Research on Tower Elevator Power Supply Mode Matching Maintenance Period and Wind Power Curtailment

Fuijing Wang1,*, Lirong Xie1,*, Fang Zhang1, Qin Chao1, Jinwei Li2

1School of Electrical Engineering, Xinjiang University, 830000, Urumqi Xinjiang, China 
2Haiwei(Xinjiang)New Energy Company, China Shipbuilding Industry Coporation, 830000, Urumqi, Xinjiang, China 

*Corresponding author e-mail: wzywwxr@163.com, *765735039@qq.com

Abstract. In order to reduce the difficulty of maintenance and increase the utilization of wind power, this paper proposes a new program of internal consumption. First of all, through the main influencing factors which contain wind speed and direction of theoretical wind power, building history NWP data and the mapping theory possible output reflection database; Secondly, using clustering method to screen the better consistency historical samples and neural network model to generate the power demand forecasting curve; Finally, the forecast curve of wasted wind power is matched with the maintenance downtime. Analysis of historical data of a wind farm in Xinjiang region show that the power supply mode of consuming wasted wind power during maintenance time is feasible. This model can effectively improve the utilization rate of wind energy, it also provides reference for related research.

1. Introduction

Up to 2017, in the context of the continuous rapid growth of China’s total installed wind power generation capacity, China’s annual wind power curtailment also reached 41.9 billion KWH [1]. In order to reduce wind power curtailment and improve the capacity of wind power consumption, studies are being carried out at home and abroad on the matching between wind farms and energy storage [2], linkage with thermal boilers [3,4], and intelligent optimal dispatch of wind power [5]. Few studies have been conducted on the consumption of wind power curtailment within wind farms themselves.

Therefore, it becomes a problem that must be solved in this paper to evaluate the wind power abandoning capacity of the predicted scenario evolution under the multi-space-time scale. However, there are few relevant literatures. However, the curtailment of wind power is closely related to the power limit of the power grid and the power loss caused by the fan fault maintenance and regular maintenance downtime. The above literatures fail to accurately distinguish the assessment and prediction of wind power abandoning, which makes it impossible to realize the matching between the wind power abandoning period and the fan repair and maintenance period proposed in this paper, and the maintenance and repair scheme can be carried out by running up and down the tower elevator of direct supply of wind power abandoning.

To sum up, this paper starts from the external factors that influence the theoretical output of the fan, the power limit of the power grid, and the power loss caused by the fan’s maintenance, repair and
shutdown. Based on the historical data of wind power, the paper takes wind information (wind speed and direction) as the main influencing sensitive factors, and obtains the theoretical power prediction curve of the wind farm through the mapping method. Taking load information (temperature and calendar) as the main influencing sensitive factors, the power demand forecast curve of power grid is obtained by fuzzy clustering neural network algorithm. The prediction curve of wind abandoning electric quantity is obtained by the difference between them. Taking the maintenance information (number of stops, duration of maintenance) as the main influencing sensitive factor, based on the theoretical power generation capacity of the fan, the power loss caused by fan failure maintenance and regular maintenance downtime was calculated. The maintenance period was shifted to the period with wind abandoning power, and the wind abandoning power consumed by the wind tunnel itself was evaluated. An example is given to verify the effect of improving the utilization rate of wind energy.

2. Concept and evaluation method of wind abandon capacity

2.1. The wind abandon quantity can be defined

Wind curtailment power should be the difference between the theoretical output and the actual output of a wind farm with wind speed in the corresponding meteorological environment. The available wind abandoning quantity $P_L$ is defined as the difference between the theoretical maximum possible output of a wind farm with wind speed $P_M$ and the power demand of the power grid and the power loss due to maintenance $P_X$ and repair downtime $P_S$. Its definition is shown in Figure 1.

![Figure 1. The constitutional diagram of the useful wasted wind power](image)

2.2. The wind abandon quantity can be defined

To wind farm access given part can use wind power, must be conducted before the evaluation and prediction and abandon the wind power of wind farms has fan maintenance plan adjustment, abandon the wind power will have wind farms with a fan during maintenance of match time translation, the outage loss power transferred to abandon the wind power electricity from the grid demand time, its design is shown in Figure 2.

![Figure 2. The idea diagram of eliminating wasted wind power.](image)
The assessment methods for absorbing available wind abandon power are shown in Figure 3, which mainly rely on the prediction method of wind abandon power of day-ahead wind farm and the adjustment method of day-ahead fan maintenance plan.

The prediction of curtailment power and time period of wind farm is mainly based on the maximum possible output of wind farm theory to predict the power $P_M$ and time period, and the power demand of power grid to predict the power $P_X$ and time period. Therefore, according to the historical data of wind power, the wind information (wind speed and direction) is taken as the main influencing sensitive factor, and the theoretical power prediction curve of wind power plant is obtained through the mapping method. The difference between the two values is used to obtain the prediction curve of wind power curtailment of wind farm.

![Figure 3.](image)

The adjustment of the day-ahead wind turbine fault repair and maintenance plan mainly depends on the type and number of sudden faults of the wind turbine on the day and the number of regular maintenance of the day-ahead wind turbine.

2.3. Main sensitive factors and algorithms affecting $P_M$, $P_X$ and $P_S$

The method of obtaining the maximum possible output predicted electricity quantity $P_M$ by the wind farm theory, the predicted electricity quantity $P_X$ by the power grid demand, and the power loss $P_S$ by the fault maintenance and planned maintenance of the wind turbine are the key links.

There are many factors influencing the maximum possible output of the wind farm theory, including wind speed, wind direction, temperature, humidity and air pressure.

3. Correlation factor mapping library method and clustering improved neural network method predict wind abandon power

Firstly, the historical samples within the range of the samples to be predicted are searched and the mapping database of relevant factors is formed. Then, the mapping database is compared with the factors of the samples to be predicted to calculate the similarity. The normalized similarity is used to form the weight of the corresponding samples.

3.1. The correlation factor mapping method predicts the maximum possible output of wind farm theory

3.1.1. Establish the database of correlation factor mapping. The selection of threshold value is a key link in the application of extreme value theory. If the field value is too small, the available data will be
few, which affects the estimation of parameters. If the domain value is too large, too many samples with too large difference will be doped, leading to biased or inconsistent estimates [16-17]. The process of building the database of the correlation factor mapping database is shown in figure 4.

**Figure 4.** The construction process of the database of related factor mapping Library.

3.1.2. Similarity model establishment. The similarity calculation formula between sample a to be tested and sample b in the mapping database is defined as follows:

\[
    r_{ab} = \frac{\sum_{k=1}^{m} (x_{ak} \cdot x_{bk})}{\sqrt{\left(\sum_{k=1}^{m} x_{ak}^2\right) \cdot \left(\sum_{k=1}^{m} x_{bk}^2\right)}},
\]

\[ (1) \]

Where, a -- the sample to be predicted; B -- sample in mapping database (b=1,2,..., n); N -- the number of selected samples; \(X_{ak}, X_{bk}\) (k = 1,2..., m) -- the corresponding quantitative index of factors.

3.1.3. Weight determination. The data to be predicted were selected as the predicted sample set for verification, and the similarity between the data to be predicted in each day in history was obtained. The following formula was used for normalization processing.

\[
    r'_{ab} = \frac{r_{ab}}{\sum_a r_a}
\]

\[ (2) \]

Where, \(r'_{ab}\) (b= 1,2,...., n) -- the similarity between historical data and data to be predicted; a -- the number of the sample to be predicted; b -- the number of the mapping sample.

3.1.4. Pattern recognition model. Then, the similarity was sorted, and d (d The calculation formula is as follows:

\[
    y_a = \sum_{b=1}^{d} r'_{ab} y_b
\]

\[ (3) \]
Where, \( b \) -- mapping sample number; \( y_b \) -- corresponding to the sample value of mapping, the weighted average predictive value of similarity ordering under various influencing factors can be obtained.

3.2. Cluster improved neural network to predict power demand

Because the training of neural network is affected by sample accuracy, data distribution and quantity and scale, the selection of training samples has a very important influence on the training of network structure.

Firstly, different historical samples were screened by fuzzy mean clustering method, and then the predicted results were obtained by neural network. The prediction model of this paper is shown in Figure 5.

3.2.1. Fuzzy mean clustering. Fuzzy c-means is a mathematical method for classifying objective things according to their different characteristics, degrees of affinity and similarity, etc. [18-21]. The clustering process is shown in Figure 6.

Fuzzy mean clustering divides fuzzy sets by minimizing squared error [20], that is:
\[ J_\beta(X,V,U) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^\beta d^2(x_j, v_i) \]  

(4)

Where, \( u_{ij} \) -- membership degree, value range is \([0,1]\), and \( 0 \leq \sum_{j=1}^{n} u_{ij} \leq n \), \( \sum_{i=1}^{c} u_{ij} = 1 \); \( v_i \) -- cluster center of class \( I \); \( N \) -- number of class members; \( \beta \) -- weight index, usually \( > 1 \); \( d(x_j, v_i) \) -- the distance from the observation point to the clustering center.

The minimization of fuzzy mean clustering is an iterative process. In each iteration, the values of \( u_{ij} \) and \( v_i \) are carried out according to the following formula:

\[
V_i = \frac{\sum_{j=1}^{n} u_{ij}^\beta x_j}{\sum_{j=1}^{n} u_{ij}^\beta} \]

(5)

\[
u_{ij} = [\sum_{k=1}^{c} \left( \frac{d(x_j, v_k)}{d(x_j, v_i)} \right)^{\beta-1}]^{-1}\]

(6)

By improving the fuzzy c-mean method selection impact given the size of the wind power characteristic value factors associated with highest samples (including wind speed prediction, atmospheric pressure prediction, the temperature forecast.

3.2.2. Bayes improved neural network method. As the neural network is a typical non-parametric model, the information of model construction comes from samples, so the training results are often unstable and prone to overfitting. Bayesian analysis should choose the maximum posterior probability among all possible weight vectors to make the calculation of the confidence interval possible.

4. Case analysis verification

The wind farm data of a wind farm in Xinjiang during the winter of 2016-2017 (November, December and January) were taken as the historical database of the prediction model. Limited by space, take the wind power as a typical example in December 2017. As shown in Figure 7, the prediction errors every 15 minutes were compared by simulation.

![Figure 7. Comparison diagram of predicted and actual wind abandoning capacity can be used.](image)
It can be seen from the statistical characteristics of the error that the error has a sharp peak and a thick tail, while the skewness is not obvious, as shown in Table 1.

| mean    | standard deviation | skewness | peakedness |
|---------|--------------------|----------|------------|
| -0.02   | 0.08               | -0.11    | 5.47       |

Due to the maintenance plan for 30 min step length, according to the day 20 h the maintenance time and restricted by wind maintenance team, at the same time, maintenance and repair of wind turbines, shall not exceed 4 sets, at the same time should be according to the actual working status of wind power, ruled out the night time at 10:00 PM (8) work schedule, according to the time sequence, screening can abandon the valid period of the wind. The original maintenance plan is adjusted according to the selected effective period to obtain the multi-generation capacity after shutdown maintenance, as shown in Table 2.

Table 2. Economic comparison before and after planned adjustment.

| downtime plan | grid electricity (MW/h) | shut down and abandon wind power (MW/h) |
|---------------|--------------------------|-----------------------------------------|
| before adjustment | 8.1                      | 10.49                                   |
| after adjustment | 4.27                     | 21.51                                   |

5. Conclusion
From the perspective of considering the relevant external influence sensitive factors, the prediction and analysis of the wind power curtailment in the working period and the time period are carried out.

Acknowledgments
This work was financially supported by National Natural Science Foundation of China, Project No. 51667021; supported by National science and technology cooperation project, Project No. 2013DFG61520; supported by Innovation Projects in Xinjiang, Project No. XJZDCX2017039;

References
[1] Qu Jixian, Liu Chun, Shi Wenhui, et al. Quick calculation method of wind rejection rate based on wind power acceptance spatial power regression model [J]. Power System Technology, 2011,41 (01):72-78.
[2] Liu Shilin, Yu Weiwei, Yao Wei. Composite Energy Storage Control Strategy for Wind Farm Power Generation Planning Tracking [J]. Acta Energiae Solaris Sinica, 2018,39 (04):1060-1068.
[3] Karl-Kiên Cao, Alejandro Nicolás Nitto, Evelyn Sperber, André Thess. Expanding the horizons of power-to-heat: Cost assessment for new space heating concepts with Wind Powered Thermal Energy Systems, Energy, 2018,Volume 164,pp. 925-936.
[4] Ren Guorui , Wan Jie , Liu Jinfu, et al. Analysis of wind power intermittency based on historical wind power data [J]. Energy,2018,Volume 150,pp. 482-492.
[5] Chen Jie, Zhan Zhongqiang. Application of higher-order statistics and wavelet packet decomposition in wind-hydrogen hybrid energy storage system [J]. Acta Energiae Solaris Sinica, 2018,39 (11): 3286-3294.