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A Short-Term Wind Power Prediction Model Based on Similar Historical Meteorological Data and WNN-HHO-BP Neural Network

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Abstract: *A short-term wind power prediction model based on similar historical meteorological data and WNN-HHO-BP neural network is proposed. Firstly, K-means clustering is used to classify the daily meteorological data into three classes as well as wavelet decomposition to decompose the data. Then, a BP neural network with Harris Hawk optimization algorithm and a BP neural network only are used for short-term prediction of wind power, and finally, the prediction results are derived and compared.*

Keywords: *wind power prediction, Harris Hawk algorithm, wavelet analysis, BP neural network, k-means clustering, meteorological data*

1. Introduction

As a renewable and clean energy source, wind energy has been developing rapidly all over the world in recent years, and with the development of new energy sources such as wind power and photovoltaic power generation in China, the problem of grid connection has gradually emerged. As the storage problem of electric energy has not been effectively solved, the problem of new energy grid connection is still in the state of exploration. Since wind power generation is intermittent and unstable, it has a huge impact on the grid after being connected to the grid, therefore, good prediction and regulation of wind power generation is an important condition for stable operation and effective consumption of wind power. Wind power prediction is necessary for both wind farms and power grids. It increases the power generation for wind farms and reduces the impact on the grid at the same time. The most important thing is the accuracy of power prediction. High precision power prediction can play a great positive role, while if the prediction accuracy is not enough it can also cause a lot of unnecessary losses.

Wind power is the process of converting the kinetic energy of wind into electricity, so the power of wind power is closely related to the weather conditions. The seasonal changes and the alternation of day and night can lead to similar weather conditions over a certain period of time. The output power of wind farms is close with the same or similar meteorological data, while different meteorological information will lead to different output power.

In recent years, scholars both at home and abroad have done a lot of work for wind power prediction, using statistical or learning methods to build models for wind power prediction using historical power time series. According to the different wind power prediction models can be divided into physical methods, statistical methods, learning methods, etc. Physical methods predict wind speed using numerical weather prediction (NWP) models based on information such as contours, roughness, obstacles, barometric pressure, and air temperature around the wind farm, and usually use the results as an inflow for other statistical models or for power prediction of new wind farms. Statistical and learning methods usually do not consider the physical process of wind speed variation, but rather establish a mapping relationship between historical statistics and wind farm output power for prediction. The prediction accuracy of these methods decreases with increasing prediction time, so they are mostly used for short-term predictions. Common statistical and learning methods include Kalman filtering, artificial neural network, wavelet discretization, support vector machine, probabilistic forecasting, chaotic forecasting, etc. in processing data, the literature [1-2] used wavelet decomposition in wind power prediction to effectively characterize the local features of wind farm output power time series.

In the short-term prediction of wind power, literature [3-9] constructed BP neural network and convolutional neural network wind power prediction models, for the problems of BP neural network's prediction accuracy is not ideal, easy to fall into local minima, etc., the convolutional neural network algorithm was established to make its stability improved; literature [4] proposed a mathematical

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morphology clustering and fruit fly optimization algorithm combined method for wind power short-term The algorithm has the characteristics of global optimization and fast optimization speed compared with the common algorithm. In addition, our scholars also proposed wind power prediction based on numerical weather forecasting, and the intelligent combination of wind power prediction using numerical weather forecasting and fuzzy clustering in the literature [5-10] used a single model prediction as the original result to obtain the optimal combination of prediction models suitable for their wind fields. And HHO is an optimization algorithm proposed in recent years, which has achieved more extensive use in wind power prediction. In the literature [6-7-8], HHO was used to optimize the BP neural network against the shortcomings of the traditional BP neural network, which in turn improved the correct rate of its network assignment recognition.

In this paper, we propose a short-term wind power prediction model based on historical similar meteorological data and WNN-HHO-BP neural network, firstly, we use K-Means clustering method to classify and use DBI metrics to check the validity of clustering, then we introduce wavelet decomposition reconstruction method to improve the accuracy, and finally, we apply the BP neural network with Harris Hawk optimization algorithm to get the best prediction model.

2. K-means clustering

2.1 Clustering principle

The k-means clustering algorithm (k-means clustering algorithm) is an iterative solution clustering analysis algorithm, which has become one of the most widely used clustering algorithms due to the advantages of simplicity and practicality and high efficiency. The current research on k-means clustering method has been relatively mature, and its steps are briefly described as the following four steps:

- Step 1: Select the initialized k samples as the initial clustering centers $a = a_1, a_2, \cdots a_k$;
- Step 2: for each sample in the dataset, calculate its distance to the kth cluster center and assign it to the class corresponding to the cluster center with the smallest distance;
- Step 3: For each category, recalculate its clustering center $a_j = \frac{1}{|c_i|}\sum_{x \in c_i} x$ (i.e., the center of mass of all samples belonging to the class);
- Step 4: Repeat the second and third operations until some abort condition (number of iterations, minimum error change, etc.) is reached.

2.2 Validity test

The Davidson Bouldin Index (DBI), also known as the classification fitness index, is a metric proposed by David L. Davis and Donald Bouldin to assess the merits of clustering algorithms. A larger index indicates greater clustering validity, and the index is calculated as follows:

$$DBI = \frac{1}{N}\sum_{i=1}^{N} \max_{j \neq i}\left(\frac{\overline{S_i} + \overline{S_j}}{\left\| w_i - w_j \right\|}\right) \tag{1}$$

Where S_i is the average distance of the data within the class to the cluster center of mass, representing the dispersion of each time series in cluster class i; $\left\| w_i - w_j \right\|$ is the distance between cluster class i and cluster class j.

3. Harris Hawk optimization algorithm

Harris Hawks Optimization (HHO) is an optimization algorithm proposed by Heidari et al. scholars from Tehran University in 2019, which has the advantages of wide global search range and fast convergence. The algorithm is mainly inspired by the unique and efficient cooperation, pursuit, and predation behaviors of Harris's hawks in the American region in nature, and is divided into three main steps: the exploration phase, the transition from exploration to exploitation, and the siege phase. The Exploitation phase is a three-step process.

ISSN 2616-5775 Vol. 6, Issue 9: 63-71, DOI: 10.25236/AJCIS.2023.060910

3.1 Target finding

Harris's hawks use their senses to find the target at a random perching location and decide on different strategies to wait for prey detection depending on the situation. Assuming that the Harris hawk has an equal chance of each perching strategy within an area q, and considering the locations of the other hawks in the team and the locations of the prey, the following equation can be used to represent its two hunting strategies:

$$P(t+1)=\begin{cases} PP_{rand}(t)-r_1\left|PP_{rand}(t)-2r_2P(t)\right| & q\geq 0.5 \\ \left(P_{prey}(t)-PP_{aver}(t)\right)-r_3\left(L_{low}+r_4(L_{upper}-L_{low}\right) & q<0.5 \end{cases} \tag{2}$$

Eq:P(t+1) is the position of the eagle at the next moment,$P_{prey}(t)$is the location of the prey ,P(t) is the current position vector of the eagle,r_1,r_2,r_3,$r_4$and q is a random number in the interval (0,1), which is updated at each iteration. L_{low} and L_{upper} Indicates the upper and lower bounds of the variable,$PP_{rand}(t)$is a random selection of eagles from the current population,$PP_{aver}(t)$is the average position in the current eagle population, which can be calculated from equation (2):

$$PP_{aver}(t)=\frac{1}{N}\sum_{i=1}^{N}P_i(t) \tag{3}$$

where N is the total number of eagles in the population,$P_i(t)$indicates the position of each eagle in the population.

3.2 Transition process

The transition process is a transfer from a search process to a siege hunting process, where the energy of the prey is greatly reduced during the prey escape process, which can be expressed as:

$$E=2E_0(1-\frac{t}{T}) \tag{4}$$

Where E is the prey escape energy factor, E_0 is a random number in the (-1,1) interval,$t-1$ is the number of completed iterations (i.e., t denotes the number of current iterations), and T is the total number of iterations.

3.3 Siege phase

In this phase, the Harris hawk performs a siege by the best target prey found in the first phase, and the prey tries to escape from the danger. Therefore, different chasing styles occur during the actual hunting process. Based on the prey's escape behavior and Harris Hawk's chasing strategy, four typical strategies are proposed in HHO to simulate the attack phase.

1) Soft Surround

This happens whenr≥0.5and|E|≥0.5. The prey still has enough energy to try to deceive the hawk by some random misleading movements (e.g., jumping) during the escape process. In these attempts, the Harris hawk will choose to surround it slowly, allowing the prey to gradually run out of energy before making a surprise attack. The process can be expressed by the following equation:

$$P(t+1)=\Delta P(t)-E\left|JP_{prey}(t)-P(t)\right| \tag{5}$$

$$\Delta P(t)=P_{prey}(t)-P(t) \tag{6}$$

$$J=2(1-r_5) \tag{7}$$

where $\Delta P(t)$is the difference between the position of the prey in the tth iteration and the current position, r5 is a random number in the (0,1) interval, and J denotes the random jump intensity of the prey during the whole escape process.

2) Hard Surround

When r≥0.5and|E|<0.5, the prey energy is almost depleted and the Harris Hawk eventually makes a

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surprise attack. In this case, the following equation can be used to update:

$$P(t+1) = P_{prey}(t) - E\left|\Delta P(t)\right| \tag{8}$$

3) Soft envelope for progressive high-speed dive

When|E|≥0.5but r<0.5, the prey has enough energy to escape the hunter's siege, and a soft siege is still constructed before the siege, and the algorithm uses an LF-based approach in this phase. This siege strategy can then be represented by the following set of equations:

$$P(x+1) = \begin{cases} A_1 & LF(A_1) < LF(P(t)) \\ A_2 & LF(A_2) < LF(P(t)) \end{cases} \tag{9}$$

$$A_1 = P_{prey}(t) - E\left|JP_{prey}(t) - P(t)\right| \tag{10}$$

$$A_2 = A_1 + S \times LF(M) \tag{11}$$

where M is the dimensionality of the objective function and S is an M-dimensional random vector.

$$LF(x) = 0.01 \times \frac{\mu \times \sigma}{\left|v\right|^{\frac{1}{\beta}}} \tag{12}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\frac{\pi\beta}{2})}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\frac{\beta-1}{2}}} \right)^{\frac{1}{\beta}} \tag{13}$$

Where v, μ is a random value in the (0, 1) interval of 1.5.

4) Hard envelope for progressive high-speed dive

When|E|<0.5andr<0.5, the prey did not have enough energy to escape and built a hard enclosure to capture and kill the prey before encircling it. Harris hawks try to minimize the distance between their average position and the fleeing prey. Therefore, the following rules were enforced in the hard siege condition:

$$P(x+1) = \begin{cases} A_1 & LF(A_1) < LF(P(t)) \\ A_2 & LF(A_2) < LF(P(t)) \end{cases} \tag{14}$$

condition:

$$A_1 = P_{prey}(t) - E\left|JP_{prey}(t) - PP_{aver}(t)\right| \tag{15}$$

$$A_2 = A_1 + S \times LF(M) \tag{16}$$

4. Multi-resolution wavelet analysis

4.1 Wavelet transform principle

Wavelet transform, one of the outstanding representatives of modern mathematical research results, is a time-frequency domain analysis method with good localization properties in both time and frequency domains compared with Fourier transform. Wavelet transform is able to decompose various interwoven signals of different frequency mixtures into blocks of information in different frequency bands. Suppose a function $\psi(t) \in L^2(R)$. Among them $L^2(R)$ denotes the square-producible real number space with Fourier transform $\hat{\psi}(\omega)$ .When $\hat{\psi}(\omega)$ Meet the conditions. That is, when equation (12) is said $\psi(t)$ is a fundamental wavelet or mother wavelet.

$$C_\psi = \int_R \frac{|\hat{\psi}(\omega)|^2}{|\omega|} \mathrm{d}\omega < \infty \tag{17}$$

Arbitrary functions $f(a) \in L^2(R)$ of the continuous wavelet transform can be expressed as:

$$W_f(a,b) = \frac{1}{\sqrt{a}} \int_R f(t) \psi(\frac{t-b}{a}) dt \tag{18}$$

For equation (14), the reformulation is expressed as:

$$f(t) = \frac{1}{C_\psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \frac{1}{a^2} W_f(a,b) \psi(\frac{t-b}{a}) \mathrm{d}a \mathrm{d}b \tag{19}$$

Where, a and b are the scale factor and translation factor, respectively.

4.2 Multi-resolution analysis

The so-called multi-resolution analysis refers to the coarse and fine observation of the target at each scale as the scale changes from large to small, which can be defined as:

$$S_0 = S_1 \oplus D_1 = S_1 \oplus D_2 \oplus D_1 \tag{20}$$

where S_0 is the zero-scale space, Sj (j=1,2...) is the scale space with scale j; Dj (j=1,2...) is the wavelet space with scale j.

For any function $f(t) \in V_0$, it can be decomposed into a detail part D1 and a large-scale generalized part S1, and then the large-scale generalized part S1 is further decomposed. This is repeated to obtain the generalized and detailed parts at any scale. Then, for any set scale J, we have:

$$f(t) = \sum_{j=-\infty}^{J} \sum_{k=-\infty}^{\infty} d_{j,k} \psi_{j,k}(t) + \sum_{k=-\infty}^{\infty} c_{j,k} \psi_{j,k}(t) \tag{21}$$

where the first term is the reconstructed sequence of each detail, and the second term is the reconstructed probabilistic sequence, $d_{j,k} = [f(t), \psi_{j,k}(t)]$ are the wavelet expansion coefficients, $C_{j,k} = [f(t), \phi_{j,k}(t)]$ is the scale expansion factor.

5. Model Building and Solution Methods

5.1 Prediction model establishment

Artificial neural networks show good intelligent characteristics due to good fault tolerance, convenient and rapid data processing, and the ability to learn independently, which are widely used in fields including automatic control, pattern recognition, data prediction, etc. In this paper, we choose BP neural network to establish the wind power prediction model, the network will continuously pass information forward through the network, and the final error will be propagated forward, and this process will be repeated until the error reaches the acceptable range, so as to establish the mapping relationship between input and output, and its basic principle is shown in Figure 1.

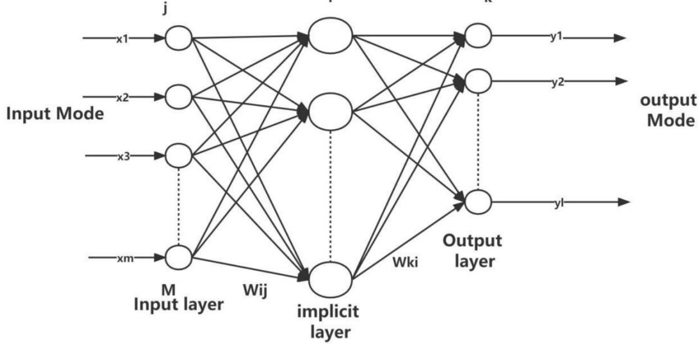


Figure 1: BP neural network structure diagram

ISSN 2616-5775 Vol. 6, Issue 9: 63-71, DOI: 10.25236/AJCIS.2023.060910

Since meteorological data contain many attribute values leading to high dimensionality, in order to obtain several attributes of meteorological data that have a strong influence on wind power, correlation coefficients are calculated according to equation (22), so as to find out the strong correlation factors that affect wind power output. Then based on this, K-Means clustering method is used for classification and the validity of clustering is checked using DBI index.

$$r_{x,y} = \frac{\sum (x-\bar{x})(y-\bar{y})}{\sqrt{\sum (x-\bar{x})^2 \sum (y-\bar{y})^2}} \tag{22}$$

To address the problem that the traditional BP neural network relies on the initial weights and thresholds during the learning process and cannot be obtained accurately, this paper uses the Harris Hawk algorithm (HHO) to optimize the weights and thresholds of the BP neural network (as shown in Figure 2). In addition, we also introduce the wavelet decomposition reconstruction to improve the accuracy. In this paper, we choose db5 to decompose the training set data into probabilistic and detailed signals, which is considered that dbN wavelets have high regularity and can better reflect the time-domain characteristics of data signals. The decomposition results of each decomposition of the training set are input into the HHO-BP neural network for learning training, and finally the component data of the day to be predicted are input for prediction and their prediction results are summed to obtain the final prediction results.

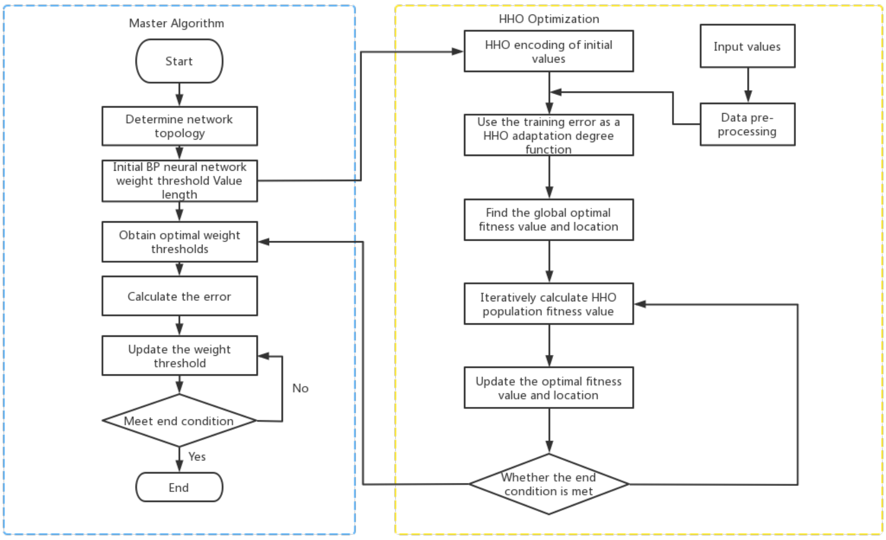


Figure 2: HHO-BP neural network algorithm solution model

5.2 Evaluation metrics

The power prediction model evaluation metrics can quantify the prediction model error characteristics. In this paper, we use three metrics for evaluation: normalized absolute error percentage, pass rate, and accuracy rate.

1) Normalized absolute error percentage

$$NMAE = \frac{1}{N}\left(\left|\frac{P_{a.i} - P_{p.i}}{P_{a.i}}\right|\right) \times 100\% \tag{23}$$

where N is the length of the data set for the day to be predicted, $P_{a.i}$ is the actual value of wind power, and $P_{p.i}$ is the predicted value of wind power.

2) Accuracy rate

ISSN 2616-5775 Vol. 6, Issue 9: 63-71, DOI: 10.25236/AJCIS.2023.060910

$$AR=\left(1-\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{P_{a.i}-P_{p.i}}{Cap}\right)^{2}}\right)\times 100\% \tag{24}$$

Where, Cap is the installed capacity of wind turbine.

3) Passing Rate

$$QR=\frac{1}{N}\sum_{k=1}^{N}B_k\times 100\% \tag{25}$$

where

$$\begin{cases}\left(1-\dfrac{P_{a.i}-P_{p.i}}{Cap}\right)\times 100\%\geq 75\% \quad B_k=1\\ \left(1-\dfrac{P_{a.i}-P_{p.i}}{Cap}\right)\times 100\%<75\% \quad B_k=0\end{cases} \tag{26}$$

6. Calculation simulation and result analysis

6.1 Raw data

The model is used to conduct simulation experiments on data from a wind farm in the Inner Mongolia region of northern China.

6.2 Analysis of historical meteorological data

6.2.1 Correlation analysis

Table 1: Relevance Ranking

wind speed of 70m (m/s)	wind speed of 50m (m/s)	wind speed of 10m (m/s)	wind direction of 10m(°)	wind speed of 30m (m/s)	Humidity 1%
0.60047555	0.60047553	0.59044024	0.58355976	0.57655170	0.56666374
wind direction of 50m (°)	Temperature 0.01℃	wind direction of 70m (°)	wind direction of 30m (°)	Airpressure 0.1hPa	
0.49900716	0.48591741	0.48511187	0.48455778	0.46015842	

According to the order of correlations in Table 1, it can be seen that the strongest correlations are found in the three cases of 70m 0.01m/s 50m 0.01m/s 10m 0.01m/s, so the first three categories are selected for analysis.

6.2.2 Analysis of clustering results

Table 2: Cluster Analysis

Clustering	1	23
	2	2
	3	36
Effective		61
Missing		0

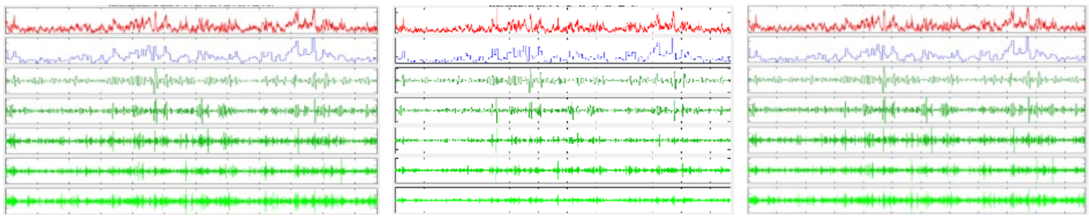
According to the clustering by SPSS in Table 2, it is known that out of 61 days from March to April, 23 days belong to category 1, 2 days belong to category 2, and 36 days belong to category 3; therefore, category 3 is used for wind power prediction.

6.3 Prediction results and analysis

6.3.1 Wavelet decomposition

According to the strong correlation analysis, the top three strong correlation data are wavelet decomposed.

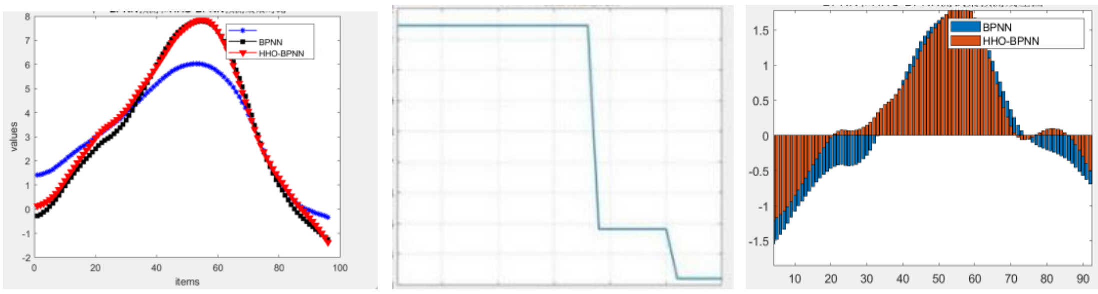
ISSN 2616-5775 Vol. 6, Issue 9: 63-71, DOI: 10.25236/AJCIS.2023.060910



(a)10mWavelet decomposition *(b)50mWavelet decomposition* *(c)70mWavelet decomposition*

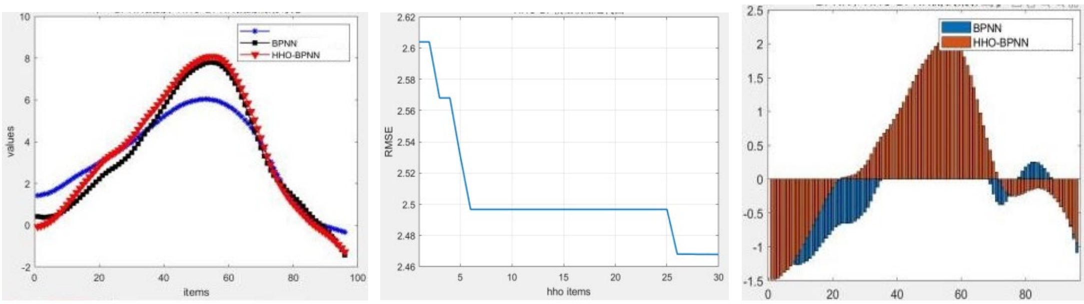
Figure 3: Wavelet decomposition

6.3.2 Predictive Analysis



(a)Effect comparison chart *(b)Iteration Chart* *(c)Residual Plot*

Figure 4: Ka Predictive Analysis



(a)Effect comparison chart *(b)Iteration Chart* *(c)Residual Plot*

Figure 5: Kd Predictive Analysis

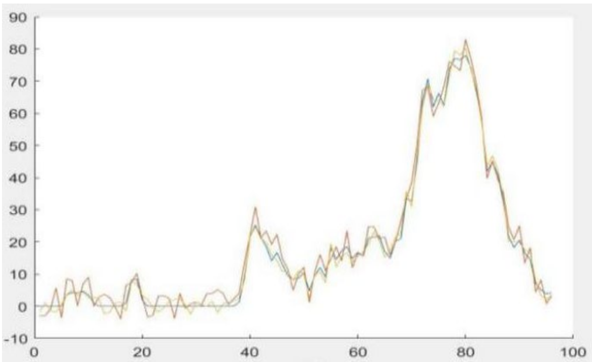


Figure 6: Contrast Chart

Table 3: Evaluation index value

	NMAE	AR	QR
BP	0.140573693	96.934%	91.667%
HHO-BP	0.071251041	98.305%	99.999%

As shown in Figs. 3,4,5,6, the predicted values after HHO-BP optimization are closer to the actual values on April 1 than those predicted by BP neural network only, and further calculations lead to Table 3. By comparing the data, it can be observed that the wind power short-term prediction scheme based on similar historical weather data and WNN-HHO-BP neural network has higher accuracy values than the scheme predicted by BP neural network only. Therefore, it can be known that the wind power short-term

ISSN 2616-5775 Vol. 6, Issue 9: 63-71, DOI: 10.25236/AJCIS.2023.060910

forecasting scheme based on similar historical meteorological data and WNN-HHO-BP neural network is better than the scheme using only BP neural network forecasting.

7. Conclusions

From the comparison of normalized absolute error percentages, it can be obtained that the error percentage of the prediction analysis using HHO-BP is lower than that of the data predicted by BP neural network only; and the accuracy of the data out of HHO-BP is higher than that of the BP neural network prediction; and the passing rate of HHO-BP is higher than that of the BP neural network prediction only. Therefore, the wind power short-term prediction model based on similar historical meteorological data and WNN-HHO-BP neural network has better prediction ability compared with BP neural network and can be applied to wind power prediction.

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