Multiobjective Wind-Thermal Generation Scheduling Considering Demand Response Programs Using Augmented Epsilon Constraint Method

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Abstract—This paper focuses on using Demand Response (DR) to cover uncertainty of wind power in Smart Grid (SG) environment. In this paper a multiobjective programming is utilized to minimize total operating cost and air pollutants emission, simultaneously. The proposed multiobjective model schedules energy and reserves provided by both of generating units and responsive loads in power systems with high penetration of wind power. The proposed generation scheduling model is solved using augmented epsilon constraint method. The best solution can be chosen by Entropy and TOPSIS methods. In the proposed model, the discrete retail customer responses to incentive-based DR programs are aggregated by Demand Response Providers (DRPs) and are submitted to ISO. Price-based DR and random nature of wind power are modeled by price elasticity concept of the demand and normal probability distribution function, respectively. In addition to up and down spinning reserve, DRPs can participate in energy market and submit their offers in the wholesale electricity market. This approach is implemented over a daily time horizon on the IEEE 30-bus test system. The results indicate the benefits of customers’ participation in energy and reserve market that in addition to compensating uncertainty of wind power reduces total operation costs and emission.

Keywords—Demand response; multiobjective programming; reserve; smart grid; wind power.

NOMENCLATURE

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>$t$, $h$</td>
<td>Index of time periods.</td>
</tr>
<tr>
<td>$i$</td>
<td>Index of generating units.</td>
</tr>
<tr>
<td>$L$</td>
<td>Index of loads.</td>
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<tr>
<td>$m$, $n$</td>
<td>Index of buses.</td>
</tr>
<tr>
<td>$k$</td>
<td>Index of wind power scenarios.</td>
</tr>
<tr>
<td>$NS_a$</td>
<td>Number of discrete points in DRP’s offer package.</td>
</tr>
<tr>
<td>$pr_k$</td>
<td>Probability of scenario $k$.</td>
</tr>
<tr>
<td>$\rho_0(t)$</td>
<td>Initial electricity price in period $t$.</td>
</tr>
<tr>
<td>$\rho(t)$</td>
<td>Electricity price in period $t$.</td>
</tr>
<tr>
<td>$d_i(t)$</td>
<td>Customer demand in period $t$ after implementation of the price-based DR program.</td>
</tr>
<tr>
<td>$F(t,h)$</td>
<td>Price elasticity of the demand.</td>
</tr>
<tr>
<td>$CSU_{it}$</td>
<td>Cost start-up of unit $i$ in period $t$.</td>
</tr>
<tr>
<td>$\pi_{iS}$</td>
<td>Capacity cost of point $S$ of DRF $L$ in period $t$.</td>
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<tr>
<td>$\pi_{iE}$</td>
<td>Energy cost of point $S$ of DRF $L$ in period $t$.</td>
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<tr>
<td>$p_i(t)$</td>
<td>Power scheduled for unit $i$ in period $t$.</td>
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<tr>
<td>$p_{\min i}$</td>
<td>Minimum power output of unit $i$.</td>
</tr>
<tr>
<td>$p_{\max i}$</td>
<td>Maximum power output of unit $i$.</td>
</tr>
<tr>
<td>$p_{\text{wind}}^L$</td>
<td>Wind power scheduled in period $t$.</td>
</tr>
<tr>
<td>$pw_{ik}$</td>
<td>Wind power in period $t$ and scenario $k$.</td>
</tr>
<tr>
<td>$p_{\text{ref}_{it}}$</td>
<td>Power output for unit $i$ in period $t$ and scenario $k$.</td>
</tr>
<tr>
<td>$RD_{it}$</td>
<td>Down-spinning reserve scheduled for unit $i$ in period $t$.</td>
</tr>
<tr>
<td>$R_{\text{ref}_{it}}$</td>
<td>Down-spinning reserve scheduled for unit $i$ in period $t$ and scenario $k$.</td>
</tr>
<tr>
<td>$RNS_{it}$</td>
<td>Non-spinning reserve scheduled for unit $i$ in period $t$.</td>
</tr>
<tr>
<td>$DR_{it}$</td>
<td>Scheduled reserve of DRP $L$ in period $t$.</td>
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<tr>
<td>$dr_{it}$</td>
<td>Deployed reserve of DRP $L$ in period $t$ and scenario $k$.</td>
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<td>$SP_{it}$</td>
<td>Wind spillage in period $t$ and scenario $k$.</td>
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<td>$f_{im}(t)$</td>
<td>Power flow through line $(m,n)$ in time period $t$ and scenario $k$. Limited to $\text{fmax}^{m,n}$.</td>
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<td>$\delta_{ntk}$</td>
<td>Voltage angle at bus $n$ in period $t$ and scenario $k$.</td>
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<td>$rd_{it}$</td>
<td>Down-spinning reserve deployed by unit $i$ in period $t$ and scenario $k$.</td>
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<td>$ru_{it}$</td>
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<td>Non-spinning reserve deployed by unit $i$ in period $t$ and scenario $k$.</td>
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<td>$\lambda_{it}$</td>
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<tr>
<td>$CSU_{it}$</td>
<td>The actual start-up cost of unit $i$ in period $t$ and scenario $k$.</td>
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probability density function (PDF)
in when the scenario In addition to spinning the stochastic 2013 Tehran, Iran in ncertainty and reduce above problems. In more scenario In addition to providing reserve, thermal generation scheduling period in ncertainty and reduce above problems. In period in electric vehicles besides reserves provided by generating units. Providing energy by these loads reduces cost and emission of generating units. This end-use customer participation which is called demand response can help system operation. DR programs are classified into two major groups: price-based and incentive-based DR programs. First group programs refer to change inelectricity consumption by end-use customer in response to dynamic prices. These programs include Time of Use (TOU) rate, Real Time Pricing (RTP), and Critical Peak Pricing (CPP) and are entirely voluntary. To access price signals, two-way communication link between the consumer and supplier is necessary that Advanced Metering Infrastructure (AMI) system provides it [6,7].

Second group 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 [8].

In recent years, many researches have been worked on covering uncertainty of wind power. In [9] a stochastic programming have been used for market clearing and considered load and wind prediction error as normal distributed random variables. In [10], the wind prediction error has been modeled by a probability density function (PDF) modeled spinning reserve provided by generation units for covering uncertainty of wind power. In addition to spinning and non-spinning reserve, demand response can also help ISOs and compensate random nature of wind power.
In [11] a price-based DR program is utilized 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 hour and so it has different behaviors in various times. Unfortunately price-based DR programs are entirely voluntary and if customers do not respond in needed time, some problems on power system will be imposed. Reference [12] has proposed an incentive-based DR program that reshapes the system load and so helps to integrate wind generation. This is not a stochastic programming method and the DR program which has been applied in this paper only provides load reduction. In [13], the imposed costs caused by wind generation uncertainty have been examined in three cases. The first case has used RTP program [14], in the second one, variable wind power has 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 effective in cost reduction.

In this paper a multiobjective mathematical programming is utilized to minimize total operating cost and air pollutants emission simultaneously. The proposed multiobjective model schedules energy and reserves provided by both of generating units and responsive loads. In the proposed model, the ISO receives the DR quantity and its offered price from Demand Response Providers (DRPs). Price-based DR also modeled by price elasticity concept of the demand. The proposed generation scheduling model is solved using augmented epsilon constraint method [15]. The best solution can be selected by Entropy and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods. These methods are introduced in [16].

The rest of this paper is organized as follows. Section II introduces the DR program models. The multiobjective mathematical programming is presented in Section III. In section IV, case study is discussed, and conclusions are given in Section V.

II. DEMAND RESPONSE MODEL

A. Price-based DR Model

Generally, consumers participate 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 [16]:

\[
E(t, h) = \frac{\partial d(t)}{\partial \rho(t)} = \begin{cases} 0 & \text{if } t = h \\ \frac{\partial \rho(t) \partial d(t)}{\partial \rho(h)} & \text{if } t \neq h \end{cases}
\]  

Equation (2) shows how much customers consume electricity to achieve minimum electricity bill in a 24 h interval while taking part in price-based DR programs [16]:

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

B. Incentive-based DR Model

In this paper it is assumed that DRPs can submit their offers to the day-ahead market. These offers are submitted for providing energy and up/down spinning reserve in this market. The provided reserves by DRPs are analogous to up/down spinning reserve services provided by generating units. The enrolled customers would decrease or increase their consumptions to provide these services and compensate unpredictable nature of wind power and also reduce air pollutants emission and operation costs. DRPs aggregate end-user customer responses and submit a package offer in the day-ahead market. This package is included amount of responses and their associated costs, as shown in Fig. 2.

If ISO accepts their offers, they will receive offered price in package and if they respond in needed time, ISO will pay them spot market price or the price offered by DRP for load reduction in the day-ahead market. Notethat if DRPs want to increase their consumptions and ISO accepts their offers, they will just receive offered price in packages and if their consumptions increase 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. 2, DR quantities and the associated costs are shown with \(m^2\) and \(\pi^1\), respectively. DR model considered in this paper is formulated as follows [12]:

\[
DR_{Rs} = \sum_{S=1}^{\infty} \frac{\Delta S_S}{\Delta S_S} ; \quad \Delta S_S = m^2_S - m^1_S \leq 0
\]

In equation (3), \(x^1_S\) is 1 if point \(S\) is scheduled in period \(t\) and 0 otherwise. It is also assumed that \(m^1_S=0\).
III. PROBLEM FORMULATION

In this section, a two-stage stochastic programming is applied to model the random nature of wind power, where the first-stage 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].

A. Objective Functions

The objective functions are given in (5) and (6) which minimized through the scheduling horizon.

\[ \text{MinCost} = \sum_{t=1}^{NT} \sum_{i=1}^{m} \left( \left( \text{CSU}_{it} + a_i P_{it}^2 + b_i P_{it} + c_i \right) p_{it} + n_{it}^R U_{it} + n_{it}^{RD} R_{it} + n_{it}^{RNS} R_{it} \right) + \sum_{t \in \text{SPDR}} \sum_{l=1}^{N_{l}} k_{l} d_{lt} + \sum_{t=1}^{NT} \sum_{k=1}^{N_{wk}} \left( \text{CSU}_{ltk} \right) + a_i P_{ltk}^2 + b_i P_{ltk} + c_i \}

\[ + \sum_{t \in \text{DRP}} \sum_{l=1}^{N_{l}} \left( \text{CSU}_{ltk} \right) + a_i P_{ltk}^2 + b_i P_{ltk} + c_i \}

The cost function includes two stages. The first-stage is associated with electricity market costs (the costs are before the realization of each wind power scenario). This stage is included the start-up, energy, spinning and non-spinning reserves offer 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 with the \( p_{it} \) probability in objective function is associated with actual operation of power system (after the realization of each scenario). This stage is included the costs associated with start-up and shutdown plan adjustment of generating units in each scenario, the costs resulting from the actual deployment of reserves by generating units and DRPs and the costs stemming from load shedding and wind spillage. Equation (6) shows the amount of emission generated by units where \( \alpha_i, \beta_i, \gamma_i, \delta_i, \) and \( \lambda_i \) are the emission coefficients and are taken from [17].

\[ \text{Emission} = \sum_{t=1}^{NT} \sum_{i=1}^{m} \left( \alpha_i \left( \frac{p_{it}^2}{\gamma_i} + \frac{\beta_i P_{it}}{\gamma_i} + \frac{\delta_i P_{it}^2}{\gamma_i} \right) \right) + \lambda_i \exp(\lambda_i p_{it}) \]
C. Second-Stage Constraints

- **Power Balance at Every Bus n:**
  \[ \sum_{i:j \in N_2} p_{i \rightarrow j}^n + \sum_{l:j \in N_2} (\text{shed}_{l \rightarrow j}^n - \text{gen}_{l \rightarrow j}^n) + (p_{w \rightarrow j} - c_{w \rightarrow j}) | j = n \]
  \[ + \left( p_{w \rightarrow j} - c_{w \rightarrow j} | j = n \right) ] \]  
  \[ + \sum_{m:j \in N_3} f_{m \rightarrow j}^n \forall n, t, k \]  
  \[ (17) \]

- **Production Limits in Scenarios:**  
  \[ p_{l \rightarrow j}^n \geq p_{\min} \quad \forall t, k \]  
  \[ p_{l \rightarrow j}^n \leq p_{\max} \quad \forall t, k \]  
  \[ (18) \]
  \[ (19) \]

- **Power Flow through Transmission Lines:**  
  \[ f_{m \rightarrow j}^n = \left( \frac{v_m^k \times \theta_{m \rightarrow j}^k}{x_{m \rightarrow j}} \right) \left( v_{j}^k \times \theta_{j}^k \right) \quad \forall t, k, (m, j) \in \text{sl} \]  
  \[ = \left( \frac{v_m^k \times \theta_{m \rightarrow j}^k}{0} \right) \left( v_{j}^k \times \theta_{j}^k \right) \quad \forall t, k, (n, j) \in \text{sline} \]  
  \[ (20) \]
  \[ (21) \]

- **DR Reserve:**  
  \[ d_{r \rightarrow j}^n = S_{s \rightarrow j}^n \Delta s_{s \rightarrow j}^n \quad \forall t, k, l \in \text{DRP} \]  
  \[ \sum_{s \rightarrow j}^n \Delta s_{s \rightarrow j}^n \quad \forall t, k, l \in \text{DRP} \]  
  \[ r_{edr}^n = S_{s \rightarrow j}^n \Delta s_{s \rightarrow j}^n \quad \forall t, k, l \in \text{DRP} \]  
  \[ (22) \]

- **Load Shedding and Wind Spillage:**  
  \[ 0 \leq \text{shed}_{l \rightarrow j}^n \leq \text{LCL}_{l \rightarrow j}^n \quad \forall t, k \]  
  \[ \leq \text{shed}_{l \rightarrow j}^n \leq \text{LCL}_{l \rightarrow j}^n \]  
  \[ (24) \]
  \[ \text{LCL}_{l \rightarrow j}^n = \left( \delta_{l \rightarrow j}^n \right) \left( L \rightarrow \sum_{i \in \text{pict}} \text{DR}_{i \rightarrow j}^n \right) \]  
  \[ \pm \sum_{i \in \text{pict}} \text{DR}_{i \rightarrow j}^n \quad \forall L \]  
  \[ \notin \text{s}^\text{np}\text{dr} \quad t, k \]  
  \[ (25) \]

- **LCL_{l \rightarrow j}^n:**  
  \[ \text{LCL}_{l \rightarrow j}^n = \alpha_{j}^n \forall L \in \text{s}^\text{npdr}, t, k \]  
  \[ \leq \text{LCL}_{l \rightarrow j}^n \leq \text{PWL}_{l \rightarrow j}^n \quad \forall t, k \]  
  \[ (26) \]

- **PWL_{l \rightarrow j}^n:**  
  \[ 0 \leq \text{PWL}_{l \rightarrow j}^n \leq \text{PWL}_{l \rightarrow j}^n \quad \forall t, k \]  
  \[ (27) \]

In equation (25), if DRPs provide up reserve (decrease their consumption), negative sign will use and positive sign otherwise.

D. Constraints Linking the First- and Second-Stage

- **Decomposition of Generator Power Outputs**
  \[ p_{l \rightarrow j}^n = p_{l \rightarrow j}^n - p_{r \rightarrow j}^n \quad \forall t, k \]  
  \[ (28) \]

- **Spinning and Non-spinning Reserves:**  
  \[ 0 \leq \text{non}_{r \rightarrow j}^n \leq \text{r}_{r \rightarrow j}^n \quad \forall t, k \]  
  \[ \leq \text{non}_{r \rightarrow j}^n \leq \text{r}_{r \rightarrow j}^n \]  
  \[ (29) \]
  \[ (30) \]
  \[ (31) \]

- **DR Reserve:**  
  \[ 0 \leq \text{dy}_{r \rightarrow j}^n \leq \text{dr}_{r \rightarrow j}^n \quad \forall t, k \]  
  \[ \leq \text{dy}_{r \rightarrow j}^n \leq \text{dr}_{r \rightarrow j}^n \]  
  \[ (32) \]

Equations (29)-(32) express that the amount of reserves in each scenario must be lower than the amount of scheduling reserves in the first-stage.

- **Generating Units Start-Up Cost Adjustments in Scenarios:**  
  \[ c_{s_{\text{n}} \rightarrow j} = \text{CS}_{\text{n}} - \text{CS}_{\text{n}} \quad \forall t, k \]  
  \[ \leq \text{CS}_{\text{n}} \geq \text{CS}_{\text{n}} \quad \forall t, k \]  
  \[ (33) \]
  \[ (34) \]
  \[ (35) \]

IV. CASE STUDY

The electricity prices are considered 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 two different case studies. In the first case, only generating units provide energy and reserves and there is no DR participation. In second case, in addition to the generators, DRPs can participate in both of energy and reserve market. They can enroll 30%, 30%, and 10% of their consumers to provide energy, up and down reserve, respectively. These above cases have been solved using the solver CPLEX under GAMS [18] software after linearization of the objective functions. The results are presented in Table II. This table provides the decomposition of costs and amount of emission in each case. The proposed generation scheduling model is solved using augmented epsilon constraint method and then by using the entropy and TOPSIS methods, the best solutions are selected in each case. In case 1, 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 inpeak hours since this unit is the most
expensive generator and its emission production is relatively high. But in case 2, ISO has more options to compensate the unpredictable nature of wind and can utilize reserves provided by generating units and also 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 needed time. For example, DRPs located at buses 2 and 6 are scheduled to decrease their consumption and DRP located at bus 4 is planned to provide down reserve.

Fig. 3. Wind power scenarios
Le Xie, Jhi decreased their loads at NAPS conference 2009, They have also reduced operation costs and air pollutants emission. In addition, in case 2, the total operation cost in case 2 is lower than case 1. As a result, in case 2, G1 is scheduled to be off in all periods even at peakhours. In this case, the loads located at buses 7, 15 and 21 are increased their consumption at valley and off-peak periods, ISO can use load reduction of volunteer customers instead of power generation of generators and reduce operation costs and emission caused by generating units. Moreover, in case 2 the loads located at buses 7, 15 and 21 participate in price-based DR and reduce their consumption at peakhours and at off-peak vice versa. As a result, in case 2, G1 is scheduled to be off in all periods even at peakhours. In this case, the loads located at buses 7, 15 and 21 have decreased their consumption with respect to the electricity price at peak periods, and so, the generating units are produced less power than case 1 in same hours. Although in case 2 the loads located at buses 7, 15 and 21 are increased their consumption at valley and off-peak periods, 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 used. Therefore, at valley and off-peak periods, ISO can use load reduction of volunteer customers located at buses 5 and 10 instead of power generation of generators and reduce cooperation costs and emission caused by generating units. As shown in table II, the total operation cost in case 2 is lower than case 1. It reduces by $679 for the scheduling horizon. However, in case 2, the DRPs’ reserve scheduling and energy cost increase, while spinning and non-spinning reserves cost and also energy cost of generating units decrease. In addition, in case 2, the amount of emission caused by generating units is 0.308 ton lesser than case 1.

V. CONCLUSIONS

In this paper, a multiobjective mathematical programming has been introduced to minimize total operating cost and air pollutants emission simultaneously. The proposed multiobjective model schedules reserves provided by both of generating units and responsive loadsto cover uncertainty of wind power. In addition to up and down provided reserves, DRPs have participated in energy market. They have also supplied required power of loads that have taken part in price-based DR at valley and off-peak periods. The results indicate the benefits of customers’ participation in energy and reserve market that in addition to compensate uncertainty of wind power reduces total operation costs and air pollutants emission.

REFERENCES


