Research on Offshore Short-term Wind Speed Prediction Based on the CSA Modeling Improved by Random Algorithm

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Abstract. Aiming at improving the prediction accuracy of offshore short-term wind speed, a model based on random cuckoo search algorithm (RCSA) and artificial neural network (ANN) was proposed. Firstly, RCSA was obtained by introducing a random factor to improve CSA, and then a RCSA-ANN model for predicting offshore short-term wind speed was established. Secondly, a wind tower was built in Luchao Port, Shanghai, offshore meteorological data were measured, and the training of the model was carried out. Finally, the precision of RCSA-ANN model was verified by comparison and analysis with BP-ANN and CSA-ANN models. The results show that the improved CSA method is simple, reliable and effective, which solves the problem that the algorithm is easy to fall into local optimum. The average error of RCSA-ANN model is not only lower than that of BP-ANN model, but also much lower than that of CSA-ANN model, and the prediction accuracy of these three models decreases in turn. RCSA-ANN model has high prediction accuracy and can precisely predict fluctuating wind speed sequences, and it also has good application potential.

1. Introduction

The wind speed prediction is of great significance for the economic dispatch of power systems with large-scale wind farms[1]. In recent years, the number of offshore wind farms has gradually increased and they have begun to be incorporated into the power grid, while the fluctuation of wind power brings threats to the grid. Hence, how to predict the wind speed at sea accurately becomes particularly crucial.

Domestic and foreign researchers have done some research on short-term wind speed prediction, and the artificial neural network (ANN) model[2] is widely used. Although relevant scholars have made some progress in the research of short-term wind speed prediction, the prediction accuracy of the ANN model still needs to be improved, which mainly depends on the optimization performance of the algorithm. Cuckoo search algorithm (CSA) is a promising group intelligence algorithm[3]. Compared with classical swarm intelligence algorithms such as genetic algorithm, artificial bee algorithm, particle swarm algorithm, etc., CSA has higher searching efficiency[4], better performance of parameter optimization[5], and its convergence and global search capability are superior to particle swarm optimization and genetic algorithms. Scholars have made more improvements to CSA for its slow convergence speed, low solution accuracy, and other shortcomings[6], but CSA also has the disadvantage of easily falling into the
local optimal solution\cite{7}, when solving complex multi-peak optimization problems, such as the optimization of the ANN model\cite{8}. The wind speed is affected by many factors, especially the local meteorological conditions\cite{9}, and the ANN model is difficult to be optimized by the general swarm intelligence algorithm, resulting in low accuracy of wind speed prediction. Consequently, there is an urgent need to further optimize CSA and improve its parameter optimization capabilities in order to obtain higher prediction accuracy.

In view of this, the random cuckoo search algorithm (Random-CSA, RCSA) is obtained by introducing the random factors into the CSA update formula, and it is used to optimize the ANN model, and then the RCSA-ANN model for offshore short-term wind speed prediction is established. The data of wind speed and environmental parameter in Luchao Port, Shanghai are measured, and the prediction performance of different algorithm training models is compared and analyzed.

2. RCSA-ANN modeling

2.1. CSA improved by random algorithm

By introducing random factors to improve CSA, RCSA is obtained, which makes its random search ability become stronger, and avoids CSA’s weakness of easily falling into local optimal solution on multi-peak problem.

The update formula of CSA can be written as\cite{3}:

\[
X_i^{t+1} = X_i^t + K \times \Delta X
\]  

(1)

where \(X_i^t\) is the \(i\)th individual in the population before the update, and \(X_i^{t+1}\) is the after. \(K\) is a matrix of individual in the population selected to be updated, and its constituent elements are 0 and 1. \(\Delta X\) is the difference between any two individual matrices in the group.

Introducing the random factor \(R\) into equation (1) can improve CSA, and then the RCSA update formula is:

\[
X_i^{t+1} = X_i^t + K \times \Delta X + R
\]  

(2)

where the elements in \(R\) are random numbers between \([-\alpha, \alpha]\), and the \(\alpha\) can be set according to the size of the actual search range.

2.2. Model training scheme

The wind measurement data sets of Shanghai Luchao Port are divided into a training set and a testing set, and RCSA is used to train the ANN model. The specific scheme is as follows:

1) The model parameters are generated randomly, and the RCSA-ANN model is trained by combining the training set. The training set consists of \(N\) groups and each group contains \(M\) kinds of parameters, environmental parameters and wind speed are respectively taken as input and output samples of the model, and the training program contains two layers of loop nesting.

2) The inner layer is a loop, which aims to minimize the training error of each group data, and the weights and bias of the ANN model is updated by equation (2). The condition of loop jump out is that the single-group training error \(\delta_i^t\) is less than \(\varepsilon\) or the cycle number \(i_2\) is greater than \(I_2\).

3) The outer layer is a loop, which aims to reduce the average error of the training set. If the average training error \(\bar{\delta}_i^t\) is bigger than \(\varepsilon\) or the loop number \(i_1\) is smaller than \(I_1\), repeat 1) to 2). The training ends when the outer training results meet the loop condition of the layer.

4) The model parameters with the least training error are selected as those of the RCSA-ANN model, which can be verified by the testing set, and the verification results are obtained.

3. Simulation and prediction of offshore wind speed in Luchao Port

3.1. Data processing
In this study, four kinds of meteorological data including wind speed, wind direction, temperature and air pressure with the height of 10m and duration of 230h are measured every 5 minutes by the offshore wind tower built in Luchao Port. Here, the data are processed into the average ones per hour, totaling 230 groups, which contains 920 data points.

Since the training data processed by the traditional normalization is difficult to train model, the following formula is employed to process the training data:

$$\tilde{x}_i = x_i - \left(\frac{1}{N} \sum_{i=1}^{N} x_i \right) / N$$

(3)

where $x_i$ and $\tilde{x}_i$ are the input data of the ANN model before and after processing respectively.

The smaller the root mean square error (RMSE) and the mean absolute percentage error (MAPE) are, the better the predicting effect is. Therefore, the two error are applied to judge the prediction accuracy of the RCSA-ANN model, and their formulas are separately listed as follows:

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

(4)

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

(5)

where $n$ is the group number of testing set, and $\tilde{y}_i$ is the corresponding wind speed value of the $i$th group predicted by the output layer of RCSA-ANN, $y_i$ is the actual wind speed value of the $i$th group.

### 3.2. Partition of the data sets

The environmental parameters are better for wind speed prediction\textsuperscript{10}, so air temperature and air pressure are selected as the input and wind speed as the output in the RCSA-ANN model. The partition of data sets can be seen in Table 1.

| Sample data | Input | Output |
|-------------|-------|--------|
| Air temperature | Air pressure | Wind speed |
| Training set | 1-190 | 1-190 | 1-190 |
| Testing set | 191-230 | 191-230 | 191-230 |

### 3.3. Examples of wind speed prediction model

In order to investigate the parameter optimizing ability of RCSA and verify the accuracy of the RCSA-ANN model, a comparative analysis of the prediction precision between BP-ANN and CSA-ANN is carried out. The prediction accuracies of the improved algorithm are different after each training due to random search, so each model is trained and predicted five times to comprehensively investigate the model performance and avoid large accidental deviations. To compare the deviation between the average value of wind speeds predicted by each model at each time point for five times and the measured one, the curves of average wind speeds predicted by BP-ANN, CSA-ANN and RCSA-ANN respectively are plotted in Figure 1.
Fig. 1 Comparison of the average wind speed predicted by each model with the measured one

It is found that the predicted wind speed of BP-ANN model is closer to the measured one, but it is higher in the period of 206h~221h. The complete failure of CSA algorithm results in the huge difference between the average wind speed predicted by CSA-ANN and the practical value. The changing trend of wind speed predicted by RCSA-ANN is basically consistent with that of the measured value, and their deviation is generally small. The prediction of BP-ANN is better than that of CSA-ANN, and RCSA-ANN presents the highest accuracy.

4. Assessment of model accuracy
To observe the prediction results of BP-ANN, CSA-ANN and RCSA-ANN models, the RMSE and the MAPE of the wind speed predicted by the three models are calculated, and they are listed in Table 2. It can be seen that RCSA-ANN model has the highest prediction accuracy no matter what kind of error, and the prediction precision of CSA-ANN, BP-ANN and RCSA-ANN increases in turn. Compared with the other two models, the prediction accuracy of RCSA-ANN is significantly improved, and the increase in amplitude is bigger compared with CSA-ANN.

Table 2 Errors of three models

|                | RCSA-ANN | BP-ANN | CSA-ANN |
|----------------|----------|--------|---------|
| $\varepsilon_a$ (m·s$^{-1}$) | 0.40     | 0.58   | 4.91    |
| $\varepsilon_m$ (%)     | 7.20     | 11.58  | 122.21  |

5. Conclusions
In this work, RCSA improved by using random factors to CSA was used to optimize ANN, and then RCSA-ANN model was obtained. By measuring the marine meteorological data of Luchao port and training the model, the analysis of short-term wind speed prediction and accuracy was finally achieved. The main conclusions are drawn as follows:

1) The improved RCSA based on random algorithm has strong search performance and well solves the problem of multi-peak feature optimization, and the improved method can be extended to other group intelligent algorithms.

2) For RCSA-ANN model, the designed training program is practical and feasible, and the obtained parameters are accurate and reliable.
3) RCSA-ANN model has good effect and high accuracy, which can provide a reference for the real-time prediction system of offshore wind speed.

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