The wind power prediction research based on mind evolutionary algorithm

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Abstract. When the wind power is connected to the power grid, its characteristics of fluctuation, intermittent and randomness will affect the stability of the power system. The wind power prediction can guarantee the power quality and reduce the operating cost of power system. There were some limitations in several traditional wind power prediction methods. On the basis, the wind power prediction method based on Mind Evolutionary Algorithm (MEA) is put forward and a prediction model is provided. The experimental results demonstrate that MEA performs efficiently in term of the wind power prediction. The MEA method has broad prospect of engineering application.

1. Introduction

The global energy crisis and global warming contributed to the rapid development of renewable energy. As a kind of renewable energy, wind energy has attracted the world's attention and affirmation[1-4]. Although wind power prediction can improve the safety and reliability of power system, the difficulty of power prediction always exists [5-6]. At present, the traditional methods of wind power prediction are as follows: time series analysis based on historical data, support vector machine (SVM)[7], neural networks, etc.

In paper[8], the auto-regressive moving average model was established by using the time series method to estimate the output of wind farm based on robust estimation. The prediction error is 5%. Qi Zhang et al. [9] introduced the present situation and related standard of wind power prediction, and optimized the wind power prediction model by neural networks. The performance of the proposed method was validated by simulation. In paper[10], a short-term wind power combination prediction method based on the overall mean empirical mode decomposition and improved Elman neural
network was proposed. The simulation results indicate that this method can not only alleviate the influence of wind power’s nonstationarity on prediction accuracy, but also avoid the modal aliasing problem caused by traditional methods. Mao et al. [11] proposed a wind speed and wind direction prediction model, and predicted the sub-power by ridgelet neural network.

In general, the time series method is used to predict the wind power by mining the data sequence, and it is suitable for short-term prediction with high prediction accuracy. Support vector machine method has changed the traditional risk minimization principle with strong generalization. Neural network method with strong robustness aims at the nonlinear characteristics of wind power. However, owing to the huge amount of training data, it is easy to fall into the local optimization.

On the basis, in this paper, the wind power prediction method based on Mind Evolutionary Algorithm (MEA) is put forward. This method optimizes the threshold value of the hidden layer weights by convergence and dissimilation, and greatly reduces the prediction error caused by the random generation of hidden layer weights’ threshold. Based on the measured data, the wind power of a wind farm in China is predicted. The simulation results verify the validity of the model.

2. Wind power data preprocessing

In the process of wind power data acquisition, there may be a lack of wind power data. Therefore, we fill the loss data before carrying out the wind power prediction. In this paper, we choose a cubic spline interpolation function.

Suppose that (n+1) points were given:

\[ a = x_0 < x_1 < x_2 < \cdots < x_n = b \]  

(1)

The cubic spline interpolation function \( S(x) \) is a cubic polynomial on each subinterval \([x_k, x_{k+1}]\), the \( m_k \) is calculated as:

\[ m_k = S'(x_k) \]  

(2)

Set \( x \in [x_k, x_{k+1}] \), the linear function pass \((x_k, m_k)\) and \((x_{k+1}, m_{k+1})\) can be expressed as:

\[ S'(x) = m_k \frac{x_{k+1} - x}{h_k} + m_{k+1} \frac{x - x_k}{h_k} \]  

(3)

where \( h_k = x_{k+1} - x_k \), According to the equation (3), the integral of function can be expressed as:

\[ S(x) = m_k \frac{(x_{k+1} - x)^3}{6h_k} + m_{k+1} \frac{(x - x_k)^3}{6h_k} + \frac{y_{k+1} - y_k}{h_k} \frac{x - x_k}{h_k} - \frac{h_k}{6}(m_{k+1} - m_k)(x - x_k) + y_k - m_k \frac{h_k^2}{6} \]  

(4)
Figure 1. Results of the cubic spline interpolation fitting.

The main steps of the cubic spline interpolation are as follows:
(1) Determine the boundary conditions;
(2) Calculate the values according to the boundary conditions and form the equations;
(3) Solve the equations and obtain $m_i$;
(4) Bring $m_i$ into $S(x)$, and obtain an approximation of any point within $[a, b]$.

Figure 1 displays the result of cubic spline interpolation fitting, and it’s basically consistent with the real wind power data.

3. The wind power prediction model based on mind evolutionary algorithm

3.1. A brief introduction to mind evolutionary algorithm
The flow diagram of the MEA algorithm is given in Figure 2.

Figure 2. The flow diagram of the MEA.

Compared with the genetic algorithm, MEA has many characteristics:
(1) The group is divided into the superior sub-population and temporary sub-population, and carry on the convergence and dissimilation operation inside sub-population, convergence of semantic coordinate, but maintain their independence.
(2) Memorize more than one generation of evolutionary information that facilitates convergence and dissimilation.
(3) There are inherent parallelism in the structure of convergence and dissimilation operation
(4) Convergence and dissimilation operation can avoid the duality in the genetic algorithm, that is, it can produce good genes and also can destroy the original good genes.

3.2. Establish the wind power prediction model
Taking the measured wind speed, ambient temperature and wind power of a fan as an example, after data preprocessing, wind speed and ambient temperature are used as input to the wind power prediction model, then construct the eigenvector, the normalized eigenvector is calculated as:

$$E = \left[ \frac{V}{\sqrt{V_i^2 + T_i^2}}, \frac{T_i}{\sqrt{V_i^2 + T_i^2}} \right]$$

(5)

**Figure 3.** The wind power prediction model based on MEA algorithm.

The wind power prediction model based on mind evolutionary algorithm is illustrated in Figure 3.

### 4. Simulation and analysis

The simulation selects wind power measured data of a wind farm, and the data acquisition period of the wind farm is 10 min, the single fan capacity is 1500KW. In order to ensure the diversity of training samples, 1900 sets of experimental data as training samples from the collected wind farm data is selected randomly to train the MEA wind power prediction model. Then 100 sets of data as test samples in the remaining data for model validation is selected randomly. The other parameters of the MEA are shown in Table 1.

| Table 1. Parameters of MEA. |
|-----------------------------|
| population / size | superior sub-population / size | temporary sub-population s / size | hidden layer / size | iteration / times |
|---------------------|---------------------------------|-----------------------------------|--------------------|-----------------|
| 200                 | 5                               | 5                                 | 5                  | 10              |

Figure 4. The first convergence operation results of wind power prediction.
Figure 4-6 show the first convergence, the second convergence, and the third convergence operation results of the prediction model obtained by MEA. When the score of the temporary sub-population is lower than the score of the superior sub-population, the convergence operation is stopped and vice versa. As shown in Figure 4, the score of the temporary sub-population reach up to 7.4, which was much higher than that of the superior sub-population. Therefore, the MEA performs a dissimilation operation and then proceeds to the next convergence operation.

Based on the results given in Figure 6, all the scores of temporary sub-population are below that of the superior sub-population, therefore, the convergence operation stopped, and the wind power prediction model obtained by MEA achieves the optimal structure.

Figure 5. The second convergence operation results of wind power prediction.

Figure 6. The third convergence operation results of wind power prediction.
Figure 7. The results of wind power prediction Based on MEA.

With the model trained before, the wind power prediction simulation is carried out by using Matlab, the prediction results are given in Figure 7. The predicted result of MEA is basically consistent with the actual wind power.

Figure 8 displays the prediction errors based on MEA with sampling time varied from 0 to 100min. The maximum error is 16%, which satisfy the requirement of the maximum error can’t exceed 25%. It shows that the mind evolutionary algorithm has high prediction accuracy and satisfy the engineering demand.

5. Conclusion and Prospect
In this paper, the wind power prediction method based on Mind Evolutionary Algorithm (MEA) is put forward and the prediction model is provided. The eigenvector consists of ambient temperature and
wind speed. The simulation results indicate that the proposed model has high prediction accuracy and laid the foundation of wind power prediction for the whole wind farm. In the future work, we can study the influence of the eigenvector and training sample on the prediction accuracy.

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