According to the numerical results, implications of the proposed model for the future practice are presented as:

- To overcome the fluctuations of the wind power generation and its consequent effects on the stability of the power system the proposed DRPs' models are applied.
- Market regulatory board need to realize effective models to reduce the impact of wind injection into the network.
- ISO and decision makers require an effective multi-purpose tool to mitigate the electricity market volatility. In this paper, we propose and implement a model of both DRPs categories as such mentioned tool.
- Two indices are defined to compare the variant DRPs. By means of these helpful instruments, market operators can compare the impact of implementation of different DR programs.
- Moreover, investment experts look for the effects of their decisions on the percentage amount of wind generation in the power system. DRSW index is calculated to help them and help ISO to make the wisest decision to increase the social welfare due to wind power generation.

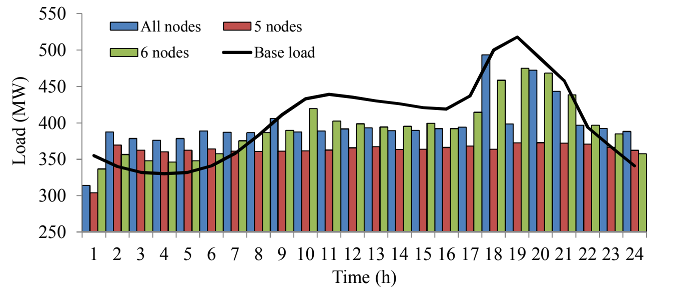

Fig. 15. Load after DB in different cases considering all nodes, 5 nodes, 6 nodes and base load

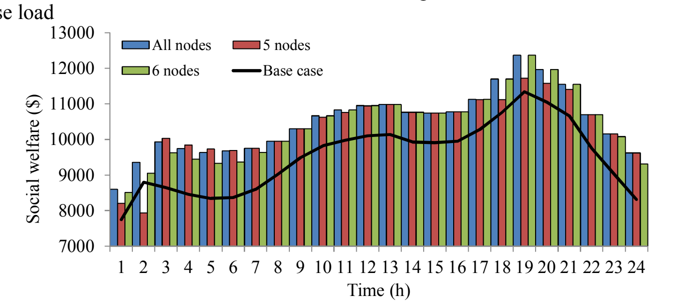

Fig. 16. Hourly social welfare in different cases considering all nodes, 5 nodes, 6 nodes and base load

VI. CONCLUSIONS

In this paper, a DR-based operation approach empowered by a two-stage SP was proposed for operational scheduling of the electricity market in the presence of RERs. In order to prove the effectiveness of the proposed DR-based operation model of the electricity market, several numerical studies were carried out. The impacts of employing both IBDR and PBDR were thoroughly investigated through two high-profile case studies. In addition, two new indices were proposed to quantify the impact of a DRP on electricity market efficiency. The numerical results showed that the presence of both wind energy and DRP led to lower prices and provided price adjustment and market efficiency. The results of this model proved that employing appropriate types of DRPs made it possible to compensate for wind generators' uncertainties and to maximize operator benefits, while inappropriate types of DRPs might decrease market efficiency. Particularly, the numerical results revealed that when the power system includes wind units, the PBDR programs have a more significant role compared to EDRP programs in reducing the Gencos' offering prices and consequently market prices during peak hours. However, based on the DRSW index, EDRP has a better influence on improving social welfare in the presence of wind power units. According to the DRPB index, the CPP program provided the highest increase in the social welfare by participation of 1 MW load in this DR program. Employing other flexible options, such as electric vehicles and energy storage, which can contribute to flexibility provision in addition to DR resources, can be considered in future works.

APPENDIX

The constraints of day-ahead and real-time sessions are presented as follows.

A. Day-ahead Constraints

Inequalities (A1) and (A2) restrict the power generation of thermal units. The up- and down-reserve limits are defined in (A3)-(A4). The inequality (A5) represents the startup constraint of thermal plants. The minimum up/down times of thermal power plants are modeled in (A6) and (A7), respectively.

$$P_{i,t} + R_{i,t}^{G\_UC} \le P_i^{\max} \quad \forall i,t \tag{A1}$$

$$P_{i,t} - R_{i,t}^{G\_DC} \ge 0 \quad \forall i,t \tag{A2}$$

$$0 \le R_{i,t}^{G\_UC} \le RU_i\,\tau \quad \forall i,t \tag{A3}$$

$$0 \le R_{i,t}^{G\_DC} \le RD_i\,\tau \quad \forall i,t \tag{A4}$$

$$SUC_{i,t} \ge SC_i\,(U_{i,t} - U_{i,t-1}) \quad \forall i,t \tag{A5}$$

$$\sum_{t'=t+1}^{t+MUT_i-1} \left(1-U_{i,t'}\right) + MUT_i\left(U_{i,t}-U_{i,t-1}\right) \le MUT_i \quad \forall i,t \tag{A6}$$

$$\sum_{t'=t+1}^{t+MDT_i-1} U_{i,t'} + MDT_i\left(U_{i,t-1}-U_{i,t}\right) \le MDT_i \quad \forall i,t \tag{A7}$$

B. Real-time Constraints

The balance between demand and supply in real time is considered for the scenarios in (A8) through taking into account the changes of wind power. Inequalities (A9)-(A10) are almost similar to (11)-(12) with this difference that constraints (A9)-(A10) are considered for all the scenarios. In (A11) and (A12), the deployed up/down reserves in the scenarios are limited to the scheduled reserve capacities in the day-ahead market. Constraint (A13) represents the net production of thermal plants in real time, which is limited in (A14). Ramp up/down limit in real time is denoted in inequalities (A15)-(A16).

$$\begin{aligned}&\sum_{i\in NG_b}\left(r_{i,w,t}^{G\_up} - r_{i,w,t}^{G\_dn}\right) + \sum_{wf\in WF_b}\left(P_{wf,w,t}^{W} - P_{wf,t}^{WP,S}\right) + \\ &asdr_{t,b,w} + LShed_{t,w,b} = -\sum_{b,b'\in NB}\left(F_{b,b',w,t} - F_{b,b',t}^{0}\right) \quad \forall b,w,t\end{aligned} \tag{A8}$$

$$F_{b,b',w,t} = \left(\delta_{b,w,t} - \delta_{b',w,t}\right)/X_{b,b'} \quad \forall (b,b'), w, t \tag{A9}$$

$$-F_{b,b'}^{\max} \le F_{b,b',w,t} \le F_{b,b'}^{\max} \quad \forall (b,b'), w, t \tag{A10}$$

$$0 \le r_{i,w,t}^{G\_up} \le R_{i,t}^{G\_UC} \quad \forall i,w,t \tag{A11}$$

$$0 \le r_{i,w,t}^{G\_dn} \le R_{i,t}^{G\_DC} \quad \forall i,w,t \tag{A12}$$

$$P_{i,w,t} = P_{i,t} + r_{i,w,t}^{G\_up} - r_{i,w,t}^{G\_dn} \quad \forall i,w,t \tag{A13}$$

$$P_i^{\min} U_{i,t} \le P_{i,w,t} \le P_i^{\max} U_{i,t} \quad \forall i,w,t \tag{A14}$$

$$P_{i,w,t} - P_{i,w,t-1} \le RU_i\, U_{i,t} + SUR_i\left(1-U_{i,t-1}\right) \ \forall i,w,t \tag{A15}$$

$$P_{i,w,t-1} - P_{i,w,t} \le RD_i\, U_{i,t-1} + SDR_i\left(1-U_{i,t}\right) \ \forall i,w,t \tag{A16}$$

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