Prioritizing the Effectiveness of a Comprehensive Set of Demand Response Programs on Wind Power Integration

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Abstract

The environmental targets set by power sectors throughout the world are the main drivers toward increasing the share of variable renewable energy sources (VRESs). Growth of VRESs will lead to a higher demand for operational flexibility due to their stochastic nature. Traditionally, conventional generation units provide the major share of additional required flexibility that may result in a higher depreciation. Motivated by this challenge, this paper investigates the potential of Demand Response (DR) as an emerging alternative in systems with significant amounts of wind power. To this end, a comprehensive set of DR programs including tariff-based, incentive-based and combinational DR programs are considered in a stochastic network-constrained market clearing framework. Afterwards, various DR programs are prioritized taking into account the system operator's economic, technical, and environmental desires. Moreover, the sensitivity of different DR programs into customer's price elasticity of demand as well as the participation level are evaluated by means of several sensitivity analyses. The obtained results can provide a guideline for the system operators to opt the most effective DR program.

Keywords—Demand response, flexibility, multi criteria decision making, stochastic programming, wind power.

NOMENCLATURES

Indices

b, b'	Index of system buses $b = 1, \ldots, NB$
i	Index of conventional units $i = 1, \ldots, NG$
j	Index of loads $j = 1, \ldots, NJ$
l	Index of transmission lines $l = 1, \ldots, L$
wf	Index of wind farms $wf = 1, \ldots, NWF$

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t, t'	Index of time periods $t = 1, \dots, NT$
w	Index of scenarios $w = 1, \dots, NW$
m	Index of segment for linearized fuel cost $m = 1, \dots, NM$

Parameters

$C_{i,t,m}^{G\_Eng}$	Offered cost of energy for generating units($/MWh)
$C_{i,t}^{G\_UC/DC}$	Offered cost of up/down capacity reserve for generating units ($/MW)
$C_{i,t}^{G\_UE/DE}$	Offered cost of up/down deployed reserve of generating units ($/MWh)
$C_{wf}^{WP\_spill}$	Cost of wind spillage($/MWh)
SC_i	Start-up cost of unit *i* ($)
MUT_i $/MDT_i$	Minimum up/down time (h)
$P_i^{\min}/P_i^{\max}$	Minimum/Maximum output of units(MW)
RU_i / RD_i	Ramp up/down limits of units(MW/h)
$P_{wf,w,t}^{W}$	Actual wind generation of wind farms(MWh)
$P_{wf,t}^{WP,\max}$	Forecasted wind generation of wind farms(MWh)
d_t^{ini}	Initial electricity demand before DR(MW)
$d_t^{Contract}$	Contracted amounts of load reduction (MW)
Inc_t / Pen_t	Incentive/Penalty values in IBDRPs($/MWh)
λ_t^{ini}	Initial electricity price before DR($/MWh)
$E_{t,t'}$	Price elasticity of demand
$e_i^{SO_2}$ / $e_i^{NO_x}$	Slope of linearized emission curve of unit *i* for SO_2 and NO_x pollutants (*lbs*/MWh)
$IE_i^{SO_2}$ / $IE_i^{NO_x}$	Initial emission of SO_2 and NO_x pollutants (*lbs*)
$Voll_{j,t}$	Value of lost load *j*($/MWh)
ρ_w	Probability of scenario w

Variables

$SUC_{i,t}$	Start-up cost of conventional units ($)
$U_{i,t}$	Binary on/off status indicator of generation units
$P^{e}_{i,t,m}$	Generation of segment m in linearized fuel cost curve(MWh)
$R^{G\_UC/DC}_{i,t}$	Scheduled up/down reserve capacity of generating units (MW)
$F^{0}_{l,t}$	Power flow through line l at the base case (MW)
$F_{l,w,t}$	Power flow through line l(MW)
$LS_{j,w,t}$	Load shedding of load j(MWh)
$P^{WP\_spill}_{wf,w,t}$	Wind power spillage of wind farms(MWh)
$r^{G\_up/dn}_{i,t,w}$	Deployed up/down spinning reserve of generating units (MWh)
$P_{i,w,t}$	Actual power generation of generation units(MW)

1. Introduction

Wind power is expected to be the most deployed Variable Renewable Energy Sources (VRESs) in future power grids [1]. Integration of wind power at high penetration levels may create essential challenges for Independent System Operators (ISOs) in different ways [2].Firstly, wind availability typically does not positively correlate with electricity demand. In other words, peak wind generation often occurred at off-peak load periods and it increases the gap between peak and off-peak periods of net load profile and consequently raises the need for greater ramp. Secondly, highly stochastic nature of wind generation may put at risk the load-generation balance at the real-time stage and impair power system security. In order to overcome these challenges and integrate the most available wind power without jeopardizing the power system with a rational cost, Demand Response (DR) has been commonly agreed as an impressive tool [3-4]. The logic behind this solution is to motivate the customers to reschedule their electricity consumption by providing incentives or changing the electricity tariffs with the aim of achieving a more flattened net load profile and potentially reducing the need for ramp services. To this end, different DR programs have been introduced by Federal Energy Regulatory Commission (FERC) including many different properties of demand-side management [5-6]. The DR programs were firstly classified into two main groups so-called, Time-Based Rate DR Programs (TBRDRPs) and Incentive-Based DR Programs (IBDRPs) [5]. However, this classification has been recently modified by adding several new DR programs as well as merging some of the initial ones [6].

Having these in mind, it seems very crucial to investigate the impacts of implementing versatile DR programs on wind power integration in order to provide a guideline for ISOs to opt the most effective DR program. In this regard, there are relevant works that have already addressed the role of DR in mitigating the variability of wind generation across transmission grids. DR resources have been modelled as peak clipping and demand shifting units with application to wind integration in [7] and [8], respectively. A load reduction DR program has been proposed in [9] with aim of decreasing the steep ramps of the net load profile caused by wind generation in an attempt to have a smoother load shape while the impacts of load recovery not considered. Yousefi et al. [10] has gone a step further by simultaneous consideration of load reduction and load recovery through price elasticity concept using a deterministic approach neglecting the randomness of wind generation. Heydarian-Forushani et al. proposed a stochastic framework for wind-thermal generation scheduling considering wind power uncertainty in the presence of DR programs [11]. However, just three DR programs including two TBRDRPs and one IBDRP have been addressed in the mentioned study. A more efficient unit commitment model based on operational cycles is developed in [12] taking into account an incentive-based DR program in the presence of high level of wind power. Impacts of DR with hybrid energy systems including the micro combined heat and power on the large-scale wind power integration has been quantitatively investigated in [13]. In [14], a flexible security-constrained model has been developed in order to achieve a secure, economic and environmentally scheduling applying a time of use pricing scheme in the presence of wind and network contingences. The other studies such as [15-17] introduced various DR exchange models for managing the variability of renewable energy resources in a market environment without considering the inherent nature of DR programs such as customer's elasticity and participation level. A comprehensive set of DR programs have been modelled and prioritized from the power market regulator point of view considering ISO, utilities and customers preferences in [18]. However, the power network, energy and reserve markets and wind generation have been ignored in [18].

Although DR programs implementation have been studied in the literature, there is no previously published paper so far which analysed the impacts of a comprehensive set of DR programs including IBDRPs, TBRDRPs and combinational DR programs on wind power integration. Moreover, most of the previous works investigated the role of DR programs from an economic viewpoint without paying attention to the technical and environmental aspects of DR on generation mixture. From an economic point of view, the most effective DR program has a more reduction in system's operation cost while from a technical perspective, it must help to decrease the conventional fleet ramp need in the presence of stochastic wind generation. Environmentally, an efficient DR program may intercept significant wind curtailment, and consequent decrease of emissions. On this basis, in this paper, DR programs are prioritized according to the ISO's economic, technical, and environmental desires by means of Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. It is worth noting that uncertainty surrounding the value of DR is one of the main obstacles to widespread deployment of DR [19]. The price elasticity of demand and customer's participation level in DR programs are two critical factors which have significant impression on DR effectiveness. On this basis, the sensitivity of each DR program to these vital factors are evaluated as it reveals an interpretation of how ISO can select a proper DR strategy regarding the DR programs dependency on elasticity and customer acceptance. In short, this paper contributes to the existing studies from the following aspects:

- To model and analyse a comprehensive set of DR programs including IBDRPs, TBRDRPs and the combinational DR programs based on price elasticity and customer benefit function, including sensitivities of both DR parameters and wind scenarios;
- To prioritize the performance of various DR programs on economic, technical, and environmental desires of ISO in the presence of wind power generation.
- To analyse DR programs regarding the customer's elasticity and customer's participation factor as two critical factors to evaluate DR program's performance.

The rest of the paper is structured as follows. Section 2 deals with modelling different types of DR programs. In order to simulate the two-stage operation of day-ahead and real-time electricity markets in the presence of wind power uncertainty, a two stage stochastic market clearing model is presented in Section 3. The multi criteria decision making procedure is explained in Section 4. The numerical studies are conducted in Section 5 and lastly, Section 6 concludes the paper.

2. Economic Model of DR Programs

DR is known as one of the potential flexible resources that can facilitate wind power integration through encouraging customers to reduce their electricity consumption in low wind periods (particularly peak hours) and increase their consumption when there is an extra amount of wind generation [20-21]. Such a change in the typical consumption pattern of customers can be achieved through changing the electricity tariffs or paying a specified incentive value. On this basis, DR programs are categorized as TBRDPs and IBDRPs [22]. The TBRDRPs contains Time of Use (TOU), Real Time Pricing (RTP) and Critical Peak Pricing (CPP) programs, whereas the IBDRPs include Emergency Demand Response Program (EDRP), Direct Load Control (DLC), Interruptible/Curtail able Services (I/C), Ancillary Services Market (A/S), Capacity Market (CAP) and Demand Bidding (DB).

DR programs are modelled based on the customer's benefit function using the price elasticity concept which is one of the most common and powerful methods in this field [18]. Elasticity represents the customer's sensitivity with respect to the electricity price changes as formulated in (1) [23]. It is worth noting that the elasticity matrix includes both load reduction and load shifting behaviour of customers and the elasticity matrix links the power consumption at each period to other periods.

$$E_{t,t'} = \frac{\Delta d_t}{\Delta \lambda_{t'}} \cdot \frac{\lambda_{t'}^{ini}}{d_t^{ini}} \tag{1}$$

The price elasticity of demand is variable due to price and quantity. However, this paper does not deal with uncertainty of DR and the considered DR model is without any uncertainty. It is a popular assumption for elasticity modelling that has been used in many previous reports such as [18]. Moreover, the elasticity of demand is an input parameter of our proposed model and obtaining precise value for price elasticity of demand is out of the scope of the current paper. It should be noted that TBRDRPs have no additional cost or income for the customers since these are usually implemented obligatory by ISOs. Despite of TBRDRPs, implementation of IBDRPs affect the net benefit of customers due to the incentive and penalty payments in various IBDRPs. On this basis, the net benefit of customer can be calculated as in (2):

$$B_t = Uti(d_t) - d_t\,\lambda_t + Inc_t\,(d_t^{ini} - d_t) - Pen_t\left(d_t^{Contract} - (d_t^{ini} - d_t)\right) \tag{2}$$

The first term of Eq. (2) is the customer's utility at hour t as a function of amount of consumption, d_t. Particularly, the customer's utility indicates the production income for industrial customers, while it is the productivity for commercial demands. The cost of customer's electricity consumption at hour t has been considered in the second term. Moreover, the income as a result of incentive payment and the penalty cost for customers who avoid to do their obligations according to the contract have been formulated through the two last terms, respectively. Note that, Δd_t indicates the changes in initial demand as a consequence of DR implementation due to price changes or an incentive payment or a penalty consideration.

In order to find the amount of demand in which the maximum customers' benefit is yield, a partial differential equation with respect to d_t is formed as below [18]:

$$\frac{\partial B}{\partial d_t} = \frac{\partial Uti}{\partial d_t} - \lambda_t - Inc_t - Pen_t = 0 \tag{3}$$

Therefore, we have:

$$\frac{\partial Uti}{\partial d_t} = \lambda_t + Inc_t + Pen_t \tag{4}$$

The most often used customer's utility function is in quadratic form as it can be seen in (5) [24]. Eq. (6) can be obtained by differentiating Eq. (5) and replacing the result in (4).It is worth noting that, $E_{t,t}$ is the self-price elasticity of demand and λ_t^{ini} denotes the initial tariff of electricity before implementing the DR [18]. Hence, the customer's consumption after DR implementation can be formulated as (7) for each time period.

$$Uti_t = Uti_t^{ini} + \lambda_t^{ini}\left(d_t - d_t^{ini}\right)\left(1 + \frac{d_t - d_t^{ini}}{2E_{t,t}d_t^{ini}}\right) \tag{5}$$

$$\lambda_t^{ini}\left(1 + \frac{d_t - d_t^{ini}}{E_{t,t}d_t^{ini}}\right) = \lambda_t + Inc_t + Pen_t \tag{6}$$

$$d_t = d_t^{ini}\left[1 + E_{t,t}\frac{\left(\lambda_t - \lambda_t^{ini} + Inc_t + Pen_t\right)}{\lambda_t^{ini}}\right] \tag{7}$$

According to the definition of price elasticity of demand, electricity tariff changes in one period can affect the consumption in the other periods. This concept is known as the cross elasticity. On this basis, the calculated single period model in (7) can be extended in order to obtain the multi period model as formulated in (8) [18]. Eq. (8) represents the optimal amount of demand from customer's point of view after participation in DR programs considering given electricity tariffs, incentive, and penalty.

$$d_t = d_t^{ini}\left[1 + \sum_{t'=1}^{NT} E_{t,t'}\frac{\left(\lambda_{t'} - \lambda_{t'}^{ini} + Inc_{t'} + Pen_{t'}\right)}{\lambda_{t'}^{ini}}\right] \tag{8}$$

It should be noted that the relation among different time periods is considered directly through elasticity matrix. Therefore, the value of modified demand at each hour may affect all the other periods as formulate in (8) [18].

3. Stochastic Network-Constrained Market Clearing Formulation

In order to simulate the two-stage operation of day-ahead and real-time electricity markets in the presence of volatile wind generation, a two stage stochastic market clearing model is conducted. The applied two-stage stochastic programming is well-known and has been used in same problems, already [25-26]. The first-stage decision variables are market-based variables, those are not dependent on scenarios occurrence including start-up and shut-down plan of each generation unit, scheduled power of generation units in energy and up/down capacity reserve markets. The second-stage decision variables are real-time scenario dependent variables that should be all together considered (according to their probability) in order to obtain a single day-ahead market clearing. The second-stage decision variables are the up/down deployed reserve by each generation unit, the involuntary load shedding by each load, and wind power spillage of each wind farm.

The proposed model aims to determine an optimal wind-thermal generation scheduling considering versatile DR programs with application to facilitate wind power integration. The objective function is the expected system operation cost which should be minimized while meeting several constraints from the ISO's view point as given in (9).

$$
\begin{aligned}
&OPC = \\
&\sum_{t=1}^{NT}\left[\sum_{i=1}^{NG}(SUC_{i,t} + MPC_i U_{i,t} + \sum_{i=1}^{NG}\sum_{m=1}^{NM} P_{i,t,m}^{e} C_{i,t,m}^{G\_Eng} \right.\\
&+C_{i,t}^{G\_UC} R_{i,t}^{G\_UC} + C_{i,t}^{G\_DC} R_{i,t}^{G\_DC}) \\
&\left.+\sum_{j=1}^{NJ}\left(Inc_t \Delta d_{j,t} - Pen_t\left(d_{j,t}^{contract} - \Delta d_{j,t}\right)\right)\right] \\
&\qquad +\sum_{t=1}^{NT}\sum_{w=1}^{NW}\rho_w\left(\sum_{i=1}^{NG} C_{i,t}^{G\_UE} r_{i,t,w}^{G\_up} - C_{i,t}^{G\_DE} r_{i,t,w}^{G\_dn}\right. \\
&\qquad \left. +\sum_{j=1}^{NJ} Voll_{j,t} LS_{j,w,t} + \sum_{wf=1}^{NWF} C_{wf}^{WP\_spill} P_{wf,w,t}^{WP\_spill}\right)
\end{aligned} \tag{9}
$$

The first and second line terms in (9) subsequently indicate the operation cost resulted from start-up, minimum production, piecewise linear fuel and up/down capacity reserve cost of generation units. The first term of the third line of (9) denotes the cost of incentive payment to customers who successfully response to IBDRPs. Moreover, the second term is the income of penalty received from customers who avoid to reduce their demand according to the contract. The other part of costs in (9) are devoted to the corrective action costs as a result of wind power scenario realization during the real-time stage. The cost terms regarding up/down deployed reserve of generation units, involuntary load shedding and wind spillage are formulated in the two last lines of (9), respectively. Note that, the considered day-ahead DR model is completely certain with no uncertainty in customer's response. On this basis, there is no variability in the amount of demand and hence, just the wind power variability should be justified in the real-time electricity market.

The objective function must be minimized subject to several constraints related to generation units, network and wind power generation, as declared in the following. The load-generation balance formulated in (10). Note that, $d_{j,t}$ in Eq. (10) is the modified demand of load j at hour t after implementing DR which is obtained through Eq. (8) and then assigned to relevant buses. Also, $P_{i,t}$ denotes the aggregated power generation of generation unit i at hour t calculated from the sum of generating unit's piecewise offered energy blocks as expressed in (11). The power flow is computed in (12) while its bounds are enforced in (13). The negative sign in left hand side of Eq. (13) is related to the direction of power flow. In fact, the power flow can be in both directions and the absolute value of power flow must be less than the maximum allowable amount in both directions.

$$
\sum_{i\in G_b} P_{i,t} + \sum_{wf\in WF_b} P_{wf,t}^{WP,S} - \sum_{j\in J_b} d_{j,t} = \sum_{l\in L_b} F_{l,t}^{0} \tag{10}
$$

$$
P_{i,t} = \sum_{m=1}^{NM} P_{i,t,m}^{e} \; , \; 0 \le P_{i,t,m}^{e} \le P_{i,m}^{\max} \tag{11}
$$

$$F_{l,t}^{0} = \left(\delta_{b,t}^{0} - \delta_{b',t}^{0}\right) / X_l \tag{12}$$

$$-F_l^{\max} \le F_{l,t}^{0} \le F_l^{\max} \tag{13}$$

The generation unit constraints are listed in (14)–(18). The minimum and maximum power output limits of generating units considering their scheduled power in both energy and reserve markets are set in (14) and (15). Up and down capacity reserves are bounded due to ramp rates as given in (16) and (17), respectively. RU and RD in Eq. (16) and Eq. (17) are ramp up and ramp down characteristic of generation units, respectively. According to these two constraints, the assigned up/down reserve capacities must be less than the up/down ramp limits. The minimum up and down time constraints on conventional generators are enforced in (18) and (19). The start-up cost of generation units is formulated in (20). The scheduled power of wind farms is bounded by 0 and its forecasted value in (21).

$$P_{i,t} + R_{i,t}^{G\_UC} \le P_i^{\max} U_{i,t} \tag{14}$$

$$P_{i,t} - R_{i,t}^{G\_DC} \ge P_i^{\min} U_{i,t} \tag{15}$$

$$0 \le R_{i,t}^{G\_UC} \le RU_i \tag{16}$$

$$0 \le R_{i,t}^{G\_DC} \le RD_i \tag{17}$$

$$\sum_{t'=t+2}^{t+MUT_i} \left(1 - U_{i,t'}\right) + MUT_i \left(U_{i,t} - U_{i,t-1}\right) \le MUT_i \tag{18}$$

$$\sum_{t'=t+2}^{t+MDT_i} U_{i,t'} + MDT_i \left(U_{i,t-1} - U_{i,t}\right) \le MDT_i \tag{19}$$

$$SUC_{i,t} \ge SC_i (U_{i,t} - U_{i,t-1}) \tag{20}$$

$$0 \le P_{wf,t}^{WP,S} \le P_{wf,t}^{WP,\max} \tag{21}$$

There are another set of constraints that should be satisfied for each scenario realization. The nodal power balance is guaranteed in (22) when each scenario occurs. The deployed up and down spinning reserves in each scenario must be less than the scheduled reserve capacities established by the market clearing as illustrated in (23) and (24), respectively. The net output power of generation units is formulated through an auxiliary variable, $P_{i,w,t}$,in (25) and restricted by (26). The $r_{i,w,t}{}^{G\_up}$ and $r_{i,w,t}{}^{G\_dn}$ can appear simultaneously in Eq. (25). However, it is worth noting that one of the mentioned variables has zero value at each time slot and the other one is not zero. This is due to the fact that just one of over or under estimation condition is happened in each time period. Ramp up and ramp down rate limits are subsequently considered in (27) and (28). Moreover, the bounds on wind power spillage and load shedding amounts are formulated in (29) and (30), respectively.

$$\sum_{i\in G_b}\left(r_{i,w,t}^{G\_up}-r_{i,w,t}^{G\_dn}\right)+\sum_{wf\in WF_b}\left(P_{wf,w,t}^{W}-P_{wf,t}^{WP,S}-P_{wf,w,t}^{WP\_spill}\right)+\sum_{j\in J_b}LS_{j,w,t}=\sum_{l\in L_b}F_{l,w,t}-F_{l,t}^{0} \tag{22}$$

$$0\le r_{i,w,t}^{G\_up}\le R_{i,t}^{G\_UC} \tag{23}$$

$$0\le r_{i,w,t}^{G\_dn}\le R_{i,t}^{G\_DC} \tag{24}$$

$$P_{i,w,t}=P_{i,t}+r_{i,w,t}^{G\_up}-r_{i,w,t}^{G\_dn} \tag{25}$$

$$P_i^{\min}U_{i,t}\le P_{i,w,t}\le P_i^{\max}U_{i,t} \tag{26}$$

$$P_{i,w,t}-P_{i,w,t-1}\le RU_i\,U_{i,t}+SUR_i\left(1-U_{i,t-1}\right) \tag{27}$$

$$P_{i,w,t-1}-P_{i,w,t}\le RD_i\,U_{i,t-1}+SDR_i\left(1-U_{i,t}\right) \tag{28}$$

$$0\le P_{wf,w,t}^{WP\_spill}\le P_{wf,w,t}^{W} \tag{29}$$

$$0\le LS_{j,w,t}\le d_{j,t} \tag{30}$$

It is worth noting that the constraints such as DC power flow and thermal limits of transmission lines have been also considered for each occurred scenario even if their mathematical formulation is omitted for the sake of conciseness.

4. Multi Criteria Decision Making Procedure

DR programs portfolio contains versatile DR programs including TBRDRPs, IBDRPs and the combinational ones. It is very crucial for the ISO to find the most effective DR program by simultaneous consideration of its economic, technical and environmental desires. Economically, DR programs have different impacts on system operation cost. From technical point of view, DR programs are required to cope with the uncertainty of wind generation so that reduce the conventional fleet ramp need. In addition, DR may lead to facilitate wind power integration and therefore decrease the emissions from environmental perspective. On this basis, three criteria are considered in this paper. The economic criteria is the system operation cost as defined in (9). Furthermore, the technical and environmental criteria are conventional unit's ramp need and total pollutant emission as formulated in (31) and (32), respectively. Note that two most popular pollutants including SO_2 and NO_x are considered to conduct emission calculation [27].

$$Ramp\,Need=\sum_{i=1}^{NG}\sum_{w=1}^{NW}\sum_{t=1}^{NT}\rho_w\left|P_{i,w,t}-P_{i,w,t-1}\right| \tag{31}$$

$$Emission=\sum_{t=1}^{NT}\sum_{i=1}^{NG}\left[\left(IE_i^{SO_2}+IE_i^{NO_x}\right)U_{i,t}+\sum_{t=1}^{NT}\rho_w\left(P_{i,w,t}\,e_i^{SO_2}+P_{i,w,t}\,e_i^{NO_x}\right)\right] \tag{32}$$

The prioritizing of DR programs is carried out from ISO's point of view considering three above mentioned criteria using TOPSIS. To this end, the economic, technical, and environmental criteria are weighted by means of entropy method [28]. Entropy is a criterion in information theory that describes the uncertainty in a discrete distribution function. First of all, it is necessary to form a decision matrix so that its elements represent the performance of the a-th alternative with respect to the k-th criteria, $\chi_{a,k}$. The calculated elements must be normalized according to Eq. (33). Note that NA in (33) is the number of alternatives (different DR programs in this paper). Then, for the k-th criteria the EE_k parameter could be formulated as (34) [28]. Finally, the deviation degree and the weight for each criteria can be obtained through (35) and (36), respectively.

$$P_{a,k} = \frac{\chi_{a,k}}{\sum_{a=1}^{NA} \chi_{a,k}} \tag{33}$$

$$EE_k = -\left(LnNA\right)^{-1} \sum_{a=1}^{NA} [P_{a,k} \times LnP_{a,k}] \qquad 0 \le EE_k \le 1 \tag{34}$$

$$dd_k = 1 - EE_k \tag{35}$$

$$W_k = \frac{dd_k}{\sum_{k=1}^{NK} dd_k} \tag{36}$$

TOPSIS is a well-known method for prioritizing that simultaneously calculates the distance of each alternative from both the ideal and the non-ideal solutions. For this purpose, the elements of decision matrix should be normalized at first using (37) and then the weighted normalized decision matrix can be obtained as formulated in (38). Afterward, the ideal and non-ideal solutions for each criteria are determined with respect to its correlation with the ISO objectives as observed in (39). It is notable that the considered economic, technical, and environmental attributes in this paper have a negative correlation such that their lower values are closer to ideal and vice versa. The distance of each alternative from ideal and non-ideal solutions is accounted by means of (40) and (41), respectively. Finally, the mean distance between each alternative and non-ideal solution is considered as decision criterion as defined in (42). The higher obtained value for C_a indicates the better alternative.

$$r_{a,k} = \frac{\chi_{a,k}}{\sqrt{\sum_{a=1}^{NA} \chi_{a,k}^2}} \tag{37}$$

$$V_{a,k} = W_k \times r_{a,k} \tag{38}$$

$$V_k^{+} = \left(\max V_{a,k} \left| k \in K^{+} \right|, (\min V_{a,k} \left| k \in K^{-} \right| \right) \quad a = 1, \ldots .NA$$
$$V_k^{-} = \left(\min V_{a,k} \left| k \in K^{+} \right|, (\max V_{a,k} \left| k \in K^{-} \right| \right) \quad a = 1, \ldots NA \tag{39}$$

$$S_a^{+} = \sqrt{\sum_{k=1}^{NK} (V_{a,k} - V_k^{+})^2} \qquad a = 1, \ldots .. NA \tag{40}$$

$$S_a^{-} = \sqrt{\sum_{k=1}^{NK} (V_{a,k} - V_k^{-})^2} \qquad a = 1, \ldots .. NA \tag{41}$$

$$C_a = \frac{S_a^{-}}{S_a^{+} + S_a^{-}} \qquad 0 \le C_a \le 1 \tag{42}$$

5. Numerical Results

In order to examine the performance of the proposed model, several numerical studies have been conducted on the modified IEEE Reliability Test System (RTS 24-bus) [29]. The conventional generation install capacity is 3105 MW while the system peak load is equal to 2850 MW. The offered cost of generating units in energy and up/down reserve markets have been extracted from [27] as shown in Table 1. The emission function slopes and the start-up emission of conventional units are the same as those for corresponding unit fuel cost curves, all multiplied by conversion factors of 0.2 and 0.5 for SO_2 and NO_x emission, respectively [27]. Moreover, the involuntary load shedding and the wind spillage costs are assumed to be 200 and 40 \$/MWh, respectively.

Table 1. Generation units cost data [27].

	Generation unit No.							
	i1-i5	i6-i9	i10-i13	i14-i16	i17-i20	i21-i23	i24	i25-i26
SC_i (\$)	87.4	15	715.2	575	312	1018.9	2298	0
MPC_i (\$)	5.25	5	7.5	8.5	6.25	15	20	0
$C_{i,t,1}^{G\_Eng}$ (\$/MWh)	23.41	29.58	11.46	18.6	9.92	19.2	10.08	5.31
$C_{i,t,2}^{G\_Eng}$ (\$/MWh)	23.78	30.42	11.96	20.03	10.25	20.32	10.66	5.38
$C_{i,t,3}^{G\_Eng}$ (\$/MWh)	26.84	42.82	13.89	21.97	10.68	21.22	11.09	5.53
$C_{i,t,4}^{G\_Eng}$ (\$/MWh)	30.4	43.28	15.97	22.72	11.26	22.13	11.72	5.66
$C_{i,t}^{G\_UC}$ (\$/MW)	10.44	14.61	5.33	8.33	4.21	8.29	4.35	2.19
$C_{i,t}^{G\_DC}$ (\$/MW)	10.44	14.61	5.33	8.33	4.21	8.29	4.35	2.19
$C_{i,t}^{G\_UE}$ (\$/MWh)	26.11	36.53	13.32	20.76	10.53	20.72	10.89	5.47
$C_{i,t}^{G\_DE}$ (\$/MWh)	26.11	36.53	13.32	20.76	10.53	20.72	10.89	5.47

There are six wind farms, each has 200 MW install capacity which are located at buses 1, 4, 6, 18, 21 and 22 as shown in Fig. 1. The wind speed scenarios are generated based on South East and North of South Australia wind speed data by means of An

Autoregressive Moving Average (ARMA) model [30]. In order to have a tractable optimization problem without extra computational difficulties, the generated scenarios are reduced to ten scenarios for each wind farm using K-means clustering technique [31]. Afterward, the remaining wind speed scenarios are transformed into wind power scenarios according to the Vestas 3 MW turbine features.

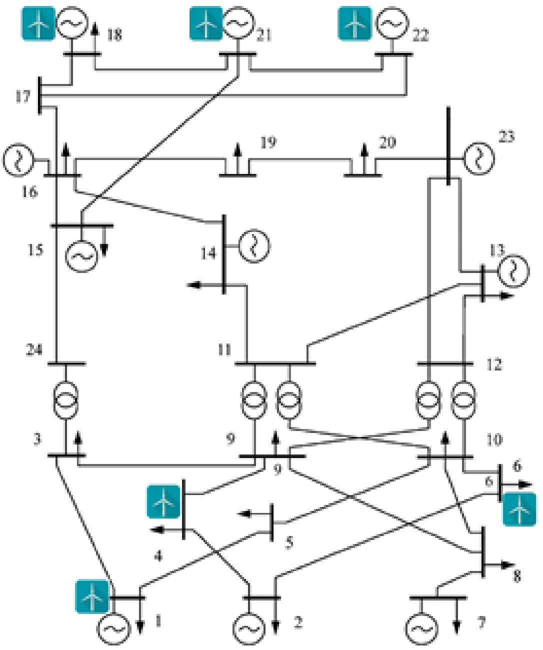


Fig. 1. Modified IEEE Reliability Test System (RTS 24-bus)

Without loss of generality, DR is assumed to be uniform among all buses in this paper. In this regard, the potential of DR implementation is considered to be 10% of the total load at each load point. Also, the values of self and cross price elasticity of demand and low-load, off-peak, and peak time intervals are illustrated in Table 2 [18].

Table 2. Piece elasticity values [18].

	Peak	Off-peak	Low-load	Period
Peak	-0.10	0.016	0.012	17:00-24:00
Off-peak	0.016	-0.10	0.010	9:00-16:00
Low-load	0.012	0.010	-0.10	1:00-8:00

The initial electricity price before DR implementation is 15 \$/MWh equal to the average of hourly electricity prices when there is no DR. The considered DR portfolio includes several TBRDRPs, IBDRPs, and combinational DR programs which are widely used programs in power market as indicated in Table 3.

Table 3. DR programs portfolio statement

DR Type	Case No.	Programs	Electricity price ($/MWh)	Incentive value at peak ($/MWh)	Penalty value at peak ($/MWh)
Base	C1	Initial load	15 flat rate	0	0
TBRDRPs	C2	TOU	5, 15, 45 at low-load, off-peak, and peak periods, respectively	0	0
	C3	TOU	7.5, 15, 30 at low-load, off-peak, and peak periods, respectively	0	0
	C4	TOU	10, 15, 22.5 at low-load, off-peak, and peak periods, respectively	0	0
	C5	RTP	12,10.7,10.2,5.7,5.4,5.4,5.5,5.7,11.1,13.9,15, 20.3,20.3,20.1,20.3,19.1,20.6,22.1,22.1,22.1, 21.9,21.2,20.3,13.8 at 1-24h	0	0
	C6	RTP	Same as case No. C5 multiplied by 1.5	0	0
	C7	RTP	Same as case No. C6 multiplied by 2	0	0
	C8	CPP	22.5 at peak period and otherwise 15	0	0
	C9	CPP	30 at peak period and otherwise 15	0	0
	C10	CPP	45 at peak period and otherwise 15	0	0
IBDRP	C11	EDRP	15 flat rate	2.5	0
	C12	EDRP	15 flat rate	5	0
	C13	EDRP	15 flat rate	10	0
	C14	I/C	15 flat rate	1.25	0.625
	C15	I/C	15 flat rate	2.5	1.25
	C16	I/C	15 flat rate	5	2.5
TBRDRPs+IBDRPs	C17	TOU+EDRP	7.5, 15, 30 at low-load, off-peak, and peak periods, respectively	5	0
	C18	RTP+EDRP	12,10.7,10.2,5.7,5.4,5.4,5.5,5.7,11.1,13.9,15, 20.3,20.3,20.1,20.3,19.1,20.6,22.1,22.1,22.1, 21.9,21.2,20.3,13.8 at 1-24h	5	0
	C19	TOU+I/C	7.5, 15, 30 at low-load, off-peak, and peak periods, respectively	2.5	1.25
	C20	RTP+I/C	12,10.7,10.2,5.7,5.4,5.4,5.5,5.7,11.1,13.9,15, 20.3,20.3,20.1,20.3,19.1,20.6,22.1,22.1,22.1, 21.9,21.2,20.3,13.8 at 1-24h	2.5	1.25

The model has been solved using CPLEX 12.5.0 under GAMS software. The impacts of different types of DR programs implementation on system load profile is shown in Fig. 2. Approximately, all types of the programs try to decrease the load level at peak period while increase the load level at low-load hours and consequently provide a flatter load profile. This will not only remove the strain on conventional generation units but also support the integration of wind power to power system.

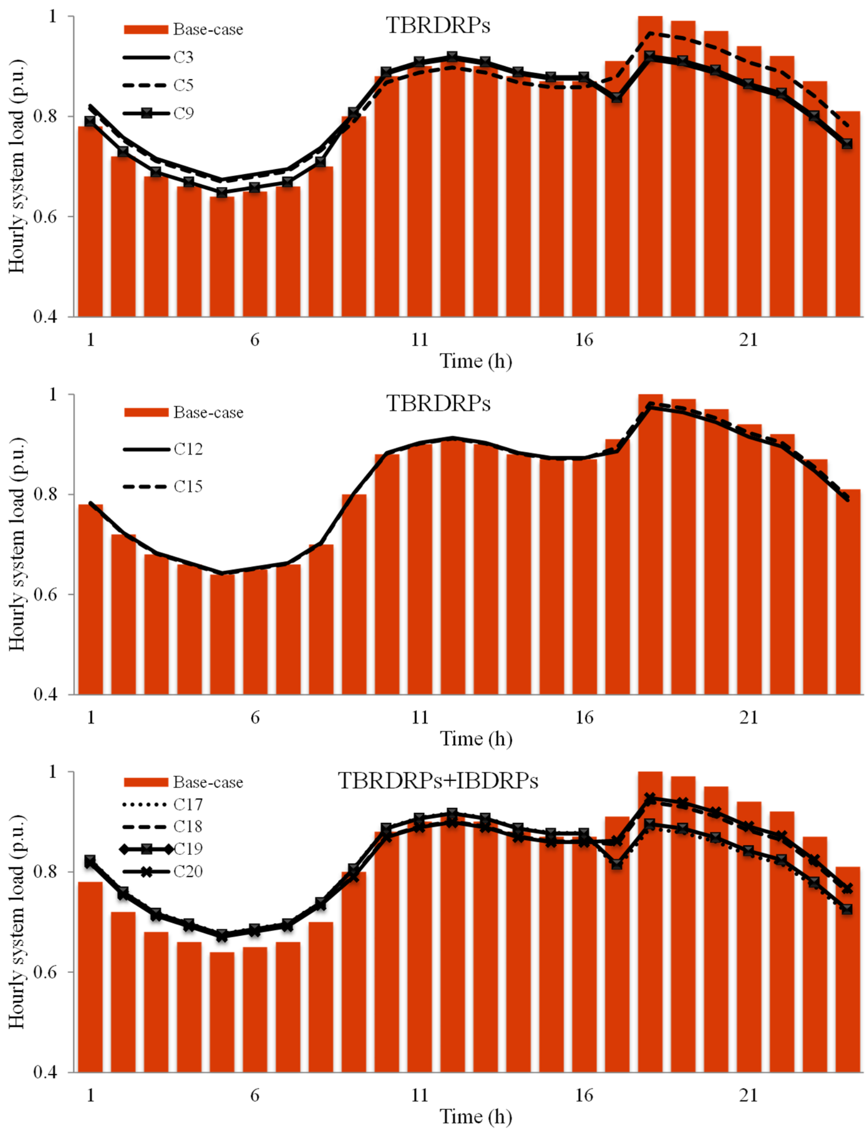


Fig. 2. Effect of various DR programs on load curve in given cases.

In order to examine the performance of DR programs, the ISO decision criteria including economic, environmental, and technical objectives have been reported in Table 4. As observed, although C7 has an impressive impact on reducing operation cost, pollutant emission and generation unit's ramp need reduction. For instance, the ramp need is decreased by 12% as a consequence of C7. According to the obtained results, it can be concluded that different DR programs have distinct and partly conflicting impacts on decision criteria.

Table 4. ISO decision criteria for 24-hour scheduling horizon

Case No.	Flexibility Metrics		
	Operation Cost ($)	Pollutant Emission (lbs)	Ramp Need (MW)
C1	538562	201816	4886
C2	487654	184332	4695
C3	510484	193088	4704
C4	524262	197781	4700
C5	524989	197756	4514
C6	493069	185747	4605
C7	464722	173797	4300
C8	523750	197596	4645
C9	509229	192718	4757
C10	484922	183588	4756
C11	534292	200188	4893
C12	532722	199297	4649
C13	530020	195989	4817
C14	535272	200405	4838
C15	532179	199242	4731
C16	528415	197839	4644
C17	504730	189978	4684
C18	517676	194683	4592
C19	504883	190883	4797
C20	518301	195513	4497

In order to compare the effectiveness of various DR programs, the considered cases (C1-C20) are prioritized by means of TOPSIS. The obtained weights for operation cost, pollutant emission, and ramp need are 0.34, 0.33, and 0.33, respectively using the entropy method. The priorities have been calculated as shown in Fig. 3. As it can be seen, C7 has the highest priority among all DR programs. Afterward, the next ranks are associated with C2, C6 and C10 with a negligible difference. The obtained results reveal that RTP program has a key role in satisfying ISO objectives since RTP is a common program in the first three high priority cases. Moreover, as shown in Fig. 3, it seems that the IBDRPs cannot be perfect alternatives by its own due to the fact that these programs have the lowest priority in comparison with other DR programs.

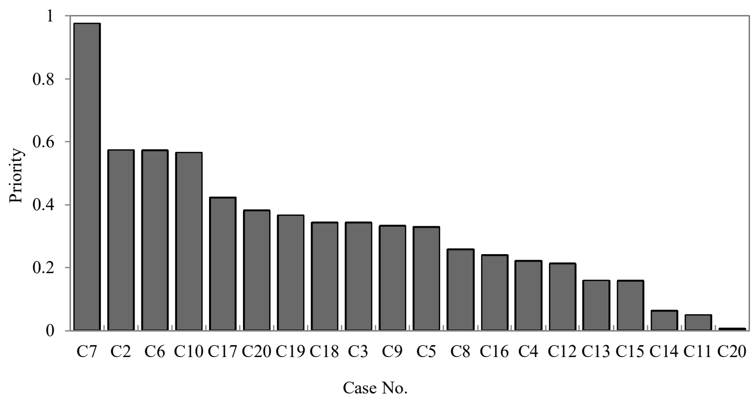


Fig. 3. DR programs priorities.

The considered DR programs have different impacts on wind power spillage amounts as shown in Fig. 4. In case C2, the wind spillage volume is decreased by 27.2% in comparison with case C1. Also, it can be noted that cases C4 and C7 to C16 are not appropriate options for improving wind integration. By comparing similar cases under RTP and TOU programs, it is observed that TOU is a more favourable program from wind integration point of view.

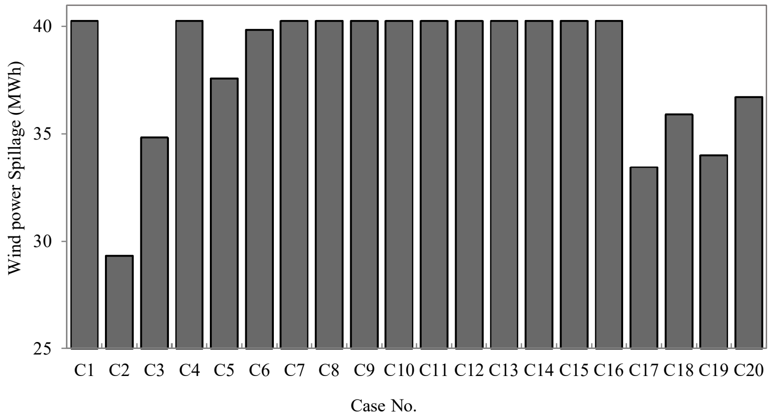


Fig. 4. Wind spillage in the given cases.

The impacts of versatile DR programs implementation on different cost terms of objective function have been demonstrated in Table 5. As observed, DR programs, particularly TBRDRPs, affect the cost of energy provision, significantly. Also, it is obvious that most of the deployed reserve is downward due to the fact that the deployed reserve cost is negative. In general, the involuntary load shedding is decreased as a result of DR implementation except that cases C5, C8, C12 and C16. For instance in case C12, increment of load shedding cost is compensated through cost reduction in other terms including energy, capacity reserve, and wind spillage costs and hence, DR is totally reasonable.

Table 5. Impact of different DR programs implementation on cost terms.

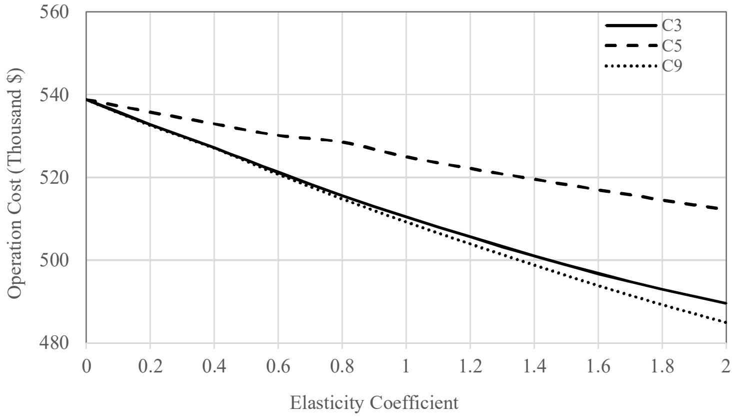
Case No.	Cost Terms ($)						
	Energy	Cap. Reserve	Dep. Reserve	Wind Spillage	Load Shedding	Incentive/Penalty	Total
C1	514076	26243	-6992	1611	608	0	535546
C2	466212	26185	-6133	1173	217	0	487654
C3	488957	26502	-6646	1393	278	0	510484
C4	502941	26388	-7168	1611	490	0	524262
C5	502932	25635	-6217	1503	1136	0	524989
C6	471809	24821	-5290	1594	135	0	493069
C7	444156	24509	-5554	1611	0	0	464722
C8	502322	26254	-7122	1611	685	0	523750
C9	485065	26335	-7014	1611	352	0	506349
C10	464309	25809	-7024	1611	217	0	484922
C11	512125	26372	-7146	1611	490	840	534292
C12	506443	25566	-6804	1611	3100	2816	532722
C13	497463	26406	-7214	1611	490	11264	530020
C14	513575	26355	-7142	1611	490	383	535272
C15	510157	26479	-7192	1611	352	772	532179
C16	502788	26022	-6897	1611	1099	3792	528415
C17	480292	26482	-6473	1338	275	2816	504730
C18	493603	26204	-6659	1436	276	2816	517676
C19	482712	26439	-6481	1360	275	577	504883
C20	496454	26204	-6676	1469	273	577	518301

The impact of line flow capacity on the considered flexibility metrics have been investigated in the presence of a set of DR programs in order to explore the influences of network on the obtained results as shown in Table 6. As observed, the limitation on transmission line capacity has a negative influence on the considered metrics for all the DR programs.

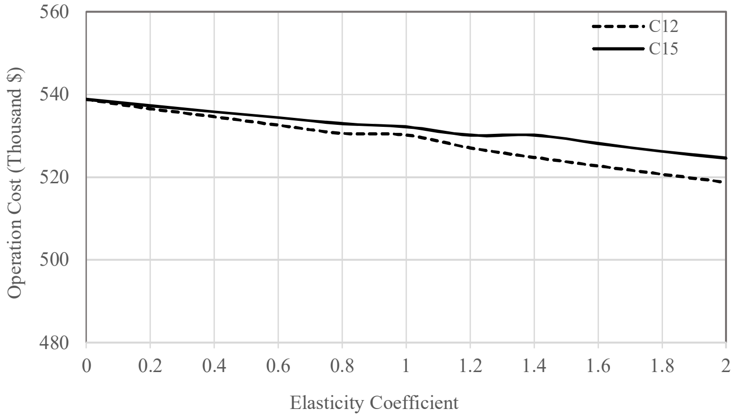
Table 6. Impact of line flow capacity on flexibility metrics in given DR programs.

Case No.	Operation Cost ($)		Pollutant Emission (lbs)		Ramp Need (MW)	
	Max. Line Flow	50% Max. Line Flow	Max. Line Flow	50% Max. Line Flow	Max. Line Flow	50% Max. Line Flow
C3	510484	528775	193088	196792	4704	4725
C5	524989	540878	197756	200493	4514	4861
C9	509229	526040	192718	195304	4757	4803
C12	532722	542867	199297	201157	4649	5030
C15	532179	545582	199242	201972	4731	5047
C17	504730	521300	189978	193953	4684	4929
C18	517676	532320	194683	197790	4592	4875
C19	504883	523391	190883	194770	4797	4936
C20	518301	534688	195513	198456	4497	4938

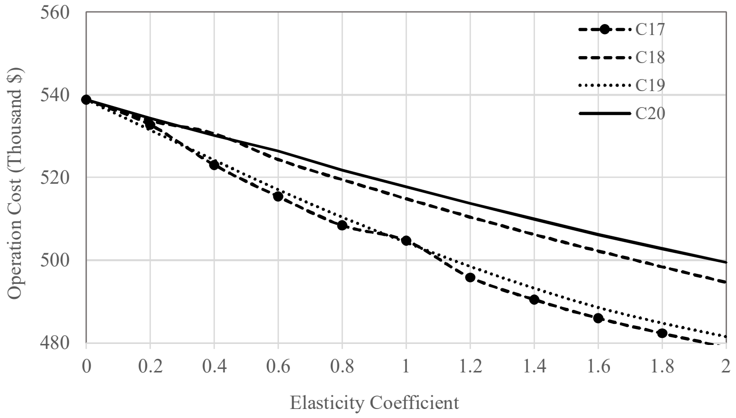
The inherent nature of DR programs is different so that their sensitivity to price elasticity of demand as well as customer's participation level is distinct. It is very essential for the ISO to find the sensitivity of versatile DR programs to these two important factors in order to select and implement an effective DR program. On this basis, the price elasticity values in Table 2 are multiplied by coefficients change from 0 to 2 applying ten equal steps. In addition, the customer's participation level is changed from 0 to 40% in a similar way. The sensitivity of several DR programs into elasticity has been investigated based on operation cost as illustrated in Fig. 5. As observed, the changes are mainly linear. However, the ramp of the changes are different. For instance, the case C9 is the most sensitive DR program to the elasticity changes in TBRDRPs. Also, the RTP sensitivity into elasticity changes is the lowest. Comparing Fig. 5(a) and Fig. 5(b) reveals that IBDRPs are less sensitive to elasticity changes in comparison with TBRDRPs. Fig. 5(c) also indicates that combining TBRDRPs and IBDRPs increase their sensitivity to elasticity changes. The sensitivity of DR programs into customer's participation level has been investigated based on operation cost changes as represented in Fig. 6.



a) TBRDRPs

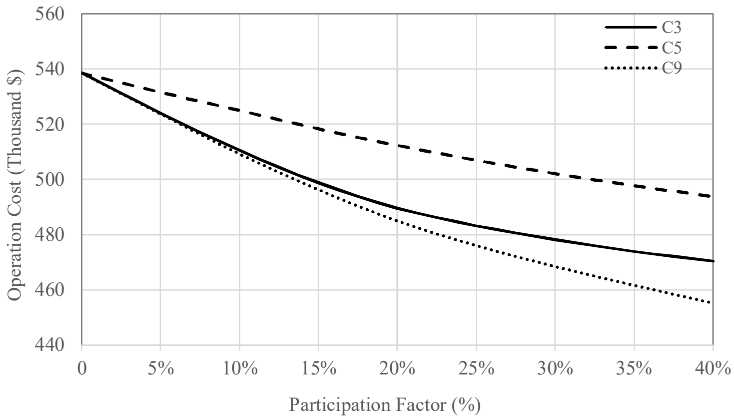


b) IBDRPs

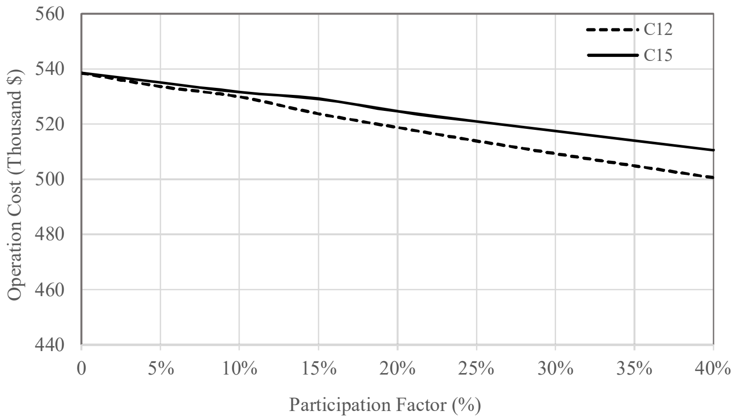


c) Combinational DRPs

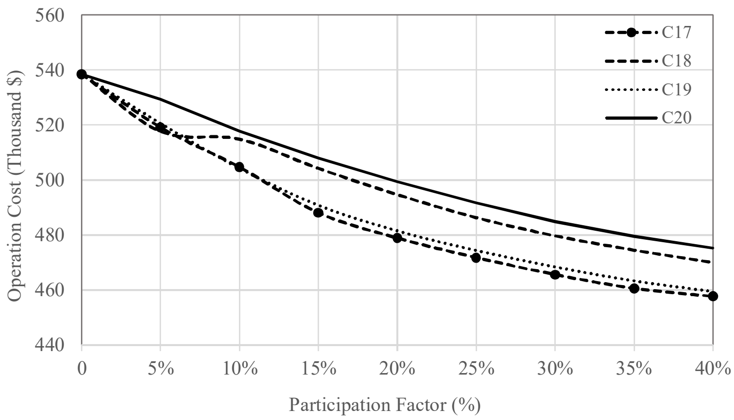
Fig. 5. Sensitivity of operation cost into elasticity in the given cases.



a) TBRDRPs



b) IBDRPs



c) Combinational DRPs

Fig. 6. Sensitivity of operation cost into participation factor in the given cases.

The standard deviation of variations in the operation cost as a result of changing elasticity and participation level is subsequently calculated as an index to determine the sensitivity of different DR programs. The less standard deviation devotes to the less sensitive DR program. The sensitivity of DR programs to price elasticity and participation level have been reported in Fig. 7.

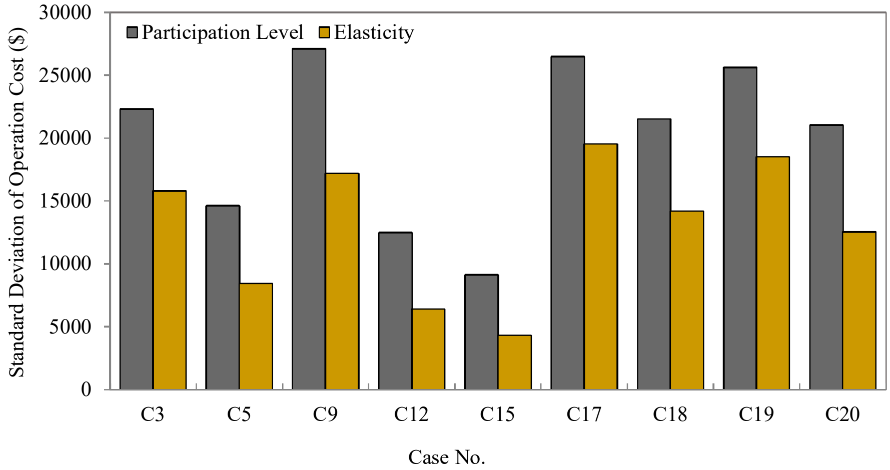


Fig.7. Standard deviation of operation cost with respect to elasticity and participation level in the given cases.

As shown in Fig. 7, the sensitivity of DR programs to participation level is more than elasticity due to the fact that the standard deviation values associate with participation level are higher in all cases. Moreover, the case C15 is less sensitive in the both factors including elasticity and participation level. Afterward, case C12 has the lower sensitivity. Due to the obtained results, it can be concluded that IBDRPs are less sensitive in comparison with other types of DR programs. In addition, the most sensitive case to participation level is C9, while C17 has the highest sensitivity with respect to the elasticity.

5. Conclusion

This paper proposed a stochastic network-constrained energy and reserve market clearing model incorporating a comprehensive DR program's portfolio to precisely evaluate the performance of different types of DR programs, including TBRDRPs, IBDRPs, and combinational DR programs on facilitating wind power integration. The proposed model investigated the effectiveness of DR programs taking into account economical, technical, and environmental preferences of ISOs applying a multi criteria decision making approach, specifically the TOPSIS technique. The key findings of several conducted analyses are summarized below:

- Even if the results may be case-sensitive, in the studied network the RTP program had a key role in meeting the ISO objectives since RTP was in the top three ranked programs;
- IBDRPs are not perfect options by their own, while their combination with TBRDRPs, particularly RTP, may lead to remarkable achievements;
- The sensitivity of DR programs to the participation level is more than the elasticity of demand.
- The IBDRPs are less sensitive into the participation level and price elasticity of demand in comparison with other types of DR programs.

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