A Hybrid Foresting Model for the Wind Energy based on Small World Optimization Algorithm and BP Neural Network

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Abstract. Wind energy is a clean and pollution-free renewable energy source, but it has the characteristics of randomness and intermittence. Therefore, it is of great economic significance and practical value to study the high-precision wind power prediction model for accurately predict the power generation of wind farms. This paper use the small world optimization algorithm (SWOA) to optimize the selection of the weights and threshold of the BP neural network, so that it has the advantages of small errors and global optimization. Then we proposes an improved BP neural network model based on the small world optimization algorithm. Afterwards, the model was applied to wind power prediction in actual wind fields. The experiment results show that SWOA can quickly and accurately find the global optimal solution of the parameters of the BP neural network model, which can further improve the SWOA-BP model to obtain better prediction performance.

1. Introduction

As a clean and renewable resource, wind energy has become an important alternative to fossil energy. However, wind energy has the characteristics of randomness, uncertainty, non-linearity, and uncontrollability, and it is not easy to establish accurate mathematical models [1-3]. With the development of artificial intelligence, many artificial intelligence algorithms and models that do not rely too much on accurate mathematical models have been introduced into the field of wind power prediction [4]. Liu et al. proposed a probabilistic spatio-temporal deep learning model which could employ advanced image recognition methods in 2020 [5]. Liu et al. developed a forecasting system based on a data pretreatment strategy, a modified multi-objective optimization algorithm, and several forecasting models in 2020 [6]. Zhao et al. constructed an optimized system. BP neural network shows superior performance in prediction, which has the advantages of self-adaptation, self-organization, better fault tolerance and robustness [7]. However, BP neural network has some disadvantages, such as the slow convergence speed of traditional algorithms and the network's susceptibility to local minima.

A new type of optimization method called the small world optimization algorithm (SWOA) appeared in recent years [8]. The principle is to transform the variables from the chaotic space to the solution space, then use the short-distance and long-distance connection of the SWOA to transfer the candidate nodes. The SWOA could escape the local minimum and show a strong search ability and capable of...
achieving global optimization [9]. Therefore, this paper first uses its optimization to select the weights and thresholds of the BP neural network, generates a small-world optimized BP neural network algorithm (SWOA-BP algorithm), and applies the model to the wind power prediction of actual wind farm. The research shows that the optimization of the parameters of the BP neural network model with the SWOA can make the parameters converging to the global optimal value, and the improved model has a better prediction effect.

2. Wind speed forecasting model

2.1 WS Small World Network

The process of establishing the WS small-world network [10] model is as follows: First, a regular network with \( N \) nodes is established, where each node is connected to its left and right neighboring \( k \) nodes, \( k \) is an even number, and each edge is randomly reconnected with probability \( P (0 \leq P \leq 1) \), which is to keep one of the endpoints of the edge unchanged and randomly connect another node in the model. Any two nodes can only have at most one edge, and each node cannot have an edge connected to itself.

According to the construction process of the above network model, the network model with different probability \( p \) is shown in Figure 1. Among the picture, \( p = 0 \) corresponds to a completely regular network, \( p = 1 \) corresponds to a completely random network, and when \( p \) is between 0 and 1, the network model is the WS small world network model. By changing the probability value, the transition of the network model from a network which is regular to a random network can be controlled.

2.2 Back propagation neural network

BP neural network is a multi-layer feedforward neural network trained by the error back-propagation algorithm, which includes an input layer, a hidden layer, and an output layer. Its structure is shown in Figure 2. The basic BP algorithm includes two processes: forward propagation of signals and back propagation of errors.

![Figure 1. Three kinds of networks](image1)

![Figure 2. BP neural network](image2)

The general weight adjustment formula of BP learning algorithm is as follows [11]:

\[
\begin{align*}
\Delta w_{jk} &= -\eta \frac{\partial E}{\partial w_{jk}} = \eta \delta_k y_j = \eta \left(d_k - O_k\right) y_j f'(net_k) \\
\Delta w_{ij} &= -\eta \frac{\partial E}{\partial w_{ij}} = \eta \delta_j x_i = \eta \left( \sum_{k=1}^{L} \delta_k w_{jk} \right) x_i f'(net_j)
\end{align*}
\]

where \( w \) indicates network weight, \( \Delta w \) is weight increment, \( E \) is error function of output node of neural network, which can be expressed as follow:

\[
E = \frac{1}{2} \sum_{k=1}^{L} \left( d_k - O_k \right)^2
\]

\( \delta_j \) is error back-propagation signal from outer layers to inner ones, \( L \) is the number of output neurons,
\( f'(net_i) \) and \( f'(net_j) \) are the derivative of transfer function of output and hidden layer, the negative sign expresses the gradient descent, the constant \( \eta \in (0,1) \) reflects the learning rate of network.

BP neural network become relatively mature in terms of network theory and performance, except for its slow learning speed. Even a simple problem generally requires hundreds or even thousands of learning to converge. In addition, when there is a local minimum in the solution space function, if the search step is small (momentum is small), then it is possible that all solutions obtained during this local solution point to the minimum.

2.3 SWOA-BP algorithm

The small world optimization problem describes the optimization process as taking into account the small world effect in the information transfer and transfer process from the candidate solution to the optimal solution in the search space. That is, a candidate node transfers to the optimal node through short-distance connections and random long-distance connections [12]. The information passed in this process is the solution of the optimization model. In view of the good optimization characteristics of SWOA, this paper uses it to optimize the weight and threshold of BP neural network.

Although the initial connection weight selection has a great influence on network training, it is not easy to obtained accurately. So SWOA can be applied to the global optimization of weights in BP neural network structure, which improves the convergence speed of BP neural network training and avoids escaping the local minimum. The SWOA-BP model as follows:

![Figure 3. SWOA-BP model](image)

3. Data and experiment results

3.1 Data collection

Real-time operating data of a wind field in Iowa, USA was used as experimental data. The data samples are real-time running data for every 5 minutes, including wind speed and power. The first 100,000 data are used as the training set of the BP neural network model, and the last 6,000 data are used as the test set of the model.
3.2. Error evaluation index
The wind power prediction error evaluation index in this paper uses $MSE$ (mean squared error), $RMSE$ (root mean squared error), $MAPE$ (mean absolute percentage error) and $R^2$. The definitions are as follows:

$$
MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2
$$

$$
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2}
$$

$$
MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right|
$$

$$
R^2 = 1 - \frac{\sum_{i=1}^{n} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}
$$

where $\hat{y}_i$ donates predictive value, $y_i$ donates actual value and $n$ donates the number of testing set.

3.3 Experiment results
Windows 10.0 operating system is used as the experiment system environment, and MATLAB 2012b is used as the software operating environment. Training sample data is formed by selecting the feature of the original data set. The process of optimizing BP neural network model parameters based on SWOA is the optimization process of fitness function. With the continuous search, some nodes with low fitness in the network are gradually eliminated, and more and more nodes with low loss function values are concentrated around the best advantage of the objective function to search for the optimal value.

Comparing the results obtained by SWOA-BP with ordinary BP, we can see that the optimized neural network fits the data of the training set better and performs better on the test set from Figure 4-7. Table 1 shows that, compared with ordinary BP, SWOA-BP has the smallest mean square error, the smallest root mean squared error and the smaller mean absolute percentage error. At the same time, the $R^2$ also
shows that the model has a higher degree of interpretation of the data set. However, due to the large amount of data, the number of hidden layer nodes in the model should not be too large in order to avoid overfitting. During the simulation process, it was found that the SWOA convergence speed is fast. Generally, the fitness function starts to reach the optimal value around the 5th generation, that is, the optimal parameter finds the optimal node, so the initial value of the maximum search generation does not need to be set very large.

Table 1. Error evaluation index

|                | RMSE  | MSE   | MAPE  | $R^2$  |
|----------------|-------|-------|-------|--------|
| SWOA-BP        | 0.3914| 0.1532| 0.0005| 0.9587 |
| BP             | 0.4902| 0.2402| 0.0008| 0.9482 |

4. Conclusion

This paper proposes a new SWOA-BP algorithm using small-world algorithm to optimize BP neural network algorithm, which adopts the advantages of BP neural network algorithm and SWOA. Matlab simulation results show that the SWOA-BP algorithm proposed in this paper has small error and converge to the global optimal value, which improves the accuracy of wind power prediction. The feasibility of the proposed forecasting method in wind power forecasting was verified, which provided a new idea for wind power forecasting research and also showed that the SWOA has certain engineering application value.

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