Wind power control strategy based on high precision prediction technology

Q Liu¹, J Zhao¹, S F Zhang¹, J Wu¹, JJFang², L H Wang² and Y G Shao³

¹School of Electrical Engineering and Automation, Wuhan University, Wuhan430072, Hubei Province, China
²Chuxiong Power Supply Bureau of Yunnan Power Grid Company, Chuxiong 675000, Yunnan Province, China
³State Grid Jiangxi Economic Research Institute, Nanchang 330096, Jiangxi Province, China

E-mail: jiez_whu@whu.edu.cn

Abstract. This paper proposes an active power control strategy for wind farms based on high-precision prediction technology. The aim of this study is to improve the absorptive capacity of large-scale wind farms, reduce network loss and promote the operation economy of wind farms. The strategy divides the active power dispatching into four layers. Based on the constraints of the safe operation of the power grid, the corresponding objective function and power allocation method for each layer are given. The result of this study shows that the strategy proposed can effectively improve the operation economy of the power grid and promote wind power consumption. Compared with the traditional control strategy, the proposed control strategy can well deal with the actual situation of large power fluctuation, and reduce the number of wind turbine start-up and shutdown.

1. Introduction
At present, China is in the transition of energy structure. Clean and low-carbonization are becoming the trend of energy economy development [1]. Wind power is an important form of utilizing clean energy, which has been developed vigorously in China, and has formed a number of large-scale wind farm groups [2]. Due to the random fluctuation of wind power output, improper control of wind power will easily affect the safe and stable operation of the power grid and the efficient delivery of wind power. Therefore, it is necessary to formulate a real-time wind power dispatching control strategy considering wind power consumption, system network loss, control accuracy, operation cost, and other multi-objective.

Affected by load fluctuation and wind speed uncertainty, when the dispatching instruction given by the system changes greatly, the output of wind farm may not respond to the dispatching instructions in time, resulting in control errors [3]. The traditional active power control method of wind power includes dispatching control by proportional distribution or by predictive power for generator tripping [4, 5]. Based on the existing strategies, a lot of improvement and research have been carried out by scholars at home and abroad. The active power allocation method for wind power limited output can be given by combining the priority list method according to [6]. Literature [7] calculates online wind power margin of the power grid based on ultra-short-term wind power prediction data of wind farms. Literature [8] classifies wind turbines based on the real-time state information of them. In
[9,10], according to the large-scale wind power access in different regional power grids, the wind active power control is realized by using automatic generation control software combined with different control algorithms. However, the control cycle of these strategies is long, and the control accuracy needs to be improved. Moreover, the constraints on the safe operation of the power grid and the frequent startup and shutdown of the units are not fully considered, which can easily lead to wind turbine losses.

The active power control strategy of wind farm can take maximum utilization of wind power and minimum start-stops of wind turbine as the control targets [11]. Literature [12] introduces the hierarchical control algorithm into wind power control. A multi-level wind farm active power optimization dispatching method is studied in literature [13]. Literature [14, 15] combines elite strategy genetic algorithm to improve hierarchical active power control strategy. However, the control sequence of each layer and the strategy coordination between layers need to be improved, and the actual situation of large fluctuation in wind farm is not well copedwith.

This paper proposes a layered wind power dispatching control strategy. The wind turbine real-time status grouping, the layered control model, the unit safe operation constraint, and the startup-shutdown constraint are comprehensively considered. Control accuracy, network loss, wind power consumption, and operation economy are taken as multi-objective. The cooperation strategy between layers and the power allocation method for each layer are given. The simulation results verified the effectiveness of the proposed strategy.

2. Target and thought of layered active power control in wind farm

Figure 1 is the layered control flow of wind active power.

- The system layer is the dispatching instruction of the power grid. Considering the limitations of active power output, the instructions are given to the wind farm group layer.
- In the wind farm group layer, the active power of each wind farm is optimized by combining the ultra-short-term active power prediction, and the dispatching instructions of subfield system are issued at the same time. The control period is 15 minutes.
- In the subfield layer, considering the wind speed and power changing trend of the wind turbine, the dynamic grouping control strategy is carried out, and then the dispatching index of each group is allocated to each wind turbine unit. The control period is 5 minutes.
- In the wind turbine unit layer, the dispatching index is achieved by adjusting the generator torque and pitch angle according to the corresponding strategy. The control period is 1 minute.
- In the feedback correction layer, the data monitoring device of the wind farm will collect the active power data feedback in real time and feed them back to the wind farm group layer and subfield grouped layer.

![Figure 1. Layered control flow of wind active power.](image-url)
3. Layered active power control model for wind power based on DSA power prediction

3.1. The layer of wind farm group
The control period is 15 minutes, aiming at maximizing the consumption of wind farm and reducing the system network loss. The objective function is as follows:

$$F_{CQ} = \min[\mu_1 P_{\text{pre}} + \mu_2 (\sum_{i=1}^{n} F_{CQ} - P_{\text{pre}})]$$

(1)

As constraints:

$$0 \leq P_{CQ}^{\text{ref}} \leq P_{CQ}^{N}$$
(2)

$$\left| P_{CQ,i+15}^{\text{ref}} - P_{CQ,i}^{\text{ref}} \right| \leq L_{N}$$
(3)

$$-P_{L_{\text{max}}} \leq P_{L} \leq P_{L_{\text{max}}}$$
(4)

$$P_{t} - P_{L_{0}} - \sum_{j=i} V_{j} \left( G_{j} \cos \theta_{j} + B_{j} \sin \theta_{j} \right) = 0$$
(5)

Double-stage hierarchical ANFIS, DSA, is used to predict the active power of wind farms. In the first layer, the wind turbine is modeled by a black box of particle swarm fuzzy system to establish the relationship between the numerical weather prediction (NWP) data and the wind speed value recorded by the actual wind farm. In the second layer, based on the actual operation of wind farms, the relationship between wind speed and wind power output characteristics is trained and fitted. Then the predicted wind speed data of the first layer are applied to the training model of the second layer to predict the wind power output of the next cycle of the wind farm. The flow chart of the prediction model is shown in figure 2.

**Figure 2.** DSA wind power prediction model.

In order to evaluate the accuracy of wind power prediction model, the mean absolute percentage error (MAPE), sum of squares error (SSE) and root mean square error (RMSE) indices are established.

$$I_{\text{MAPE}} = \frac{100}{N} \sum_{i=1}^{N} \left| \frac{P_{\text{pre}} - P_{\text{true}}}{P_{\text{true}}} \right|$$

(6)

$$I_{\text{SSE}} = \sqrt{\sum_{i=1}^{N} \left( P_{\text{true}} - P_{\text{pre}} \right)^{2}}$$

(7)
\[ I_{\text{RMSE}} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (P_{\text{true}} - P_{\text{pre}})^2} \]  

(8)

3.2. The layer of grouped subfield
The feedback value of active power data is obtained every minute, and the wind speed \( v_{t+k} \) of a single wind turbine for the next 5 minutes can be predicted by the prediction model. Considering the random fluctuation of the wind turbine's own output, it is necessary to multiply the predicted reference value by the output limiting factor \( \beta \) as the final predicted active power \( P_{\text{pre}}^{\text{mn}} \).

\[ P_{\text{pre}}^{\text{mn}} = \beta \bar{P}_{\text{mn},t+k}, \quad k = 1,2,\ldots,5 \]  

(9)

\[ \bar{P}_{\text{mn},t+k} = \frac{1}{5} \sum_{i=1}^{5} P_{\text{mn},t+k} \]  

(10)

\[ P_{\text{pre}}^{\text{mn}} = f(v_{t+k}), \quad k = 1,2,\ldots,5 \]  

(11)

Where \( \beta \) is 0.9, which can absorb wind power as much as possible while ensuring reliable active power output.

The wind farm data monitoring device can obtain the historical active power before 5 minutes \( P_{\text{mn}}^{\text{old}} \) and the actual active power at that time \( P_{\text{mn}}^{\text{rea}} \). The active power change rate of the \( n \)-th wind turbine in the \( m \)-th group can be obtained by the formula (12).

\[ k_{\text{mn}} = \frac{\bar{P}^{\ast} \tau - \bar{P}^{\ast} \tau^2}{\tau^2 - \tau} \]  

(12)

Where \( \bar{P}^{\ast}, \tau \) is the coefficient value calculated by fitting \( P_{\text{mn}}^{\text{old}}, P_{\text{mn}}^{\text{rea}} \) and \( P_{\text{pre}}^{\text{mn}} \) according to the principle of the least square method.

The wind turbine grouping is based on table 1. Figure 3 shows the dynamic grouping process.

| Table 1. Wind turbine grouping. |
|--------------------------------|
| No. | Grouping basis | Grouping type |
|-----|----------------|---------------|
| 1   | Low wind speed and \( k_{\text{mn}} > 0 \) | \( X_1 \) |
| 2   | Low wind speed and \( k_{\text{mn}} \approx 0 \) | \( X_2 \) |
| 3   | Low wind speed and \( k_{\text{mn}} < 0 \) | \( X_3 \) |
| 4   | High wind speed and \( k_{\text{mn}} > 0 \) | \( X_4 \) |
| 5   | High wind speed and \( k_{\text{mn}} \approx 0 \) | \( X_5 \) |
| 6   | Waiting for(wind turbines waiting for instructions to be started at any time) | \( X_6 \) |
| 7   | Outage unit(shut down or exited due to malfunction or safety issues) | \( X_7 \) |
Figure 3. Wind turbine grouping process.

The objective function of this layer is the minimum internal loss of the wind farm and the maximum wind power consumption.

\[
F_{ZC} = \min \{ \delta_1 \sum_{i=1}^{n} P_{ZC_i}^{\text{ins}} + \delta_2 \sum_{i=1}^{n} P_{ZC_i}^{\text{ref}} - P_{C_{Q}}^{\text{ins}} \} 
\]

(13)

Where \( \delta_1, \delta_2 \) are 0.2 and 0.8 respectively, which can consume as much wind power as possible while reducing internal losses of wind farms.

As constraints:

\[
s.t. \ 0 \leq P_{ZC_i}^{\text{ref}} \leq P_{ZC_i}^{N} 
\]

(14)

\[
\left| \frac{P_{ZC, t+5}^{\text{ref}} - P_{ZC, t}^{\text{ref}}}{P_{ZC, t}^{\text{ref}}} \right| \leq L_{Z\text{N}} 
\]

(15)

3.3. The layer of grouped wind turbine unit

The strategy of the unit’s output adjustment in this layer takes 1 minute as the control period, and the active power that needs to be adjusted in the next period is:

\[
\Delta P = \sum_{n=1}^{N} (P_{p_{\text{ref}, n+1}}^{\text{pre}} - P_{p_{\text{ref}, n}}^{\text{pre}}) - (P_{f+1}^{\text{ins}} - P_{f}^{\text{ins}}) 
\]

(16)

The power adjustment strategy is shown in figure 4. \( \Delta P_1 - \Delta P_7 \) is the maximum power adjustment for each type of unit and \( \Delta P_1 \) is the sum of the minimum generating power. The maximum power adjustment of each unit is determined by the actual operation power and the maximum generation power. In figure 4, \( \Delta P_{10} - \Delta P_{15} \) are the remaining power adjustments of wind farms during the calculation process.
Start
Input the value of dispatching instruction and output change limit

Calculate power adjustment of wind farm $\Delta P$

- $\Delta P > \Delta P_{\text{cut}}$
  - Shut down one by one
- $\Delta P + \Delta P_{\text{cut}} > \Delta P$
  - Adjust the output of the unit by category
- $\Delta P > \Delta P_{\text{cut}}$
  - Start the unit by category

End of active power allocation

**Figure 4.** Flowchart of active power allocation strategy.

3.4. The layer of feedback correction

This layer carries out the feed-forward compensation of the control system through real-time monitoring of wind power output. In order to balance the contradiction between error feedback and computational complexity, this paper carries out error analysis and feedback correction from two perspectives. From the perspective of the wind farm, in view of the errors caused by the power prediction method itself and the system control accuracy, the prediction model is corrected by the actual errors summarized by the wind farm. The corrected model is shown in equations (17)-(20).

$$P_{i,T} = P_i + H \mathbf{g}$$  \hspace{1cm} (17)

$$H = [h_{i,1}, L, h_{i,T}]$$  \hspace{1cm} (18)

$$h_{i,k} = \frac{1}{T} \sum_{k=1}^{T} e_{i,k}, k = 1, 2, L, T$$  \hspace{1cm} (19)

$$e_{i,k} = P_{i}^{\text{true}} - P_{i}^{\text{true}}$$  \hspace{1cm} (20)

From the perspective of a single wind turbine, the feedback of the wind turbine itself is a real-time correction. The feedback reaction speed of the wind turbine itself is faster and the control process is simpler. Because the self-feedback correction period of the wind turbine is short, the actual active power data $P_{i}^{\text{true}}$ can be directly fed back to formula (8), so that the purpose of the correction can be achieved immediately through its own rolling optimization process.

4. Example analysis

A wind farm in southwestern China is taken as an example. The wind farm consists of 66×1.5MW
units, 61×2.5MW units and a total installed capacity of 251.5 MW.

In order to analyze the strategy of wind power forecasting, the following methods are used for power forecasting. The results are shown in figure 5(a) and table 2.

![Figure 5](image)

**Figure 5.** Active power curve under different strategies. (a) Wind power prediction curve and (b) Active power control curve.

**Table 2.** Prediction error statistics.

| Method | MAPE (%) | SSE/MW | RMSE (%) |
|--------|----------|--------|----------|
| 1      | 11.37    | 57.63  | 9.91     |
| 2      | 10.02    | 49.82  | 8.56     |
| 3      | 8.15     | 32.49  | 6.23     |

Method 1: Support vector machine model was used.
Method 2: The improved combination forecasting model was used.
Method 3: The proposed DSA model.

From figure 5(a) and table 2, it can be seen that the power prediction curve of method 3 almost coincides with the actual power curve and has high prediction accuracy. Compared with methods 1 and 2, MAPE of method 3 decreased by 3.22% and 1.87%, SSE decreased by 25.14 and 17.33, and RMSE decreased by 3.68% and 2.33%, respectively.

The following four control strategies are selected from different angles for wind power control. The results are shown in figure 6.

**Strategy 1:** Proportional control strategy;
**Strategy 2:** An improved hierarchical control strategy in reference [7];
**Strategy 3:** Generator tripping control strategy;
**Strategy 4:** The control strategy of this paper.

From the 24-hour active power control curve of the wind farm shown in figure 5(b), it can be seen that the active power control curve obtained in strategy 4 is more suitable for dispatching instructions.

From the comparison of the control results under different strategies shown in figures 6(a)-6(c) and table 3 (Q is the total power that exceeds the dispatching curve by ±1%, t is the average response time), it can be seen that the proposed control strategy can better and more accurately track the dispatching power instructions. At 11:00-21:00, the IRMSE of strategy 4 is reduced by 1.45% compared with strategy 2, and the startup and shutdown number of the wind turbine is reduced by 28 times. Therefore, it can reduce the control error more effectively, avoid frequent startup and shutdown, and achieve good control and optimization results.
the number of unit start-up and shutdown, and good control and optimization results.

The strategy proposed is based on DSA model for wind power prediction. Its predicted power between 12:00 and 18:00.

From figure 6(d), it can be seen that the total wind power consumption of strategy 4 is 4030.08 MW·h during the dispatching period, which is 5.64% higher than strategy 2. Therefore, strategy 4 can maximize wind power consumption while reducing the system network loss, so as to better improve the operation economy of the power grid.

Comparing the start-stop times and output of the units under different strategies shown in figure 6(e), strategy 4 can well complete the adjustment requirements of system dispatching instructions. During the 3h period shown in figure 9, the number of unit startup and shutdown times is reduced by 67 times compared with strategy 3, which effectively reduces losses of wind turbines and improves the operation economy.

5. Conclusions
The strategy proposed is based on DSA model for wind power prediction. Its $I_{MAPE}$, $I_{SSE}$, $I_{RMSE}$ index values are low and the prediction accuracy is high.

The proposed strategy can accurately and effectively track the system dispatching instructions, with high control accuracy, fast response speed, and can well cope with the situation of large power fluctuation. $I_{RMSE}$ of the control results is reduced during the dispatching period. At the same time, the frequent dispatching of wind turbines is avoided, and good control and optimization results were achieved. The example shows that the strategy can effectively reduce the network loss, improve the wind power consumption capacity and enhance the economy of the system operation.
The wind turbine dynamic grouping strategy effectively reduces the network losses, and greatly reduces the number of start-up and shutdown during the dispatching period compared with the generator tripping strategy, which is of great significance to reduce the cost of power generation.

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Appendices

### Table A. Nomenclature

| Symbol | Description |
|--------|-------------|
| $P_{\text{ref}}$, $P_{\text{pre}}$ | active power instruction value and prediction value for wind farm $i$ |
| $L_{\text{N}}$ | limit of the ramp rate for wind power |
| $P_{\text{ref}}^{+(-)}$, $P_{\text{max}}^{+(-)}$ | maximum forward(reverse) transmission power of the line |
| $P_{\text{pre}}$, $P_{\text{ins}}$ | wind power actual output and forecasting output at $t$ time |
| $P_{\text{ref}}$, $P_{\text{pre}}$ | active power instruction value and prediction value for wind farm $i$ |
| $H$ | error correction matrix |
| $N_{\text{CQ}}$ | installed capacity of a single unit in subfield layer |
| $L_{\text{ZNL}}$ | limit of wind turbine climbing rate. |
| $P_{\text{pre}}$, $P_{\text{ins}}$, $P_{\text{ref}}$, $P_{\text{pre}}$ | active power prediction value for the next control cycle of the $n$-th wind turbine in the $m$-th group, and the actual active power |
| $L_{\text{los}}$ | active power loss of wind turbine $i$ |
| $Z_{\text{CQ}}$ | installed capacity of a single unit in subfield layer |
| $e$ | error matrix in last control cycle $T$ |

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