A stochastic framework for the grid integration of wind power using flexible load approach

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Abstract

Wind power integration has always been a key research area due to the green future power system target. However, the intermittent nature of wind power may impose some technical and economic challenges to Independent System Operators (ISOs) and increase the need for additional flexibility. Motivated by this need, this paper focuses on the potential of Demand Response Programs (DRPs) as an option to contribute to the flexible operation of power systems. On this basis, in order to consider the uncertain nature of wind power and the reality of electricity market, a Stochastic Network Constrained Unit Commitment associated with DR (SNCUCDR) is presented to schedule both generation units and responsive loads in power systems with high penetration of wind power. Afterwards, the effects of both price-based and incentive-based DRPs are evaluated, as well as DR participation levels and electricity tariffs on providing a flexible load profile and facilitating grid integration of wind power. For this reason, novel quantitative indices for evaluating flexibility are defined to assess the success of DRPs in terms of wind integration. Sensitivity studies indicate that DR types and customer participation levels are the main factors to modify the system load profile to support wind power integration.

Keywords: Wind power integration, Demand response programs, Flexible load, Stochastic programming.

1. Introduction

The predominant share of conventional fossil fuel units in the electricity supply mix has increased concerns on climate change, energy security and price volatility. To address these concerns, many power systems have started changing their energy generation portfolios to include significant amounts of renewable energy resources [1]. Although most renewable energy resources have a dramatic installed capacity growth in the recent years, the development of wind power has enhanced much more, especially. The global installed wind generation capacity increased from 10 megawatts (MW) in 1980 to 282 gigawatts (GW) by the end of 2012 [2].

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However, uncertain and non-dispatchable characteristics of wind power compared to other conventional plants may pose important challenges to power system operation. Highly intermittent nature of wind power may impair power system's balance between supply and demand and lead to system reliability endangerment as well as higher operation costs. Furthermore, ramping requirement of the system in the presence of wind generation is more than the case where no wind power is generated. In such situation, existing generation units must ramp up and down more frequently and operate in de-rated capacity. As a result, the average operating efficiency will be decreased [3].

On this basis, a challenge that system operators are facing with large-scale integration of wind power is how to cope with and mitigate the wind variability and forecast uncertainties. To address the mentioned challenges, several different studies have conducted on large-scale grid integration of wind power. In this regard, providing a more flexible power grid is a common aim that can be seen in all previous researches. To achieve that aim, several solutions are presented for power system operators in former publications which can be classified into three major categories:

1) Utilizing energy storage technologies.
2) Providing additional reserve capacity throughout electricity market and improving market mechanism, rules and structures.
3) Using flexible demand side resources.

In a tremendous share of the previous researches utilization of a storage device alongside wind farms has been suggested. Rabiee et al. [4] review various storage systems for wind power applications. In addition, Jannati et al. [5] compare the ability of four different types of the energy storage systems to mitigate wind power fluctuations. Zafirakis and Kaldellis [6] propose an optimization model to determine the rated power and capacity of a Compressed Air Energy Storage (CAES) to accommodate high wind power penetration in remote island networks. A dynamic optimization model is presented by Loisel [7], which simulates the key role of CAES under two development scenarios for European Commission (EC) and French Transmission System Operator (RTE) by 2030.

Combined operation of wind-hydrogen based, wind-flywheel based, and wind-pumped based energy storage systems are discussed by [8], [9], and [10], respectively. Also, applying a hydro power plant as a supplemental unit beside wind farms is another solution which is taken into consideration for reducing the intermittent impacts of wind generation[11].

Another set of papers have proposed new market structures to facilitate wind power integration. Weber [12] discusses some key feature of the short-term adjustments required by wind energy and the necessity of intraday markets. The obtained results of a realistic case related to Australian National Energy Market (NEM) have been outlined in [13] which investigate policy and market design to facilitate wind integration. Other studies such as [14], [15], and [16] investigate additional reserve capacity requirements for reliable grid integration of wind power through electricity market environment, belonging to the second category. It is worthy to note that, application of deterministic approaches in wind-thermal scheduling problems is not effective due to the stochastic behaviour of wind generation. Hence, many recent papers focused on stochastic programming approaches as it has exerted in [15]-[16].

The third group of researches includes flexible demand side resources such as Plug in Hybrid Electric Vehicles (PHEVs) and Demand Side Management (DSM) solutions, particularly Demand Response (DR). Electric Vehicles (EVs) have been proposed as an option to alleviate the diversity between the electricity supply and demand in systems with high penetration of wind power as emphasized in [17], [18], and [19]. In addition to EVs, some papers investigated the major role of DR in compensating wind power uncertainties. The possible impacts of DR on power system operation with high penetration of wind power have been analysed in [20]-[21]. Many researches have been investigated to detail the impacts of DR on wind integration. Sioshansi and Short [22] evaluate the effects of a price-based DR program on the usage of wind power. Precisely, the impacts of Real-Time Pricing (RTP) implementation on increasing both the percentage of load that is served by wind generation, and potential wind generation is examined. In the paper, DR is implemented under a RTP tariff considering own price elasticity, only. Demand side resources have been considered in the form of peak clipping and demand shifting units with application to wind integration [23]-[24]. Parvania and Fotuhi-Firuzabad [25] propose an incentive-based DR program in order to achieve a smoother load profile and decrease the steep ramps of the net load (load minus wind power) caused by wind generation in a market-based environment. The drawback with this work is that the DR program used in this reference only provides load reduction. Yousefi et al. [26] has gone a step further by considering load reduction as well as load recovery using the self and cross price elasticity concept.

The above mentioned studies use deterministic approaches while wind power has a stochastic nature. Moreover, quantitative metrics have not been addressed for the concept of flexibility in the literature. Most of flexibility studies are based on multi-temporal simulation of power system operation. In other words, a detailed simulation is required to calculate the mentioned metrics, in order to analyse and estimate the flexibility level of a system.

On this basis, this paper presents a two stage Stochastic Network Constrained Unit Commitment incorporating DR (SNCUCDR) with application to wind power integration in which various types of voluntary DR programs are also taken into account. The contributions of this paper are threefold:

- Investigating the effects of various voluntary DR types, DR participation levels and electricity tariffs on providing a flexible load profile and facilitating grid integration of wind power.
- Quantifying the flexibility concept by proposing novel technical and economic indices to evaluate the impact of various DR programs implementation on flexibility enhancement.
- Stochastic scheduling of both generation units and responsive loads in power systems with high penetration of wind power to minimize total operating cost and air pollutant emissions, simultaneously.

The rest of this paper is organized as follows. Section 2 deals with modelling the proposed DR programs. Mathematical formulation of the problem is given in section 3. Section 4 introduces novel indices for evaluating the effectiveness of different DR programs on wind integration. Simulation results are presented in section 5. Finally, section 6 outlines conclusions.

2. Economic model of responsive loads

DR comprises some reactions taken by the end-use customers to decrease or shift the electricity consumption in response to change in the price of electricity or a specified incentive payment over time. Several studies have described the advantages of DR in electricity markets [27]-[28]. According to the benefits of DR programs for achieving reliable and efficient electricity markets, the programs have been legalized and implemented in several countries [29]. Aghaei and Alizadeh [30] assess DR benefits in seven categories: economic; environmental; pricing; market efficiency; customer services; lower cost electric system and services; risk management and reliability. DR programs are categorized into two basic groups, called Price-Based Programs (PBPs) and Incentive-Based Programs (IBPs) [31]. It should be note that, IBPs are classified into three subsets namely; voluntary, mandatory, and market clearing programs. Each of these groups is consisted of several programs as depicted in Fig. 1. These DR programs are discussed in more detail in [29].

"See Fig. 1 at the end of the manuscript".

In order to model responsive load, the current paper uses the concept of elasticity of demand to model load reduction and load recovery by participants in DR programs. In this context, the comprehensive economic model of DR programs developed by Aalami et al. [32] is considered to indicate the necessity of DR programs in providing a flexible load profile. This provided flexibility can potentially increase wind power integration into the grid in a cost effective way.

In this paper, both the priced-based and incentive-based DR programs are taken into account. The highlighted boxes in Fig. 1 refer to the considered voluntary DR programs implemented to achieve flexible load in the paper.

2.1. Price-based DR model

Price-based DR programs persuade end-use customers to decrease or shift their demand by changing electricity tariffs. The paper considers Time-of-Use (TOU) and Real-Time Pricing (RTP) programs with a rationale view. The main reason is that the Critical Peak Pricing (CPP) applied in emergency conditions in a few days of a year, therefore the program is not considered as a permanent implemented DR program such as TOU and RTP.

In order to represent the customer's sensitivity to change in electricity tariffs, the current paper uses the concept of elasticity of demand. Elasticity is defined as the load's reaction to the electricity price. As the elasticity increases, the load sensitivity to price increases as well. In fact, the elasticity is used to estimate the load reduction and load recovery by DR participants. The price elasticity of demand in t-th period versus t'-th period can be defined as it can be seen in Eq. (1). Actually, demand can react to change in electricity tariffs in one of followings. A set of loads is reduced without recovering it later, the so-called fixed loads. Such loads have sensitivity just in a single period and it is called "self-elasticity". This value is always negative. Some loads could be moved from the peak periods to off-peak periods as required, namely transferable loads. Such behaviour is called multi period sensitivity and it is evaluated by "cross-elasticity". This value is always positive. The concepts of self and cross-elasticity are represented by Eq. (2).

$$E(t,t') = \frac{\partial d(t)}{\partial \rho(t')} . \frac{\rho_0(t')}{d_0(t)} \qquad t' = 1,2,3,...,24 \tag{1}$$

where

$$\begin{cases} E(t,t') \le 0 & if \quad t = t' \\ E(t,t') \ge 0 & if \quad t \ne t' \end{cases} \quad and \quad \frac{\partial d(t)}{\partial \rho(t')} = constont \;\; for\, t,t' = 1,2,...,24 \tag{2}$$

If the value of electricity from customer's point of view for using $d(t)$ during hour t is considered as $B(d(t))$, the customer net benefit can be calculated as follows:

$$NB = B(d(t)) - d(t).\rho(t) \tag{3}$$

As mentioned previously, the first term in Eq. (3) indicates the income of customer from the use of $d(t)$ in hour t, and the last term in Eq. (3) is related to electricity cost in hour t. It should be note that calculation of $B(d(t))$ is behind the scope of the current paper and more details are given in [33].

To maximize the customer's net benefit, the derivate of Eq. (3) should be equal to zero:

$$\frac{\partial NB}{\partial d(t)} = \frac{\partial B(d(t))}{\partial d(t)} - \rho(t) = 0 \tag{4}$$

As a consequence:

$$\frac{\partial B(d(t))}{\partial d(t)} = \rho(t) \tag{5}$$

In general, the customer's net benefit is considered as a quadratic function of his/her consumption as follow [33]:

$$B(d(t)) = B_0(t) + \rho_0(t)\left[d(t) - d_0(t)\right]\left\{1 + \frac{d(t) - d_0(t)}{2E(t,t)d_0(t)}\right\} \tag{6}$$

By differentiating Eq. (6) and substituting the results in Eq. (5), the initial price-based economic load model will be obtained as shown in Eq. (7):

$$d(t) = d_0(t)\left\{1 + \frac{E(t,t)\left[\rho(t) - \rho_0(t)\right]}{\rho_0(t)}\right\} \tag{7}$$

According to the concept of the cross elasticity, a change in the electricity price in hour t' may cause the load variation in hour t as represent in Eq. (8).

$$d(t) = d_0(t) + \sum_{\substack{t'=1 \\ t' \neq t}}^{24} E(t,t')\frac{d_0(t)}{\rho_0(t')}\left[\rho(t') - \rho_0(t')\right] \tag{8}$$

As a result of the combination of Eqs. (7) and (8), the comprehensive price-based DR model will be obtained as shown in Eq. (9).

$$d(t) = d_0(t)\left\{1 + \sum_{t'=1}^{24} E(t,t').\frac{[\rho(t') - \rho_0(t')]}{\rho_0(t')}\right\} \tag{9}$$

Equation (9) indicates the optimum amount of customer consumption in a 24 hours period while participating in price-based DR programs.

2.2. Incentive-based DR model

Incentive-based DR programs are also encouraging customers to change their typical demand in return for a specified incentive payment. Emergency DR Program (EDRP) is a voluntary incentive-based program which considers no penalty for customers. Since in most communities reward leads to a significant improvement in subjects' behaviour in compare with punishment [34], and the fact that EDRP also provides more right choice for customers in comparison with Direct Load Control (DLC) program, therefore among all DR programs fall in IBPs category, EDRP is chosen in this paper.

Unlike price-based DR programs, implementation of EDRP imposes some cost to Independent System Operators (ISOs). This cost is related to the incentive payments to customers for their load reduction in specific hours and formulate as bellow in each hour:

$$C_{EDRP}(t) = A(t) \times \left(d_0(t) - d(t)\right) \tag{10}$$

Therefore, the customer net benefit can be calculated as it can be seen in Eq. (11):

$$NB = B(d(t)) - d(t).\rho(t) + A(t).\left(d_0(t) - d(t)\right) \tag{11}$$

Through the similar procedure explained in the former subsection in details, the final EDRP model will be achieved:

$$d(t) = d_0(t)\left\{1 + \sum_{t'=1}^{24} E(t,t').\frac{A(t')}{\rho_0(t')}\right\} \tag{12}$$

By substituting the above equation in Eq. (10), the cost of customer's participation in EDRP from ISO perspective can be formulated as Eq. (13):

$$C_{EDRP}(t) = d_0(t)\left\{\sum_{t'=1}^{24} E(t,t').\frac{A^2(t')}{\rho_0(t')}\right\} \tag{13}$$

From Eq. (13), it can be concluded that $C_{EDRP}(t)$ is a quadratic function of incentive as shown in Fig. 2. The function can be accurately approximated by a piecewise linear model as represent in Eq. (14).

$$C_{EDRP}(t) = \sum_{n=1}^{NS} v_n(t) AS_n(t) \tag{14}$$

"See Fig. 2 at the end of the manuscript".

3. Problem description and formulation

The objective of the proposed SNUCDR model is to schedule conventional units and DR resources such that the total operation costs of the system with large amount of wind power are minimized as well as air pollutant emissions. In this regard, a two stage stochastic network constrained market clearing procedure which links demand and supply-side resources to the generation scheduling problem presented. The applied two stage stochastic programming is well-known and has been used in same problems, already [35]-[36].

The first-stage actually represents the decisions to be declared as hourly unit commitment statuses of thermal generation units, while the second stage represents possible instances of the wind-power generation that should be altogether considered (according to their probability) in order to obtain a single day-ahead market clearing. Indeed, the main purpose of the proposed stochastic programming model is to decide the commitment status of generation units in day-ahead market for high wind penetrated power grids.

It is worthy to note that, although the present paper uses stochastic programming model, for the sake of simplicity, the DR programs are given in their deterministic form. Hence, the only stochastic parameter appertains to wind farm generation. The main objective of this formulation is to determine an optimal wind-thermal generation scheduling considering different DR programs with the aim of increasing system flexibility to facilitate wind power integration. The schematic of proposed model is shown in Fig. 3.

Mathematically, SNCUCDR is a decision making problem with an objective function should be minimized while satisfying several equality and inequality constraints from the ISO’s point of view.

"See Fig. 3 at the end of the manuscript".

The objective function for SNCUCDR can be represented as:

$$
\begin{aligned}
Min \quad & \sum_i \sum_t \left[\left(SU_i . y_{it} + SD_i . z_{it} \right) + \left(C_{it}^{SR} \cdot SR_{it} + C_{it}^{NSR} \cdot NSR_{it} \right) \right] \\
+ \sum_s \omega_s \cdot & \left(\begin{array}{l}
\sum_i \sum_t \left[\underline{F}_i . I_{it} + \sum_{m=1}^{NSF_i} (P_{its}^{e}(m) \cdot C_i^{e}(m)) \right] + \sum_i \sum_t \left[(sr_{its} \cdot C_{it}^{re}) + (nsr_{its} \cdot C_{it}^{nre}) \right] \\
+ \sum_i \sum_t \left[\underline{Em}_i . I_{it} + \sum_{m=1}^{NSE_i} \left[ECC^{SO_2} \cdot (q_{its}(m) \cdot e_i^{SO_2}(m)) + ECC^{NO_x} \cdot \left(q_{its}(m) \cdot e_i^{NO_x}(m) \right) \right] \right] \\
+ \sum_t \left[\pi_{FIT} \cdot W_{st}^{\mathrm{int}} + \pi_{cur} \cdot W_{st}^{curt} \right] \\
+ \sum_t C_{EDRP}(t)
\end{array} \right)
\end{aligned}
\tag{15}
$$

In Eq. (15), the first two terms are start-up and shout-down costs of unit i at hour t pertaining to the first-stage stochastic programming model which is not depend on scenarios occurrence. In addition, in order to ensure that the scheduled wind is safely integrated to the grid, both the spinning reserve and non-spinning reserve capacities are formulated by the next two terms. The other lines in the objective function are related to the second-stage of stochastic programming formulation, corresponding to scenarios realization. In the second line, the generation unit cost function is linearized by a set of piecewise blocks. Afterwards, the cost of deploying spinning and non-spinning reserve is represented. Due to the environmental concern, emission should be taken into account in the objective function as well as operation cost, simultaneously. Typically, emission is expressed using a quadratic function. In this paper, the third line is dedicated to emission cost which is approximated in a piecewise manner similar to cost function. In order to encourage wind generation units to participate more actively in power production, some incentive mechanisms have been used to promote share of wind power all over the world.

The most well-known mechanism used is the Feed-In-Tariff (FIT) incentive mechanism which has been considered in the present paper [37]. In addition, there may be moments in the scheduling horizon that limiting constraints of transmission network do not let the integration of wind power.

On this basis, wind power curtailment cost is also considered in the objective function. The two last mentioned costs are embedded in the fourth line. Finally, the last term is associated to the EDRP cost as expressed in Eq. (14). The constraints are as follows:

- Start-up and shut-down costs constraints

The relation between start-up and shut-down indicators and commitment status of unit is represented by Eq. (16) [38]:

$$y_{i,t+1} - z_{i,t+1} = I_{i,t+1} - I_{i,t} \tag{16}$$

It is not possible that a unit be started-up and shut-down at an hour simultaneously, therefore [38]:

$$y_{it} + z_{it} \le 1 \tag{17}$$

$$0 \le z_{it} \le 1 \tag{18}$$

- Power balance constraints at each bus

To ensure the power system security, hourly generation and load dispatch in each scenario must satisfy power balance constraint at each bus. In this regard, DC load flow equation is applied as it can be seen in Eq. (19).

$$\sum_{i \in G_b} \left[P_{its}^{tot} - P_{bt}^{\mathrm{mod}} + \left(W_{st}^{\mathrm{int}} - W_{st}^{curt} \right)\Big|_{b=wind-bus} \right] = \sum_{l \in L_b} F_{lts} \tag{19}$$

where,

$$P_{its}^{tot} = P_i^{\min} I_{it} + \sum_{m=1}^{NSF_i} P_{its}^{e}(m) + sr_{its} + nsr_{its} \tag{20}$$

$$0 \le P_{its}^{e}(m) \le P_i^{\max}(m) \tag{21}$$

Moreover, in the Eq. (19), P_{bt}^{mod} is the modified demand of bus b at hour t after implementing DR which is allocated to appropriate buses as represent in Eqs. (22) and (23) for price-based and incentive-based DR programs, respectively.

$$P_{bt}^{\mathrm{mod}} = LD_b \cdot \left\{ (1-\eta_d) d_0(t) + \eta_d\, d_0(t) . \left[\sum_{t'=1}^{24} E(t,t') . \frac{[\rho(t') - \rho_0(t')]}{\rho_0(t')} \right] \right\} \tag{22}$$

$$P_{bt}^{\mathrm{mod}} = LD_b \cdot \left\{ (1-\eta_d) d_0(t) + \eta_d\, d_0(t) . \left[\sum_{t'=1}^{24} E(t,t') . \frac{A(t')}{\rho_0(t')} \right] \right\} \tag{23}$$

In addition, Eqs. (24) and (25) indicate transmission line flow through line l and transmission capacity limits:

$$F_{lts} = \left(\delta_{bts} - \delta_{b'ts} \right) / X_l \tag{24}$$

$$-F_l^{\max} \le F_{lts} \le F_l^{\max} \tag{25}$$

- Spinning and non-spinning reserve constraints

In order to ensure that the scheduled wind is safely integrated into the grid, both the spinning reserve and non-spinning reserve are considered. Equations (26) and (27) express the spinning and non-spinning reserve limits. Also, the deployed reserves in each scenario should be lower than the amount of scheduled capacity reserve in the first stage. These constraints are given by Eqs. (28) and (29). Also, it is assumed that the provided spinning reserve should be synchronized within 10 minutes' notice as shown in Eq. (30).

$$0 \leq SR_{it} \leq P_i^{\max} \cdot I_{it} \tag{26}$$

$$0 \leq NSR_{it} \leq P_i^{\max} \cdot \left(1 - I_{it}\right) \tag{27}$$

$$0 \leq sr_{its} \leq SR_{it} \tag{28}$$

$$0 \leq rns_{its} \leq NSR_{it} \tag{29}$$

$$sr_{its} \leq \left(\frac{10}{60}\right).RU_i \tag{30}$$

- Generation unit individual constraints

Eq. (31) indicates maximum and minimum power generation bounds of conventional units. Also, Eqs. (32) and (33) represent the generation unit ramp up and down constraints, respectively. Furthermore, minimum up and down time constraints of generation units are shown by Eqs. (34) and (35), respectively.

$$P_i^{\min} \cdot I_{it} \leq P_{its}^{tot} \leq P_i^{\max} \cdot I_{it} \tag{31}$$

$$P_{its}^{tot} - P_{i(t-1)s}^{tot} \leq RU_i .I_{it} + P_i^{\min} \cdot (1 - I_{i(t-1)}) \tag{32}$$

$$P_{i(t-1)s}^{tot} - P_{its}^{tot} \leq RD_i .I_{i(t-1)} + P_i^{\min} \cdot (1 - I_{it}) \tag{33}$$

$$\sum_{t'=t+2}^{t+UT_i} (1 - I_{it'}) + UT_i \cdot (I_{it} - I_{i(t-1)}) \leq UT_i \tag{34}$$

$$\sum_{t'=t+2}^{t+DT_i} I_{it'} + DT_i \cdot (I_{i(t-1)} - I_{it}) \leq DT_i \tag{35}$$

- Wind power constraints

The amount of integrated wind power must be less than the available wind generation. Also, just both the amounts of curtailed wind power and integrated wind power are positive variables. These issues are addressed in Eq. (36). Eq. (37) ensures that the summation of integrated and curtailed wind power will be less than the available wind power.

$$0 \leq W_{st}^{\text{int}} \leq W_{st}^{\max}, \quad W_{st}^{curt} \geq 0 \tag{36}$$

$$W_{st}^{\text{int}} + W_{st}^{curt} \leq W_{st}^{\max} \tag{37}$$

4. Performance metrics

Strong growth of wind power increases the need for ramp up/down services by the conventional generation units. In order to provide the ramping requirements of the system, increasing system flexibility seems a crucial issue. In fact, the more flexibility means the less regulation services.

Due to technical restrictions of conventional generating units, such as ramp rates constraints, minimum up/down times, etc., the need for more flexible resource is essential. In the 24st wind task of the International Energy Agency (IEA), which investigates issues, impacts, and economics of wind power grid integration, DR resources were introduced as the most flexible and cost effective option to facilitate the grid integration of wind power [39]. In this regard, since load changes are very important for regulated activities of wind power, some novel measures have been proposed in this paper.

Based on this, in order to investigate the impact of different DR programs on facilitating grid integration of wind power, a novel measure is introduced. Average DR Benefit (ADRB) represents the decrease in system operation cost as a result of 1 MWh additional integration of wind power. In the other words, this measure represents the impression of DR implementation on the average cost reduction of 1 MWh additional wind power injection to the power system. The measure is presented in Eq. (38).

$$ADRB = \frac{1}{24}\sum_{t=1}^{24}\frac{\left[TCost_t^{NoDR} - TCost_t^{DR}\right]}{\sum_s \omega_s W_{st}^{\text{int}}} \tag{38}$$

Moreover, in order to measure the impact of DR programs on the load curve and consequently facilitating grid integration of wind power, three other measures are proposed. Based on this, load turbulence index (LTI) is proposed to indicate the smoothness of the load curve. The lower LTI shows the smoother load curve and the easier regulation. The index is presented in Eq. (39). Another feature of load curve that is very important for regulated activities is the rate of demand change. The bigger changes of demand causes the more difficult following the load. On this basis, maximum load up and down indices (MLU and MLD) are utilized to measure the maximum rate of demand changes. The measures are presented in Eqs. (40) and (41), respectively.

$$LTI = \frac{1}{24}\sum_{t=1}^{24}\left|d(t) - d(t-1)\right| \Big/ d(t) \tag{39}$$

$$MLU = \max\left\{d(t) - d(t-1), \quad t = 1,\dots,24\right\} \tag{40}$$

$$MLD = \max\left\{d(t-1) - d(t), \quad t = 1,\dots,24\right\} \tag{41}$$

In the next section, the mentioned indices are applied to investigate the results more precisely.

5. Numerical studies

Numerical studies have been accomplished to illustrate the abilities of the proposed model. For this purpose, the modified IEEE-RTS is considered assuming the 6 hydro units which were in bus 22 are excluded. Instead of hydro units, a wind farm with 1200 MW installed capacity (almost 28% of total generation capacity) is assigned to bus 22. Due to the targets set by many developed countries, this portion of wind power is considered as high penetration. The system peak load is assumed to be 2670 MW corresponding to 1 p.u. in the load curves. Details of the mentioned test network can be found in [40]. It is presumed that generation units submit their offers to produce energy based on their marginal incremental costs given in Table 1. The capacity cost of spinning and non-spinning reserves are considered to be at the rates of 25% and 20% of the highest incremental cost of producing energy, respectively. Also, the deployed reserve cost is considered to be equal to the highest incremental cost of energy production. In addition, two most popular pollutants are considered to conduct emission cost calculations. The pollution coefficients are assumed as presented in Table 2. The environmental cost coefficient of pollutants are assumed to be 0.5 \$/kg for SO_2 emissions and 3 \$/kg for NO_x emissions [41].

"See Table 1 at the end of the manuscript".

"See Table 2 at the end of the manuscript".

In order to model the wind power generation in each hour, a Weibull distribution is considered for wind speed as in [42]. Then a similar procedure as it has been explained in [42] is used to obtain the corresponding wind power. Different realizations of wind power production can be modelled using a scenario generation process based on Roulette Wheel Mechanism (RWM). At first, the distribution function is separated into several class intervals. Afterwards, each interval is related to a certain probability achieved by the PDF. Consequently, due to the various intervals and the mentioned probabilities, RWM is utilized to generate hourly scenarios, as in [43]. The higher numbers of scenarios produce a more accurate model to consider the mentioned uncertainties. However, it yields an unmanageable optimization problem. Hence, a scenario reduction technique is considered, using K-means clustering technique [44], resulting in a scenario tree with ten independent scenarios as shown in Fig. 4. It should be noted that, the wind farm installed capacity is considered as the base value in this figure.

"See Fig. 4 at the end of the manuscript".

The value of FIT incentive and wind curtailment cost are assumed to be 25 and 30 \$/MWh, respectively. The value of wind curtailment cost is selected higher than the value of FIT incentive in order to encourage system operator to integrate maximum wind power. The self and cross price elasticities of demand have been extracted from [32] and are illustrated in Table 3.

It should be noted that calculation of arithmetical values of price elasticity is a complex procedure which may vary widely across different sectors (residential, industrial and commercial) and regions. Moreover, simultaneous data between marginal prices and consumption are needed, which is usually hard to acquire.

"See Table 3 at the end of the manuscript".

The initial electricity prices (i.e. ρ_0) are assumed to be 24.1 \$/MWh equal to the average of hourly electricity prices in the base case. Also, Table 4 summarizes tariff related to TOU and RTP programs in details. The obtained results are analysed in different case studies. These cases have been solved on a PC, 2.3MHz with 4 GB of RAM under General Algebraic Modelling System (GAMS) software. The computation times in all the studies are about 40–75 seconds regarding CPLEX. In order to clarify the dimension of the mathematical programming problem, the optimization statistics for the TOU program (TYPE 2) are given in Table 5. The base-case in the following figures is referred to no DR implementation.

"See Table 4 at the end of the manuscript".

"See Table 5 at the end of the manuscript".

Effect of various scenarios of wind speed on power generation of different system buses have been indicated in Fig. 5. In the figure, the generated powers with and without presence of EDRP have been presented. Moreover, the maximum participation level of EDRP is considered to be 10%. It should be noted that, for the sake of simplicity, the generation of only four buses that have the most sensitivity to implementation of DRPs have been presented in this paper. As it can be seen, the different scenarios of wind speed affect the hourly generation of Bus 1, Bus 2 and Bus 7 more than the one of the other buses (e.g. Bus 23). Utilization of EDRP causes that Bus 1 generates in all hours and, contrary to the base case, it injects power to the grid in hours 2 to 5. In addition, impact of ERDP on Bus 1 and Bus 2 is more than on other buses. The amount of generation of Bus 1 considering the utilization of EDRP is less than the one in base case in hours 9, 12 to 14, 17 to 20 and 22. In Bus 2, although EDRP cannot cause the bus to generate in hours between 2 and 6, it reduces the amount of generation of the bus in almost all hours between 8 and 21. Moreover, it can be seen that the generation of Bus 7 is less than the base case in hours 1, 11, 15, 16 and 21. It can be observed from Fig. 5 that, different scenarios of wind significantly affect the generation of Buses 1, 2 and 7 in some hours. For instance, the amount of generation of Bus 2 in hour 15 can change from 30 to 112 MW according to different scenarios of wind. This can show the high sensitivity of the mentioned bus to the generation of the wind farm (that stands on Bus 22) in that hour. This significant sensitivity can be also seen in hour 21 for the mentioned bus.

Meanwhile, Bus 23 has an insignificant sensitivity to the generation of the wind farm. For the sake of simplicity, in the remainder of numerical studies, the expected value resulted from scenarios of wind speed is been presented. Impact of different DRPs on power generation of different system buses have been illustrated in Figs. 6-8.

"See Fig. 5 at the end of the manuscript".

"See Fig. 6 at the end of the manuscript".

"See Fig. 7 at the end of the manuscript".

"See Fig. 8 at the end of the manuscript".

The impact of EDRP on generated power in different buses has been indicated in Fig. 6. As it can be seen, by utilization of EDRP the generation of buses is reduced in most hours. Furthermore, by increasing the level of participation in EDRP the power generation is decreased more in those hours. This impact for Buses 1, 2 and 23 is more than for other buses. For instance, the amount of generation of Bus 7 has minor changes by increasing the level of participation in EDRP. Meanwhile, the generation of Bus 23 changes from 657 MW (in the base case) to 578 MW (in participation level of EDRP equal to 30%) in hour 19 (approximately 12% generation reduction). Moreover, the amount of generation of Bus 1 is changed from 68 MW (in the base case) to 30 MW (in 30% participation level) in hour 17 (approximately 56% generation reduction). Similarly, Bus 2 generates 65% less by 30% participation level of EDRP in hour 11. It should be mentioned that, implementation of EDRP can increase the amount of generation only in Bus 1 in hours 1 to 6.

Fig. 7 shows that generation power in buses 1 and 2 has been increased in hours 1 to 6 by implementing RTP. The generation increase for Bus 1 with RTP implementation is 15 MW more than the one with EDRP utilization. The amount of generation of Bus 1 in 30% participation level of RTP in hour 17 is equal to 30 MW, which is the same as 30% participation level of EDRP. By comparing Fig. 6 and Fig. 7, it can be observed that there is no significant difference between implementation of EDRP and RTP on the power generation of buses.

The effect of the first considered type of TOU on the power generation of system buses has been illustrated in Fig. 8. As it can be seen, the power generation of buses 1, 2 and 23 changed significantly by implementing TOU. On this basis, the generation of buses 1 and 2 becomes equal to the constant amount of 30 MW in most hours. Moreover, this amount is equal for different levels of participation in TOU, i.e. 10%, 20% and 30%. The generation of Bus 23 is drastically decreased by utilizing TOU.

In peak hours, the power generation of the mentioned bus from 660 MW (in base case) is reduced to about 550 MW (in 10% participation level), 410 MW (in 20% participation level) and 275 MW (in 30% participation level). As it can be observed, the TOU program is more effective than the RTP program to reduce the power generation of the buses.

It should be noticed that, implementation of the first type of TOU with 30% participation level causes the generation of buses 1, 2 and 7 to be increased in off-peak period (hours 23 and 24). This means that, the system needs more generation in the mentioned hours due to the increase of demand. The minimum operation costs of the electricity system considering various DRPs have been compared in Fig. 9. As it can be seen, for all DRPs the increase of maximum participation level of DR causes the total operation cost to be decreased. In addition TOU-Type2 can cause the minimum operation cost among different DRPs. Behind the second type of TOU program, TOU-Type1, TOU-Type3 and EDRP are the most effective DRPs to decrease the operation cost. It can be observed that RTP has the least effect to minimize the operation cost.

"See Fig. 9 at the end of the manuscript".

Impact of the mentioned DRPs on the terms of operation cost has been presented in Fig. 10. As it can be seen, although EDRP can significantly reduce the fuel and pollution costs, the market payments to responsive demands duo to take part in the program causes the effect of EDRP on the operation cost to be less than all three types of TOU. In addition, TOU-Type2 can decrease the fuel and emission costs better than other DRPs.

"See Fig. 10 at the end of the manuscript".

Fig. 11 shows the changes of daily load curve because of various DRPs. As it can be seen, EDRP can decrease the amount of load peak and consequently it can produce a flatter load curve compared to the base case, although it has no significant effect on demand in low-load and off-peak periods. Moreover, RTP has an insignificant effect on the load curve compared to other DRPs; whereas, TOU programs can reduce the demand peak and also increase the low-load and off-peak demand. Therefore, the programs can cause the load curve to be smoother. It is noteworthy that, implementation of TOU programs with 20% and 30% participation level causes that the hour of demand peak is changed and shifted to hour 23. As it can be observed from Figs. 11 (c) to 11 (e), if the system operator aims to have smoother load curves, using very different prices for different hours of a day (e.g. implementation of the third type of TOU program) can cause negative impacts and even cause some higher demand peaks.

"See Fig. 11 at the end of the manuscript".

The effect of various types of DRP on the prices of electricity market has been presented in Figs. 12 and 13. As it can be seen, EDRP and TOU are more effective than RTP to change the market prices. These two DRPs can stabilize the prices of energy market in different hours. Only at hour 23 an increase in the energy price can be seen because the hour is when the generation of wind power is reduced and the system demand is increased due to TOU programs (in 30% participation level).

Since the TOU programs can shift some parts of load in peak period to off-peak, price in off-peak periods is increased. Fig. 12.b. indicates that by growing the maximum level of participation in DRPs and by increasing the difference between peak and off-peak tariffs (e.g. type3) the time of price peak can be changed. In other words, the price peak can shift to off-peak periods, especially if the low cost generation units cannot generate in the periods. As it can be observed, at hour 23 when the wind power is low and a part of peak load shifts to the hour, market price is increased. It should be mentioned that, implementation of different DRPs not only decreases the high energy prices (during peak period), but also causes that lower prices (e.g. hour 7) are increased compare to base case and become approximately equal to other prices, especially by implementing TOU programs.

"See Fig. 12 at the end of the manuscript".

"See Fig. 13 at the end of the manuscript".

The effect of the mentioned DRPs on the hourly total operation cost has been illustrated in Figs. 14 and 15. As it can be seen, the DRPs can reduce the operation costs in peak period because of decreasing the electricity loads and consequently electricity prices. In these figures, the high amount of operation cost in hour 1 is because of the start-up cost of required units. As it can be observed, in most hours the operation cost is decreased by utilizing DRPs. However, implementation of TOU programs causes an increase in operation cost in off-peak and low-load periods because of the load shifting feature. For instance, at hour 23 when the wind power is low and demand is increased, operation cost is significantly increased.

"See Fig. 14 at the end of the manuscript".

"See Fig. 15 at the end of the manuscript".

In Figs. 16 to 19, the various DRPs have been compared using the proposed indices. As it can be seen, the second type of TOU program has the highest ADRB, hence the program has the most effect on decreasing the operation cost due to wind power generation. However, the mentioned program can produce high load turbulence as reflected in all of LTI, MLU and MLD indices. The second type of TOU program has been followed by the first type of TOU program regarding the index of ADRB.

TOU-Type1 causes acceptable load turbulence in comparison with the other DRPs. This program has been followed by TOU-Type3 to have the higher ADRB. However, according to LTI, MLU and MLD indices the DRP has caused the highest load turbulence among the studied programs. TOU-Type3 program has been followed by the EDRP to have the higher ADRB index. According to LTI, MLU and MLD indices the EDRP has created less load turbulence than TOU-Type1. Finally, the ADRB index shows that the RTP program has the least effect on reducing the operation cost because of wind power generation compared with other DRPs.

"See Fig. 16 at the end of the manuscript".

"See Fig. 17 at the end of the manuscript".

"See Fig. 18 at the end of the manuscript".

"See Fig. 19 at the end of the manuscript".

6. Conclusions

This paper provided a decision making framework for system operators in order to select the best DR program facilitating wind power integration, considering technical, economic and environmental aspects. For this purpose, the effectiveness of various DR programs implementation on system flexibility was investigated considering the role of customer participation level, electricity tariffs, and optimal incentive values. To quantify the flexibility concept and compare different DR programs effectiveness, novel technical and economic indices were proposed. These proposed measures can be used as a guideline for system operators in order to harness the system to cope with wind power uncertainty using optimal DR programs in different conditions. On this basis, not only the maximum available wind power will be integrated, but also the system operation costs will be decreased in an appropriate way. Applying other flexible resources, which can contribute to the required flexibility besides DR resources, can be considered in future works.

Nomenclature

Indices

b	Index of system buses
i	Index of generating unit
l	Index of transmission line
m	Segment index for linearized fuel cost
n	Segment index for linearized total incentive curve
s	Index of scenarios

t, t'	Index of hours
NSE_i NSF_i	Number of segments for the piecewise linearized emission and fuel cost curves of unit *i*
NS	Number of segments for the piecewise linearized total incentive curve
Parameters	
$AS_n(t)$	Slope of segment *n* in linearized total incentive curve in hour *t* (MWh)
$C_i^e(m)$	Slope of segment *m* in linearized fuel cost curve of unit *i* ($/MWh)
$d_0(t)$	Initial electricity demand (MW)
C_{it}^{SR}	Offered capacity cost of spinning reserve provision of unit *i* in hour *t* ($/MW)
C_{it}^{NSR}	Offered capacity cost of non-spinning reserve provision of unit *i* in hour *t* ($/MW)
C_{it}^{re}	Offered energy cost of spinning reserve provision of unit *i* in hour *t* ($/MWh)
C_{it}^{nre}	Offered energy cost of non-spinning reserve provision of unit *i* in hour *t* ($/MWh)
$e_i(m)$	Slope of segment *m* in linearized emission curve of unit *i* (kg/MWh)
ECC	Environmental cost coefficient of pollutants ($/kg)
$E(t,t')$	Elasticity of demand
$\underline{Em}_i$	Lower limit on the emission cost of unit *i* ($/h)
$\underline{F}_i$	Lower limit on the fuel cost of unit *i* ($/h)
LD_b	Demand contribution of bus *b* (MW)
$P_i^{\min}/P_i^{\max}$	Minimum/ Maximum output limit (MW)
RU_i/RD_i	Ramp up/down (MW/h)
SU_i/SD_i	Start-up/shutdown cost of unit *i* ($)
UT_i/DT_i	Minimum up/down time (h)
$W_{st}^{\max}$	Available wind power (MWh)
X_l	Reactance of line *l*
η_d	Customer participation level in DRPs
π_{FIT}	FIT incentive value ($/MWh)

π_{cur} Cost of wind power curtailment ($/MWh)

$\rho_0(t)$ Initial electricity price ($/MWh)

ω_s Probability of wind power scenario *s*

Variables

$C_{EDRP}(t)$ Cost of customer's participation in EDRP ($)

F_{lts} Power flow through line *l* in hour *t* of scenario *s* (MW)

I_{it} Binary status indicator of generating unit *i* in hour *t*

y_{it}/z_{it} Binary start-up/shutdown indicator of unit *i* in hour *t*

$P_{its}^{e}(m)$ Generation of segment *m* in linearized fuel cost curve (MWh)

P_{bt}^{mod} Modified demand of bus *b* in hour *t* after implementing DR (MW)

P_{its}^{tot} Total scheduled power of unit *i* in hour *t* of scenario *s* (MW)

SR_{it} Scheduled spinning reserve of unit *i* in hour *t* (MW)

NSR_{it} Scheduled non-spinning reserve of unit *i* in hour *t* (MW)

sr_{its} Deployed spinning reserve of unit *i* in hour *t* of scenario *s* (MWh)

nsr_{its} Deployed non-spinning reserve of unit *i* in hour *t* of scenario *s* (MWh)

$q_{its}(m)$ Generation of segment *m* in linearized emission curve (MWh)

$v_n(t)$ Award of segment *n* in linearized total incentive curve in hour *t* ($/MWh)

W_{st}^{int} Integrated wind power in hour *t* of scenario *s* (MWh)

W_{st}^{curt} Curtailed wind power in hour *t* of scenario *s* (MWh)

δ_{bts} Voltage angle at bus *b* in hour *t* of scenario *s* (rad)

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Figure captions

Fig. 1. Classification of DR programs.

Fig. 2. Piecewise linear total incentive for a typical hour.

Fig. 3. Framework of implementing proposed SNCUCDR.

Fig. 4. Considered wind power generation scenarios.

Fig. 5. Effect of various scenarios of wind speed on power generation in different buses considering 10% maximum participation level of EDRP.

Fig. 6. Effect of EDRP on power generation in different buses.

Fig. 7. Effect of RTP on power generation in different buses.

Fig. 8. Effect of TOU on power generation in different buses.

Fig. 9. Effect of various DRPs on the optimal operation cost.

Fig. 10. Effect of various DRPs on the different terms of operation cost.

Fig. 11. Effect of various DRPs on load curve.

Fig. 12. Effect of various DRPs on market price.

Fig. 13. Effect of various types of TOU on market price.

Fig. 14. Effect of various DRPs on hourly operation cost.

Fig. 15. Effect of various types of TOU on hourly operation cost.

Fig. 16. Effect of various DRPs on the proposed index LTI.

Fig. 17. Effect of various DRPs on the proposed index MLU.

Fig. 18. Effect of various DRPs on the proposed index MLD.

Fig. 19. Effect of various DRPs on the proposed index ADRB.

Table captions

Table 1. Generation unit energy offering information.

Table 2. Pollution emission coefficients.

Table 3. Piece elasticity values.

Table 4. Demand response programs tariffs.

Table 5. Optimization statistics for TOU (type 2) program.

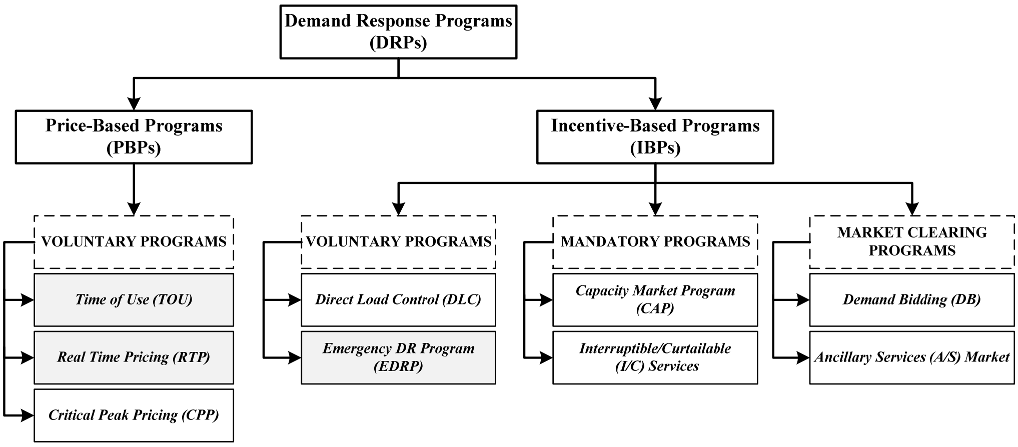


Fig. 1. Classification of DR programs.

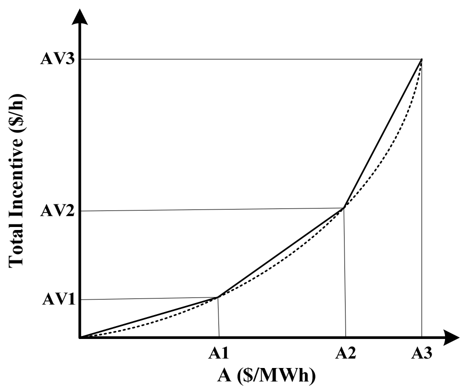
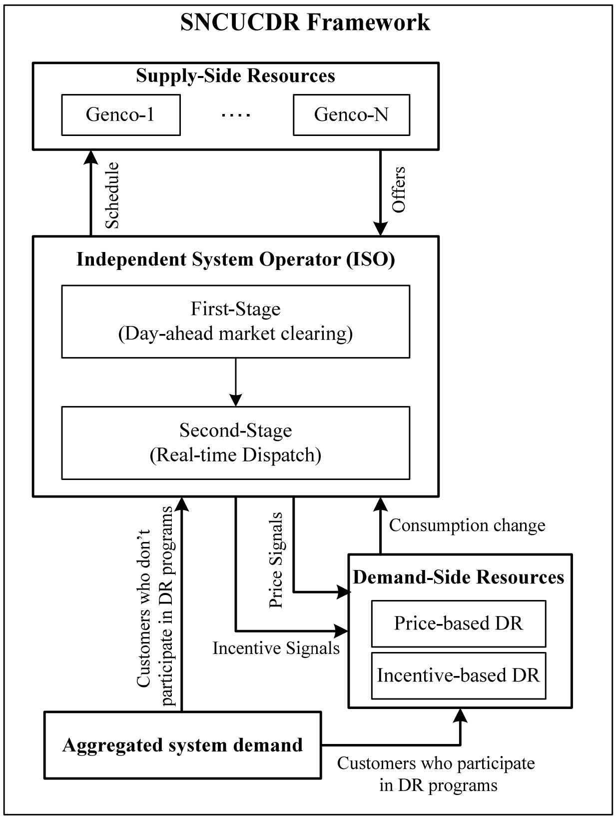


Fig. 2. Piecewise linear total incentive for a typical hour.



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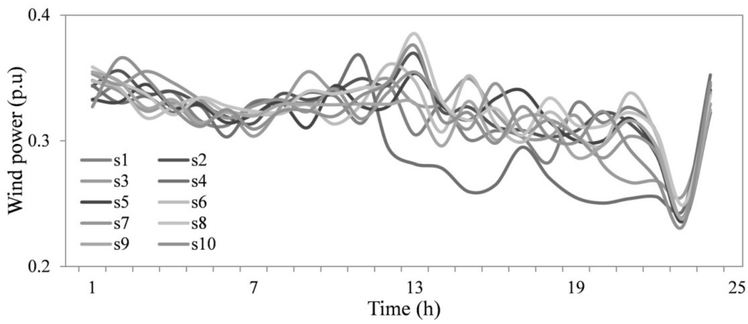


Fig. 4. Considered wind power generation scenarios.

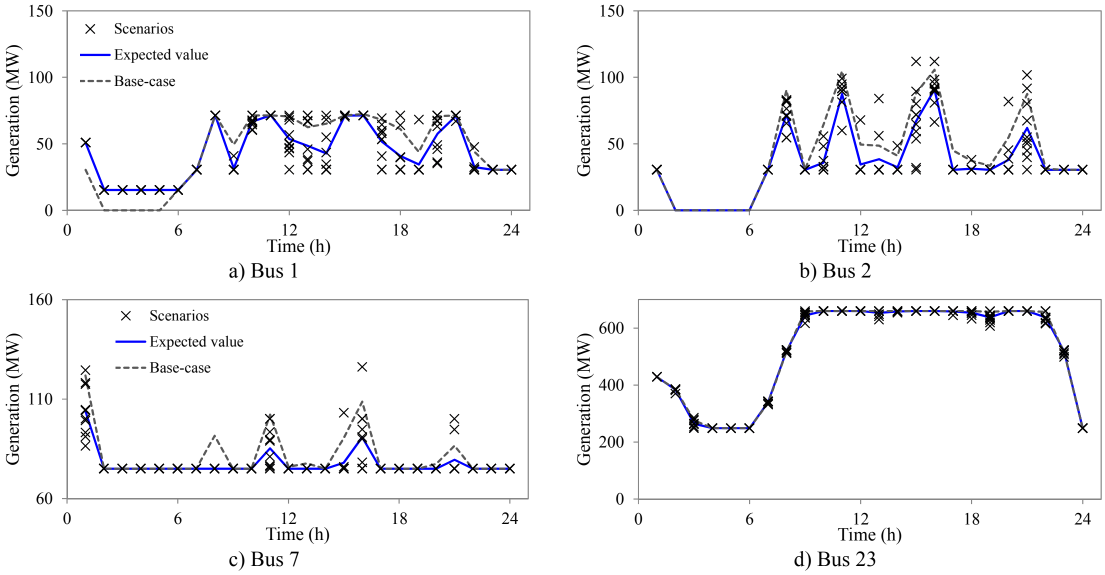


Fig. 5. Effect of various scenarios of wind speed on power generation in different buses considering 10% maximum participation level of EDRP.

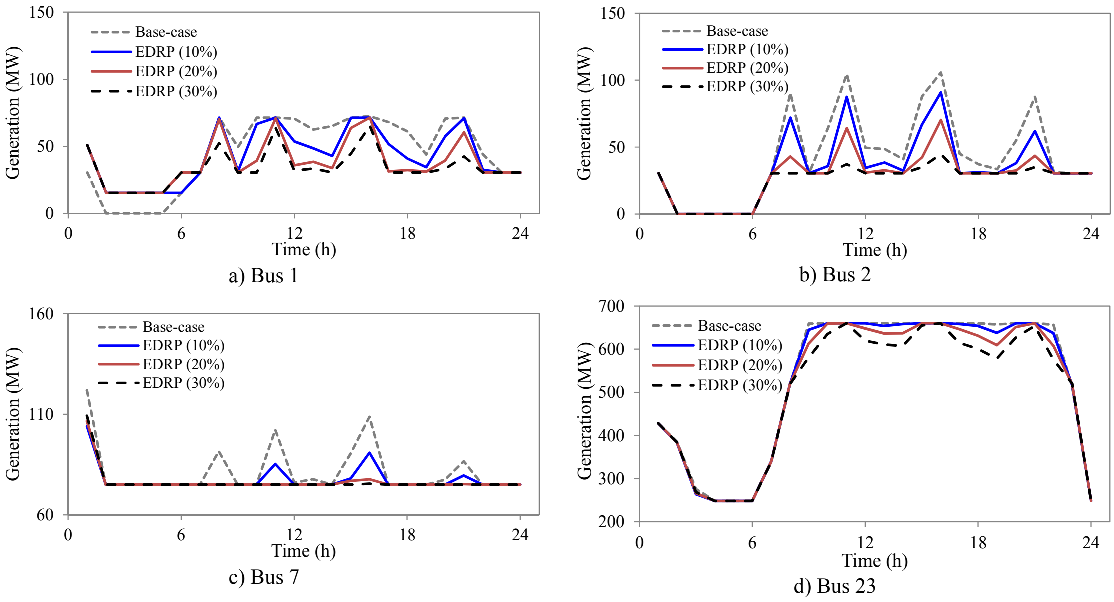


Fig. 6. Effect of EDRP on power generation in different buses.

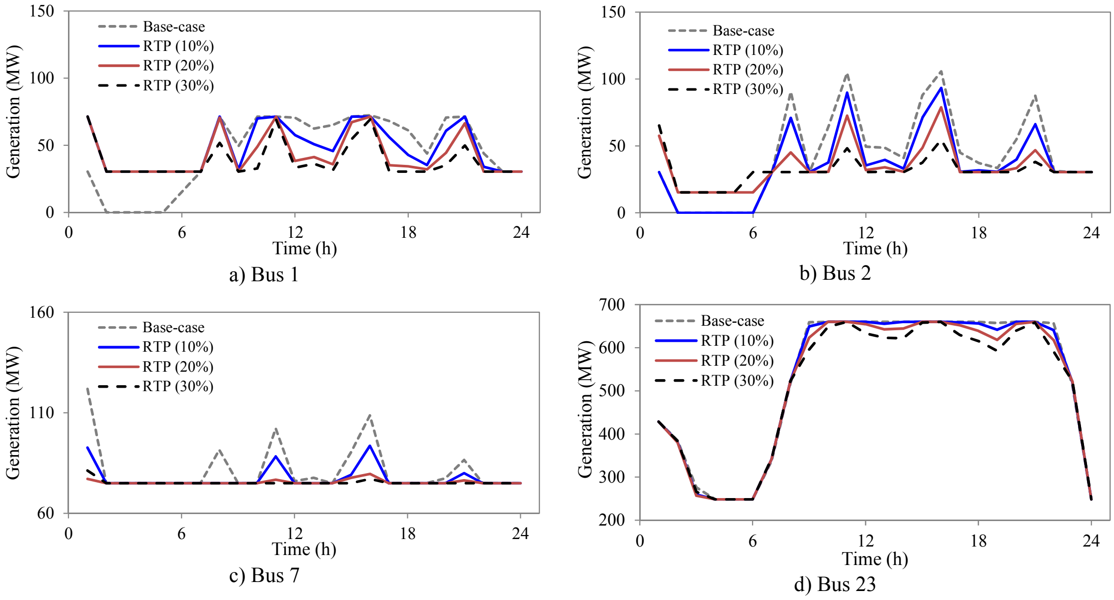


Fig. 7. Effect of RTP on power generation in different buses.

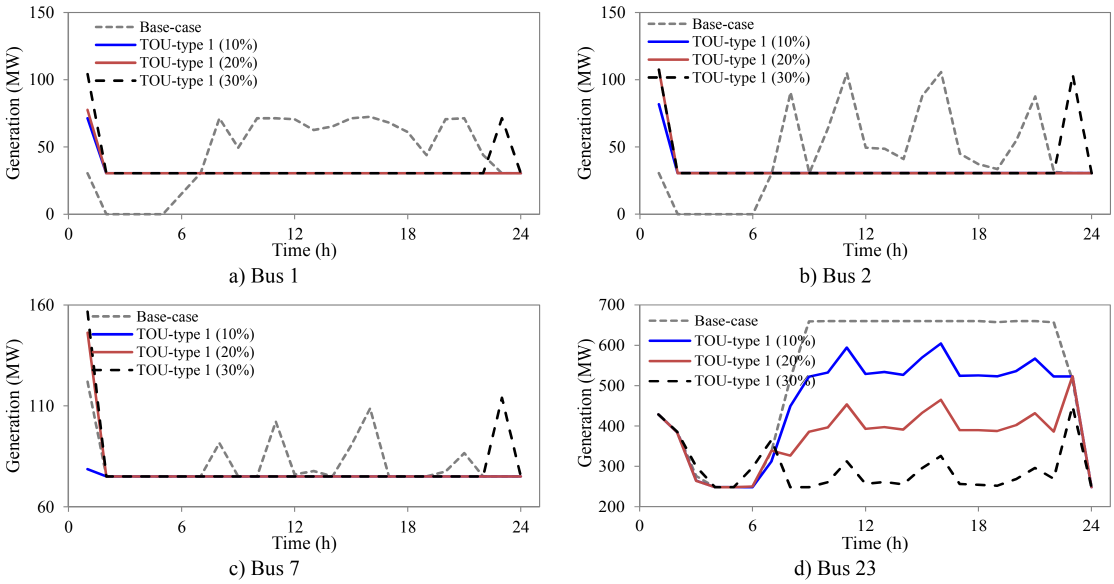


Fig. 8. Effect of TOU on power generation in different buses.

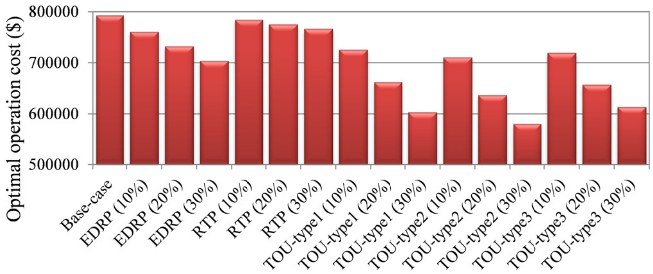


Fig. 9. Effect of various DRPs on the optimal operation cost.

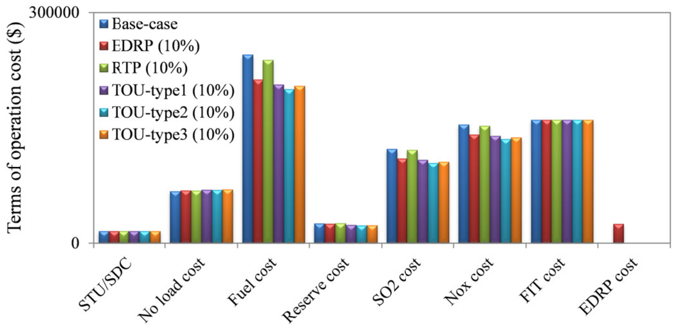


Fig. 10. Effect of various DRPs on the different terms of operation cost.

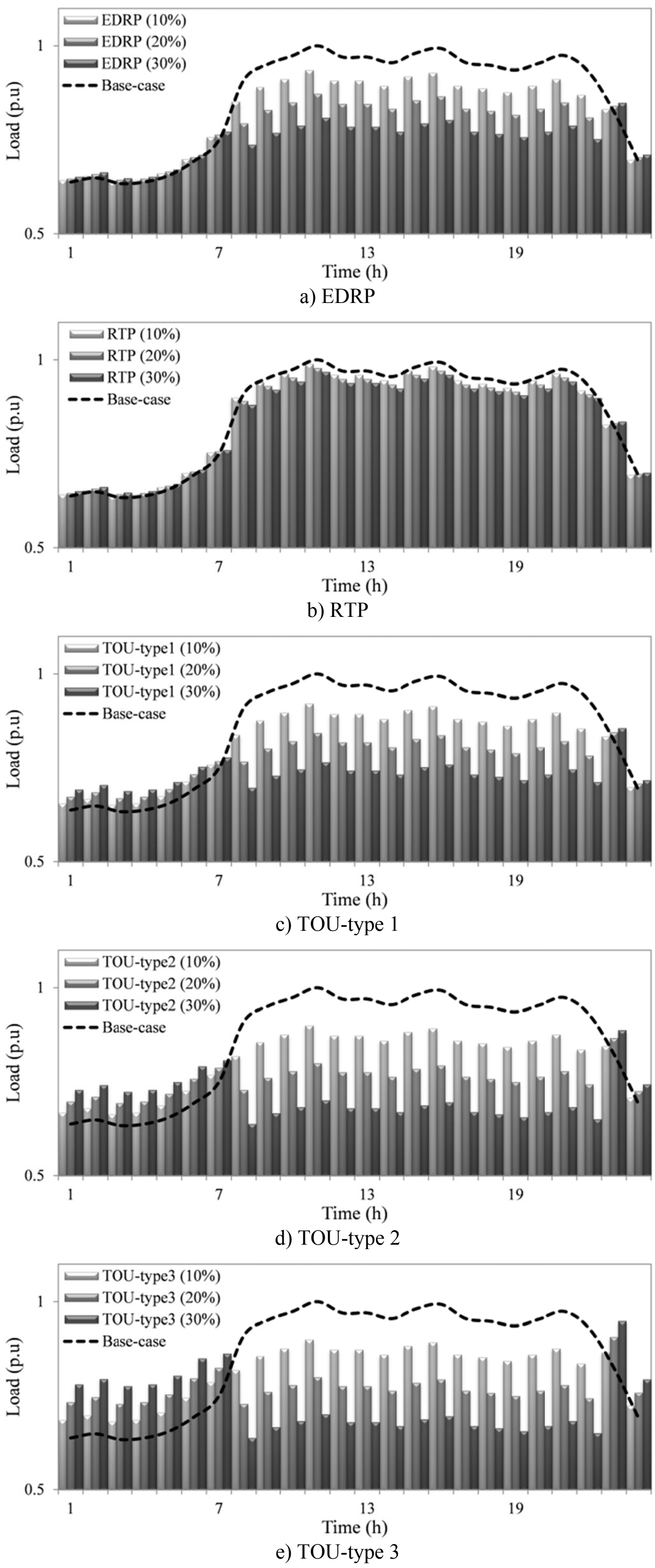
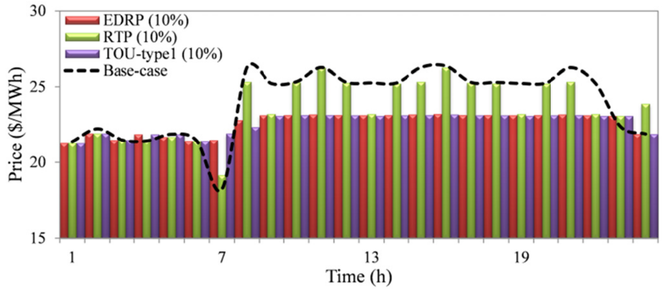
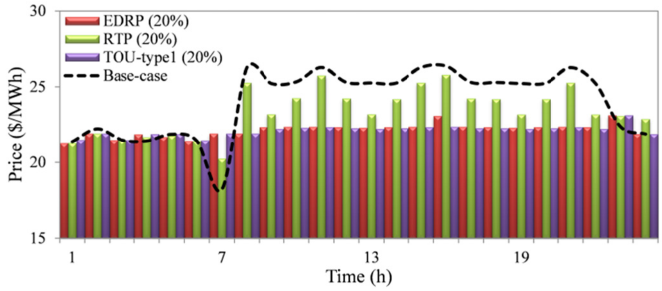


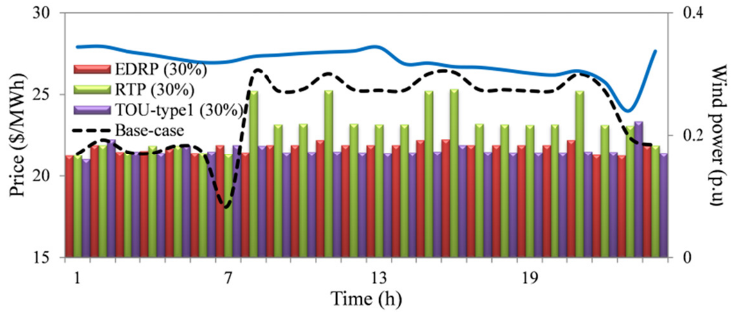
Fig. 11. Effect of various DRPs on load curve.



a) 10% of the maximum DR participation level

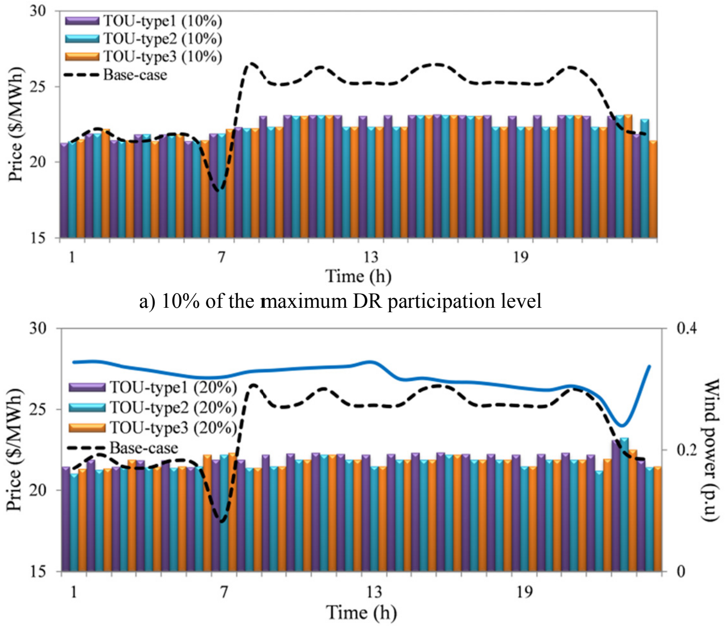


b) 20% of the maximum DR participation level



c) 30% of the maximum DR participation level

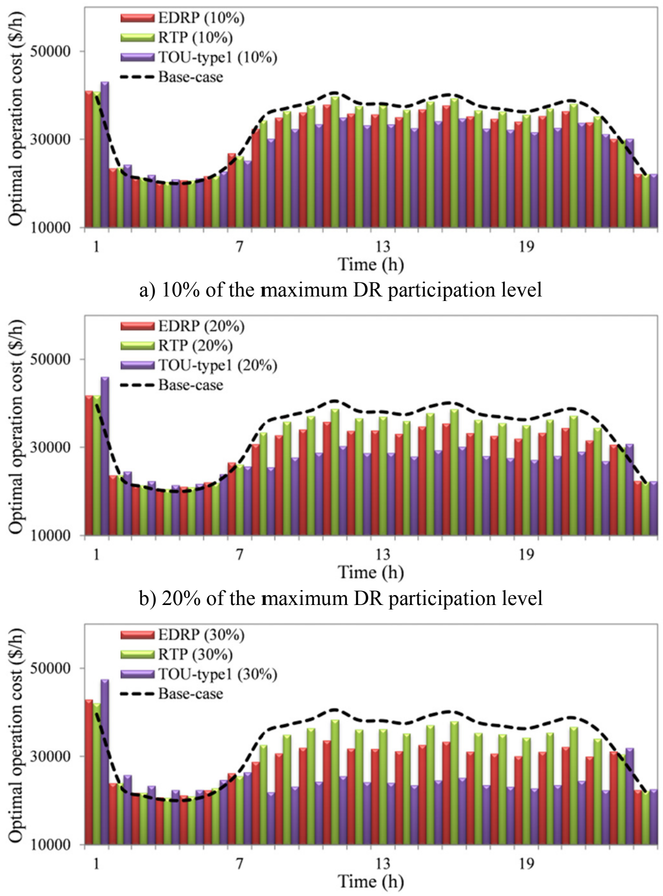
Fig. 12. Effect of various DRPs on market price.



a) 10% of the maximum DR participation level

b) 20% of the maximum DR participation level

Fig. 13. Effect of various types of TOU on market price.

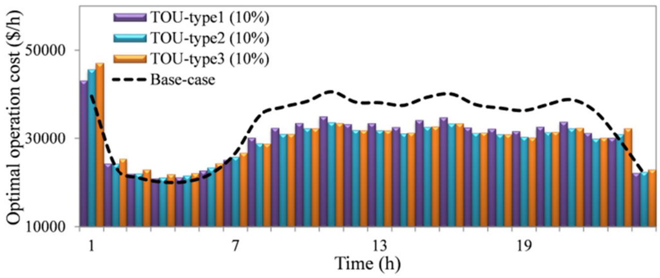


a) 10% of the maximum DR participation level

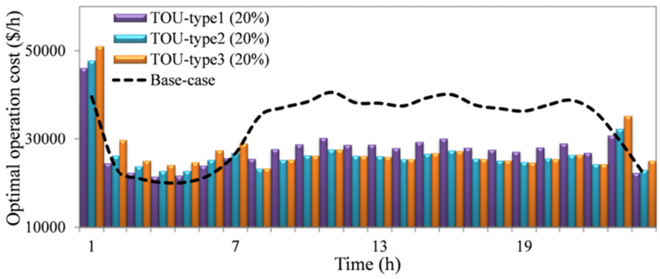
b) 20% of the maximum DR participation level

c) 30% of the maximum DR participation level

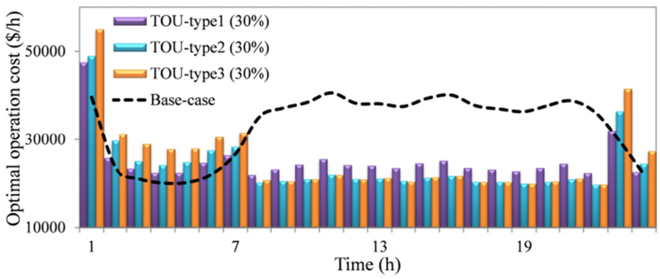
Fig. 14. Effect of various DRPs on hourly operation cost.



a) 10% of the maximum DR participation level



b) 20% of the maximum DR participation level



c) 30% of the maximum DR participation level

Fig. 15. Effect of various types of TOU on hourly operation cost.

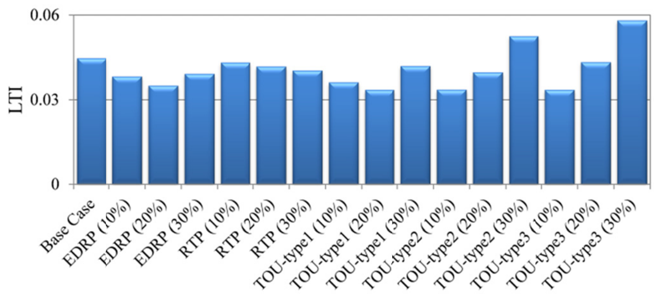


Fig. 16. Effect of various DRPs on the proposed index LTI.

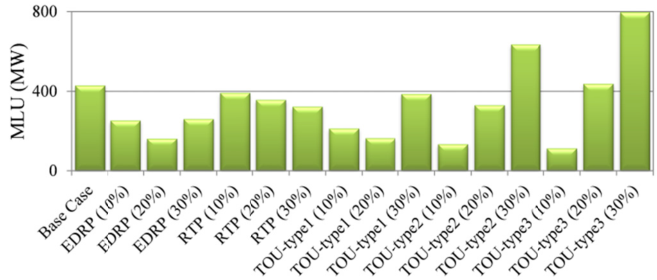


Fig. 17. Effect of various DRPs on the proposed index MLU.

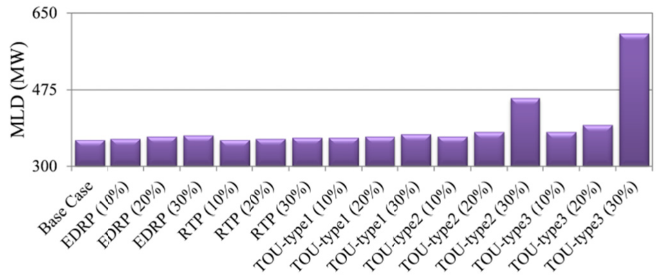


Fig. 18. Effect of various DRPs on the proposed index MLD.

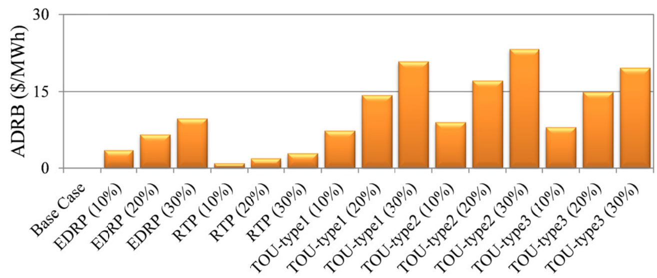


Fig. 19. Effect of various DRPs on the proposed index ADRB.

Table 1

Generation unit energy offering information

Unit No.	Piece wise linearization parameters (MW)				Energy bidding data			
	$P_i^{\min}$	$P_{it}^e(1)$	$P_{it}^e(2)$	$P_i^{\max}$	$C_i^e(1)$	$C_i^e(2)$	$C_i^e(3)$	$\underline{F}_i$
1-5	2.4	5.6	8.8	12	26.02	26.19	26.37	24
6-9	4	9.3	14.7	20	37.9	38.03	38.17	118
10-13	15.2	35.5	55.7	76	13.82	14.19	14.56	76
14-16	25	50	75	100	18.56	18.86	19.17	210
17-20	54.2	87.8	121.4	155	11.4	11.72	12.04	120
21-23	68.9	111.6	154.3	197	23.57	23.79	24.01	239
24	140	210	280	350	11.4	11.61	11.83	132
25-26	100	200	300	400	8.08	8.46	8.85	272

Table 2

Pollution emission coefficients

Unit No.	Unit type	SO2 pollution coefficients				NOx pollution coefficients			
		kg/MWh			\$/h	kg/MWh			\$/h
		$e_i^{SO_2}(1)$	$e_i^{SO_2}(2)$	$e_i^{SO_2}(3)$	$\underline{Em}_i$	$e_i^{NO_x}(1)$	$e_i^{NO_x}(2)$	$e_i^{NO_x}(3)$	$\underline{Em}_i$
1-5	Gas	0.9	1.0	1.1	3.2	2.3	2.5	2.8	6.6
6-9	Gas	0.9	1.1	1.3	15.3	2.2	2.8	3.2	36.8
10-13	Coal	11.5	12.7	14.7	175.8	1.9	2.0	2.2	31.2
14-16	Oil	4.2	4.5	4.8	105.6	1.9	2.0	2.2	48.5
17-20	Coal	9.9	10.3	10.8	537.9	1.7	1.8	1.9	94
21-23	Oil	4.3	4.3	4.4	296.1	1.9	1.9	2.0	135.1
24	Coal	10.2	10.7	11.2	1427.1	1.8	1.8	1.9	247.8
25-26	Nuclear	0	0	0	1	0	0	0	1

Table 3

Piece elasticity values

	Peak	Off-peak	Low-load	Period
Peak	-0.10	0.016	0.012	8-22
Off-peak	0.016	-0.10	0.010	1-7
Low-load	0.012	0.010	-0.10	23-24

Table 4

Demand response programs tariffs

Hour	DR Programs Tariffs				Hour	DR Programs Tariffs			
	TOU			RTP		TOU			RTP
	TYPE 1	TYPE 2	TYPE 3			TYPE 1	TYPE 2	TYPE 3	
1	16	12	8	21.4	13	36.15	48.2	72.3	25.3
2	16	12	8	22.2	14	36.15	48.2	72.3	25.3
3	16	12	8	21.5	15	36.15	48.2	72.3	26.3
4	16	12	8	21.4	16	36.15	48.2	72.3	26.4
5	16	12	8	21.9	17	36.15	48.2	72.3	25.3
6	16	12	8	21.4	18	36.15	48.2	72.3	25.3
7	16	12	8	21.2	19	36.15	48.2	72.3	25.2
8	36.15	48.2	72.3	26.3	20	36.15	48.2	72.3	25.3
9	36.15	48.2	72.3	25.2	21	36.15	48.2	72.3	26.3
10	36.15	48.2	72.3	25.3	22	36.15	48.2	72.3	25.2
11	36.15	48.2	72.3	26.3	23	24.1	24.1	24.1	22.4
12	36.15	48.2	72.3	25.3	24	24.1	24.1	24.1	21.9

Table 5

Optimization statistics for TOU (type 2) program

No. of single constraints	No. of single variables	No. of discrete variables	No. of iterations	Solution time (s)
395586	281566	9480	70290	64