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# The role of demand response in single and multi-objective wind-thermal generation scheduling: A stochastic programming

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ABSTRACT

This paper focuses on using DR (Demand Response) as a means to provide reserve in order to cover uncertainty in wind power forecasting in SG (Smart Grid) environment. The proposed stochastic model schedules energy and reserves provided by both of generating units and responsive loads in power systems with high penetration of wind power. This model is formulated as a two-stage stochastic programming, where first-stage is associated with electricity market, its rules and constraints and the second-stage is related to actual operation of the power system and its physical limitations in each scenario. The discrete retail customer responses to incentive-based DR programs are aggregated by DRPs (Demand Response Providers) and are submitted as a load change price and amount offer package to ISO (Independent System Operator). Also, price-based DR program behavior and random nature of wind power are modeled by price elasticity concept of the demand and normal probability distribution function, respectively. In the proposed model, DRPs can participate in energy market as well as reserve market and submit their offers to the wholesale electricity market. This approach is implemented on a modified IEEE 30-bus test system over a daily time horizon. The simulation results are analyzed in six different case studies. The cost, emission and multiobjective functions are optimized in both without and with DR cases. The multiobjective generation scheduling model is solved using augmented epsilon constraint method and the best solution can be chosen by Entropy and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) methods. The results indicate demand side participation in energy and reserve scheduling reduces the total operation costs and emissions.



## 1. Introduction

SG (Smart Grid) is an intelligent electricity network that uses information and communication technologies in the power system. Smart Grid technology could reduce many problems in the electric power industry such as limitation of fossil fuels and air pollution emission by using renewable energy resources [1]. It could be said that the wind energy plays the most effective role in the future of power generation, in comparison to other types of renewable energies. The electricity generation provided by wind farms is relatively cheap and the efficient way to reach air pollutants emission reduction goals [2]. But besides the above benefits, wind energy has variable and random nature and this problem imposes challenges to power system. To overcome this problem, power systems need some resources to compensate the wind power generation forecasting uncertainty. These resources are utilized to maintain the real time balance between production and consumption during operation of the power system.

In current power systems, ISOs (Independent System Operators) consider enough spinning and non-spinning reserves provided by generators for compensation of unpredictable nature of wind power [3]. Unfortunately these reserves generate emission, make some generating units be operated in non-optimal output and additional generators become committed [4]. In smart grid, ISOs have more options to make up for this uncertainty and reduce above problems. In other words, smart grid technologies help ISOs use DR (Demand Response) programs, energy storage units and plug-in electric vehicles beside reserves provided by generating units to compensate the random nature of wind power in a more efficient and cost-effective way [5].

End-use customers can decrease consumption, when the system faces a shortage in production caused by lack of wind, or increase it when the wind blows is high. So, these responsive

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loads provide reserve and reduce the amount of reserve provided by generating units. In addition to providing reserve, responsive loads can also participate in energy markets and compete with generator production. Providing energy by these loads reduces cost and emission of generating units. This End-use customer participation which is called demand response can help power system to be more efficiently, economically and securely operated. DR programs are classified into two major categories: price-based and incentive-based DR programs. First category programs refer to change in electricity consumption by end-use customer in response to dynamic prices. These programs include TOU (Time of Use) rate, RTP (Real Time Pricing), and CPP (Critical Peak Pricing) and are entirely voluntary. To access price signals, two-way communication link between the consumer and supplier is necessary that AMI (Advanced Metering Infrastructure) system provides it [6,7]. Second category programs are designed by operators and include Direct Load Control, Interruptible/Curtailable service, Demand Bidding, Emergency DR, Capacity Market, and Ancillary services market program. These programs give participating customers incentive payments and can consider penalties for customers that enroll but do not respond in needed time, depending on the program types and conditions. Fig. 1 shows classification of DR programs. These DR programs are discussed in more detail in Ref. [8].

In recent years, many researches have been worked on covering uncertainty of wind power. In Ref. [9] a stochastic programming has been used for market clearing and considered load and wind prediction error as normal distributed random variables. In Ref. [10], a method for dealing with the short-term active power scheduling of a stand-alone system has been presented. In this method, the fuel cost of diesel units and $CO_2$ emission are minimized while the operation constraints are satisfied. Moreover, the maximum wind and solar PV powers with uncertainties are modeled using fuzzy sets. In Ref. [11], the wind prediction error is modeled by a PDF (probability density function) and used spinning reserve provided by generation units for covering uncertainty of wind power. In Ref. [12], a modified teaching-learning algorithm has been proposed to cope with a probabilistic multiobjective wind-thermal dispatch problem. The economic/environment dispatch model has considered the uncertainties in load demand and wind speed as input random variables of the systems. However, the demand side participation is not taken into account in the paper.

In addition to spinning and non-spinning reserve, demand response can also help ISOs and compensate random nature of wind power. In Ref. [13] price-based DR is used to change the consumption of end-user customers when wind blow is different from its predictive value. In this paper, demand is a function of price in each period, so it has different behaviors in various times. Unfortunately, price-based DR programs are voluntary and if customers do not respond in needed time, some problems on power system will be imposed. The impact of demand side management strategies on the power system operation with high penetration of renewable energy sources has been analyzed in Ref. [14]. The results have evidenced that demand side management strategies can lead to a significant delay in the investment in new generation capacity and improve the operation of the existing installed capacity. In Ref. [15], an incentive-based DR program is proposed that reshapes the system load and so helps to integrate wind generation. This is not a stochastic programming method and the DR program used in this reference only provides load reduction. In Ref. [16], the imposed costs that are caused by wind generation uncertainty have been examined in three cases. The first case has used RTP program [17], in the second one, variable wind power has been modeled by scenario tree and the third has combined the two above cases. Although all of them reduce costs, the first one is more effective than the second and the third case is the most successful in cost reduction.

In present paper, a two-stage stochastic programming is utilized to minimize total operating cost and air pollutants emission, separately and simultaneously. The proposed model schedules energy and reserves provided by both of generating units and responsive loads. In the presented model, ISO receives DR quantity and its offered price from DRPs (Demand Response Providers). Price-based DR also is modeled by price elasticity concept of the demand. The multiobjective generation scheduling model is solved by using augmented epsilon constraint method [18]. The best solution can be selected by Entropy and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) methods.

The rest of this paper is organized as follows. In Section 2 market structure and the proposed DR programs are introduced. The DR programs models are described in Section 3. The program formulation is presented in Section 4. In Section 5 the multiobjective wind-thermal generation scheduling and also epsilon constraint, Entropy and TOPSIS methods are introduced. Case study is discussed in Section 6, and conclusions are given in Section 7.

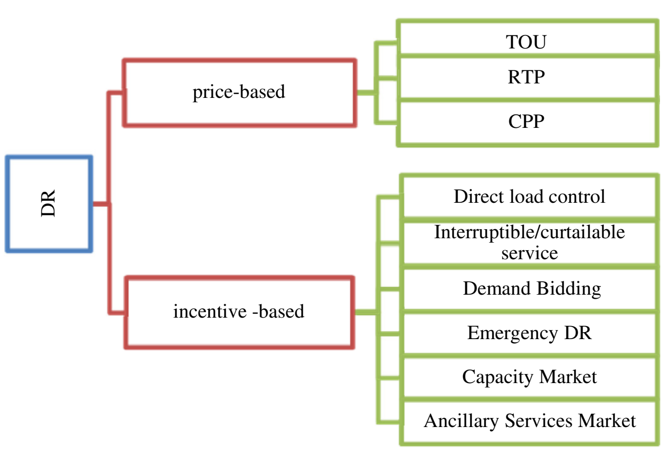


**Fig. 1.** Classification of demand response programs.

## 2. Problem description

### 2.1. Market structure

In this paper, a day-ahead market is used that its structure is shown in Fig. 2. As can be observed in this figure, ISO receives bids from GENCOs (generating companies) and DRPs for providing energy and reserves. Also, ISO will be aware of hourly demands by DISCOs (distribution companies). Moreover, some customers will alter their consumption after receiving price signals. Note that customer response to price signals is entirely voluntary, but for the sake of simplicity, it is assumed that costumers will change their consumption with respect to electricity prices. Finally, ISO will simultaneously schedule energy and reserves in a power system with high penetration of wind power by considering above items, transmission system constraints and different objective functions.

### 2.2. Demand response

As already mentioned, DR programs are divided into incentive-based and price-based DR programs. In this paper two incentive-based DR programs have been used that ancillary services market

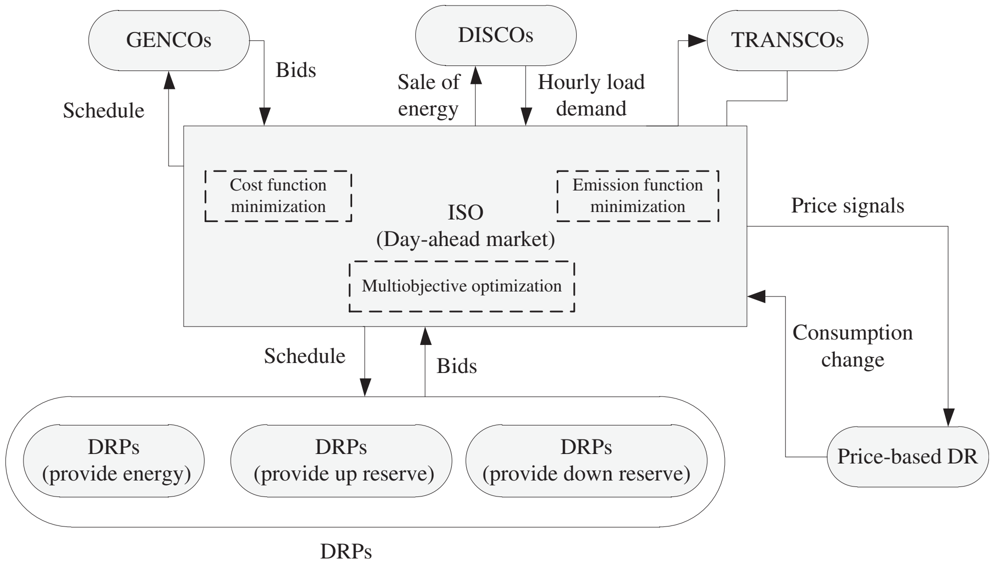


**Fig. 2.** Day-ahead market structure.

program provides up/down reserves and demand bidding program has been utilized for providing energy. In addition, it is assumed that customer can take part in price-based DR programs and modify their consumption according to electricity prices. However, this requires an appropriate communication infrastructure for the transmission of price signals to consumers. Therefore, we have assumed that smart grid and its communication infrastructure has already been installed and is operative.

## 3. Demand response model

In this paper, both the price-based and incentive-based DR models are taken into account through the proposed method. In the price-based DR model, the load shifting and load curtailment are considered while in the incentive-based DR model, there is not load shifting and just load change is taken into account. Moreover, consumers who contribute to the incentive-based DR programs could participate in the reserve market as well as the energy market.

### 3.1. Price-based DR model

Generally, consumers get involved in price-based DR programs to reduce their electricity bills. In other words, they can improve system reliability in an indirect way.

In this regard, a model which represents the changes of load with respect to change of the price is presented. Load sensitivity with respect to the electricity price is called elasticity that is formulated as follows [19]:

$$E(t,h) = \frac{\rho_0(h)}{d_0(t)}\frac{\partial d(t)}{\partial \rho(h)} \quad \begin{cases} E(t,h) \le 0 \text{ if } t = h \\ E(t,h) \ge 0 \text{ if } t \ne h \end{cases} \tag{1}$$

where $\rho(h)$ is the electricity price in period $h$, $d(t)$ is the customer demand in period $t$ after responding to the price-based DR program and $\rho_0(h)$ and $d_0(t)$ are the initial amount of electricity price and customer demand in periods $h$ and $t$, respectively.

If electricity prices change into diverse periods, customers could response to the alterations into two ways:

1) Some loads can just be on and off such as lighting systems and therefore cannot be transferred to other periods. This load's elasticity is called self-elasticity and always has a negative amount.
2) Some loads can be shifted to off-peak periods, unlike the first group. This load's elasticity is called cross-elasticity and always has a positive amount.

So, self and cross-elasticity are represented as a matrix 24 × 24 for 24 periods:

$$\begin{bmatrix} \frac{\Delta d(1)}{d_0(1)} \\ \frac{\Delta d(2)}{d_0(2)} \\ \frac{\Delta d(3)}{d_0(3)} \\ \cdots \\ \frac{\Delta d(24)}{d_0(24)} \end{bmatrix} = \begin{bmatrix} E(1,1) & \cdots & E(1,24) \\ \vdots & \ddots & \vdots \\ E(24,1) & \cdots & E(24,24) \end{bmatrix} \times \begin{bmatrix} \frac{\Delta \rho(1)}{\rho_0(1)} \\ \frac{\Delta \rho(2)}{\rho_0(2)} \\ \frac{\Delta \rho(3)}{\rho_0(3)} \\ \cdots \\ \frac{\Delta \rho(24)}{\rho_0(24)} \end{bmatrix} \tag{2}$$

where $\Delta d(.)$ represents the load change after implementation of price-based DR program and $\Delta\rho(.)$ stands for the amount of price change in each period.

The diagonal and off-diagonal elements of elasticity matrix show self-elasticity and cross-elasticity, respectively. Also, the $h$th column of this matrix expresses that how price change in period $h$ bears on the demand during the rest of time. If the entries, which are the above of diagonal elements, are zero, it means that customers will increase their consumption before going to the expensive periods in order to avoid encountering these periods. Furthermore, if the entries that are the below of diagonal elements are nonzero, customers will postpone their consumption and wait for lower prices.

In this paper, it is assumed that customers alter their consumption from $d_0(t)$ to $d(t)$ after receiving electricity prices. This change can lead to either lower or higher electricity consumption. So, the amount of $d(t)$ can be lower or more than the amount of $d_0(t)$. If it is presumed that $B(d(t))$ be electricity value from customer's perspective for using $d(t)$ in period $t$, the net profit of customer in this period will become as follows:

$$\mathrm{NP} = B(d(t)) - d(t)\rho(t) \tag{3}$$

As already raised, $B(d(t))$ is the electricity worth from customers' point of view. As a case in point, if the demand of an industrial customer is $d(t)$ in period $t$, $B(d(t))$ is equal to customer's income from selling goods which are earned by electricity usage amount of $d(t)$. With generalizing this issue to all customers, $B(d(t))$ is the value of electricity for customers that is calculated based on value engineering and using statistical data. Calculation of $B(d(t))$ is out of scope of this paper. This value is just taken as an input data of system according to the definition in Ref. [19]. More details of electricity value and consumption function are available in Refs. [20,21].

The second term in Equation (3) represents the electricity cost in period $t$. For maximizing the customer's benefit, the derivative of this equation should be zero:

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

Therefore:

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

In initial demand, the above equations will modify as follows:

$$\mathrm{NP}_0 = B(d_0(t)) - d_0(t)\,\rho_0(t) \tag{6}$$

$$\frac{\partial \mathrm{NP}_0}{\partial d(t)} = \frac{\partial B(d_0(t))}{\partial d(t)} - \rho_0(t) = 0 \tag{7}$$

$$\frac{\partial B(d_0(t))}{\partial d(t)} = \rho_0(t) \tag{8}$$

$$\frac{\partial^2 B}{\partial d^2} = \frac{\partial \rho}{\partial d} = \frac{1}{E}\frac{\rho_0}{d_0} \tag{9}$$

The Taylor expansion of $B(d(i))$ is as follows:

$$B(d(t)) = B(d_0(t)) + \frac{\partial B(d_0(t))}{\partial d(t)}[d(t) - d_0(t)] + \frac{1}{2}\frac{\partial^2 B(d_0(t))}{\partial d^2(t)}[d(t) - d_0(t)]^2 \tag{10}$$

By using of Taylor expansion of $B(d(i))$ and Equations (8) and (9), we will have:

$$B(d(t)) = B(d_0(t)) + \rho_0(t) \times [d(t) - d_0(t)] \times \left\{1 + \frac{[d(t) - d_0(t)]}{2E(t,t)d_0(t)}\right\} \tag{11}$$

By differentiating the above equation and substituting the result in Equation (5), the initial price-based DR programs model will be made:

$$d(t) = d_0(t) \times \left\{1 + E(t,t) \times \frac{[\rho(t) - \rho_0(t)]}{\rho_0(t)}\right\} \tag{12}$$

The above equation shows the optimum consumption amount with considering electricity price in period $t$ that customer's benefits will be maximized by it.

If electricity price varies in period $h$, the demand in period $t$ will change as follows (regardless of price increase in period $t$):

$$d(t) = d_0(t) \times \left\{1 + \sum_{\substack{h=1 \\ h \neq t}}^{24} E(t,h) \times \frac{[\rho(h) - \rho_0(h)]}{\rho_0(h)}\right\} \tag{13}$$

By combining Equations (12) and (13), the final price-based DR model will be achieved:

$$d(t) = d_0(t) \times \left\{1 + E(t,t) \times \frac{[\rho(t) - \rho_0(t)]}{\rho_0(t)} + \sum_{\substack{h=1 \\ h \neq t}}^{24} E(t,h) \times \frac{[\rho(h) - \rho_0(h)]}{\rho_0(h)}\right\} \tag{14}$$

Equation (14) shows how much customers consume electricity to accomplish minimum electricity bill in a 24 h interval while participating in price-based DR programs [19].

### 3.2. Incentive-based DR model

Incentive-based DR programs encourage customers to alter their consumption. In this paper, consumers who take part in the ancillary services market DR program can choose decrease or increase of their consumption, depending on their needs, and so provide up/down reserves. More details of ancillary service DR program and its features are available in Ref. [22]. These provided reserves by end-use customers are analogous to up/down spinning reserve services provided by generating units and can compensate unpredictable nature of wind power and also reduce operation costs. Moreover, customers that enroll in the demand bidding program reduce their consumption and compete with generating units for energy generation and therefore the use of this option can reduce air pollutants emission as well as operation costs. In other words, the system operator makes use of both the energy reduction and reserve capacity of consumers in energy and reserve scheduling in order to operate the power system economically and more reliable.

In this paper, it is assumed that DRPs submit their offers to the day-ahead market. These offers are submitted for providing energy and up/down spinning reserves in this market. DRPs aggregate end-user customer responses and submit an offer package in the day-ahead market. This package is included the amounts of response and their associated costs, as shown in Fig. 3.

Regarding DPRs' participation in the reserve scheduling, if ISO accepts DRPs' offers, they will receive offered price for accepting to be standby for providing reserve capacity. Then, if their load curtailments are needed, they will be called by system operator and will be paid either the spot market energy price or the price that was offered by DRP for load reduction in the day-ahead market. Therefore, the reserve price makes an incentive to customer to participate in reserve market as well as energy market [15].

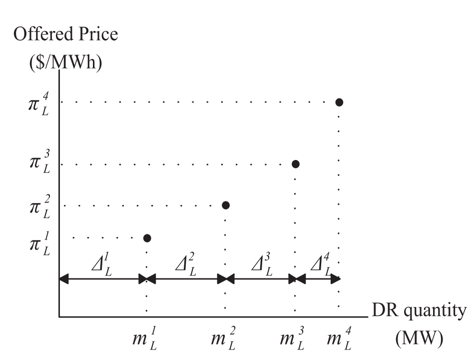


**Fig. 3.** DRP's offer package.

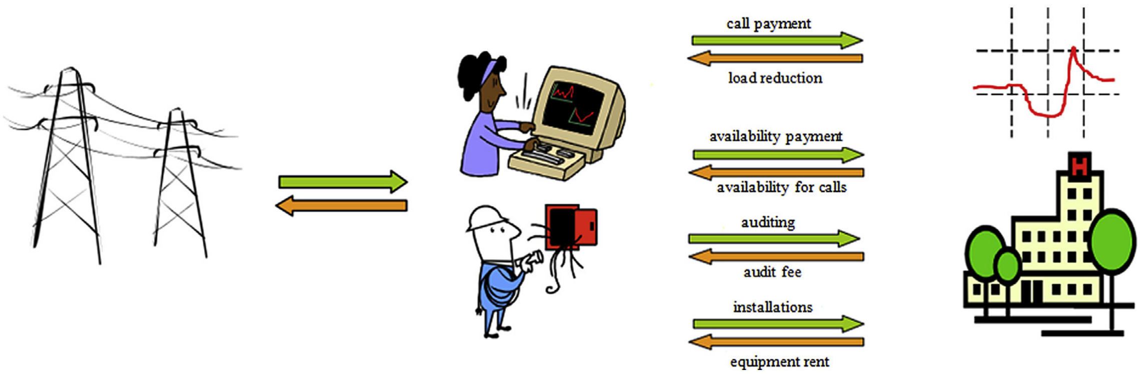


**Fig. 4.** Data flow among DRPs and other sections [23].

Note that if DRPs tend to increase their consumption and ISO accepts their offers, they will just receive offered price in packages and if their consumption increases in needed time, they will have to pay energy cost themselves. However, this energy cost is lower than the energy cost when customers do not participate in DR. In Fig. 3, DR quantities and the associated prices have been shown with $m_L^S$ and $\pi_L^S$, respectively. DR model considered in this paper is formulated as follows [15]:

$$\mathrm{DR}_{Lt} = \sum_{S=1}^{\mathrm{NS}_L} \Delta_{Lt}^S z_{Lt}^S \tag{15}$$

$$\Delta_{Lt}^S = m_{Lt}^S - m_{Lt}^{S-1};\ s = 1,2,\ldots,\mathrm{NS}_L \tag{16}$$

where $\mathrm{NS}_L$ represents the number of discrete points in $\mathrm{DRP}_L$'s offer package, $z_{Lt}^S$ is a binary variable associated with point $S$ of $\mathrm{DRP}_L$ in period $t$ that will be 1 if point $S$ is scheduled in period $t$ for $L$th DRP and will be 0 otherwise. It is also assumed that $m_{Lt}^0 = 0$.

In price-based DR programs, customers modify their consumption with regard to electricity prices and so they do not submit any offers in electricity market. On the other hand, in incentive-based DR programs, the customers offer their load change amount and price to the system operator. After scheduling, the system operator informs the DRPs whose offers are accepted in energy and reserve scheduling [15,22].

Generally, DRPs are organizations or companies that know DR programs and market rules. In fact, they are like bridges that connect customers to market. These companies contract with customers who would like to take part in DR programs, according to type of customers load (industrial, commercial, residential). In addition to collecting customer responses and participation in energy and reserve markets, DRPs provide incentive payments for customers, install control and communication devices in customer premises and also evaluate DR programs to help improve them in the future (Fig. 4).

In this paper, DPRs can participate in the incentive-based DR programs for providing energy or up/down reserves. Therefore, the DPRs do not take part in load shifting program. The load shifting program is just considered for price-based DR program.

## 4. Problem formulation

In this section, a two-stage stochastic programming is used to model the random nature of wind power, where first-stage is associated with electricity market, its rules and constraints and the second-stage is related to actual operation of the power system and its physical limitations in each scenario of wind power. The formulation of problem can be distinguished in four parts: objective functions, the first-stage constraints, the second-stage constraints and the constraints that link the first and second-stage [3].

In general, there are two methods in order to integrate wind power into unit commitment scheduling:

1) Wind power is considered as a negative load [9]; it is defined the net load as the difference between the demand and the wind power forecasts. So, the load demand is replaced by net load term in the unit commitment problem.
2) Wind power is considered as an independent energy resource [3]; however, wind power generation is not treated the same as conventional generator. The stochastic nature of wind power is modeled through the unit commitment problem.

In the first method, the forecasted value of wind power is considered as the output result market clearing procedure. Thus, the outputs that result from the market-clearing procedure are the decision variables corresponding to this particular scenario. In this paper, the second method is utilized since it realizes a better implementation of stochastic process [24].

It is worth to note that in real-time (actual time of operation), the output of wind farm is not considered changing or reducing. In other words, as much as wind energy that is available in real-time will be consumed, and the deviation from the scheduled wind power will be compensated by up or down reserves provided by thermal units or responsive loads. Since in this paper, the proposed model is used for energy and reserve scheduling for next day (day-ahead scheduling), the actual value of wind power at each hour of next day is not exactly clear. In other words, there is forecasting error for the predicted wind generation, and as a result, the wind farm output may increase or decrease in real-time. Moreover, scheduling of thermal units power output is dependent on the available wind power at each hour. Therefore, the operator should consider a scheduled value for wind power generation and then schedule the thermal units in order to meet the load demand. In the proposed model, the wind power for each hour of next day is scheduled based on the normal probability distribution function. So, based on objective function, there is a trade-off between the scheduled wind power and allocated reserve capacity in order to reduce cost or emission.

### 4.1. Objective functions

The objective functions are given in Equations (17) and (18) which are minimized throughout the scheduling horizon.

$$F^{\text{cost}}=\sum_{t=1}^{NT}\left\{\sum_{i=1}^{NG}\left(\text{CSU}_{it}+a_iP_{it}^2+b_iP_{it}+c_i+\pi_{it}^{\text{RU}}\text{RU}_{it}+\pi_{it}^{\text{RD}}\text{RD}_{it}\right.\right.$$
$$\left.+\pi_{it}^{\text{RNS}}\text{RNS}_{it}\right)+\sum_{L\in S_{\text{DRP}}^{\text{ru}}\text{ or }S_{\text{DRP}}^{\text{rd}}}\text{rCDR}_{Lt}+\sum_{L\in S_{\text{DRP}}^{e}}\text{ECDR}_{Lt}$$
$$\left.-\sum_{L=1}^{NL}\pi_{Lt}d_L(t)\right\}+\sum_{t=1}^{NT}\sum_{k=1}^{Nk}\text{pr}_k\left\{\sum_{i=1}^{NG}\left(\text{CCSU}_{itk}+a_ip_{itk}^{G^2}\right.\right.$$
$$\left.+b_ip_{itk}^{G}+c_i\right)\pm\sum_{L\in S_{\text{DRP}}^{\text{ru}}\text{ or }S_{\text{DRP}}^{\text{rd}}}r\text{EDR}_{Ltk}+\sum_{L=1}^{NL}\text{VOLL}_{Lt}\text{shed}_{Ltk}$$
$$\left.+\text{SC}_t\text{SP}_{tk}\right\} \tag{17}$$

where NT, NG, Nk and NL are the number of time periods, generators, wind scenarios and loads, respectively; $\text{CSU}_{\text{it}}$ is the start-up cost of unit $i$ in period $t$; $P_{it}$ is power scheduled for unit $i$ in period $t$; $a_i$, $b_i$ and $c_i$ are the quadratic cost function coefficients of the $i$th generator; $\text{RU}_{it}$, $\text{RD}_{it}$ and $\text{RNS}_{it}$ are, respectively, up, down and non-spinning reserves scheduled for unit $i$ in period $t$; $\pi_{it}^{\text{RU}}$, $\pi_{it}^{\text{RD}}$ and $\pi_{it}^{\text{RNS}}$ are, respectively, the offer costs of the up, down, and non-spinning reserves of unit $i$ in period $t$; $\text{rCDR}_{Lt}$ represents the capacity cost of reserve provided by DRP $L$ in period $t$ that is just calculated for the sets of DRPs which provide up and down reserve ($S_{\text{DRP}}^{\text{ru}}$ and $S_{\text{DRP}}^{\text{rd}}$); $\text{ECDR}_{Lt}$ is the cost of energy provided by DRP $L$ in period $t$ that is considered for set of DRPs which provide energy ($S_{\text{DRP}}^{e}$); $d_L(t)$ is the scheduled demand for customer $L$ in period $t$ that is equal to initial load of customer ($d_0(t)$) in price-based DR program and $\pi_{Lt}$ is the utility of consumer $L$ in period $t$; $\text{pr}_k$ stands for probability of scenario $k$; $\text{CCSU}_{itk}$ is the start-up cost adjustment of $i$th generator in period $t$ and scenario $k$; $p_{itk}^{G}$ is power output for unit $i$ in period $t$ and scenario $k$; $\text{rEDR}_{Ltk}$ is energy cost of reserve provided by DRP $L$ in period $t$ and scenario $k$ for $S_{\text{DRP}}^{\text{ru}}$ and $S_{\text{DRP}}^{\text{rd}}$; $\text{VOLL}_{Lt}$ represents the value of lost load for customer $L$ in period $t$ and $\text{shed}_{Ltk}$ is load shedding for customer $L$ in period $t$ and scenario $k$; $\text{SC}_t$ is the wind spillage cost in period $t$ and $\text{SP}_{tk}$ is the wind spillage in period $t$ and scenario $k$.

The cost function $F^{\text{cost}}$ includes two stages. The first-stage is associated with electricity market costs (the costs before the realization of each wind power scenario). This stage is included in the start-up, energy, spinning and non-spinning reserves costs, offered costs of generating units and the scheduling cost of up/down reserves and energy from DRPs minus the demand utility. The second-stage that has considered $\text{pr}_k$ probability in objective function is associated with actual operation of power system (after the realization of each scenario). This stage is included in the costs associated with start-up and shutdown plan adjustment of generating units in each scenario, the costs that stems from the actual dispatch of reserves by generating units and DRPs and the load shedding and wind spillage costs.

Equation (18) shows the amount of emission generated by units where $\alpha_i$, $\beta_i$, $\gamma_i$, $\zeta_i$, and $\lambda_i$ are the emission coefficients and are taken from Ref. [25].

$$F^{\text{emission}}=\sum_{t=1}^{NT}\sum_{i=1}^{NG}\alpha_i+\beta_iP_{it}+\gamma_iP_{it}^2+\zeta_i\exp(\lambda_iP_{it}) \tag{18}$$

### 4.2. First-stage constraints

The constraints are as follows,

- Market balance:

$$\sum_{i=1}^{NG}p_{it}+p_t^{\text{wind}}=\sum_{L=1}^{NL}d_L(t)-\sum_{L\in S_{DRP}^{e}}\text{DR}_{Lt}+\sum_{L\in S^{\text{PBDR}}}(d(t)-d_L(t))\forall t \tag{19}$$

where $p_t^{\text{wind}}$ is the wind power scheduled in period $t$, $\text{DR}_{Lt}$ presents the amount of DR provided by $S_{\text{DRP}}^{e}$ and the final term shows the load change which is carried out by set of loads that participate in price-based DR program ($S^{\text{PBDR}}$).

- Production limit:

$$P\text{min}_iu_{it}\le p_{it}\le P\text{max}_iu_{it}\quad\forall\ i,\ t \tag{20}$$

where $P\text{min}_i$ and $P\text{max}_i$ are the lower and upper limits of $i$th generator's power output, respectively and $u_{it}$ is a binary variable (1 if unit $i$ is scheduled in period $t$ and 0 otherwise).

- Wind generation limit:

$$p\text{min}_t^{\text{wind}}\le p_t^{\text{wind}}\le p\text{max}_t^{\text{wind}}\quad\forall t \tag{21}$$

- Spinning and non-spinning reserve limits:

$$0\le\text{RU}_{it}\le(P\text{max}_i-p_{it})u_{it}\quad\forall i,t \tag{22}$$

$$0\le\text{RD}_{it}\le(p_{it}-P\text{min}_i)u_{it}\quad\forall i,t \tag{23}$$

$$0\le\text{RNS}_{it}\le P\text{max}_i(1-u_{it})\quad\forall i,t \tag{24}$$

- DR costs:

$$\text{rCDR}_{Lt}=\sum_{S=1}^{NS_L}\Delta_{Lt}^{S}\pi_{Lt}^{S}z_{Lt}^{S}\quad\forall t,\ L\in S_{\text{DRP}}^{\text{ru}}\text{ or }S_{\text{DRP}}^{\text{rd}} \tag{25}$$

$$\text{ECDR}_{Lt}=\sum_{S=1}^{NS_L}\Delta_{Lt}^{S}\pi e_{Lt}^{S}z_{Lt}^{S}\quad\forall t,\ L\in S_{\text{DRP}}^{e} \tag{26}$$

where $\pi_{Lt}^{S}$ and $\pi e_{Lt}^{S}$ are the capacity and energy cost of point $S$ of DRP $L$ in period $t$, respectively.

- Generating units start-up cost:

$$\text{CSU}_{it}\ge\lambda_{it}^{\text{SU}}(u_{it}-u_{i,t-1})\quad\forall i,t \tag{27}$$

$$\text{CSU}_{it}\ge 0\quad\forall i,t \tag{28}$$

where $\lambda_{it}^{\text{SU}}$ presents the start-up offer cost of unit $i$ in period $t$.

### 4.3. Second-stage constraints

- Power balance at every bus $n$:

$$\sum_{i:(i,n)\in S_G}p_{itk}^{G}+\sum_{L:(L,n)\in S_L}(\text{shed}_{Ltk}-\text{LC}_{Ltk})$$
$$+(\text{pw}_{tk}-\text{SP}_{tk}|\text{if}\,n=\text{windpowerbus})=\sum_{m:(n,m)\in S_{\text{line}}}f_{tk}^{n,m},\forall n,t,k \tag{29}$$

where $S_G$, $S_L$ and $S_{\text{line}}$ are the set of generating units, loads in each bus and transmission lines, respectively; $\text{pw}_{tk}$ is the wind power in period $t$ and scenario $k$ and $f_{tk}^{n,m}$ is power flow through line ($n$,$m$) in period $t$ and scenario $k$ limited to $f\text{max}^{\text{n,m}}$.

- Production limits in scenarios:

$$p_{itk}^{G} \geq \text{pmin}_i y_{itk} \quad \forall i,\ t,\ k \tag{30}$$

$$p_{itk}^{G} \leq \text{pmax}_i y_{itk} \quad \forall i,\ t,\ k \tag{31}$$

where $y_{itk}$ is a binary variable that will be 1 if unit $i$ is scheduled in period $t$ and scenario $k$.

- Power flow through transmission lines:

$$f_{tk}^{n,m} = \frac{(\delta_{ntk}-\delta_{mtk})}{x_{nm}} \quad \forall t,\ k,\ (n,m)\in\ S_{\text{line}} \tag{32}$$

$$-f\text{max}^{n,m} \leq f_{tk}^{n,m} \leq f\text{max}^{n,m} \quad \forall t,\ k,\ (n,m)\in S_{\text{line}} \tag{33}$$

where $\delta_{ntk}$ is the voltage angle at bus $n$ in period $t$ and scenario $k$ (rad) and $x_{nm}$ is the reactance of line ($n$,$m$). In this paper, a dc power flow technique has been used because the proposed model focuses on active power and reserve scheduling. So, we can ignore the reactive power and voltage calculations in this paper. Moreover, the dc load flow allows us to use MILP (Mixed-integer linear programming) optimization that has some advantages in comparison with non-linear optimization method. The AC power flow turns the proposed model into a MINLP (Mixed-Integer Non-linear Programming) optimization.

- DR reserve:

$$\text{dr}_{Ltk} = \sum_{S=1}^{\text{NS}_L} \Delta_{Lt}^{S} v_{Ltk}^{S} \quad \forall t,\ k,\ L\in S_{\text{DRP}}^{\text{ru}} \text{ or } S_{\text{DRP}}^{\text{rd}} \tag{34}$$

$$rEDR_{Ltk} = \sum_{S=1}^{NS_L} \Delta_{Lt}^{S} \pi e_{Lt}^{S} v_{Ltk}^{S} \quad \forall t,\ k,\ L\in S_{\text{DRP}}^{\text{ru}} \text{ or } S_{\text{DRP}}^{\text{rd}} \tag{35}$$

where $dr_{Ltk}$ is the deployed reserve of DRP $L$ in period $t$ and scenario $k$ and $v_{Ltk}^{S}$ is a binary variable associated with point $S$ of $\text{DRP}_L$ in period $t$ and scenario $k$.

- Load shedding and wind spillage:

$$0 \leq \text{shed}_{Ltk} \leq \text{LC}_{Ltk} \quad \forall L,\ t,\ k \tag{36}$$

$$\text{LC}_{Ltk} = \left( d_L(t) - \sum_{L\in S_{\text{DRP}}^{e}} \text{DR}_{Lt} \pm \sum_{L:\in S_{\text{DRP}}^{\text{ru}} \text{ or } S_{\text{DRP}}^{\text{rd}}} \text{dr}_{Ltk} \right) \quad \forall L \notin S^{\text{PBDR}}, t, k \tag{37}$$

$$\text{LC}_{Ltk} = d(t) \quad \forall L\in S^{\text{PBDR}},\ t,\ k \tag{38}$$

$$0 \leq \text{SP}_{tk} \leq \text{pw}_{tk} \quad \forall t,\ k \tag{39}$$

In Equation (37), if DRPs provide up reserve (decrease their consumption), negative sign will be used.

### 4.4. Constraints linking the first- and second-stage

- Disintegration of generator power outputs

$$p_{itk}^{\text{G}} = p_{it} + ru_{itk} - rd_{itk} + rns_{itk} \quad \forall i,\ t,\ k \tag{40}$$

where $\text{ru}_{itk}$, $\text{rd}_{itk}$ and $\text{rns}_{itk}$ are the up, down and non-spinning reserve deployed by unit $i$ in period $t$ and scenario $k$, respectively.

- Spinning and non-spinning reserves:

$$0 \leq \text{ru}_{itk} \leq \text{RU}_{it} \quad \forall i,\ t,\ k \tag{41}$$

$$0 \leq \text{rd}_{itk} \leq \text{RD}_{it} \quad \forall i,\ t,\ k \tag{42}$$

$$0 \leq \text{rns}_{itk} \leq \text{RNS}_{it} \quad \forall i,\ t,\ k \tag{43}$$

- DR reserve:

$$0 \leq \text{dr}_{Ltk} \leq \text{DR}_{Lt} \quad \forall t,\ k,\ L\in S_{\text{DRP}}^{\text{ru}} \text{ or } S_{\text{DRP}}^{\text{rd}} \tag{44}$$

Equations (41)–(44) express that the amount of reserve in each scenario must be lower than the amount of scheduling reserve in the first-stage.

- Generating units start-up cost adjustments in scenarios:

$$\text{CCSU}_{itk} = \text{CSU}_{itk} - \text{CSU}_{it} \quad \forall i,\ t,\ k \tag{45}$$

$$\text{CSU}_{itk} \geq \lambda_{it}^{\text{SU}} \left( y_{itk} - y_{i,t-1,k} \right) \quad \forall i,\ t,\ k \tag{46}$$

$$\text{CSU}_{itk} \geq 0 \quad \forall i,\ t,\ k \tag{47}$$

where $\text{CSU}_{itk}$ is the actual start-up cost of unit $i$ in period $t$ and scenario $k$.

## 5. The multiobjective wind-thermal generation scheduling

The cost minimization is not only the goal of power system operation, but the emission minimization is also important. Power generation by fossil fuel units (despite the cheapest units) will lead to different emission generation such as $SO_2$, $CO_2$, $NO_x$ and $SO_x$. So nowadays, with increasing concerns over environmental issues, it seems indispensable to reduce operational costs and emission, simultaneously. There are various types of power plants in a typical power system. Each type of power plant has different operation cost and emission rates [26,27]. As an illustration, the operation cost (fuel cost) of coal plants is lower than gas-fired power plants while the gas plants have lower emission of air pollutants comparing to coal fired ones [28]. Moreover, some new power plants with cutting-edge technology are installed with high capital cost and, instead, have low emission. Hence, there is a challenge in scheduling of conventional power plants (like coal and natural gas power plants). In other words, how should diverse types of power plants be scheduled to reach both minimum cost and emission goals. Thus, the challenge between cost and emission objective functions causes ISO to be confronted with a problem in finding a particular solution. In this situation, ISO should trade-off between these objective functions in order to choose the preferred solution. So, the objective function can be presented as follows:

$$\min\left(F^{\text{cost}}, F^{\text{emission}}\right) \tag{48}$$

This multiobjective function can be optimized by using different methods such as epsilon constraint [18], Imperialist competitive algorithm [29] and then the best solution can be found by AHP, Entropy, TOPSIS fuzzy methods and so forth. In this paper, the Equation (48) is optimized by epsilon constraint method and the preferred solution is acquired by Entropy and TOPSIS methods.

### 5.1. Epsilon constraint method

In general, the multiobjective optimizing programs consist of several objective functions which should be optimized in a feasible region. The structure of these programs can be considered as follows [18]:

$$\begin{aligned}&\min\left(f_1(x),\ldots,f_p(x)\right)\\ &s.t.\quad x\in S\end{aligned} \tag{49}$$

In this model, $f_i(x)$ is the $i$th objective function and $S$ determines a feasible region.

The first step in epsilon constrain method determines the range of objective functions that are used as constraint. For this, the best and worst solutions of these objective functions should be determined. The best solutions can be found by optimizing them, separately, but finding the worst solutions is relatively difficult. They can be estimated by pay-off table. Generally, for optimizing the multiobjective programming by epsilon constraint method, the following steps must be performed:

1) Calculate pay-off table

For calculation of pay-off table, the first objective function should be optimized:

$$\min f_1(x) = z_1^* \tag{50}$$

Then, the second objective function will be optimized by adding following constraint:

$$f_1(x) \le z_1^* \tag{51}$$

If the optimum amount of the second objective function is $z_2^*$, the third objective function will be optimized by adding constraints (51) and (52):

$$f_2(x) \le z_2^* \tag{52}$$

This process will continue until all objective functions become optimized. So, the pay-off table will be made as follows:

$$\text{Pay}-\text{off table} = \begin{pmatrix} z_1^* & z_2^* & \cdots & z_p^* \\ \vdots & & \ddots & \vdots \\ y_1^* & y_2^* & \cdots & y_p^* \end{pmatrix} \tag{53}$$

The maximum amount of each column in this table is associated with the worst amount of each objective function. Note that if the goal is to maximize the objective functions, the minimum amount of each column will be chosen.

2) Select the main and subsidiary objective functions

After making the pay-off table, decision maker selects an objective function as the main function and the range of other objective functions (subsidiary objective functions) will be determined, according to the first step.

3) Division of subsidiary functions range

After selecting subsidiary objective functions and determining ranges of them, these ranges will be divided into equal intervals. For instance, it is assumed that in pay-off table Equation (53) the second objective function is a subsidiary function and its range is $(z_2^*, y_2^*)$. By dividing this range to $l$ equal intervals, we will have:

$$k = \frac{y_2^* - z_2^*}{l} \tag{54}$$

$$e_2 = z_2^* + n \times k \quad n = 1,2,\ldots l-1 \tag{55}$$

4) Objective function optimization

After performing the above steps, the final objective function in epsilon constraint method should be optimized. This objective function can be represented as follows:

$$\begin{aligned}&\min\left(f_1(x) - \varepsilon \times \left(s_2/r_2 + s_3/r_3 + \ldots + s_p/r_p\right)\right) \ , 10^{-6} \le \varepsilon \le 10^{-3}\\ &s.t. \begin{cases} f_2(x) + s_2 = e_2 \\ f_3(x) + s_3 = e_3 \\ \quad\vdots \\ f_p(x) + s_p = e_p \end{cases}\end{aligned} \tag{56}$$

In Equation (56), $f_1(x)$ is main objective function and other objective functions are considered as subsidiary functions. Also, $s_i$ is a positive ancillary variable and $r_i$ determines the range of $i$th objective function that will be achieved from pay-off table. The above objective function should be optimized for each $e_i$. So, $l$ solutions will be found that the best solution should be chosen by Entropy and TOPSIS methods.

### 5.2. Selecting the best solution

Decision making is an important part of the human life. Everybody in every situation faces different options that should choose the best one among them. In general, there are many different methods such as AHP, TOPSIS, fuzzy AHP, fuzzy TOPSIS and so on (they are called MADM (Multi Attribute Decision Making)) that facilitate selection of the best option. Each of the mentioned methods can be applied by system operator. In this paper, Entropy method is used to model uncertainty in alternatives and its results are utilized in TOPSIS method.

#### 5.2.1. Entropy method

Entropy is a known method for achieving attribute weights in MADM programs. This method needs a decision matrix that its elements should be normalized as follows [30].

$$D = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \tag{57}$$

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad , i = 1,\ldots m, \quad j = 1,\ldots,n \tag{58}$$

In matrix Equation (57), $x_{ij}$ is the performance of $i$th alternatives with respect to $j$th attribute. Also, Equation (58) normalizes the decision matrix. The following equations determine the weights of attributes:

$$h_j = -h_0 \sum_{i=1}^{m} \left[P_i \times \text{Ln}\ \text{P}_i\right] \quad , j = 1,\ldots,n \tag{59}$$

$$d_j = 1 - h_j \quad ,j = 1,\ldots,n \tag{60}$$

$$W_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad ,j = 1,\ldots,n \tag{61}$$

where $h_0$ is called Entropy constant and is calculated as follows:

$$h_0 = (\text{Ln m})^{-1} \quad m = \text{number of alternatives}$$

This constant has a positive sign. If the decision maker considers factors to prioritize attributes ($\lambda_j$), the improved weights will be determined as follows.

$$\text{IW}_j = \frac{\lambda_j \times w_j}{\sum_{j=1}^{n} \lambda_j \times w_j} \quad ,j = 1,\ldots,n \tag{62}$$

*5.2.2. TOPSIS method*

As already mentioned, TOPSIS is a MADM program that ranks $m$ alternatives with respect to $n$ attributes. Under this method,

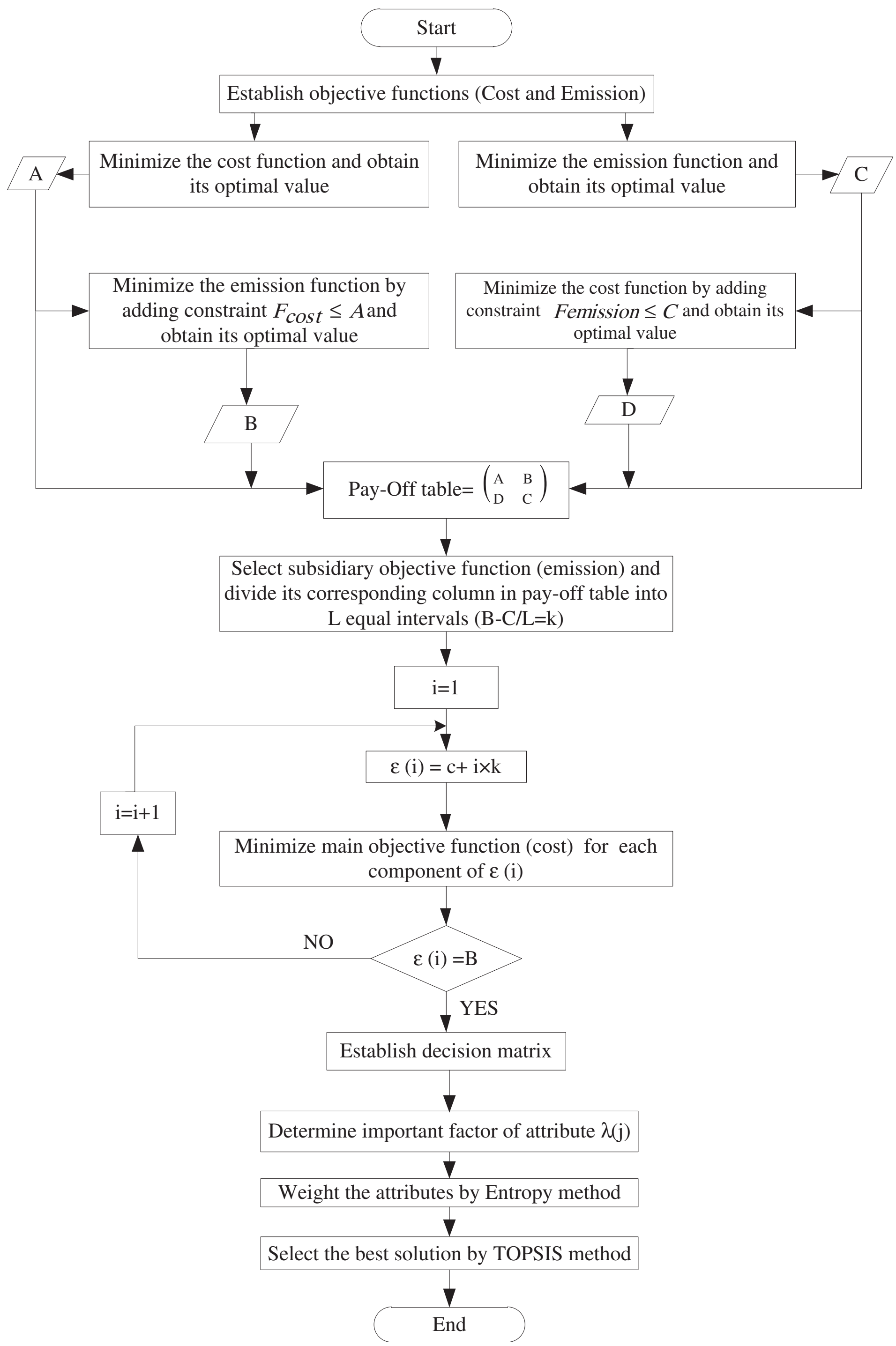


**Fig. 5.** Multiobjective wind-thermal generation scheduling.

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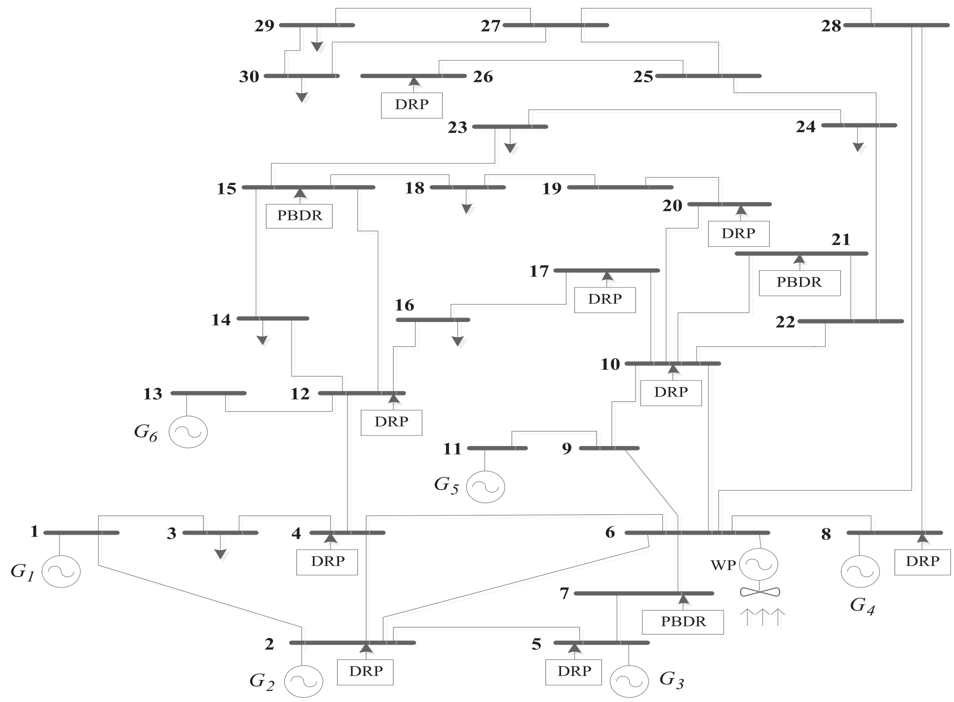


**Fig. 6.** The modified IEEE 30-bus test system.

an alternative that has the least distance with positive ideal solution and the most distance with negative ideal solution is selected. The positive ideal solution maximizes benefit attributes and minimizes cost attributes. This method consists of six steps [31]:

1) Establish decision matrix

The first step in TOPSIS method is making the decision matrix that each of its rows is related to an alternative and each of its columns represents an attribute.

2) Normalize decision matrix as follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{ij}^2}} \quad ,i = 1,\ldots m, \quad j = 1,\ldots,n \tag{63}$$

3) Calculate the weighted normalized decision matrix:

$$v_{ij} = \mathrm{Iw}_i \times r_{ij} \quad ,i = 1,\ldots m, \quad j = 1,\ldots,n \tag{64}$$

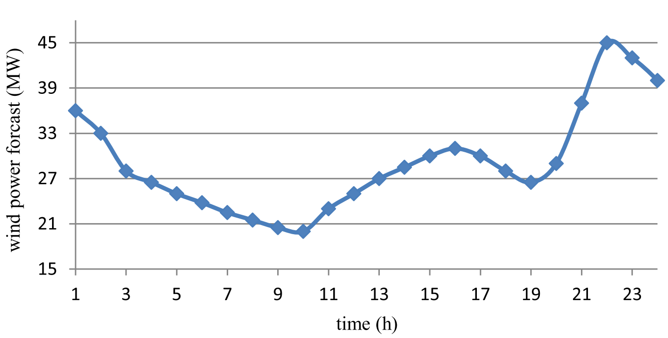


**Fig. 7.** The forecasted value of wind power.

where $\mathrm{Iw}_i$ are the weights obtained in Entropy method.

4) Determine positive and negative ideal sets:

$$A^+ = \left\{v_1^+, v_2^+, \ldots, v_i^+\right\} = \left\{\left(\max v_{ij} \middle| i \in I'\right), \left(\min v_{ij} \middle| i \in I''\right)\right\} \tag{65}$$

$$A^- = \left\{v_1^-, v_2^-, \ldots, v_i^-\right\} = \left\{\left(\min v_{ij} \middle| i \in I'\right), \left(\max v_{ij} \middle| i \in I''\right)\right\} \tag{66}$$

where $I'$ is the set of benefit attributes and $I''$ represents set of cost attributes.

5) Calculate the distance of each alternative from positive and negative ideal sets

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^+\right)^2} \quad ,i = 1,\ldots m \tag{67}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^-\right)^2} \quad ,i = 1,\ldots m \tag{68}$$

6) Determine a criterion for finding the best alternative

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad ,i = 1,\ldots m \tag{69}$$

The most appropriate alternative maximizes the above criterion.

**Table 1**
Price elasticity.

| | Valley | Off-peak | Peak | Period |
|---|---|---|---|---|
| Valley | −0.1 | 0.01 | 0.012 | 1–9 |
| Off-peak | 0.01 | −0.1 | 0.016 | 10–19 |
| Peak | 0.012 | 0.016 | −0.1 | 20–24 |

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**Table 2**
Generators data.

| Generator | $Pmin_i$ | $Pmax_i$ | $\lambda_{it}^{SU}$ | $a_i$ | $b_i$ | $c_i$ | $\pi_{it}^{RU}$ | $\pi_{it}^{RD}$ | $\pi_{it}^{RNS}$ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 5 | 50 | 20 | 100 | 200 | 10 | 19 | 16 | 30 |
| 2 | 5 | 60 | 20 | 120 | 150 | 10 | 20 | 15 | 28.5 |
| 3 | 5 | 100 | 40 | 40 | 180 | 20 | 18 | 14 | 29 |
| 4 | 5 | 120 | 20 | 60 | 100 | 10 | 19 | 21 | 29.5 |
| 5 | 5 | 100 | 40 | 40 | 180 | 20 | 18 | 15 | 50 |
| 6 | 5 | 60 | 20 | 100 | 150 | 10 | 16.5 | 14.5 | 28.5 |

Fig. 5 shows the flowchart of the proposed multiobjective wind-thermal generation scheduling by using epsilon constraint, Entropy and TOPSIS methods.

## 6. Case study

The proposed model is tested on a modified IEEE 30-bus test system illustrated in Fig. 6 over a daily time horizon that its data is taken from Ref. [32]. The wind farm is located at bus 6. In this paper, the normal PDF is divided into five intervals with different values in order to model the wind power generation at each period. Each wind generation value at a specific period has a probability of occurrence. This probability is calculated based on normal PDF. The calculation of the probability values of each interval is described in Ref. [33]. The standard deviation of PDF is considered 0.1 of wind prediction with a mean of the wind prediction value shown in Fig. 7. The value of lost load and wind spillage cost are assumed to be 1000 and 2000 \$/MWh. The demand price elasticity parameters have been extracted from Ref. [19] and are shown in Table 1. The generator characteristics have been taken from Ref. [25] which are given in Table 2. The cost and emission curves of generating units are shown in Fig. 8, the types of services provided by DRPs are presented in Table 3 and the hourly load is given in Table 4.

The electricity prices are assumed as 30 \$/MWh in flat rate, 12, 20 and 50 \$/MWh at valley, off-peak and peak periods, respectively. The loads located at buses 7, 15 and 21 take part in price-based DR. The simulation results are analyzed in six different case studies. In cases 1 and 2, the operator optimizes operational costs for which, in case 1 generating units provide energy and reserve and there is no DR participation, but in case 2, in addition to generators, DRPs can also participate in both of energy and reserve market. They can enroll 30%, 30%, and 10% of their customers to provide energy, up and down reserve, respectively. In cases 3 and 4, emission objective function is optimized for which, in case 3, DR is not considered and in case 4 it is taken into account. In these cases $NO_x$ and $SO_x$ are considered as emissions. The multiobjective optimizations without and with DR are examined in cases 5 and 6, respectively.

These cases have been solved on a PC, 2.6 MHz with 8 GB of RAM under GAMS software [34] after linearization of the objective functions [35]. The solution time was 300.0 s. Regarding CPLEX

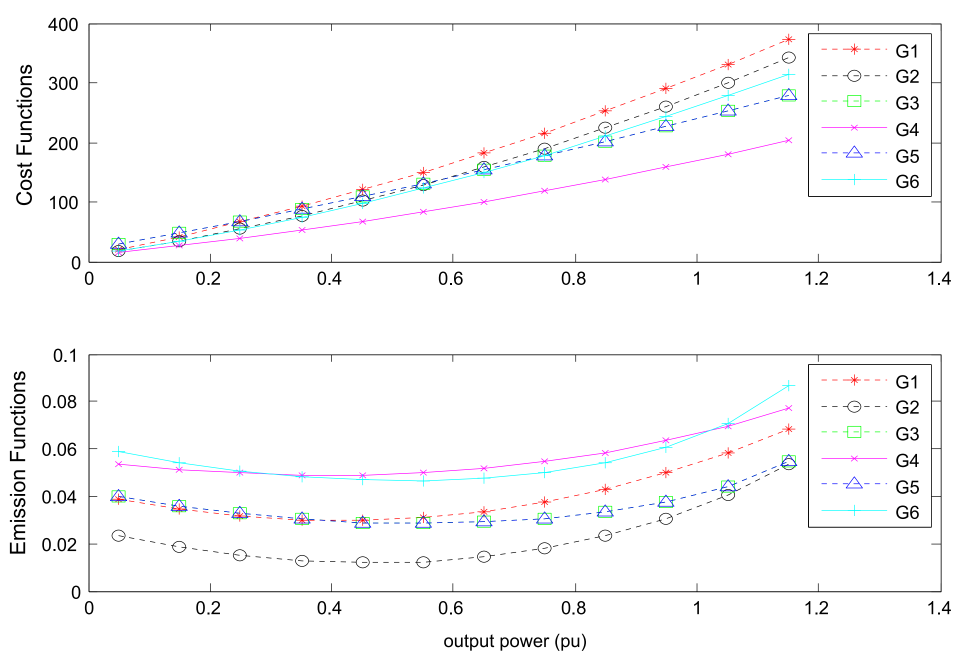


**Fig. 8.** The cost and emission curves of generating units.

**Table 3**
DRP offers.

| Kind of service | DRP no. | S (x% of total response) | | | $\pi_{Lt}^{S}$ (\$/MWh) | | | $\pi e_{Lt}^{S}$ (\$/MWh) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| Energy ($S_{DRP}^{e}$) | 5 | 33% | 66% | 100% | – | | | 4.5 | 8 | 15 |
| | 10 | 100% | – | – | – | | | 5 | – | – |
| Up reserve ($S_{DRP}^{ru}$) | 2 | 50% | 100% | – | 10 | 15 | – | 20 | 35 | – |
| | 8 | 33% | 66% | 100% | 15 | 19 | 27 | 40 | 43 | 48 |
| | 12 | 50% | 100% | – | 14 | 16 | – | 37 | 39 | – |
| | 17 | 50% | 100% | – | 19 | 21 | – | 33 | 35 | – |
| | 20 | 100% | – | – | 17 | – | – | 26 | – | – |
| | 26 | 100% | – | – | 11 | – | – | 24 | – | – |
| Down reserve ($S_{DRP}^{rd}$) | 4 | 50% | 100% | – | 10 | 11 | – | 30 | 35 | – |

**Table 4**
Hourly load.

| *t* | Load | *t* | Load | *t* | Load |
|---|---|---|---|---|---|
| 1 | 330 | 9 | 200 | 17 | 280 |
| 2 | 280 | 10 | 230 | 18 | 265 |
| 3 | 265 | 11 | 250 | 19 | 290 |
| 4 | 250 | 12 | 270 | 20 | 370 |
| 5 | 238 | 13 | 285 | 21 | 450 |
| 6 | 225 | 14 | 300 | 22 | 430 |
| 7 | 215 | 15 | 310 | 23 | 400 |
| 8 | 205 | 16 | 300 | 24 | 360 |

solver, as our model is a MILP optimization, the CPLEX is a good choice for solving the large-scale MILP problems [36]. CPLEX optimizer is designed to solve large, difficult problems quickly and with minimal user intervention. For problems with integer variables, CPLEX uses a branch and cut algorithm which solves a series of LP sub-problems. MILP has become a very popular approach for solving UC problems due to its lower time of calculation [37].

### *6.1. Cases 1 and 2 — the operation costs optimization without/with DR*

In this part, the results of cost minimization are compared in two different cases including without and with DR. With participation of incentive-based loads in energy and reserve markets and also customers located in buses 7, 15 and 21 who take part in price-based DR and alter their consumption according to Fig. 9, the wind-thermal generation scheduling are different in both the cases.

As shown in Fig. 9, customers reduce their consumption in peak periods when the electricity prices are relatively high and shift it to lower electricity price periods (valley and off-peak). Therefore, the power system scheduling will be altered after DR participation. For example, G1 is the most expensive unit in IEEE 30-bus system and the operator should not schedule it for power generation, according to cost minimization. Nevertheless, in case 1, the operator has to engage this unit in power system scheduling to provide energy in peak periods which it eventually leads to the dramatic increase in operational costs. While in case 2, the operator has extra options to provide energy. In other words, load participation in energy market and customers respond to high prices in peak periods culminate in G1 decommitment in these periods.

In valley and off-peak periods, customers augment their consumption and respond to price changes. Moreover, in case 1, the operator has to schedule the low amount of wind power in view of high price of up spinning reserve. In other words, if wind power was scheduled to generate higher output level, the reserve requirements would increase and therefore the operational cost would rise. However, in case 2, the operator can make use of demand side reserves and compensate uncertainty of wind power. Indeed, the operator can schedule wind power in higher amount than case 1 (Fig. 10), when confronts lower prices than generation side reserve prices, and so decommit some expensive units, compensate wind power fluctuations with both of demand and generation side reserves and finally minimize the operational costs.

Fig. 11 shows the cost of reserve scheduling in cases 1 and 2. As shown, the reserve cost has been reduced by load participation in whole study period. This cost reduction is about $840 within 24 periods.

### *6.2. Cases 3 and 4 — the air pollutants emission optimization without/with DR*

In this part, the outcomes of air pollutants emission minimization are compared in two different cases including without and with DR programs. Note that the operators more often than not

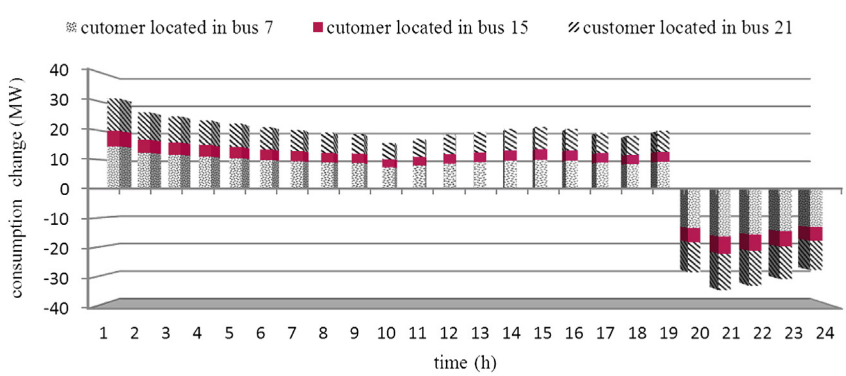


**Fig. 9.** Consumption change of costumers in TOU program.

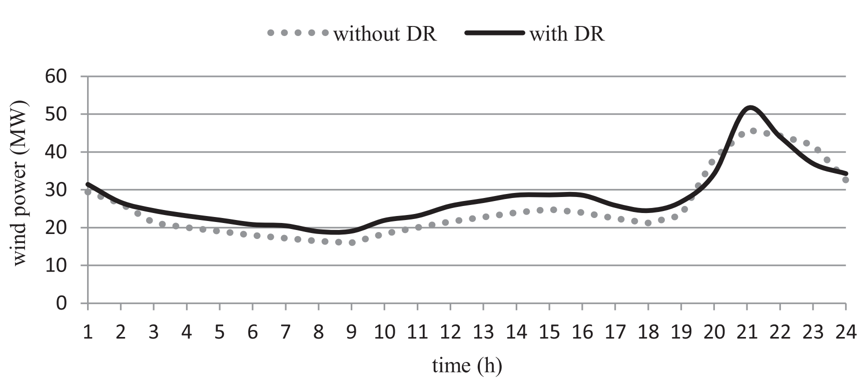


**Fig. 10.** The wind power with and without DR.

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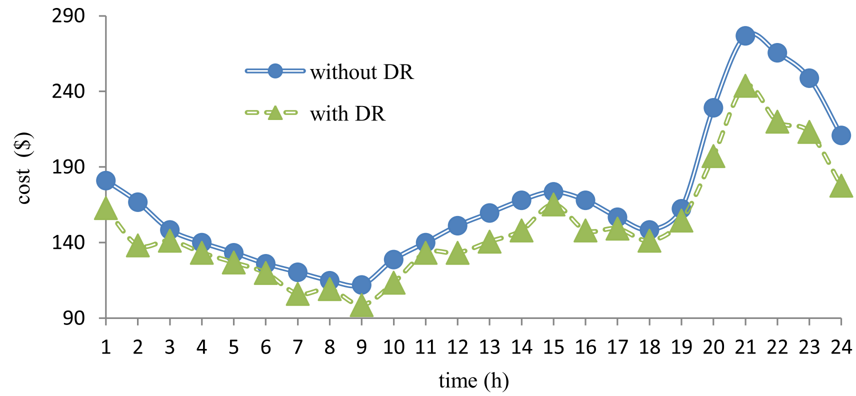


**Fig. 11.** The reserve cost before and after DR implementation.

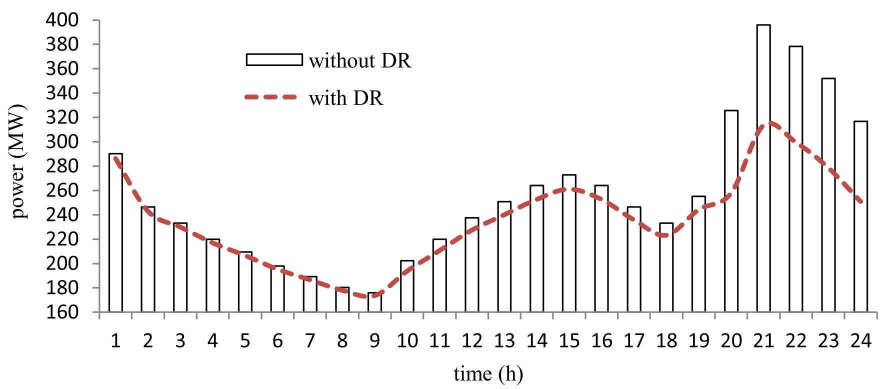


**Fig. 12.** The output of generating units before and after DR implement.

consider emission with other objective functions (such as operational costs) to take account of all operational goals. In other words, their goal is not only the emission minimization, but also the optimization of other objective functions (operational cost especially). Therefore, in this paper the emission optimization is just discussed to examine the role of DR in emission reduction.

When the goal is to reduce air pollutants emission, the operators strive to use generators that produce lower emission as well as schedule maximum wind power generation. Since the cost reduction is not considered in this part and the operator only wants to reduce emission, so in case 3 – unlike cases 1 and 2 that the cheapest generating units (G4 and G6) provided energy – G6 is off all the time and G4 is only scheduled to be committed in peak periods because of high emission of these units.

In case 4, loads participation in energy market and price-based DR program have been taken into account for which, the air pollutants emission becomes 0.314 tons less than case 3 (without DR). Indeed, in case 4, some generating units with high emission level has been decommitted due to DR programs. For example, in case 3, the operator has to turn on G4 in peak periods to provide energy requirements. However, in case 4, this unit has been committed only at 21:00 h. Even though customers located in buses 7, 15 and 21 have been increased their consumption in valley and off-peak periods, this consumption addition has been compensated by loads participation in energy reduction program and, as a result, the operator has not needed to use production of generating units in these periods. Fig. 12 shows the scheduled power of generating units before and after implementing DR programs.

In Fig. 12, the difference between scheduled powers of generating units pertains to customer participation in DR programs. So, the surface under dashed line is lesser than another one because of load curtailment. In other words, when the customers participate in DR program and accept to reduce their consumption at a specific hour, it allows the system operator to reduce the scheduled power of generating units.

### 6.3. Cases 5 and 6 – the multiobjective optimization without/with considering DR

In this part, the results of simultaneous optimization of cost and emission are compared in two different cases including without and with considering DR. The results are presented in Table 5. This table demonstrates the disintegration of costs and amount of emission in each case.

**Table 5**
The result of multiobjective optimization.

| | Total operation cost ($) | The amount of emission (ton) | Energy cost of units ($) | Energy cost of DRPs ($) | Generation-side reserves scheduling cost ($) | DRP reserves scheduling cost ($) |
|---|---|---|---|---|---|---|
| Case 5 | 32119.58 | 3.554 | 13598.35 | – | 4281.75 | – |
| Case 6 | 31441.24 | 3.246 | 13566.34 | 1210.15 | 2260.46 | 1285.96 |

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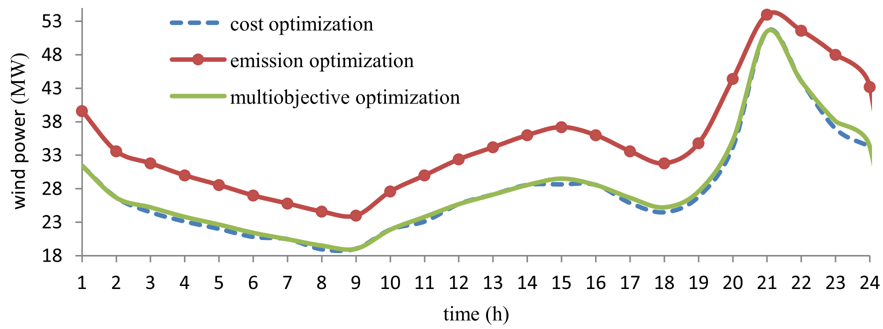


**Fig. 13.** Wind power in different optimizations.

The proposed decision making technique is capable of considering a specific attitude of the system operator in its decision procedure. Thus, in order to show that capability, a non-equal weight for cost and emission is selected. In other words, the multiplier of objective functions priority ($\lambda_j$ in Entropy method) has been decided to be 0.6 and 0.4 for operational cost and emission, respectively. Indeed, it is assumed that the cost is a little more important than the emission for the system operators; it is just an assumption to show the role of decision maker in the TOPSIS technique. The proposed multiobjective generation scheduling model is solved using augmented epsilon constraint method and then by applying the Entropy and TOPSIS methods, in which, solution no.3 is chosen in the fifth case and in the sixth case, solution no.5 is selected (among 10 solutions).

In case 5, ISO has only compensated uncertainty of wind power by spinning and non-spinning reserves and no DR is available. In this case, G1 is only scheduled to be on in peak periods because this unit is the most expensive generator and its emission production is relatively high. Nevertheless, in case 6, ISO has more options to compensate unpredicted nature of wind power and can utilize reserves provided by generating units as well as up/down reserves provided by DRPs. Therefore, customers will increase or decrease their consumption and help the operation of power systems with high penetration of wind power in due time. For instance, DRPs located at buses 2 and 26 are scheduled to decrease their consumption and DRPs located at buses 4 is also scheduled to provide down reserve. Furthermore, in this case, DRPs located at buses 5 and 10 submit their offers in energy market and compete with generator production. In addition, in case 6 the loads located at buses 7, 15 and 21 participate in price-based DR and reduce their consumption at peak periods and vice versa at off-peak. As a result, in this case, G1 is scheduled to be off in all periods even at peak periods. In spite of the fact that these loads have increased their consumption at valley and off-peak periods in case 6, they are supplied by DRPs that are participated in energy market (DRPs located at buses 5 and 10) and small amount of power produced by the generators is used. Hence, in this case, ISO can use load reduction of volunteer customers instead of committing generators and reduce operation costs and emission caused by these units. As shown in Table 5, the total operation cost in case 6 is lower than case 5. It reduces by $679 for the scheduling horizon. Moreover, in case 6, the amount of emission caused by generating units is 0.308 tons lesser than that of case 5. However, it should be noted that using of DR in energy market depends on emission curve of generating units (Fig. 8) and also DRPs' offered prices. As shown in Fig. 8, when production of generating units is reduced and curves of these generators come close to $P\min_i$, the emission will increase. In other words, although loads participation in energy market does not generate emission, it may increase emission in an indirect way. Consequently, the operator cannot use all capacities of DR in energy market even if its offered price by DRPs is low. This subject is also true for wind power commitments. If ISO uses high amount of wind power in order to reduce emission, the reserves cost and emission will increase. Figs. 13 and 14 show scheduled wind power and the amount of demand reduction as a DR program in three cases (cases 2, 4 and 6).

As can be observed in Figs. 13 and 14, ISO schedules lesser wind power and DR in day-ahead market in the majority of periods when the goal is cost optimization. Since if more wind power is scheduled and ISO purchases all capacity of DR, the reserve and energy costs will increase (due to high prices in endpoints of DRPs energy offer package). It is worth to note that in this proposed method, all available wind output will be utilized in real time regardless of the kind of objective function. In other words, the amount of wind output in real time will not be reduced due to economic reasons. For instance, according to Fig. 13, the scheduled wind power at hour 20:00 in the multiobjective optimization is 35 MW. Let's assume, the wind power suddenly increase to 45 MW in real time. In this case, the operator calls the down reserves provided by thermal units and responsive loads that were scheduled in the day-ahead scheduling program. Therefore, the additional wind power is not reduced, but the thermal units decrease their generation output by

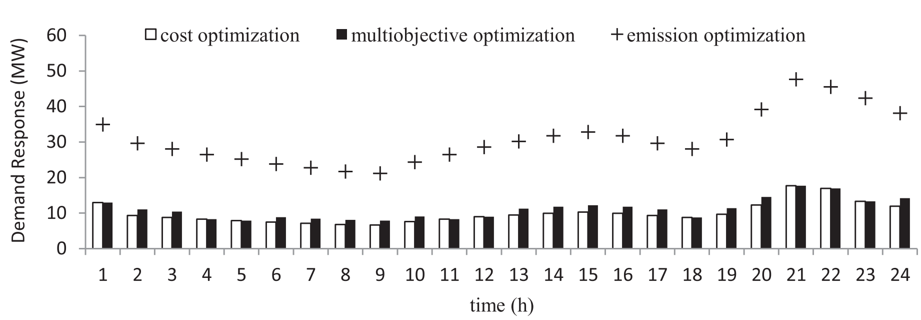


**Fig. 14.** Loads participation in energy market.

**Table 6**
The results of different objective functions optimization -without and with DR.

| | Cost optimization | | Emission optimization | | Multiobjective optimization | |
|---|---|---|---|---|---|---|
| | Wind power | Generating units | Wind power | Generating units | Wind power | Generating units |
| Without DR | Minimum use | Use of G1 in peak periods | Maximum use | Use of G4 in peak periods | Second case (with DR) uses wind power more than first case | Use of G1 in peak periods |
| With DR | More than first case (without DR) | Decommitment of G1 | | Use of G1 at 21:00 h. | | Decommitment of G1 |

10 MW (as scheduled reserve capacity) to keep the balance between generation and consumption. Also, the responsive loads may increase their consumption as a scheduled reserve capacity in order to use additional wind power generation.

When the goal is emission optimization, more wind power and DR are scheduled because the cost optimization is not important in this case. However, this may be in conflict with the fact that more wind power and DR in energy market may result in increasing emission in an indirect way (according to Fig. 8 and the reduction of generators outputs). It should be noted that in this case, committing more wind power and DR in energy market turn off generators that generate high amount of emission (G4 and G6). Furthermore, Figs. 13 and 14 demonstrate that the curves of multiobjective optimization stand between the curves of cost and emission optimization. Nonetheless, the curves in multiobjective optimization is closer to curves of cost optimization as objective functions priority is selected 0.6 and 0.4 for cost and emission, respectively. Table 6 summarizes the above results in all the cases.

## 7. Conclusions

In this paper, a two-stage stochastic programming has been introduced to minimize total operating cost and air pollutants emission in six different case studies. The proposed stochastic model schedules reserves provided by both of generating units and responsive loads to cover uncertainty of wind power. In addition to up and down reserves, DRPs have participated in energy market. Moreover, in the proposed model, the effect of price-based DR program has been considered through the scheduling procedure. The results indicate that customers participation in energy and reserve market compensates the wind power forecasting uncertainty as well as reduces the total operational cost and air pollutant emissions.

## References

[1] Schneider KP, Chassin D, Chen Y, Fuller JC. Distribution power flow for smart grid technologies. In: IEEE conference 2009.
[2] Pousinho HMI, Mendes VMF, Catalão JPS. A stochastic programming approach for the development of offering strategies for a wind power producer. Electric Power Syst Res 2012;89:45–53.
[3] Morales JM, Conejo AJ, Pérez Ruiz J. Economic valuation of reserves in power systems with high penetration of wind power. IEEE Trans Power Syst 2009;24(2):900–10.
[4] Vazquez O. Optimizing the spinning reserve requirements. PhD thesis. University of Manchester; May 2006.
[5] Brady D, Gramlich R. Getting smart about wind and demand response. Available from: www.windsystemsmag.com; 2009 [accessed 26.08.13].
[6] Conejo AJ, Morales JM, Baringo L. Real-time demand response model. IEEE Trans Smart Grid 2010;1(3):236–42.
[7] Engelen AG, Collins JS. Choices for smart grid implementation. In: IEEE conference 2010.
[8] Albadi MH, Saadany EFE. A summary of demand response in electricity markets. Elec Power Syst Res 2008;78(11):1989–96.
[9] Bouffard F, Galiana FD. Stochastic security for operations planning with significant wind power generation. IEEE Trans Power Syst 2008;23(2):306–16.
[10] Hong Ying-Yi, Lin Jie-Kai. Interactive multi-objective active power scheduling considering uncertain renewable energies using adaptive chaos clonal evolutionary programming. Energy 2013;53:212–20.
[11] Ge J, Zhang LZ, Wang F. Study on the optimization method of spinning reserve schedule in wind power integrated power system based on chance-constrained programming. In: IEEE international conference on power system technology 2010.
[12] Rasoul Azizipanah-Abarghooee, Taher Niknam, Alireza Roosta, Reza Malekpour Ahmad, Mohsen Zare. Probabilistic multiobjective wind-thermal economic emission dispatch based on point estimated method. Energy 2012;37(1):322–35.
[13] Xie L, Young Joo J, Ilic MD. Integration of intermittent resources with price-responsive loads. In: NAPS conference 2009. North American.
[14] Pina A, Silva C, Ferrão P. The impact of demand side management strategies in the penetration of renewable electricity. Energy 2012;41(1):128–37.
[15] Parvania M, Fotuhi Firuzabad M. Integrating load reduction into wholesale energy market with application to wind power integration. IEEE Syst J 2012;6(1):35–45.
[16] Madaeni SH, Sioshansi R. The impacts of stochastic programming and demand response on wind integration. Available from: www.iwse.ohio-state.edu; [accessed 26.08.13].
[17] Sioshansi R. Evaluating the impacts of real-time pricing on the cost and value of wind generation. IEEE Trans Power Syst 2010;25(2):741–8.
[18] Torabi SA, Hamedi M, Ashayeri J. A multi-objective optimization approach for multi-head beam-type placement machines. CentER Discussion Paper, Tilburg University; December 2010.
[19] Aalami HA, Moghaddam M, Yousefi GR. Demand response modeling considering interruptible/curtailable loads and capacity market programs. Appl Energy 2010;87(1):243–50.
[20] Reiss P, White M. Household electricity demand, revisited. Rev Econ Stud 2005;72:853–83.
[21] Filippini M, Pachauri S. Elasticities of electricity demand in urban Indian households. CEPE Working Paper; 2002. p. 16.
[22] FERC, Staff Report. Assessment of demand response and advanced metering; 2006. AD06–2.
[23] Ikaheimo J, Evens C, Karkkainen S. DER aggregator business: the Finnish case. VTT research report. Available from: http://www.ece.hut.fi/enete/DER_Aggregator_Business_Finnish_Case.pdf; 2009 [accessed 26.08.13].
[24] Birge JR, Louveaux F. Introduction to stochastic programming. New York: Springer-Verlag; 1997.
[25] Vahidinasab V, Jadid S. Joint economic and emission dispatch in energy markets: a multiobjective mathematical programming approach. Energy 2010;35:1497–504.
[26] Steen M. Greenhouse gas emissions from fossil fuel fired power generation systems. EUR 19754 EN. Joint Research Centre/Institute for Advanced Materials, European Commission; 2000.
[27] Cost and performance baseline for fossil energy plantsBituminous coal and natural gas to electricity, vol. 1; 2007. Final report DOE/NETL.
[28] Tarjanne R, Kivistö A. Comparison of electricity generation costs. Research report EN A-56. Lappeenranta University of Technology; 2008, ISBN 978-952-214-588-8; 2008. Available from:, http://urn.fi/URN.
[29] Abedinia O, Amjady N, Kiani K, Shayanfar HA, Ghasemi A. Multiobjective environmental and economic dispatch using imperialist competitive algorithm. Int J Tech Phys Probl Eng 2012;4(2):63–70.
[30] Hosseinzadeh Lotfi F, Fallahnejad R. Imprecise Shannon's entropy and multi attribute decision making. Entropy 2010;12(1):53–62.
[31] Shih HS, Shyur HJ, Standley Lee E. An extension of TOPSIS for group decision making. Math Comput Model 2007;45:801–13.
[32] Kuri B, Li F. Valuing emissions from electricity generation: towards a low carbon economy. In: IEEE power engineering society general meeting 2005.
[33] Ortega-Vazquez MA, Kirschen DS. Estimating the spinning reserve requirements in systems with significant wind power generation penetration. IEEE Trans Power Syst 2009;24(1):114–24.
[34] Brooke A, Kendrick D, Meeraus A, Raman R, Rosenthal RE. GAMS, users guide. Washington, DC: GAMS Development Corporation; 1998.
[35] Partovi F, Nikzad M, Mozafari B, Mohamad Ranjbar A. A stochastic security approach to energy and spinning reserve scheduling considering demand response program. Energy 2011;36:3130–7.
[36] The ILOG CPLEX 2008 [Online]. Available from: http://www.ilog.com/products/cplex/.
[37] Koch T, Achterberg T, Andersen E, Bastert O, Berthold T, Bixby RE, et al. MIPLIB 2010. Math Programming Comput 2011;3(2):103–63.

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