Power System Stochastic Unit Commitment Model for Large-scale Wind Power Integration Considering Demand Side Resources

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Abstract. As the uncertainty output characteristics of wind power, the large-scale wind power integrated to the grid, has brought new challenges to power system operation. Based on the uncertainty characteristics of wind power, this paper establishes the wind power output model, then focuses on the positive effects of price-based demand response (PDR) and incentive-based demand response (IDR), which are allowed to participate in the power balance, on the unit commitment (UC) with high wind power penetration, and establishes the PDR and IDR models. Based on the chance constrained programming, this paper proposes a stochastic UC model with large-scale wind power integration considering demand side resources (DSR). Stochastic simulation combined with particle swarm optimization (PSO) algorithm was presented to solve this model. At last, the model is proved feasibly and effectively by testing the IEEE 10 machines system.

1. Introduction

In recent years, wind power has developed rapidly worldwide as a clean energy source. However, the uncertainty of wind power output has brought great challenges to the power system. Therefore, it is of great significance to excavate the flexibility resources on demand side and coordinate optimize resources on the supply side and the demand side. Reference [1] studied the influence of the day-ahead PDR and the in-day IDR on the wind power consumption in wind power integrated system. Based on the risk constraint theory, reference [2] studies the peaking benefits of demand response (DR) such as excited-load and interruptible load. However, the above references are based on the traditional deterministic scheduling model, and the DR they consider is not comprehensive. Based on the chance constrained method, reference [3] studied the system scheduling model that uses the demand side response to improve wind power consumption, but the model does not optimize resources on the supply side and the demand side jointly.

Under the above background, this paper adopts stochastic chance-constrained programming to establish a UC model of large-scale wind power integration system with consideration of coordinated
optimization of resources on the supply side and the demand side, and studies the effect of time-of-use pricing (TOU) and IDR on improving the flexibility of power system and promoting the consumption of wind power. Stochastic simulation combined with PSO algorithm was presented to solve this model.

2. Wind Power Output Forecasting Model
Based on the prediction of wind speed and wind power output in reference [4], this paper predicts the wind power output curve by point forecast, and obtains the interval prediction of wind power output by considering the wind power prediction error of ±20% up and down deviation. Figure 1 is a diagram of the prediction interval of the total output of a wind farm with 80% confidence probability.

![Wind power output curve](Figure 1. Diagram of 80% confidence probability for certain wind farm total power output prediction.)

3. Response Mode of DSR Participating in Scheduling Optimization

3.1. Response Mode of PDR
PDR refers to a load response method in which the user responds to changes of the retail price and adjusts the demand for electricity accordingly[5]. TOU pricing is an electricity price response method that is divided into several different price levels according to the time characteristics of the load curve. The price is utilized to guide the user to actively adjust the power demand to achieve load transfer and peak load shifting. The price elasticity matrix of electricity demand is used to establish a DR model which is based on TOU pricing, and the self-elasticity coefficient $\varepsilon_{t,t}$ and cross-elastic coefficient $\varepsilon_{t,h}$ are used to measure the impact of TOU pricing on electricity demand.

\[
\varepsilon_{t,t} = \frac{\partial d_t}{\partial \rho_t} / \rho_t
\]
\[
\varepsilon_{t,h} = \frac{\partial d_t}{\partial \rho_h} / \rho_h
\]

where $d_t$ denotes the electric power demand at time $t$, and the electricity prices and $h$ are $\rho_t$ and $\rho_h$, respectively. $d_t$ can be formulated as follows:

\[
d_t = d_{0t} \times \left[ \varepsilon_{t,t} \times \frac{\rho_t - \rho_{0t}}{\rho_{0t}} + \sum_{h=1}^{T} \varepsilon_{t,h} \times \frac{\rho_h - \rho_{0h}}{\rho_{0h}} \right]
\]

where $d_{0t}$ denotes the initial electric power demand before the response. $\rho_{0t}$ and $\rho_{0h}$ respectively represent the reference electricity price and $h$ before the electricity price changes.

3.2. Response Mode of IDR
IDR refers to a DR method in which the DR implementing agency motivates users to immediately reduce or increase the load demand when the electric power supply is tight or excessive by
3

formulating policies. The IDR studied in this paper mainly includes direct load control (DLC), interruptible load (IL), electric vehicles (EV) with two-way adjustment capability, and energy storage, etc. The scheduling cost of IDR is divided into two parts: capacity compensation cost and power compensation cost. And the power compensation is in the form of stepped compensation.

The invoking cost of IDR is as follows:

\[
F_{IDR} = \sum_{d=1}^{N_d} (C_d \cdot D_{d, IDR}^{IDR}) + \sum_{i=1}^{T} \left( \sum_{d=1}^{N_d} (C_{E, dm}^{+} \cdot d_{dm, i}^{+}) + \sum_{d=1}^{N_d} (C_{E, dm}^{-} \cdot d_{dm, i}^{-}) \right)
\]

(4)

where the first and second items on the right side are the capacity cost and the power cost of IDR respectively. \(F_{IDR}\) is the total scheduling cost of IDR during the scheduling period. \(C_d\) is the unit capacity response cost of IDR ($/MW). \(D_{d, IDR}^{IDR}\) is the response capacity of the user \(d\) participating in IDR. \(C_{E, dm}^{+}\) and \(C_{E, dm}^{-}\) are respectively the cost of per unit increase and decrease generated energy corresponding to segment \(m\) on IDR price curve ($/(MW\cdot h)$), and \(d_{dm, i}^{+}\) and \(d_{dm, i}^{-}\) are respectively the increase and decrease generated energy. \(N_d\) is the number of users participating in IDR.

4. A Chance-constraint-programming-based UC Model Considering Large-Scale Wind Power and DSR

4.1. Stochastic Chance Constrained Programming with Uncertain Theory

Power system scheduling optimization with large-scale wind power is a nonlinear integer programming problem with random variables. This paper uses chance constrained programming to describe this randomness and its impact. Its mathematical description can be expressed as follows:

\[
\begin{align*}
\min & \quad \bar{f}(x) \\
\text{s.t.} & \quad P_t \left\{ f(x, \xi) \leq \bar{f}(x) \right\} \geq \beta \\
& \quad P_t \left\{ g_i(x, \xi) \geq 0, i=1,2,\ldots,p \right\} \geq \alpha
\end{align*}
\]

(5)

where \(x\) is an n-dimensional decision vector. \(\xi\) is a random vector with a known probability density function. \(f(x, \xi)\) is an objective function. \(g_i(x, \xi)\) is constraint function. \(P_t \{ \cdot \} \) is the probability that an event is established in \(\{ \cdot \} \). \(\alpha\) and \(\beta\) are respectively the confidence level of the constraint condition and the objective function which is pre-set by the decision maker. \(\bar{f}(x)\) is the minimum value of the objective function when the probability level is \(\beta\).

4.2. Objective Function

The optimization goal of the model established in this paper is to minimize the total operating cost.

\[
F = \min \ E \left[ F_G + F_{IDR} + F_{pena} \right]
\]

(6)

where \(F\) denotes the total operating cost. \(F_G\) denotes the operating cost of units, including fuel cost and on-off cost. \(F_{IDR}\) denotes the invoking cost of IDR. \(F_{pena}\) denotes the cost of the wind abandonment and load shedding when the system has insufficient peak capacity.

\(F_G\) can be formulated as follows:

\[
F_G = \sum_{i=1}^{N_r} \sum_{t=1}^{T} \left[ f_{j,i}(P_{Gi,t}) + u_{i,t}(1-u_{i,t-1})S_{i,j} \right]
\]

(7)
where $N_G$ is the number of units and $f_{i,t}$ ($\bullet$) is the operating cost of the unit $i$ during the period $t$. $P_{G_{i,t}}$ denotes the active output of unit $i$. $u_{i,t}$ is a 0-1 variable. The power-on is 1 and the power-off is 0. $S_{i,t}$ denotes the on-off cost of unit $i$.

$F_{pena}$ can be formulated as follows:

$$F_{pena} = \sum_{i=1}^{T} C_{w}^{pena} * q_{i,t}^{wind} + \sum_{i=1}^{T} C_{t}^{pena} * q_{i,t}^{load}$$

where $C_{w}^{pena}$ and $C_{t}^{pena}$ are the unit penalty cost for the wind abandonment and load shedding respectively. $q_{i,t}^{wind}$ and $q_{i,t}^{load}$ are the abandoned wind electricity the load shedding electricity respectively.

4.3. Constraint Condition

1) System Electricity Power Balance Constraint

$$\sum_{i=1}^{N_G} P_{G_{i,t}} + (P_{w,t} - q_{i,t}^{wind}) = P_{d,t} + a_{t}^{TOU} + (\sum_{d \in IDR}^{N_d} d_{d,t}^{dm} - \sum_{d \in IDR}^{N_d} d_{d,t}^{dm}) - q_{i,t}^{load}$$

Where $P_{w,t}$ is the total output of the wind farm. $P_{d,t}$ is the load of the system. $a_{t}^{TOU}$ is the amount of change of the response power to TOU pricing.

2) System Rotation Reserve Constraint

$$P_{t} \left\{ \sum_{i=1}^{N_G} u_{i,t} \left( P_{G_{i,t}}^{max} - P_{G_{i,t}} \right) + \sum_{d \in IDR}^{N_d} D_{d,t}^{max} \geq R_{dup,t} + R_{wup,t} \right\} \geq \beta_{1}$$

$$P_{t} \left\{ \sum_{i=1}^{N_G} u_{i,t} \left( P_{G_{i,t}}^{min} - P_{G_{i,t}} \right) + \sum_{d \in IDR}^{N_d} D_{d,t}^{max} \geq R_{ddn,t} + R_{wdn,t} \right\} \geq \beta_{2}$$

where $P_{G_{i,t}}^{max}$ and $P_{G_{i,t}}^{min}$ are respectively the upper and lower limit of the electricity power provided by unit $i$. $D_{d,t}^{max}$ and $D_{d,t}^{min}$ are respectively the upper and lower limit of the load reduction and increment that can be provided by the user $d$ in the form of IDR. $R_{dup,t}$ and $R_{wup,t}$ are respectively the standby requirements of positive rotation for load and wind power. $R_{ddn,t}$ and $R_{wdn,t}$ are respectively the standby requirements of negative rotation for load and wind power. $P_{t} \{ \bullet \}$ is the probability that the event in $\{ \bullet \}$ is established. $\beta_{1}$ and $\beta_{2}$ respectively denote the confidence level of positive and negative rotation reserve of given system.

3) Electricity Power Constraint in Each Time Period

$$-D_{d,t}^{TOU} \leq a_{t}^{TOU} \leq D_{d,t}^{TOU}$$

where $D_{d,t}^{TOU}$ is the limit value of response power for the user participating in TOU pricing.

4) Constraint of IDR

$$\left\{ 0 \leq d_{d,t}^{+} \leq D_{d}^{+} \right\}$$

$$\left\{ 0 \leq d_{d,t}^{-} \leq D_{d}^{-} \right\}$$

where $D_{d}^{+}$ and $D_{d}^{-}$ respectively denote the upper and lower limits of the load that the IDR user $d$ is allowed to increase and decrease.
5. PSO Algorithm Based on Stochastic Simulation

In this paper, the stochastic simulation technique is combined with the quantum-inspired binary particle swarm optimization (QBPSO) algorithm to solve the chance constrained programming model.

The specific solution process is as follows:
1) Set system parameters, random simulation parameters and particle swarm parameters.
2) Optimize the load change of the PDR and obtain the optimized load curve.
3) Using random simulation technology, randomly generate $N_s$ strips 24-hour wind power output curve according to the wind power output model.
4) Using PSO to randomly generate $N_p$ feasible original conventional unit on-off population matrices.
5) Verify the particle swarm matrix using stochastic simulation technology, and check whether the particle on/off state at each moment satisfies the confidence level $\beta_1$ and $\beta_2$ for the $N_s$ samples. If not, correct the on/off combination of particles at that moment. Check again until the condition is met.
6) Calculate the fitness of each particle, update the individual extremum of the particle and the global extremum of the particle swarm.
7) update the position and speed of particles, and repeat steps 5) and 6) until the termination condition is met.
8) Obtain the optimal day-ahead UC results meeting random programming constraints.
9) Based on the results obtained in step 8), the real-time economic dispatching of the system is carried out. According to the wind power output probability distribution, the Monte Carlo simulation method is used to obtain $N$ strips wind power random output curves as wind power output scenarios for real-time economic dispatch. And obtain a new net load curve based on day-ahead PDR optimization;
10) According to the day-ahead UC strategy, the real-time economic dispatching is carried out to verify whether the on-off strategy under the confidence level can meet the real-time peaking demand within the day. If not, invoke the IDR first. Abandon wind or cut load, or increase the confidence level of system if still not satisfied.
11) Output system economic dispatch results under $N$ wind power output scenarios in step 9), and calculate the expectation value of system scheduling under the confidence level.

6. Simulation Results

In this section, the IEEE 10 machine system example is used. The number of random simulations is set to 5000, the particle population size is set to 40, and the number of algorithm iterations is set to 100. The self-elastic coefficient $\varepsilon_{i,j}$ is -0.2, and the cross-elastic coefficient $\varepsilon_{i,b}$ is 0.033.

In order to explain the impact of PDR and IDR on the operation cost of large-scale wind power system, this section compares the operation costs of the system under different operation cases. The results are shown in Table 1.

| case | total fuel | On-off | Wind abandonment | Load shedding | IDR |
|------|------------|--------|------------------|---------------|-----|
| 1    | 493 020    | 435 970 | 5 550            | 6 000         | 45 500 | - |
| 2    | 435 072    | 427 442 | 5 380            | 2 250         | 0    | - |
| 3    | 442 960    | 433 354 | 6 450            | 2 900         | 0    | 255.6 |
| 4    | 437 500    | 431 378 | 5 900            | 0             | 0    | 221 |

It can be seen from Table 1 that under the power supply structure of this paper and the same confidence level, when considering DSR into the UC, the total operating cost and fuel cost are
reduced. And wind abandonment and load shedding no longer occur. In order to analyse the reasons for the above results, this section further analyses the impact of TOU and IDR on operational scheduling.

![Figure 2. Load curves with or without TOU](image1)

![Figure 3. Diagram of system operation with IDR participated](image2)

Figure 2 shows the load curves with or without TOU. It can be seen that the system load curve has a corresponding change after the TOU is considered into UC. This is because TOU is an interactive way between the power generation side and the user side. By increasing the electricity price during the peak load period and lowering the electricity price during the load period, the power consumption mode can be affected, and the load curve is optimized.

Figure 3 shows the effect of IDR. The day-ahead net load curve does not completely coincide with the in-day net load curve, which is due to the forecast error of wind power output. During original low load period (e.g. 2h), the actual output of wind power is greater than the predicted output, and the negative rotation is insufficient. Therefore, the system increases the load by invoking IDR to avoid abandoning the wind power. During original peak load period (e.g. 12h), the actual output of the wind power is less than the predicted output, and the active rotation is insufficient. Therefore, the system interrupts the load by invoking IDR to avoid random load shedding.

### 7. Conclusion

Based on comprehensively optimizing DSR and power generation side resources, this paper establishes a stochastic UC model based on opportunity constrained programming with large-scale wind power integration, and uses stochastic simulated PSO algorithm to solve the model. Through the analysis of the example, the following conclusions are drawn: 1) Deal with the uncertainty of wind power output by using opportunity constrained programming, and optimize the total operating cost of the system by setting a reasonable confidence level. 2) Improve the wind power consumption space, reduce the system load shedding, and reduce the total cost of system operation total cost by rational allocation and appropriate invoking of DSR.

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### References

[1] Liu X C, Wang B B, Li Y, et al. Stochastic unit commitment model for high wind power integration considering demand side resources [J]. Proceedings of the CSEE, 2015, 35(14): 3714-3723.

[2] Yang N, Wang B, Liu D C, et al. An integrated supply-demand stochastic optimization method considering large-scale wind power and flexible load [J]. Proceedings of the CSEE, 2013, 33(16): 63-69.

[3] Ai X, Liu X. Chance constrained model for wind power usage based on demand response [J]. Journal of North China Electric Power University: Natural Science Edition, 2011, 38(3): 17-22.

[4] R. Doherty, M. O'Malley. A new approach to quantify reserve demand in systems with significant installed wind capacity [J]. IEEE TRANSACTIONS ON POWER SYSTEMS, 2005, 20(2): 587-595.

[5] Zhang Qin, Wang Xifan, Wang Jianxue, et al. Survey of demand response research in deregulated...
electricity markets[J]. Automation of Electric Power Systems, 2008, 32(3): 97-106 (in Chinese).