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Research on Wind Speed Prediction Model Based on WOA-LSTM

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Abstract: *To tackle the issues of haphazardness of LSTM model boundaries and slow model intermingling speed, work on the exactness of wind speed forecast model, and better work on the security and economy of wind power age frameworks, this paper proposes an improved LSTM based on the Whale Optimization Algorithm (WOA), and conducts simulation analysis based on the US meteorological data. The exploration results show that:1) Through persistent preparation to track down reasonable hyperparameters and confirm them, it is observed that the attributes of the WOA calculation can successfully track down the worldwide ideal answer for upgrade the boundaries of the LSTM model; 2) Compared with the traditional LSTM neural network prediction model, the WOA-LSTM reduces the root mean square error (RMSE) and mean absolute error (MAE) by 0.43035 and 0.23115, respectively, and improves the goodness of fit (R^2) by 0.03763. It shows that the model has better accuracy and stability for wind speed prediction.*

Keywords: *Whale Algorithm; Long and Short-term Neural Memory Network; Wavelet Noise Reduction; Wind Speed Prediction*

1. Introduction

In recent years, with the depletion of traditional resources such as oil and natural gas and the aggravation of environmental pollution, the proportion of clean energy in the total energy has gradually increased. As one of the environmentally friendly power age techniques, wind power age shows a pattern of high development. However, due to the randomness and intermittency of wind speed, wind power has certain volatility and instability. Whenever wind power is associated with the power framework, it will cause huge changes in the voltage of the power framework, which truly influences the steady activity of the power matrix. Therefore, wind speed prediction can effectively guide the fan power control, improve the stability of the system, and ensure the safe and stable operation of the power system.

In the process of wind speed prediction, due to the influence of weather, human factors, etc., wind speed has obvious randomness. Therefore, accurate prediction of short-term wind speed can reduce the reserve capacity of the power system, improve the penetration rate of wind power penetration, and maximize wind power penetration. Financial advantages of power market financial aspects. The wind speed prediction model is a complex nonlinear system, and the prediction accuracy is affected by many factors, so advanced information processing technology, such as data mining technology and artificial intelligence, needs to be adopted.

At present, domestic and foreign scholars have done a lot of research on wind speed prediction. The usually utilized transient breeze speed expectation models include: statistical models, artificial neural network models, combined models, and models considering spatial correlation or monsoon characteristics. Yang Xiyun et al [1] proposed an ARIMA model based on wavelet transform to predict the wind speed of wind farms. Han Shuang et al [2] conducted comparative experiments on wind speed prediction with continuous method, ARIMA model, and BP neural network model, and concluded that the intelligent algorithm is superior to the traditional algorithm to a certain extent. Gu Yue et al [3] proposed a BP neural network group structure model to achieve the complementary advantages of each sub-network, thereby improving the prediction accuracy. Although these methods can solve nonlinear problems, they are prone to problems when dealing with time series and are not so accurate when predicting random wind speeds. In addition, although deep learning has obvious advantages in the prediction of a large amounts of data, it is prone to the problem of gradient explosion when dealing with time series prediction, resulting in a decrease in the accuracy of the prediction.

In view of the shortcomings of the current short-term wind speed prediction model for time series

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problems, a few researchers proposed a long momentary memory (LSTM) calculation to settle the angle blast problem [6]. This paper proposes to optimizethe WOA calculation to streamline the hyperparameters of LSTM, track down reasonable hyperparameters, and contrast and the conventional LSTM model, to find a superior forecast model for wind speed.

2. WOA-LSTM neural network model

2.1. WOA whale optimization algorithm

The LSTM algorithmic program is a neural network algorithmic program with distinctive blessings for addressing statistic issues. This model improves the semipermanent dependence drawback in RNN and has higher prognosticative ability for unstable statistic information. However, its hyperparameters principally believe expertise or random choice, that isn't solely time-consuming, however additionally the chosen hyperparameters might not be best, leading to poor prediction results.

In 2016, MIRJALILI et al[9] proposed a brand new heuristic improvement algorithmic rule for simulating the searching behavior of humpback whales, known as whale optimisation algorithmic rule. The algorithmic rule was galvanized by the special hunting technique of humpback whales, a forage behavior referred to as bubble-net hunting. Humpback whales first create a large number of spiral bubbles around their prey to surround it, and then hunt it. Humpback whales have two predation strategies during the predation process, one is the contraction mechanism, and the other is the spiral update position strategy. Since it has multiple search strategies, it is easier to find the global optimal solution, which makes it better than traditional optimization algorithms.

The first predation strategy is that whales swim directly, individuals tend to the optimal individual position, and hunt within a certain spatial range. The shrinkage and surround formula is as follows:

$$\vec{D} = \left|\vec{C}\overrightarrow{X^*}(t) - X(t)\right| \tag{1}$$

$$\vec{X}(t+1) = \overrightarrow{X^*}(t) - \vec{A} \cdot \vec{D} \tag{2}$$

Where t represents the current iteration, $\overrightarrow{X^*}$ is the position vector of the best solution obtained so far, $\vec{X}$ is the position vector, $\vec{A}$ and $\vec{C}$ are the coefficient vectors, and the calculation formula is as follows:

$$\vec{A} = 2\vec{a}\vec{r} - \vec{a} \tag{3}$$

$$\vec{C} = 2\vec{r} \tag{4}$$

Where a is a constant, the value range is [0,2], in a decreasing form, the update method is $a = 2 - \frac{2t}{M}$, M is the maximum number of iterations; r is a random number on [0,1].

The second predation strategy is that whales use a spiral bubble net to drive away their prey, gradually narrowing their prey range while constantly updating their position. The purpose is to reduce the value of a in equation (3). In this process, the value range of A is [-a, a]. When the range changes, the value of a also changes accordingly. If A is within [-1,1], the whale will update its position by swimming in a spiral. The spiral formula is as follows:

$$\vec{X}(t+) = \overrightarrow{D^*} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(t) \tag{5}$$

$$\overrightarrow{D^*} = \left|\overrightarrow{X^*}(t) - \vec{X}(t)\right| \tag{6}$$

Where D^* is the distance between the current best position of the ith whale and the target prey; b is the logarithmic spiral shape constant; l is a random number on [-1,1].

Since the whale performs the bubble net contraction and the spiral movement to update the position at the same time during the hunting process, the probability of these two behaviors is set to be 1/2, where p is a random number in [0,1], and the formula is as follows:

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$$X(t+1) = \begin{cases} \overrightarrow{X^*}(t) - \vec{A} \cdot \vec{D} & p < 0.5 \\ \overrightarrow{D^*} \cdot e^{bl} \cdot \cos(2\pi l) + \overrightarrow{X^*}(t) & p > 0.5 \end{cases} \tag{7}$$

During the hunting process, in order to reach the global optimal position, the whale will continuously search in the area to update its position. The formula is as follows:

$$\vec{D} = \left| \vec{C}\overrightarrow{X_{rand}}(t) - X(t) \right| \tag{8}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}}(t) - \vec{A} \cdot \vec{D} \tag{9}$$

In the formula, $\overrightarrow{X_{rand}}$ is the position of the randomly selected whale.

2.2. WOA-LSTM neural network model

The training accuracy and training fitting speed of neural network models are closely related to the determination of initial parameters. In the setting of the learning rate, if the initial learning rate is too high, the deviation value will be too large, the fitting will not be possible, the learning rate will be too low, and the convergence speed will be slow. For training samples, setting acceptable weights will improve the accuracy of prediction.For the number of hidden layer nodes, setting too small may lead to unsuitability, and too many may lead to overfitting. Using the whale optimisation algorithmic rule, the neural network is trained by sorting out the optimum worth within the international space to work out the optimum optimum learning rate and therefore the number of neurons within the hidden layer. This paper adopts the mean square error (MSE) as the loss function of the whale algorithm. The MSE calculation formula is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2 \tag{10}$$

When the loss value reaches the lower limit set in advance, the optimized parameter value is obtained. To sum up, the algorithm flow of wind speed prediction model based on WOA optimization LSTM is shown in Figure 1.

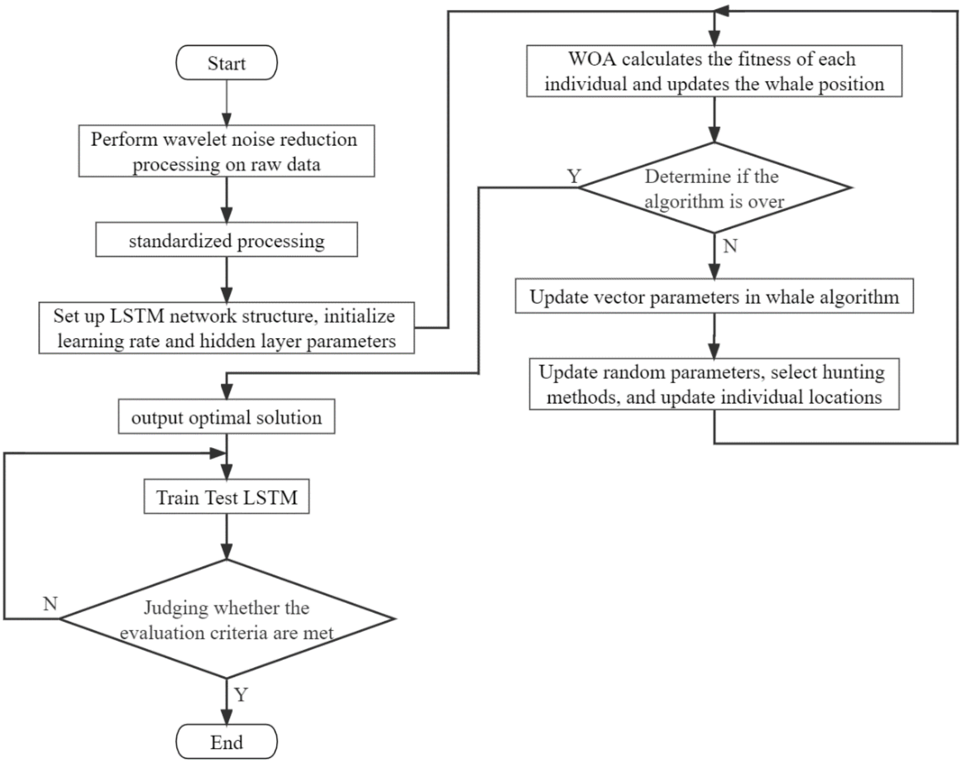

Figure 1: WOA-LSTM model flow chart

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3. Case Analysis

3.1. Data sources

The experimental data uses open source data released by the National Renewable Energy Laboratory in the United States, including the meteorological data recorded by the station from January 26, 2022 to February 26, 2022. Meteorological data were recorded throughout the day. After process, the sampling interval was twenty minutes, and a complete of 2304 sets of information were obtained.

3.2. Data preprocessing

3.2.1. Standardization

After identification, there are some outliers and null values in the original data, the normal distribution test is carried out on the overall data, and it is found that it does not obey the normal distribution, then the boxplot is used to determine the outliers. For the determined outliers and null values, the mean value of the two data before and after is corrected and filled. In addition, in order to eliminate the influence of the value difference between the data, prevent overfitting and improve generalization, it is necessary to adopt the min-max normalization method, normalize the original data through linear transformation, and map the data proportionally to [0, 1] interval, and facilitate comprehensive analysis to address the comparability of data. Among them, the min-max normalized transformation formula is:

$$x^* = \frac{x - min}{max - miin} \tag{11}$$

In formula (11), min is the minimum value of the data in the sample, and max is the maximum value of the data in the sample.

3.2.2. Wavelet Noise Reduction Processing

In order to reduce the data noise, speed up the model convergence speed, and improve the prediction accuracy, firstly, wavelet noise reduction processing should be carried out on the data. Wavelet sound decrease is basically accomplished by coming up with the information to the relating wavelet space. At the same time, according to the different properties and mechanisms of noise and the noise wavelet coefficients at different scales, it is necessary to select an appropriate threshold to make the wavelet coefficient greater than the threshold, and set the wavelet coefficient less than the threshold to Zero performs wavelet coefficient processing on the signal containing noise, and finally achieves the effect of overall noise reduction. Through repeated experiments, the wavelet basis is determined as a sym5 function with the characteristics of orthogonality, bi-orthogonality and tight support, and the threshold function adopts minimaxi. The result of wavelet noise reduction can be obtained from this, as shown in Figure 2.

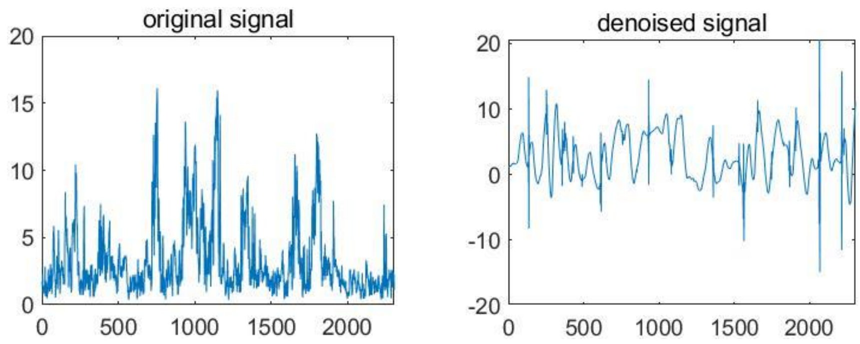

Figure 2: Schematic diagram of wavelet noise reduction results

3.3. Example calculation

In order to fully verify the effectiveness of WOA-LSTM model in wind speed prediction, a comparative experiment of WOA-LSTM and LSTM neural network prediction is designed. LSTM model are optimized using the whale improvement rule. within the iterative process, the WOA algorithmic rule unendingly adjusts the parameters of the initial LSTM model till it adjusts to the LSTM neural network model with a smaller error value.

3.3.1. Simulation of WOA-LSTM

The LSTM model optimized by the whale algorithm is used to predict the wind speed. First, the sample set is divided, and the first 2232 groups of data are used as the training set, and the last 72 groups of data are used as the test set; MSE is used as the fitness function of the whale algorithm. The population is selected as 5, the number of iterations is 100, the initial parameters of the hidden layer node n and the initial learning rate ε are in the range of [1, 200] and [0.001, 0.01].

After simulation training, the results of the WOA-LSTM model are consistent with the real wind speed in general trend. The goodness of fit (R^2) is 0.9445. When the wind speed fluctuation is tiny, the prediction curve of the model primarily coincides with the actual wind speed curve; once the wind speed fluctuation is giant, the prediction of the model can have a particular error.

Use the trained WOA-LSTM model to measure and calculate 72 sets of data in the test set, and compare them with the predicted values of the traditional LSTM model. The predicted comparison results are shown in Figure 3:

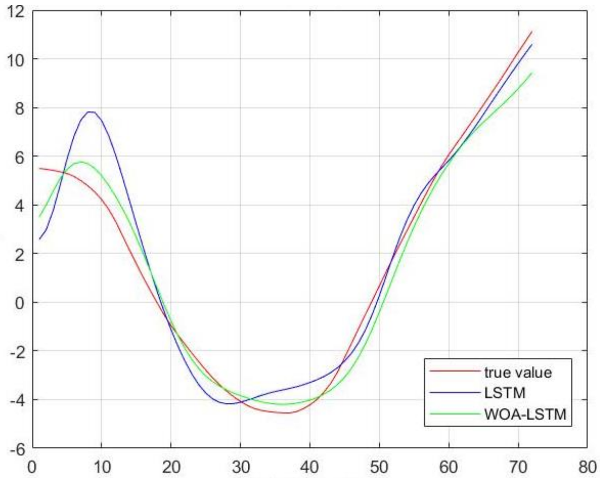

Figure 3: Prediction Comparison Chart

It can be seen from Figure 3 that the prediction results of the LSTM model and also the WOA-LSTM model ar typically consistent with the real wind speed. once the wind speed fluctuation is little, the prediction curves of the 2 models essentially coincide with the particular wind speed curve; once the wind speed fluctuation is giant, the prediction error of the WOA-LSTM model is smaller than that of the LSTM model. so as to additional intuitively mirror the prediction result of the WOA-LSTM model, the error analysis index was introduced to check the model error. The error analysis results ar shown in Table 1.

Table 1: Comparison of LSTM and WOA-LSTM

Model	RMSE	MAE	R^2
LSTM	1.2146	0.8735	0.9374
WOA-LSTM	0.78425	0.64235	0.97503

It can be seen from Table 1 that compared with the LSTM model, the WOA-LSTM model has a decrease of 0.43035 and 0.23115 in the indicators RMSE and MAE respectively, and an increase of 0.03763 in the indicator R^2. Therefore, compared with the LSTM model, the WOA-LSTM model projected during this paper contains a higher prediction and simulation result on wind speed, and is additional appropriate for short-run wind speed prediction.

4. Conclusion

Wind speed prediction is an important part of wind power generation, which has great economic value and social significance. In this paper, the wavelet denoising method is used to reduce the data noise, the whale optimization algorithm is used to optimize the LSTM network for short-term wind speed prediction, the learning rate of the LSTM model and the number of hidden layer nodes are optimized, and the best model is obtained for wind speed prediction. The simulation results show that, compared with LSTM neural network, WOA-LSTM has obvious advantages in the approximation ability and generalization performance of high-dimensional functions, and the training speed is also improved to a

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certain extent. The predicted result is closer to the actual wind speed value, and has higher prediction accuracy and higher engineering application value.

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