Stochastic Dispatching of Wind Power Considering Errors of Power Prediction

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Abstract: Aiming at the stochastic dispatch problem brought by wind power, the expected model of wind power considering the errors of power prediction is established according to stochastic programming theory. And the calculation steps based on Monte Carlo stochastic simulation and genetic algorithm are proposed. An IEEE 30-bus example with wind farms is given to verify the feasibility and effectiveness of the method. The result shows that the stochastic dispatch method based expected value model can quantify the uncertainty caused by the prediction error of wind power well and optimize the expected value of wind power accommodation. It plays a positive role in improving dispatching level and promoting wind power accommodation.

1. Introduction
In recent years, wind power technology has been developed rapidly in China. Since 2016, the cumulative installed capacity and additional installed capacity of wind power in China have ranked first in the world. However, due to the influence of natural resource condition, the characteristic of wind power output shows strong intermittence, randomness and volatility. When large-scale wind power farms integrate into the power grid, the traditional power system are confronted with comprehensive challenges. Especially, in the early development stage of wind power, wind power abandonment phenomena occurred frequently in some areas of China and aroused great attention from all sectors of society, because of some factors such as: uncoordinated development between grid and generation planning, dis-orderly development, insufficiency of transmission and regulation capacity, etc. In general, the influence factors of wind power accommodation can be classified into two aspects [1-3]: the first are the objective conditions such as: load demand, regulation capacity of power system, transmission capacity, etc. the second are the dispatching countermeasures such as: wind power generation monitoring, forecasting, coordinated control measures, etc [4]. Among them, the dispatching level of wind power is the key factor to determine the maximum accommodation quantity of wind power under existing objective conditions mentioned above.

In current time, with the continuous improvement of wind power forecasting ac-curacy and the standardization of forecasting information management, the dis-patch strategy based on short term and ultra-short term power forecasting in-formation has been widely researched and applied. However, the uncertainty of wind power dispatching scheme caused by prediction error still exist objectively.
How to quantify the uncertainty caused by prediction error and improve the confidence level of wind power dispatching decision-making have been the urgent problem to be solved [5-8].

Focused on the problems mentioned above, an expectation dispatching model of wind accommodation based on stochastic programming theory is established with the objective of maximum wind electricity accommodation. In this model, the constraint conditions such as: output limitation, ramping rate, etc. and an algorithm combined Monte Carlo simulation and genetic algorithm are proposed to solve the optimal model. Then, a case study based on IEEE 30-bus system containing wind farms is shown to verify the feasibility and effectiveness of this method.

2. Stochastic Decision-Making Principle Based on Expected Value Model

In the real world, many random variables appear in decision-making of some fields such as: management engineering, economy and so on. These mathematical programming problems with random variables are called stochastic programming. For the random variables appearing in stochastic programming problems, different methods are provided according to different decision purpose and technical requirements, such as: expectation model, chance-constrained programming and related opportunity programming [9].

Under constraints, the decision-making model that optimizes the expected value of the objective function is called the expected value model. The general mathematical expression of the single objective expectation model is shown as follows:

$$\max E[f(x,\xi)]$$

s.t. 

\[
\begin{cases} 
E[g_j(x,\xi)] \leq 0 & j = 1,2,\ldots,p \\
E[h_k(x,\xi)] = 0 & k = 1,2,\ldots,q 
\end{cases}
\]  

Where: \(x\) is N-dimensional decision variables; \(\xi\) is t-dimensional random vector with probability density function \(\Phi(\xi): f(x,\xi)\) is the objective function; \(g_j(x,\xi)\) and \(h_k(x,\xi)\) are stochastic constraint function. \(E\) is the expected value operator. Thus, shown as below:

\[
E[f(x,\xi)] = \int f(x,\xi) \Phi(\xi) d\xi 
\]

\[
E[g(x,\xi)] = \int g(x,\xi) \Phi(\xi) d\xi 
\]

\[
E[h(x,\xi)] = \int h(x,\xi) \Phi(\xi) d\xi 
\]

If \(\xi\) is discrete random vector with distribution function \(\text{Pr}(\xi = \xi_i) = \theta_i, i \in I\) (\(I\) is the sequence number set ). Then:

\[
E[f(x,\xi)] = \sum_{i \in I} \theta_i f(x,\xi_i) 
\]

\[
E[g(x,\xi)] = \sum_{i \in I} \theta_i g(x,\xi_i) 
\]

\[
E[h(x,\xi)] = \sum_{i \in I} \theta_i h(x,\xi_i) 
\]

When the feasible solution \(x^*\) is the optimal solution of the expected value model, for any feasible solution \(x\), inequality \(E[f(x^*,\xi)] \geq E[f(x,\xi)]\) holds.
3. Expected Value Model of Stochastic Dispatching for Wind Power Accommodation

Because that the prediction error of wind power presents some probability distribution characteristics. Therefore, wind power as a random variable makes the traditional deterministic dynamic economic dispatching process for conventional units becomes a stochastic programming problem with random variables.

3.1. Objective Function

The maximum expected value of wind power accommodation is set as the optimal object of dynamic dispatching model, which is shown as below:

$$\max f = E \left[ \sum_{i=1}^{T} \sum_{j=1}^{W} \left( P_{wji} \cdot \Delta t \right) \right]$$  \hspace{1cm} (9)

Where, \( \Delta t \) is unit time; \( T \) is the number of time periods in the dispatching cycle; \( W \) is the number of wind farms; \( P_{wji} \) is the actual power output of the \( j \)-th wind farm in the \( i \)-th time period.

In the actual dispatching process, on the one hand, the abandoned electricity and rate of wind power are used as evaluation indexes of accommodation level. In which, the abandoned electricity is equal to the difference between theoretical output and actual output of wind power, and abandoned rate is equal to the ratio of abandoned electricity to theoretical electricity of wind power. On the other hand, based on the day-ahead power prediction curve, the dynamic economic dispatching scheme is decided with the objective of minimum generation cost of whole power system. When the cost of wind power generation is neglected, the initial objective shown in formula (9) can be equivalent to the minimum generation cost of whole power system, shown as formula (10):

$$\min f = E \left[ \sum_{i=1}^{T} \sum_{k=1}^{G} \left( a_k \cdot P_{gki}^e \cdot \Delta t \right) \right]$$  \hspace{1cm} (10)

Where, \( G \) is the number of conventional units; \( P_{gki}^e \) is the actual power output of the \( k \)-th conventional unit in the \( i \)-th time period; \( a_k \) is the generation cost coefficient of the \( k \)-th conventional unit.

3.2. Constraint Conditions

The constraint conditions of power system dynamic dispatching containing wind-farms include power balance constraint of power system, spinning reserve constraint of power system, power upper/lower limitation of conventional generation unit, ramping rate limitation of adjusting generation unit. At the same time, the security and stability constraints on system-level must be also satisfied, such as: margin of transmission capacity, voltage level, etc. The security and stability are independently checked by power system simulation. Therefore, the security and stability are not analyzed in the stochastic optimization of this paper.

1) Power balance constraint of power system

$$\sum_{k=1}^{G} P_{gki}^e + \sum_{j=1}^{W} P_{wji}^e - P_{Di}^e - P_{Li}^e = 0$$  \hspace{1cm} (11)

Where, \( G \) is the number of conventional units; \( P_{gki}^e \) is actual power output of the \( k \)-th conventional unit in the \( i \)-th time period; \( P_{Di}^e \) is the load power of power system in the \( i \)-th time period; \( P_{Li}^e \) is the system loss in the \( i \)-th time period.

2) Spinning reserve constraint of power system

$$\sum_{k=1}^{G} \left( P_{k,\max} - P_{gki}^e \right) \geq P_{Ri}$$  \hspace{1cm} (12)
\[
\sum_{i=1}^{G} (P_{ki}^i - P_{ki,\text{min}}) \geq P_{ki,\text{r}}
\]

Where, \( P_{ki,\text{r}} \) is the upper spinning reserve requirement in the \( i \)-th time period; \( P_{ki,\text{r}} \) is the lower spinning reserve requirement in the \( i \)-th time period.

3) Power output limitation of conventional unit

\[
P_{ki,\text{min}} \leq P_{ki}^e \leq P_{ki,\text{max}}
\]

Where, \( P_{ki,\text{max}} \) is the maximum power output of the \( k \)-th conventional unit; \( P_{ki,\text{min}} \) is the minimum power output of the \( k \)-th conventional unit.

4) Power output constraint of wind farm

\[
0 \leq P_{ji}^\varepsilon \leq P_{ji}^\varepsilon + \varepsilon_{ji}
\]

Where, \( P_{ji}^\varepsilon \) is predicted power value of the \( j \)-th wind farm in the \( i \)-th time period; \( \varepsilon_{ji} \) is the prediction error of the \( j \)-th wind farm in the \( i \)-th time period with probability density function \( \Phi_j(\varepsilon) \).

5) Ramping rate limitation of adjusting generation unit

\[
-R_{k,i} \cdot t_{\text{max}} \leq P_{ki}^e - P_{ki,(i-1)}^e \leq R_{k,i} \cdot t_{\text{max}}
\]

Where, \( t_{\text{max}} \) is the maximum allowable ramping time; \( R_{k,i} \) is the upper ramping rate of the \( k \)-th adjusting generation unit; \( R_{k,i} \) is the lower ramping rate of the \( k \)-th adjusting generation unit.

3.3. Algorithm Step

An algorithm combined Monte Carlo simulation and genetic algorithm here are proposed to solve the optimal model. The specific algorithm steps are shown as below [11-12]:

1) Setting model and algorithm parameters, including: sampling times \( N_m \); population size of genetic algorithm \( \text{pop}_\text{size} \); crossover probability \( P_c \); mutation probability \( P_m \); genetic generations \( N_g \), etc.

2) Sampling of wind power prediction errors: according to the given error distribution function \( \Phi(\varepsilon) \) and time resolution of wind power prediction \( \Delta t \); Samples of wind power prediction error \( \varepsilon \) are extracted as follows:

\[
\varepsilon = \left[ \varepsilon_1, \ldots, \varepsilon_m, \ldots, \varepsilon_{N_m} \right]
\]

\[
\varepsilon_m = \left[ \varepsilon_{m1}, \ldots, \varepsilon_{m1}, \ldots, \varepsilon_{mT} \right]
\]

Where, \( \varepsilon_m \) is power prediction error sample of the \( m \)-th wind farm; \( \varepsilon_{m1} \) is the value of prediction error of the \( m \)-th wind farm in the \( i \)-th time period.

3) Calculation of optimal dispatching model: based on each prediction error sample, the corresponding time sequence scenario of wind power output is established. Then the genetic algorithm is used to solve the maximum value \( f_m \) of wind power accommodation and the start-up mode vector \( P_m^e \) of conventional unit under each scenario.

4) Expected value calculation of wind power accommodation indexes: based on the maximum value of wind power accommodation and the start-up mode vector of conventional unit under each scenario, the expected values are calculated, which take into account the probability of each scenario.
\[
f = \lim_{N \to \infty} \left( \frac{1}{N} \sum_{n=1}^{N} f_n \right)
\]

\[
\eta = \lim_{N \to \infty} \left( \frac{1}{N} \sum_{n=1}^{N} \eta_n \right)
\]

\[
E[P_m] = \lim_{N \to \infty} \left( \frac{1}{N} \sum_{n=1}^{N} P_m \right)
\]

According to the law of large numbers, when the number of samples tends to be infinite, the mean value of samples approximates the expected value of random variable. Therefore, when the Monte Carlo sampling times are large enough, the mean value of wind power accommodation approximately equal to the expected optimal value of wind accommodation, considering the uncertainty caused by power prediction errors.

4. Case Study

The feasibility and effectiveness of model and algorithm are verified on IEEE 30-bus system. The benchmark capacity of system is 100 MVA; the bus 1 is the balanced node; the bus 20 is the grid connection point of the wind farm, and the installed capacity of wind farm is 6 pu. The spinning reserve coefficient and the grid-loss coefficient are set as 5% of the system load. The algorithm parameters are set as follows: sampling times \( N_m = 100 \); population size of genetic algorithm \( pop_{-size} = 100 \); crossover probability \( P_c = 0.9 \); mutation probability \( P_m = 0.1 \); genetic generations \( N_g = 100 \). The day-ahead prediction errors of wind power obeys normal distribution \( N(\mu, \sigma) \), and \( \mu = 0 \), \( \sigma = 0.06 \). The parameters of conventional units are shown as Table 1. Among them, “H” means hydropower; “F” means coal-fired thermal power units; “G” means gas-fired thermal power units.

| Unit number | Type | Maximum output/pu | Minimum output/pu | Ramping rate/(pu/min) |
|-------------|------|-------------------|-------------------|-----------------------|
| 1           | H    | 2.0               | 0.50              | 0.50                  |
| 2           | H    | 1.0               | 0.25              | 0.30                  |
| 3           | F    | 0.6               | 0.15              | 0.02                  |
| 4           | F    | 0.8               | 0.20              | 0.02                  |
| 5           | G    | 0.4               | 0.10              | 0.20                  |
| 6           | G    | 0.4               | 0.10              | 0.20                  |

The prediction value of wind power \( P_w \) and load requirement \( P_d \) are shown as Table 2. In order to reduce the computational complexity, the time resolution is set as 1 hour.

Through calculation and analysis, the stochastic dispatching scheme for wind power accommodation are obtained considering the influence of uncertain factors, which is shown in Table 2. In order to meet the requirement of wind power accommodation, conventional units should minimize the power output under the constraints of power balance, spinning reserve, and ramping rate, etc. the expected value of day-ahead generation plan of whole conventional units is 4805.4MWh.

| Time | Predicted value (p.u.) | Stochastic scheduling solution (MW) |
|------|------------------------|-----------------------------------|
|      | \( P_w \) | \( P_d \) | \( G1 \) | \( G2 \) | \( G3 \) | \( G4 \) | \( G5 \) | \( G6 \) | \( W \) |
| 1    | 52.35             | 27.15                        | 52.31 | 27.40 | 16.87 | 22.11 | 11.64 | 11.64 | 63.51 |
| 2    | 52.12             | 26.77                        | 51.60 | 26.79 | 16.57 | 21.74 | 11.26 | 11.26 | 54.37 |
| 3    | 52.02             | 26.66                        | 51.64 | 26.70 | 16.48 | 21.60 | 11.16 | 11.16 | 45.10 |
| 4    | 50.94             | 26.46                        | 50.90 | 26.42 | 16.68 | 21.78 | 11.41 | 11.41 | 42.01 |
The wind power accommodation result of stochastic dispatching is shown in Fig.1. The expected value of accommodated wind electricity is 1196.44MWh, and is 19.87% of the total load demand. Expected value of abandoned wind electricity is 151.71MWh. Expected value of abandoned rate is 11.68%. The period of wind electricity abandonment mainly occurs between 1:00 at night and 7:00 in the morning. During these time periods, the system load is on a low level, and the accommodation space is limited.
5. Conclusion
The accommodation level of wind power depends not only on the accommodated space of the power system itself under physical constraints, but also on the level of power system dispatching. On the one hand, the continuous improvement of wind power prediction accuracy provides important decision information support for wind power dispatching. On the other hand, the prediction errors of wind power always exist, which make the wind power dispatching scheme uncertain to some extent. In this paper, an expectation dispatching model of wind accommodation based on stochastic programming theory is established with the objective of maximum wind electricity accommodation. Then, a case study based on IEEE 30-bus system containing wind farms is shown to verify the feasibility and effectiveness of this method. This model quantifies the uncertainties caused by the prediction errors of wind power in the form of expected value. It can provide quantitative decision-making indexes for dispatcher of power system under stochastic dispatching scenarios. This method has a certain practical value in engineering. In the next stage, the cost factors of wind power accommodation will be researched and quantified in stochastic dispatching models, to adapt to development of power ancillary service market in China.

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