Power Dispatching Considering Copula Correlation of Multiple Wind Farms Generation

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Abstract. The dynamic economic dispatching of power system connected with multiple wind farms is a typical stochastic programming problem. How to model the randomness of wind power and how to solve this complex stochastic optimization problem are the key points. In this paper, copula theory is used to formulate the correlation of multi-wind farms generation. Then, the dynamic economic dispatching model is founded with the fuel consumption, gas pollution emission fees and purchase costs as the optimized objective. The two-stage compensation algorithm is then introduced to solve the dispatching problem. In this algorithm, the conventional (nonstochastic) decision variables and stochastic variables are decoupled, which separate the dynamic dispatching model into two stage modes. The optimal dispatching result is worked out by iteration between the two stage models. Case studies on IEEE118-bus system show that the proposed algorithm can drastically reduce computational burden, and satisfy the actual requirements of engineering practice.

1. Introduction

Wind power has developed rapidly in recent years. However, wind turbines are prevented from being controlled as conventional fossil-fuel units because of the fluctuation and uncertainty caused by wind power generation [1], creating great challenges for power economic dispatch (ED) [2]. The ED of the power network with multiple wind farms is becoming a popular research topic.

Grid scheduling can be divided into static scheduling and dynamic scheduling. In a power system using wind power, its strong uncertainty and volatility make it more suitable for the dynamic economic dispatch model [3]. Short-term wind power prediction is frequently used to determine wind farm output directly, coping with prediction errors through spinning reserves [4-5]. [6] establishes a dynamic economic dispatch model concerning wind power, based on the wind speed forecasting method and the Monte Carlo stochastic simulation sampling technology. [7] propose an active power dispatch model based on the adaptive scene method. Its application to the economic dispatch model provides a quantitative risk analysis for wind power that is possibly overestimated and underestimated in the expected value [8]. However, those methods only focus on the study of the single wind farm output, and don’t consider the correlations between wind farms in the same climate zone. Therefore, it is necessary to formulate correlations of multi-wind farms, build the joint distribution model between
multiple wind farms to describe their generation characteristics and mutual dependence. To solve the above problems, this paper proposes a method to generate a joint probability distribution of wind farm output power based on the copula correlation theory. Take the IEEE118 system as an example; the performance of t-copula is superior at describing the upper and lower tail dependence existing in multiple wind farms. It can be seen that two-stage algorithm based on the copula theory is effective in dealing with solving the DED problem.

2. Copula joint distribution model for describing correlation among multi wind farm output

2.1. Copula theory

The copula connect function can simplify the stochastic dependence between a multivariate model build, with specific displays in: 1) characterizing the non-normal nature of a single random variable; 2) capturing the nonlinear, asymmetric and the upper and lower tail correlation by the correlation indicator; 3) connecting the marginal distribution of each variable function into joint distribution function.

2.2. Modeling steps of Copula joint distribution among multi wind farms

Step1: Form the cdf $F(x_i)$ of the wind farm power output $x_i$ by using kernel density estimation method.

Step2: Use cumulative integration to transform $F_i(x_i)$ to uniform distribution.

Step3: Generate the joint copula that corresponds to the output of multi wind farms. Unknown parameters $\theta$ of five types of copula functions can be obtained using a two-stage maximum likelihood function method.

3. Dynamic economic dispatching of power grid containing multi wind plants

3.1. Objective Function

Taking into account the economic benefits and social responsibility of the Power Grid Corp, the dynamic optimization scheduling of power system is actually an objective optimization problem closely connected to the total fuel consumption, pollution gas emission costs. Therefore, the objective is the sum of these objects that can be expressed as follows:

$$f_c = f_1 + f_2 + f_3$$

(1)

Where $f_c$ represents the total scheduling cost, composed of three components: total energy consumption $f_1$, cost of polluting gaseous emissions $f_2$, electricity purchase cost $f_3$. Details of $f_1, f_2, f_3$ are shown in (2), (3) and (4).

$$f_1 = \sum_{i=1}^{T} \sum_{t=1}^{N} C_{r} \left(A_{i,2} \cdot P_{ai}(t)^2 + A_{i,1} \cdot P_{ai}(t) + A_{i,0}\right)$$

(2)

where $T$ denotes the total interval of scheduling periods, $N$ denotes the number of conventional generators, $C_{r}$ denotes the unit fuel price for the conventional generator $i$, $A_{i,2}, A_{i,1}, A_{i,0}$ denote the consumption characteristic coefficients of the conventional generator $i$. $P_{ai}(t)$ denotes the active power output of generator $i$ at interval $t$.

$$f_2 = \sum_{i=1}^{T} \sum_{t=1}^{N} C_{p} \left(B_{i,2} \cdot P_{ai}(t)^2 + B_{i,1} \cdot P_{ai}(t) + B_{i,0}\right)$$

(3)

where $C_{p}$ denotes the emission trading price, $B_{i,2}, B_{i,1}, B_{i,0}$ denote the characteristic coefficient of the pollution emissions of the conventional generator $i$; for the gas turbine, the hydroelectric generating unit and the pumped storage unit the coefficient is 0.

$$f_3 = \sum_{i=1}^{T} \sum_{t=1}^{N_{k}} (C_{wind} \cdot P_{wi}(t))$$

(4)
Where $C_i$ denotes the pool purchase price of conventional generator $i$, $C_{\text{wind}}$ denotes the purchase price of wind farm, $N_W$ denotes the number of wind farms, and $P_{Wk}(t)$ denotes the active power output of wind farm $k$ at interval $t$.

3.2. Unit operation constraints

1) Power balance constraints:

$$\sum_{i=1}^{N} P_{Gi}(t) + \sum_{k=1}^{N_W} P_{Wk}(t) = P_{\text{Load}}(t)$$ (5)

2) The capacity limits on a conventional generator:

$$P_{Gi,\text{min}} \leq P_{Gi}(t) \leq P_{Gi,\text{max}}$$ (6)

3) The ramping response rate limits on a conventional generator:

$$\left\{ \begin{array}{ll} P_{Gi}(t-1) - P_{Gi}(t) & \leq r_d \times T_r \\ P_{Gi}(t) - P_{Gi}(t-1) & \leq r_u \times T_r \end{array} \right.$$ (7)

4) The capacity limits on a wind farm:

$$P_{Wk,\text{min}} \leq P_{Wk}(t) \leq P_{Wk,\text{max}}$$ (8)

5) The ramping response rate limit on a wind farm refers to the amount of output of the unit in the unit time can’t exceed the specified range in unit time. It is defined as follows:

$$\left\{ \begin{array}{ll} P_{Wk}(t-1) - P_{Wk}(t) & \leq r_{\text{dil}} \times T_r \\ P_{Wk}(t) - P_{Wk}(t-1) & \leq r_{\text{ul}} \times T_r \end{array} \right.$$ (9)

6) Spinning reserve constraint; this paper uses the positive rotation capacity compensation to compensate the influence of wind power output or underestimate the system load.

$$\sum_{i=1}^{N} P_{Gi,\text{max}} + \sum_{k=1}^{N_W} P_{Wk}(t) \geq (1 + \gamma) P_{\text{Load}}(t)$$ (10)

7) Water quantity constraints on hydroelectric units;

$$\sum_{i \in G_{\text{hyd}}} P_{Gi}(t) \leq E_{i,\text{hyd}}$$ (11)

8) Gas quantity constraint on a gas power plant;

$$\sum_{i \in G_{\text{gas}}} P_{Gi}(t) \leq E_{i,\text{gas}}$$ (12)

9) Power balance of generating and pumping on storage units is defined as follows:

$$\xi \times \sum_{i \in G_{\text{ps}}} P_{Gi}(t) + \sum_{i \in G_{\text{ps}}} P_{Gi}(t) = 0$$ (13)

11) State transfer equation between adjacent periods is defined as follows:

$$\begin{array}{c} I_{\text{gen}}^1 \leq 1 - I_{\text{gen}}^{n-1}, \quad i \in G_{\text{ps}} \\ I_{\text{gen}}^n \leq 1 - I_{\text{gen}}^{n-1}, \quad i \in G_{\text{ps}} \end{array}$$ (14)

10) Capacity constraints of pumped storage power station;

$$\sum_{i \in G_{\text{ps}}} P_{Gi}(t) = E_{i,\text{ps}}$$ (15)

where $P_{\text{Load}}(t)$ represents the load forecast value at the interval $t$, $P_{Gi,\text{min}}$ and $P_{Gi,\text{max}}$ are the upper and lower active power output limit values of the commercial unit, $r_d$ and $r_u$ denote the commercial unit’s downward and upward climb rate, $T_r$ is the length of a running time, $P_{Wk,\text{min}}$ and $P_{Wk,\text{max}}$ represent the upper and lower active power output limit values of wind farm, $r_{\text{dil}}$ and $r_{\text{ul}}$ denote the wind farm’s downward and upward climb rate, $\gamma$ is the deviation percentile for load forecasting. $G_{\text{hyd}}$ and $G_{\text{gas}}$ represent the hydropower and electricity units, $E_{i,\text{hyd}}$ and $E_{i,\text{gas}}$ denote the daily limit of water
and gas, \( \xi \) represents conversion efficiency of the pumped storage unit generally taken as 75\%, \( G_p \) denotes the pumped storage unit, \( I^m \) is a 0-1 variable. When unit \( i \) pumps at the time \( t \) the value is 1 and if it is not pumping the value is 0. \( I^m \) is a 0-1 variable. When unit \( i \) generates at the time \( t \) the value is 1, and when it is not generating the value is 0. \( P_{G_i}(t) \) denotes the active power output of a pumped storage unit at interval \( t \). When its value is negative pumping power and when positive it is called generating power. \( E_m \) represents the maximum allowable power generation capacity for a pumped storage power station.

4. The solution of power dynamic economic dispatching

The stochastic optimization problem can be expressed as formula (16):

\[
\min f(x,\omega) \\
\text{s.t. } A(x,\omega) \leq b \\
Dx \leq d \\
C\omega \leq e
\]

(16)

Where “(16-(1))” represents the constraints that contain the random variable and the normal variable, “(16-(2))” denotes the constraints that don’t contain the random variable, and “(16-(3))” is the constraints that only contain the random variable. \( x \) the decision variable and \( \omega \) represents the random variable. For the finally obtained decision variable \( x^* \), the random variable \( \omega \) can cause the constraint “(16-(1))” to be destroyed. Therefore, the compensation variables \( y(\omega) \) and the compensation matrix \( W \) are introduced to satisfy “(16-(1))” shown in (17)

\[ A(x,\omega) + Wy(\omega) \leq b \]

(17)

However, the introduction of compensation variables will cause additional compensation fees for the penalty of damaged constraints. Obtaining the minimum value of the original objective should minimize the compensation fee, \( y(\omega) \) should satisfy the optimization problem shown in (18).

\[
Q(x,\omega) = \min q(\omega)y(\omega) \\
\text{s.t. } A(x,\omega) + Wy(\omega) \leq b, y(\omega) \geq 0 \\
C\omega \leq e
\]

(18)

Where \( q(\omega) \) represents cost factor.

If the distribution function of \( \omega \) is known, the expected value of the compensation fees is obtained; refer to “(19)”.

\[ EQ(x,\omega) = \int q(\omega)y(\omega)p(\omega)d\omega \]

(19)

In this way, the original planning problem is transformed into two stages with compensation as follows:

\[
\min f(x) + EQ(x,\omega) \\
\text{s.t. } Dx \leq d, x \geq 0
\]

(20)

The key to solving “(20)” is to determine the appropriate amount of compensation \( y(\omega) \). The solving step is: hypothesis the decision which is variable from stage one “(18)” and then determine variable compensation \( y(\omega) \) from stage two “(20)”; the new value of \( x \) can be solved by substituting \( y(\omega) \) into stage one. Lastly, the optimal solution of the model can be obtained through the two-phase interaction.

5. Case Studies

In this case, the power dynamic economic dispatch of 24 hours in the IEEE118 system has been analyzed. The system consists of 52 coal-fired units with an installed capacity of 100MW and three wind farms located in node 12, node 54 and node 106.

5.1. Establishment of joint distribution for multiple wind farm

Here the windy period is used as an example to provide the construction process of the copula
probability distribution model. The experiments of two wind farms show that t-Copula has the best performance in describing the correlation of wind farm output. And the Ellipse copula cluster is more suitable in the construction of a joint distribution model for three variables. Figure 1 shows the evaluation parameter results for t-copula, Gaussian-copula and the sample.

![Figure 1. Evaluate parameter results for copula function and sample.](image)

(1) Considering correlation of multi-wind farms

Based on the joint probability density function of three wind farms of the 24-hour time period, the DED results can be seen in Figure 2.

![Figure 2. The result of active power dispatch with two strong correlation Wind Plant integrated](image)

As is shown in Figure 2, the corresponding power purchase cost is greater than the less-windy season while its cost of coal consumption and emissions is reduced, which is caused by the large wind power output during the windy period.

(2) Not considering the correlation

Suppose that two wind farms are independent of each other, we use the kernel density estimation to obtain the marginal distribution and get the joint probability density function. The grid dynamic economic dispatch results are as follows:

![Figure 3. The result of active power dispatch with no correlation Wind Plant integrated](image)
A comparison between Figure 2 and Figure 3 shows that, for the windy period, considering the correlation of multiple wind farms has a greater daytime generating capacity that corresponds more with power purchase costs while the cost of coal consumption and emissions is reduced; for the less windy period, considering correlation of multiple wind farms has less daytime generating capacity, corresponds less with power purchase costs while the cost of coal consumption and emissions is increased.

6. Conclusion
In this paper, the copula theory are used to formulate the correlations among multi-wind farms generation, and the numerical integral based two-stage compensation algorithm are introduced to solve the dynamic economic dispatching problem. Some conclusions are brought forth as follows.

1) In our case studies, the t-copula function can best describe the correlation of multi-wind farms generation. The upper and lower tail dependence of wind farms makes the scheduled wind generation to be higher in the windy season, and lower in the less windy season.

2) The two-stage compensation algorithm is introduced to solve the economic dispatching problem considering multiple wind farm correlations. It has drastically reduced computation time and makes the dispatching scheme approach to the actual as far as possible.

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Reference
[1] Liao HL, Wu QH, Li YZ, Jiang L. “Economic emission dispatching with variations of wind power and loads using multi-objective optimization by learning automata,” Energy Conversion & Management, vol. 87, pp. 990–999, July, 2014.
[2] Mohseni-Bonab SM, Rabiee A, “Mohammadi-Ivatloo B. Voltage stability constrained multi-objective optimal reactive power dispatch under load and wind power uncertainties: A stochastic approach,” Renewable Energy, vol. 85, pp. 598-609, Month, July, 2015.
[3] Li YZ, Wu QH, Li MS, et al, “Mean-variance model for power system economic dispatch with wind power integrated,” Energy, vol. 72, no. 7, pp. 510-520, Month, June, 2014.
[4] Kou P, Gao F, Guan X, “Stochastic predictive control of battery energy storage for wind farm dispatching: Using probabilistic wind power forecasts,” Renewable Energy, vol. 80, pp. 286-300, Month, August, 2015.
[5] Yuan X, Chen C, Yuan Y, et al, “Short-term wind power prediction based on LSSVM–GSA model,” Energy Conversion & Management, vol. 101, pp. 393–401, Month, September, 2015.
[6] Mokryani G, Siano P, “Combined Monte Carlo simulation and OPF for wind turbines integration into distribution networks,” Electric Power Systems Research, vol. 103, no. 8, pp. 37–48, Month, May, 2013.
[7] Hetzer J, Yu D. C., Bhattacharai K, “An economic dispatch model incorporating wind power,” IEEE Transactions on Energy Conversion, vol. 23, no. 2, pp. 603-611, Month, June, 2008.
[8] Liu Xian, Xu Wilsun, “Economic load dispatch constrained by wind power availability: a here-and-now approach. Sustainable Energy,” IEEE Transactions on Sustainable Energy, vol. 1, no. 1, pp. 2–9, Month, April, 2010.