Wind power short-term power forecasting based on Improved Grey Wolf algorithm and Optimized Generalized Regression Neural Network

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Abstract. Aiming at the problem of wind turbine output prediction, a wind power prediction method based on Improved Gray Wolf algorithm and optimized generalized regression neural network is proposed in this paper. Firstly, according to the daily similarity of wind speed and wind power, cluster analysis is used to classify the data. Considering that the degree of each factor affecting wind power output changes, based on the selection of similar days, an improved gray wolf algorithm is introduced to optimize the weight of each influencing factor. The two models of the first mock exam are selected to input the radial single mode function RBF and the back propagation (BP) network to predict the output of the wind turbine separately. The prediction results of the two models are input to the generalized regression neural network optimized by the Wolf Wolf algorithm and the nonlinear combination forecasting is carried out. The basis models are used to predict the output of the wind turbine. The example analysis of an area shows that the model can be closer to the real value in the peak and valley of the prediction curve and has higher prediction accuracy than the combined prediction model of single BP, RBF and non optimized general regression neural network (GRNN).

1. Introduction
Wind energy is one of the most abundant resources in renewable energy, and its application prospect is quite broad. Wind power generation has become a mature and popular trend in power generation technology.

However, wind power generation has the disadvantages of randomness and intermittence. With the continuous increase of wind power grid connection, wind power grid connection is bound to bring problems in power grid stability and system scheduling [1-3]. Therefore, the prediction of wind power has become the key to solve the above problems. The wind power prediction method mainly takes the predicted wind speed and wind power value as the starting point [4-5]. The research shows that the wind speed changes periodically with the passage of time every day. That is, there is a certain daily similarity. Therefore, there is a certain relationship between the daily weather conditions and the change trend of wind power. For a wind farm, the daily similarity of wind power can be judged by using the daily similarity of closely related weather information.

At present, many methods have been proposed and applied in the short-term prediction technology of wind power at home and abroad. BP neural network prediction is often used for wind power prediction. However, in the threshold selection project, it is easy to fall into local optimization. In this
paper, gray wolf algorithm is used to improve. After model training, many kinds of short-term power prediction models of wind farms can be obtained.

2. Application of cluster analysis method

2.1. Wind power output analysis based on cluster analysis
Cluster analysis is a common method to deal with physical or abstract sets. Its essence is to effectively classify data on the basis of similarity. This method is used to describe data, measure the similarity between different data sources, and classify data into different clusters[6]. In this paper, K-means clustering, the most classical of dynamic clustering methods, is used [7]. This method classifies the data by the distance balance between the data, and divides each sample into the category closest to the mean for clustering.

The similarity measure of sample text must be adopted before classifying the samples. This measure compares the similar elements of the n-dimensional sample vector, and classifies the samples with high similarity into the same category. The measurement method used in this paper is Euclidean distance measurement. The idea of the proposed method is to use daily as the data object and define a 7-dimensional NWP vector, which is the average value of daily air pressure, minimum and maximum value of daily air temperature, minimum and maximum value of daily wind speed, sinusoidal mean value of daily wind direction, and cosine mean value, respectively. Since the data dimension is different in each dimension, normalization is performed before data delivery and back normalization is performed after data output.

2.2. Selection of similar days
The method of selecting similar days is to find out the relationship between the days to be measured and the grouping of cluster analysis on the basis of cluster analysis. When selecting similar days, temperature, air pressure and wind speed are comprehensively considered, but the influence of the three factors on wind power output is not invariant. Therefore, an adaptive similarity day selection method is proposed. When calculating the final similarity, the weighted average method is not used, but the respective weights of influencing factors are given, and the improved algorithm is used to optimize the weights to obtain a comprehensive similarity \( \sigma_j \). The calculation formula can be shown as follows:

\[
\sigma_j = c_1 \gamma_j + c_2 \Gamma_j + c_3 \eta_j
\]  

In equation (1): \( \gamma_j \) is the temperature; \( \Gamma_j \) is the air pressure; \( \eta_j \) is the wind speed; \( C1, C2 \) and \( C3 \) are weight coefficients respectively.

3. Prediction model and practical process

3.1. Nonlinear combination prediction based on optimized GRNN
Nonlinear combination forecasting is an important development direction of time series trend forecasting [8]. As a network of nonlinear regression analysis, GRNN is good at solving nonlinear combination problems. The single BP and RBF neural network are used to predict, and the results of the two groups of prediction models are used as the input of GRNN. Finally, GRNN is used for nonlinear combination prediction to obtain the final wind power prediction value. Experiments show that the prediction accuracy of the proposed nonlinear combined model is higher than that of each single prediction model. However, the prediction effect of GRNN network is closely related to its own smoothing factor. If the smoothing factor is too large, the output value of GRNN is closer to the average value of all samples. On the contrary, if the value of the smoothing factor tends to 0, its predicted value will only be very close to the training sample. Once the value to be predicted is not
included in the training set, the prediction accuracy may be very low. Therefore, the smoothing factor needs to be optimized to achieve the best prediction effect.

3.2. Improved gray wolf algorithm

According to the action behavior of gray wolf hunting, the process can be described as three stages: encirclement, pursuit and attack, and the final arrest of prey is the optimal solution.

Firstly, the mathematical description of the process of gray wolf searching prey and gradually surrounding is as follows:

\[ D = |CX\alpha(t) - X(t)| \]  
\[ X(t + 1) = X\beta(t) - AD \]  
\[ A = 2ar - al \]  
\[ C = 2r \]  
\[ r_i = \text{rand}(0,1) \]

In equation (2)(3)(4)(5)(6): \( t \) is the number of current iterations; \( C \) is the synergy coefficient vector; \( A \) is the convergence coefficient vector; \( a \) is the convergence factor in the iteration. In the iterative optimization of the whole algorithm, its value decreases linearly from 2 to 0; \( X\alpha(t) \) is the position vector of gray wolf in the \( t \)-th iteration; \( X(t) \) is the position of prey after iteration \( t \); \( r \) is the random vector of each element in \([0,1]\); \( I \) is the unit vector.

Secondly, through continuous updating \( \alpha \), \( \beta \), \( \delta \) Wolf location, and finally determine the location of prey. The mathematical description of the hunting process of gray wolves is as follows:

\[ X\alpha = X\alpha - AD\alpha \]  
\[ X\beta = X\beta - AD\beta \]  
\[ X\delta = X\delta - AD\delta \]

In equation (7)(8)(9): \( X\alpha \), \( X\beta \), \( X\delta \) is the bit vector of \( \alpha \), \( \beta \), \( \delta \) in the current population; \( D\alpha \), \( D\beta \), \( D\delta \) is the distance between the current gray wolf and \( \alpha \), \( \beta \), \( \delta \); \( X \) represents the current position of gray wolf; \( A1 \), \( A2 \) and \( A3 \) are convergence coefficients; \( X(t + 1) \) is the position of the next generation of gray wolves.

Although the conventional grey Wolf algorithm (GWO) has better performance than most smart optimization methods, it is not suitable for dealing with high complexity functions. And how to improve the balance between global search and local convergence is one of the important directions to improve the performance of the Grey Wolf algorithm [8].

In the original gray wolf algorithm, the position of the candidate wolf is updated by the average of the positions of the three optimal wolves. This selection method ignores the relationship of the strict hierarchy of the three wolves. Therefore, this paper proposes a method with the best individual weight \( \alpha \), \( \beta \) and \( \delta \) average strategy. The corresponding weight is calculated through their respective fitness values, as shown in equations (10) and (11) [9]:

\[ X(t + 1) = \frac{X\alpha(t) + X\beta(t) + X\delta(t)}{3} \]
In equation (10)(11): $\text{fit}_i (i = \alpha, \beta, \delta)$ is the fitness value of the corresponding individual; $X(t), X(t), X(t)$ is the location of the optimal individual $\alpha, \beta, \delta$; $X(t+1)$ is the next generation of candidate wolves.

The improved GWO is used to optimize the smoothing factors of each factor weight coefficient $C1, C2, C3$ and GRNN $\sigma$, get the best model.

3.3. Wind power short-term power prediction based on Improved Grey Wolf algorithm optimized generalized regression neural network

According to the above-mentioned cluster analysis method and GRNN nonlinear combination prediction model, after data classification, the improved gray wolf algorithm is used to optimize the smoothing factor and the weight coefficients of daily air pressure, daily temperature and wind speed in GRNN. The main steps of optimizing the wind power short-term power prediction model of generalized regression neural network based on the improved gray wolf algorithm are as follows.

- Step 1 collect the historical actual data of the wind farm, including actual power and actual meteorological data.
- Step 2 classify the sample data according to the sine of daily pressure, daily temperature, daily wind speed and daily wind direction based on cluster analysis.
- In step 3, the daily air pressure, daily temperature and wind speed are introduced to calculate the similarity of each factor, and the weight coefficients $C1, C2$ and $C3$ are given to each factor to calculate the correlation between the predicted day and the historical day.
- In step 4, the improved GWO is used to optimize the smoothing factors of each factor weight coefficient $C1, C2, C3$ and GRNN $\sigma$, get the best model.
- In step 5, BP and RBF neural networks are used to predict respectively to obtain two groups of predicted values.
- In step 6, the two groups of neural network prediction values are used as the optimized GRNN input variables for nonlinear combination prediction to obtain the final wind power output prediction value.

4. Experimental description and result analysis

The actual wind turbine output in an area is predicted to verify the effectiveness. The improved gwo-grnn is used to establish the combined prediction model. Taking a wind farm in Liaoning Province as an example, the NWP data and the actually measured wind power data of the wind farm from November to December 2015 are analyzed. The data resolution is recorded as 15 min, the prediction step is recorded as 95 points, and the prediction date is December 10, 2019. In order to better display the results, the comparison methods are set as three prediction models: BP neural network, RBF neural network and original GRNN combined prediction. Figure 1 shows the prediction results. As can be seen from Figure 1, GRNN combined prediction model and gwo-grnn combined prediction model have higher prediction accuracy than single BP and RBF neural network, while gwo-grnn can be closer to the real value in the peak and valley of the prediction curve and have higher prediction accuracy.
accuracy than GRNN prediction model.

Figure 1. Transmission frequency - efficiency graph

5. Conclusion
Aiming at the problem that it is difficult to accurately predict the wind turbine, based on the classification of wind power data by cluster analysis, a wind power output prediction method based on Improved Gray Wolf algorithm is proposed. The following conclusions are drawn through example analysis.

(1) cluster analysis is used to divide the wind power sample data and classify the samples, so as to find the category similar to the forecast day and eliminate the data with large difference from the forecast day.

(2) compared with the conventional similar day selection method, the adaptive similar day selection method optimized by the improved gray wolf algorithm obtains a more accurate similar day, which is of great value to improve the accuracy of wind power prediction.

(3) using the advantages of the improved gray wolf algorithm, the smoothing factor is further optimized on the basis of GRNN combined prediction, so that the improved GRNN can quickly converge to a better solution, and has more accurate prediction accuracy than the other three models.

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