Research Article

Short-term wind power prediction using an improved grey wolf optimization algorithm with back-propagation neural network

Liming Wei, Shuo Xu* and Bin Li

College of Electrical and Computer Technology, Jilin Jianzhu University, Changchun, Jilin, P.R.China

*Corresponding author. E-mail: 1445862661@qq.com

Abstract

A short-term wind power prediction method is proposed in this paper with experimental results obtained from a wind farm located in Northeast China. In order to improve the accuracy of the prediction method using a traditional back-propagation (BP) neural network algorithm, the improved grey wolf optimization (IGWO) algorithm has been adopted to optimize its parameters. The performance of the proposed method has been evaluated by experiments. First, the features of the wind farm are described to show the fundamental information of the experiments. A single turbine with rated power of 1500 kW and power generation coefficient of 2.74 in the wind farm was introduced to show the technical details of the turbines. Original wind power data of the whole farm were preprocessed by using the quartile method to remove the abnormal data points. Then, the retained wind power data were predicted and analysed by using the proposed IGWO–BP algorithm. Analysis of the results proves the practicability and efficiency of the prediction model. Results show that the average accuracy of prediction is ~11% greater than the traditional BP method. In this way, the proposed wind power prediction method can be adopted to improve the accuracy of prediction and to ensure the effective utilization of wind energy.

Keywords: wind power prediction; back-propagation neural network; improved grey wolf optimization; IGWO

Introduction

In recent years, wind energy has become the world’s fastest-growing sustainable energy source due to its economic viability, convenience and high efficiency. The demand for wind energy is increasing worldwide [1–3]. However, due to the intermittent and uncontrollable nature of wind, it is essential to predict accurately the wind speed for operation efficiency, management and system protection. Accurate prediction of wind power can not only be significant for the wind farm and the power supply system, but also allows a balance between maximizing reliability and minimizing operating costs [4–6].

The two main categories of wind power prediction approaches are the physical method and the statistical method, depending on their prediction models. On the one hand, the physical method of wind power prediction is finally realized by the wind-speed power curve that is obtained by calculations involving meteorology, latitude, altitude, terrain and other key factors of the wind farm. On the other hand, the statistical method of wind...
which is less complicated than the physical method [7–10]. In this way, the statistical method is more suitable for short-term wind power prediction than the physical method.

A back-propagation (BP) neural network as a classic neural network is significant in the power prediction field due to its advantages including strong parallel processing ability, autonomous learning ability and non-linear fitting ability [11–13]. However, a BP neural network also has some drawbacks. One of the drawbacks is that it is easy to fall into local minimization [14–16]. In order to improve its performance, an improved grey wolf optimization (IGWO) algorithm, which is one sort of swarm intelligence algorithm, has been adopted to optimize the parameters in this paper. The proposed IGWO–BP method is able to improve the convergence precision of the algorithm. Experiments were carried out to evaluate the performance of the proposed method. Results demonstrated the effectiveness and efficiency of the model [17–19].

In summary, a short-term wind power prediction method with the IGWO–BP model is proposed in this paper in order to promote the prediction performance. The method is adopted to optimize the BP neural network in several steps. First, the parameters of the neural network are optimized by using the global optimization ability of the grey wolf algorithm. Then, the prediction model of the neural network is established and the network training is completed. Finally, the short-term wind power prediction is completed by using the measured data. In addition, experiments based on the wind power data, which were obtained from a wind farm in Northern China, were carried out to evaluate the performance of the established model. By comparing with the traditional BP neural network model, the IGWO–BP model proposed in this paper has a better prediction effect.

1 Prediction model

1.1 BP neural network algorithm

The BP neural network is one of the most widely used and applied algorithms (Fig. 1). Because of its good self-learning ability, generalization ability and fault tolerance, the BP neural network has been widely used in the field of power load forecasting. The structure of BP neural network is shown in Fig. 1. At the same time, wind power forecasting is an important part of power load forecasting. In structure, the BP neural network is generally divided into three layers: input layer, hidden layer and output layer. Because the BP network is a feedforward neural network, its signal propagates forward and error propagates backward. The BP network has the advantages of simple structure, easy operation and strong non-linear fitting ability. But it is easy to find only a local optimal solution and has a slow convergence speed.

![Fig. 1: BP neural network topology.](https://academic.oup.com/ce/article/6/2/1053/6542949)

1.2 Basic grey wolf algorithm

Due to the above shortcomings of the BP neural network algorithm, the grey wolf algorithm, as a global optimization algorithm, has been adopted to improve the network structure by finding better thresholds and weights of the BP algorithm. The grey wolf algorithm is a new algorithm, appearing in recent years. It establishes a mathematical model and obtains the optimal solution by simulating the hunting process of wolves [6, 10, 20].

In this paper, the grey wolf algorithm, which is based on a social animal in nature with an extremely strict hierarchy, has been adopted to improve the BP algorithm in order to speed up the convergence speed and wind power prediction accuracy. Based on its hierarchy, wolves are divided into four levels, which are \( \alpha, \beta, \delta \) and \( \omega \). Wolf \( \alpha \) is the leader and Wolf \( \beta \) is the deputy leader. Wolf \( \delta \) is the subordinate wolf and Wolf \( \omega \) is the ordinary wolf. The corresponding mathematical models of the four wolves are the best solution, the second-best solution, the third-best solution and the rest of the solutions to be selected from. This algorithm can be described in the following three aspects including search and surround, kill prey and attack target. A schematic diagram of the grey wolf algorithm is shown in Fig. 2.

![Fig. 2: Schematic diagram of the grey wolf algorithm.](https://academic.oup.com/ce/article/6/2/1053/6542949)

**1.2.1 Search and surround**

In this stage, wolves act together to search for the target. They approach the target step by step until they find the final target. Then the most suitable wolves for \( \alpha, \beta \) and \( \delta \) can be determined. Their locations are updated by the following Equations (1)–(4):

\[
\vec{D} = \left| \vec{X}_P(t) - \vec{X}(t) \right| \tag{1}
\]

\[
\vec{X}(t + 1) = \vec{X}_P(t) - \vec{A} \cdot \vec{D} \tag{2}
\]

\[
\vec{A} = 2a\vec{r} - \vec{C} \tag{3}
\]

\[
\vec{C} = 2\vec{r} \tag{4}
\]

In the above equations, \( \vec{A} \) and \( \vec{C} \) are coefficient vectors, \( \vec{D} \) is the distance between the individual wolf and the target, \( t \) is the number of iterations, \( \vec{X} \) is the grey wolf position and \( \vec{X}_P \) is the target prey location. Then, the algorithm leads to the next stage.

**1.2.2 Kill prey**

In this stage, Wolves \( \alpha, \beta \) and \( \delta \), which are determined by Equations (1)–(4), spread position information to Wolf \( \omega \) and the other wolves; their positions are also updated. In the following equations, \( \vec{X}_a, \vec{X}_b \) and \( \vec{X}_s \) represent the positions of Wolves \( \alpha, \beta \) and \( \delta \), respectively. \( \vec{D}_a, \vec{D}_b \) and \( \vec{D}_s \) represent the distances between the other individuals and Wolves \( \alpha, \beta \) and \( \delta \). Then, the algorithm moves to the final stage.

\[
\vec{D}_a = \left| \vec{C}_a\vec{X}_a - \vec{X} \right| \tag{5}
\]

\[
\vec{D}_b = \left| \vec{C}_b\vec{X}_b - \vec{X} \right| \tag{6}
\]


1.2.3 Attack target

In this stage, the optimal position of the target can be determined by the positions of Wolves α, β, and δ, and the searching area has been gradually reduced in this process. When the random variable A is greater >1, the searching approach is a global search. On the contrary, when A is <1, the wolves start to attack the target by local optimization search.

1.3 Improved method and model establishment

1.3.1 Improvement method

Although the standard grey wolf algorithm has good optimization ability with the continuous iterative process, the balance between its development ability and exploration ability can be problematic. This is due to the reason that the balance of the two capabilities is only determined by the parameter A. In the iterating process, the development capability will be greatly enhanced and the exploration capability will be continuously weakened. It causes slow optimization speed of the algorithm and the potential to obtain local optimal solutions.

In order to overcome the above drawbacks, a method is proposed to optimize its convergence factor. In the standard grey wolf algorithm, the convergence factor decreases linearly. However, this method ignores the relationship between global search and local search. In the actual hunting process, it is necessary to search a large range by means of fast search at the beginning. Then, as it is getting closer and closer to the target, it is necessary to reduce the step size and carry out optimized search to avoid missing extreme points. Therefore, a sigmoid function has been selected which is fast before the decline period and slow after the decline period. This function is adopted to improve the calculation formula of the convergence factor:

$$D_a = |c_2x - \bar{x}|$$  \(7\)

$$\bar{x}_1 = x_1(t) - \bar{A}_1 \cdot D_a$$  \(8\)

$$\bar{x}_2 = x_1(t) - \bar{A}_2 \cdot D_a$$  \(9\)

$$\bar{x}_3 = x_1(t) - \bar{A}_3 \cdot D_a$$  \(10\)

$$\bar{x}(t+1) = \frac{\bar{x}_1 + \bar{x}_2 + \bar{x}_3}{3}$$  \(11\)

1.3.2 Establishment of the IGWO–BP wind power prediction model

The BP neural network algorithm is easy to use for local optimal solutions due to its convergence performance. However, this will cause errors that cannot be neglected in wind power prediction results. The grey wolf algorithm has the ability to accelerate the convergence speed of the model. Meanwhile, it improves the prediction accuracy of the model. Therefore, on the one hand, the weight and threshold of the neural network are used as the location information of the wolf group. On the other hand, the optimization ability of the grey wolf algorithm is applied to obtain the optimal weight and threshold of the neural network. In this way, the neural network can be optimized in order to find the global optimal solution and complete the wind power prediction.

The prediction model was established by several steps. First, the wind power data were divided into a training set and a test set according to the ratio of 7:3. The quartile method was used to preprocess the data and the training set was applied as the input of the prediction model to train the model. Then, the parameters of the prediction model were initialized. The training times, learning rate and other parameters were set accordingly. Next, the maximum number of iterations and population value of the grey wolf algorithm were set. The network model was constructed according to the above parameters and then the model was trained with the training set data. The average error of the output value was taken as the individual fitness value. The locations of targets and wolves were updated according to Equations (1)–(4). Meanwhile, the individual position was updated and the individual fitness values Equations (5)–(11) were calculated. The local and global optimal solutions were compared to obtain the optimized prediction. Finally, it was necessary to determine whether the in-

Fig. 2: Schematic diagram of grey wolf algorithm.
individual meets the termination conditions. The optimal weight and threshold could be output if requirements were satisfied, and the optimal parameters were adopted to construct the IGWO–BP wind power prediction model.

2 Experiments

2.1 Wind farm information
Northeast China is one of the regions with abundant wind resources in China. The wind farms in Northeast China have been built in areas with abundant wind energy resources, relative flat terrain and small population density. The annual average wind speed can reach 6–8 m/s in these wind farms [21–23].

In this paper, the cooperative wind farm is located in the eastern part of Inner Mongolia, where the annual average wind speed can reach 7 m/s and even more. It is a typical wind farm in this area and part of the wind farm is shown in Fig. 4. As can be seen in the photo, the vegetation in the site is sparse. The terrain with desert grassland is quite flat and is suitable for building wind farms. The current capacity of the wind farm is 300 MW. The types of wind turbines in this site are FD77-1500 and FD119-3000. This wind farm covers an area of 88 km², with an average altitude of ~230 m. Its longitude and latitude are 121.324 E and 43.604 N.

The annual average wind speed of the wind farm is ~7.69 m/s and the annual equivalent full load hours is ~2154 hours.

2.2 Power characteristic of a single turbine
The power characteristic of a single turbine, which is FD77-1500, is described in this section. According to the datasheet provided by its manufacturing company, the minimum cut-in and maximum cut-out wind speeds are 3 and 25 m/s, respectively. Its rated power is 1500 kW at a rated wind speed of 12 m/s. Meanwhile, the calculation formula of the power generation coefficient is:

$$K_G = \frac{\text{Swept area}}{\text{Rated power}}$$

The sweeping area of the FD77-1500 fan is 4656.63 m² and the rated power is 1500 kW. Therefore, the power generation coefficient $K_G$ of the FD77-1500 fan is 2.7356. This coefficient is able to meet the requirements in this wind farm. Besides, there are also some key advantages of this turbine including high efficiency, ability for avoiding overload and good braking performance.

The measured wind power versus the wind-speed curve of this turbine is shown in Fig. 5. Due to the fluctuation of the actual wind speed, the fan starts when the wind speed is close to 3 m/s. As can be seen from Fig. 5, when the wind speed is 2.8 m/s, the wind turbine starts to operate and to generate electricity. When the wind speed reaches 12 m/s, the power of the wind turbine tends to be stable and the rated power is reached at 1500 kW.

The wind speed and wind power were measured by the sensors in the turbine. According to the datasheet of the turbine, the measurement scope of wind speed of the sensor is from 0.5 to 50 m/s. Compared to the datasheet, the measured curve in Fig. 5 is quite close to the curve in the datasheet. The measured data have been adopted and processed in the following sections in order to evaluate the performance of the proposed wind power prediction model in this paper.

2.3 Data preprocessing
Data preprocessing is an important step before building the prediction model. With this process, the prediction accuracy and performance of the model can be improved by removing abnormal data. In the actual production, abnormal data can be obtained for
many reasons such as electromagnetic interference, wind fluctuation, sensor error or failure of various parts of the turbine.

The abnormal data can be divided into three types according to their characteristics as shown in Fig. 6, which contains the overall original collected data. First, the abnormal data of Type A are those that suddenly attain maximum value. They are not following the trend of the wind speed. Second, the distributed data with random values that are separated from the main curve can be catalogued as Type B abnormal data. Third, those data with a minimum value are Type C abnormal data.

In order to improve the performance of the model, data preprocessing has been carried out in this paper. It can be seen that the number of anomalous data points is lower than the original number of data points, and the anomalous data can be handled by the quartile method. This algorithm divides data into four parts according to their order from small to large. Each part accounts for 25% of all data points. The four parts contain three key data values, namely lower quartile Q1, median Q2 and upper quartile Q3. In this paper, raw data of wind power are represented as X = (x₁, x₂, …, xₙ) in the time series, where x₁ < x₂. In this equation, n represents the total amount of data and m is one piece of data. Then, all of the raw data can be divided into four equal parts by using the three key data points Q1, Q2 and Q3 in the quartile. The median Q2 in the wind power data series X is calculated as follows:

\[ \text{Median Q2} = \frac{x_{\frac{m}{2}} + x_{\frac{m}{2} + 1}}{2} \]  

The first and third quartiles of the wind power data series X are calculated as follows:

When n = 2k, k = 1, 2, …, the calculation is as follows:

\[
\begin{align*}
Q_1 &= 0.75x_{k+1} + 0.25x_{k+2} \\
Q_2 &= 0.25x_{2k+2} + 0.75x_{2k+3}
\end{align*}
\]

When n = 4k + 1, k = 0, 1, 2, …, the calculation is as follows:

\[
\begin{align*}
Q_1 &= 0.75x_{k+1} + 0.25x_k \\
Q_2 &= 0.25x_{2k+2} + 0.75x_{2k+1}
\end{align*}
\]

After the lower quartile Q1 and the upper quartile Q3 are obtained through the above calculation, the interquartile range IQR is solved by:

\[ IQR = Q_3 - Q_1 \]  

According to the equations above and references, IQR is used to determine the internal limit scale of wind power data series X [24]:

\[ F_1, F_2 = [Q_1 - \mu_1IQR, Q_3 + \mu_2IQR] \]  

Generally, if the coefficient \( \mu_1 = \mu_2 = 1.5 \) is outside the internal limit of \( F_1, F_2 \), then the data point can be determined as abnormal data and removed. Otherwise, it is normal data and can be adopted for wind power model prediction. The preprocessed result is shown in Fig. 7. It can be seen that the abnormal data are basically eliminated and the rest of the data points can be adopted to represent the wind power in the following section.

### 2.4 Short-term wind power prediction

The experimental data were measured by the sensors installed in the turbines. The sampling time was 15 minutes and the total experimental time was 3 days. The wind speed of the turbines was measured and the average wind speed in the wind farm during the 3 days can be calculated for further analysis. Although the measurement scope of the sensors is from 0.5 to 50 m/s, most of the measured wind speeds were in the range of 1–16 m/s.
Then, the wind-speed data of the wind farm were programmed and analysed by using MATLAB 2020. The model parameters were then set accordingly, including the BP neural network training times set to 100, accuracy set to 0.0001, learning rate set to 0.01, input layer set to three nodes, hidden layer set to seven nodes and output layer set to one node. The number in the grey wolf population was set to 50. The maximum number of iterations and training were set to 50 and 1000, respectively. The initial search space was set to [–0.5,0.5].

The results of prediction using the BP neural network model alone are shown in Fig. 8. It can be seen that some of the predicted values are quite different from the actual values because the BP neural network is trapped in the local optimum. In this way, the prediction cannot be performed accurately.

The results of prediction using the IGWO–BP model are shown in Fig. 9. By comparing with Fig. 8, it can be seen that the accuracy of the prediction has been enhanced. This is due to the reason that the situation of falling into the local optimal solution has been improved. In this way, the predicted value tends to approach the measured value.

Meanwhile, the experiment of error comparison between the two algorithms was carried out and the result is shown in Fig. 10. Based on the experiment, it can be seen that the BP network optimization parameters obtained using the grey wolf algorithm can effectively improve the accuracy of the prediction model by avoiding the situation of falling into the local optimum.

In order to evaluate the performance of the proposed IGWO–BP model and the traditional BP model, the short-term wind power prediction evaluation index was established by using the wind power prediction management method of the National Energy
The daily average prediction accuracy $r_1$ can be expressed as:

$$ r_1 = 1 - \sqrt{\frac{1}{144} \sum_{k=1}^{144} \left( \frac{y_k - \bar{y}_k}{\text{Cap}} \right) \times 100 \%} \times 100 \% \quad (19) $$

In this equation, Cap represents the wind power capacity, $y_k$ represents the actual power in $k$ time periods, and $\bar{y}_k$ represents the predicted power in $k$ time periods.

Meanwhile, $r_2$ of the qualified rate of the daily average predicted power can be expressed as:

$$ r_2 = \frac{1}{144} \sum_{k=1}^{144} B_k^i \times 100 \% \quad (20) $$

In this equation, the value of $B_k^i$ can be obtained by using:

$$ \left[ 1 - \frac{|y_k - \bar{y}_k|}{\text{Cap}} \right] \times 100 \% \geq 75 \% \quad (21) $$

where $B_k^i$ is 1. Otherwise, its value is equal to 0.

The comparison results of the evaluation indexes of the two prediction models for the predicted power of the wind farm are shown in Fig. 9 and Fig. 10.
shown in Table 1. It can be seen that the accuracy rate can be optimized from 0.72 to 0.83 and the qualified rate is also increased from 0.73 to 0.85. The overall enhanced performance between the proposed IGWO–BP method and traditional BP method is ~11%.

Therefore, it can be summarized that the improved IGWO–BP model can effectively improve the prediction accuracy of wind power generation. With the proposed IGWO–BP method, the parameters of the BP network can be optimized. The model error and signal mutation can be reduced. The general enhanced performance rate is ~11% and the output results are able to approach the measured values, suggesting the effectiveness and enhanced performance of the proposed method compared with the traditional BP model method.

3 Conclusion

In the research of short-term wind power prediction of wind farms, in order to overcome the shortcomings of the traditional BP network, such as poor generalization ability and slow convergence speed, this paper establishes a short-term wind power prediction model based on IGWO–BP by using the improved grey wolf algorithm to optimize the network structure of the BP algorithm. By introducing the actual wind data of a wind farm in Northeast China as an experimental example, the experimental results show that, compared with the traditional BP network model, IGWO–BP has a faster convergence speed and stronger generalization ability, and effectively improves the prediction accuracy of wind power. By comparing the evaluation indexes, the accuracy is improved by 11% and the qualified rate is improved by 12%, indicating that the IGWO–BP prediction model has certain engineering application value.

Funding

This work is supported by the science and technology research project of Jilin Provincial Department of Education (No. JJKH20210260KJ). This work is supported by the Jilin Provincial Department of Education (No. JJKH20210260KJ).

Conflict of interest

None declared.

Author contributions

S.X.: conceptualization, methodology, writing—original draft preparation, visualization; L.W.: formal analysis, investigation, funding acquisition, resources, project administration and supervision; B.L.: writing—review and editing. All authors have read and agreed to the published version of the manuscript.

References

[1] Liu H, Chen D, Lin F, et al. Wind power short-term forecasting based on LSTM neural network with dragonfly algorithm. J Phys Conf Ser, 2021, 1748:032015.
[2] Du, P, Wang J, Guo Z. Research and application of a novel hybrid forecasting system based on multi-objective optimization for wind speed forecasting. Energy Convers Manage, 2017, 150:90–107.
[3] Song, J, Wang J, Lu H. A novel combined model based on advanced optimization algorithm for short-term wind speed forecasting. Appl Energy, 2018, 215:643–658.
[4] Niu, X, Wang J, Lu H. A combined model based on data preprocessing strategy and multi-objective optimization algorithm for short-term wind speed forecasting. Appl Energy, 2019, 241:519–539.
[5] You K, Xiong Y, Jia Y, et al. Short term prediction method of wind power based on PCC–RBF network. Motor and Control Applications, 2021, 48:41–45 + 104.
[6] Ding J, Chen G, Yuan K. Short-term wind power prediction based on improved grey wolf optimization algorithm for extreme learning machine. Processes, 2020, 8:109.
[7] Rawa, M, Abusorrah A, Bassi H, et al. Economical-technical-environmental operation of power networks with wind-solar-hydropower generation using analytic hierarchy process and improved grey wolf algorithm Am Shams Eng J, 2021, 12:2717–2734.
[8] Song, D, Liu J, Yang Y, et al. Maximum wind energy extraction of large-scale wind turbines using nonlinear model predictive control via Yin-Yang grey wolf optimization algorithm Energy, 2021, 221:119866.
[9] Altan, A, Karasu S, Zio E. A new hybrid model for wind speed forecasting combining long short-term memory neural network, decomposition methods and grey wolf optimizer Appl Soft Comput, 2021, 100:106996.
[10] Wang, C, Zhang S, Xiao L, et al. Wind speed forecasting based on multi-objective grey wolf optimization algorithm, weighted information criterion, and wind energy conversion system: a case study in Eastern China Energy Coners Manage, 2021, 243:114402.
[11] Zhang, P, Wang Y, Xiao L. Short-term wind power prediction using GA-BP neural network based on DBSCAN algorithm outlier identification. Processes, 2020, 8:157.
[12] Zhang Y, Chen B, Pan G. A novel hybrid model based on VMD-WT and PCA-BP-RBF neural network for short-term wind speed forecasting. Energy Coners Manage, 2019, 195:180–197.
[13] Gao Y, Qu C, Zhang K. A hybrid method based on singular spectrum analysis, firefly algorithm, and BP neural network for short-term wind speed forecasting. Energies, 2016, 9:757.
[14] Ren C, An N, Wang J. Optimal parameters selection for BP neural network based on particle swarm optimization: a case study of wind speed forecasting Knowledge-based Systems, 2014, 56:226–239.
[15] Wang J, Fang K, Pang W. Wind power interval prediction based on improved PSO and BP neural network. J Electr Eng Technol, 2017, 12:989–995.
[16] Zhang Y, Chen B, Zhao Y, et al. Wind speed prediction of IPSO-BP neural network based on Lorenz disturbance. IEEE Access, 2018:53168–53179.
[17] Fu W, Wang K, Li C. Multi-step short-term wind speed forecasting approach based on multi-scale dominant ingredient chaotic analysis, improved hybrid GWO-SCA optimization and ELM. Energy Coners Manage, 2019, 187:356–377.
[18] Pan JS, Shani J, Zheng SG. Wind power prediction based on neural network with optimization of adaptive multi-group salp swarm algorithm. Cluster Comput, 2021, 24:2083–2098.
[19] Li Y, Wang S, Chen Q. Comparative study on some new swarm intelligence optimization algorithms. Computer Engineering and Application, 2020, 56:1–12.
[20] Turnari MM, Suid MH, Ahmad MA. A modified grey wolf optimizer for improving wind plant energy production Indonesian Journal of Electrical Engineering and Computer Science, 2020, 18:1123–1129.
[21] Kang L. Research on Ultra-short-term Wind Resource Prediction of Wind Farm in Complex Terrain. Masters dissertation. Inner Mongolia University of Technology, Hohhot, 2017.

[22] Le TH. A combined method for wind power generation forecasting. Arch Electr Eng, 2021, 70:991–1009.

[23] Su, H, Duan X, Wang D, et al. Optimization of periodic maintenance for wind turbines based on stochastic degradation model. Arch Electr Eng, 2021, 70:585–599.

[24] Zhao K. Research on Wind Power Prediction Method. Masters dissertation. Lanzhou University of Technology, Lanzhou, 2020.