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Assessment of Offshore Wind Resources, Based on Improved Particle Swarm Optimization

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Abstract: It is crucial to understand the characteristics of wind resources and optimize wind resources in the area that is being considered for offshore wind farm development. Based on the improved particle swarm optimization (IPSO) and the back propagation neural network (BPNN), the IPSO-BP hybrid intelligent algorithm model was established. The assessment of wind resource characteristics in the eastern waters of China, including average wind speed, extreme wind speed, wind power density, effective wind energy hours and wind direction distribution were all calculated. Additionally, the wind speed throughout the different years in Luchao Port, a famous seaport in China, was predicted. The results revealed that the wind power density is approximately 300 W/m^2 all year round and that the effective wind energy hours take up about 92% per hour. It was also identified that the wind direction distribution is stable in Luchao Port, implying that there are better wind energy resource reserves in this region. The IPSO-BP model has a strong tracking performance for wind speed changes, and can accurately predict the wind speed change in a short period. In addition, the prediction error of the IPSO-BP model is smaller when the time of training data is closer to the target one, and it can be controlled within a 5% range.

Keywords: wind resource assessment; offshore wind farm; improved particle swarm optimization; wind power density; wind speed prediction

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1. Introduction

Due to environmental issues and the need for energy supply security, renewable energy has been listed in the world's agenda [1]. Notably, wind energy is one of the most cost-effective renewable energy sources in areas with abundant wind resources, and it has been widely used worldwide [2]. Guo et al. [3] analyzed the wind energy resource utilization in the context of the coordinated development in the Beijing-Tianjin-Hebei region of China. It should be stressed that the problem of wind curtailment is serious in China as it not only restricts the development of renewable energy, but also brings economic losses to enterprises and society. Tran et al. [4] studied the wind energy resources of Phuquoc Island in Vietnam, and proved that wind energy can be used as an energy source for about 300,000 rural non-electric households. So far, China has the largest wind power generation capacity worldwide, followed by the United States. Yet, China's utilization of this installed capacity trails that of the U.S by a significant gap [5]. Soder et al. [6] predicted that wind energy will generate 20% of the electricity in the U.S by 2030. However, the contribution of wind power to cover the electricity demand is less certain than conventional power sources. Therefore, the capacity value of wind power is smaller than that of conventional plants. With the global carbon reduction consensus reached and China's '3060' double carbon target proposed, offshore wind power has become the face of the technology frontier and is one of the important development directions in the field of renewable energy [7]. Wind energy is an environment-friendly clean energy, and in the feasibility study stage of the construction of offshore wind farms, a reliable wind resource assessment of the proposed area is required [8]. Due to the randomness, volatility and low energy density of wind speed, which leads to the low reliability of the power system operation, the accuracy of wind speed prediction is critical. Accurate wind speed prediction ensures the safe operation of wind farms and the flexible dispatch of power grids connected with new energy sources. Meanwhile, it is also crucial when performing maintenance scheduling and evaluation of the feasibility of building a wind farm in a particular area.

There are two main methods for evaluating wind resources at present: an evaluation, based on the observation of the historical data from weather stations or wind towers, and a numerical simulation of the wind energy resource evaluation [9]. Nevertheless, these methods have strong limitations, complexities and a low accuracy. Due to its low resolution, the first method can only reflect the distribution of wind energy resources in a region in a macroscopic manner, and cannot accurately quantify the wind energy reserves. For the accurate wind energy resource assessment, numerical simulation techniques still have to be applied. A probability distribution model, among which the Weibull distribution model is the most suitable method for wind energy resources evaluation, is used to evaluate the wind energy resources. Yu et al. [10] proposed to use a two-parameter Weibull model to evaluate the wind resources in the Bohai Sea of China, based on the Nakagami and Rician distributions. Compared with the two-parameter Weibull distribution, the three-parameter one has better fitting with good results in the no-wind zone or at the low wind speed [11]. However, when there are more parameters, and when the operation speed is slower, the timeliness cannot meet the requirements [12].

To improve the fitness and the accuracy of the probability distribution function, relevant researchers employed intelligent algorithms to evaluate the wind resources. A forecasting method for wind and solar power generation, based on a machine learning algorithm, was proposed [13]. Acikgoz et al. [14] modified the extreme learning machine, but in terms of two, three and 4 h ahead, the wind power forecast performances were quite different. Meanwhile, Eum et al. [15] applied numerical simulations to estimate the wind resources near Jeju Island in China, but the estimated results were significantly affected by the choice of the data set. This is because the study only focused on determining the most appropriate wind field for hindcast simulations. Abedinia et al. [16] put forward a comprehensive prediction method, based on the improved wavelet transform. Al-Shaikhi et al. [17] proposed a hybrid model to estimate the wind speed at different heights, based on the measurements at lower heights using the particle swarm optimization (PSO) and long short-term memory (LSTM). Mohandes et al. [18] analyzed the predictability of wind speed with heights and employed the recurrent neural network (RNN) model for predicting the wind speed 12 h ahead of time, using 48 previous hourly values. Salman et al. [19] put forward a short-term, multi-dimensional prediction of the wind speed, based on LSTM. However, the accuracy of LSTM may be compromised with the inclusion of exogenous features in the training sets and the duration of the prediction ahead. Back propagation (BP) [20–23] and improved particle swarm optimization (IPSO) [24–27] have been widely used in the wind energy resource evaluation, but the BP neural network (NN) has the shortcomings of a local minimization and a slow convergence speed. Combining the BPNN model with the PSO algorithm can effectively avoid the local optimal problem [28,29]. The adaptive PSO can combine the advantages of different training algorithms, to evaluate the wind resources, has stronger learning capabilities, global search capabilities, and can avoid the shortcomings of the BPNN from falling into the local optimum [30]. The wind resource assessment method, based on the hybrid NN not only comprehensively considers the geographical location information around the wind farm, but also improves the accuracy of wind resource assessment [31]. Through using the PSO algorithm to optimize the BPNN, this can accurately and effectively identify the type of wind turbine gearbox fault [32].

In summary, the combination of the PSO algorithm and the BPNN is a theoretically feasible modelling method. However, the hybrid model, based on the above two algorithms, is less used in the wind resource assessment. Therefore, an IPSO-BP hybrid intelligent algorithm prediction model is established, based on the IPSO and BPNN in this study. The number of nodes in the input and output layers of the BP module is determined by the wind measurement data and the prediction accuracy. In addition, the global optimal solution is obtained by the IPSO, so as to evaluate the wind resources in the Luchao Port area off the coast of China. Finally, a more practical wind speed variation law is obtained. This provides significant guidelines to help engineers make decisions in designing and manufacturing wind farms, from the assessment of offshore wind resources.

2. Hybrid Intelligent Algorithm Modeling

2.1. Assessment Parameters of the Wind Resources

Wind power density, also known as wind energy one, refers to the wind energy that the air flow passes through per unit of the cross-sectional area in a unit time [33,34]. The calculation formula of the average wind power density D_{wp} is:

$$D_{wp} = \frac{1}{2}\rho v^3 \tag{1}$$

$$\rho = \frac{1.276}{1 + 0.00366t} \times \frac{p - 0.378e}{1000} \tag{2}$$

where ρ is the air density, kg/m^3; t is the average temperature, °C; e is the average steam pressure, hPa; v is the instantaneous wind speed, m/s. The calculated air density is 1.231 kg/m^3. The effective wind speed refers to when the wind speed reaches the point where the turbine can be started until it is cut off due to the strong winds. In general, the effective wind speed in research and production is considered within the range of 3~25 m/s [35]. Analyzing the characteristics of the effective wind speed can provide reference for the renewable energy development and wind farm design. Due to the different wind speeds and wind turbines in different regions, there are different divisions of the effective wind speed range [36].

Wind speed is involved in wind resource assessment parameters. Therefore, how to accurately establish an intelligent optimization model to effectively predict the offshore wind speed is the key.

2.2. BPNN Model

The BP algorithm of the multilayer neural network is essentially a mathematical model, that simulates the structure of the human brain, connects a large number of neurons together and weighs them, and the basic structure is shown in Figure 1.

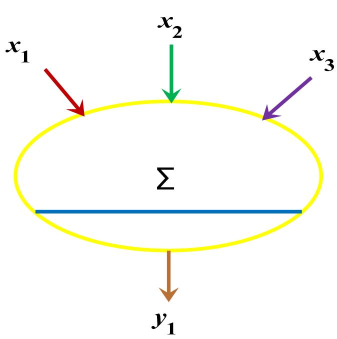


Figure 1. Basic structure of the artificial neural network.

The variables x_i and y_i are the input and output signals, respectively, in Figure 1, and the transformation of the j-th neuron in the above model can be described as:

$$y_j = f\left(\sum_i w_{ij}x_i - \theta_j\right) \quad (3)$$

where w_{ij} is the connection weight; θ_j is the offset signal, which used to adjust the excitation threshold of neurons.

2.3. PSO Model

The PSO algorithm, as a simple and effective optimization algorithm, is applied to the theoretical model of the wind resource assessment, and it converts birds into theoretical particles and expands from the two-dimensional space to the three-dimensional one. The idea behind this algorithm comes from the group thinking reflected in the foraging process of birds. In general, individual organisms do not coordinate themselves. However, whole groups of organisms often exhibit the ability to deal with complex problems, known as groupthink.

The position of particles i in the three-dimensional space is recorded as a vector $X_i = (x_1, x_2, \cdots, x_d)$, and the flight speed is denoted as a vector $V_i = (v_1, v_2, \cdots, v_d)$. The particle searches at a variable speed in the solution set, and the speed is adjusted in real time, according to its own search experience and other particles' experiences. The flow chart is illustrated in Figure 2.

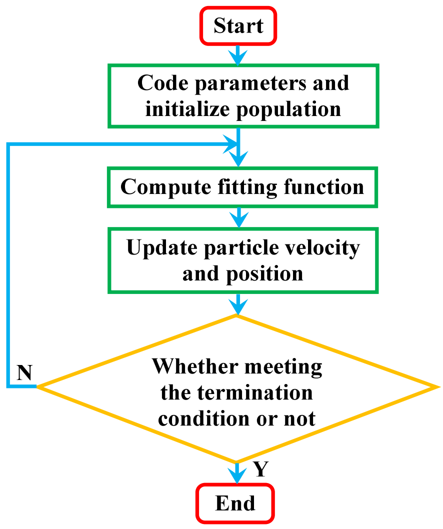


Figure 2. Flow chart of the PSO algorithm.

Although the PSO algorithm is simple and efficient, it is likely to fall into the problem of the local extremum and strong dependence of the optimization performance on the value of the algorithm parameters [37]. Therefore, in order to solve the above two problems and improve the accuracy and the reliability of the PSO algorithm for the wind resource assessment, a prediction model of a hybrid intelligent algorithm, combined with the PSO algorithm and artificial neural network model is applied in this study.

2.4. IPSO-BP Prediction Model

The IPSO-BP hybrid intelligent algorithm model encodes the parameters, initializes the population, and calculates the initial global extremum, and then decodes and calculates the fitness function. Finally, if the calculation result meets the end condition, the network parameters are output. If not, one can update the particle speed and position, control the random variation of the genes, update the extreme value, and return to decoding. The specific prediction process is displayed in Figure 3.

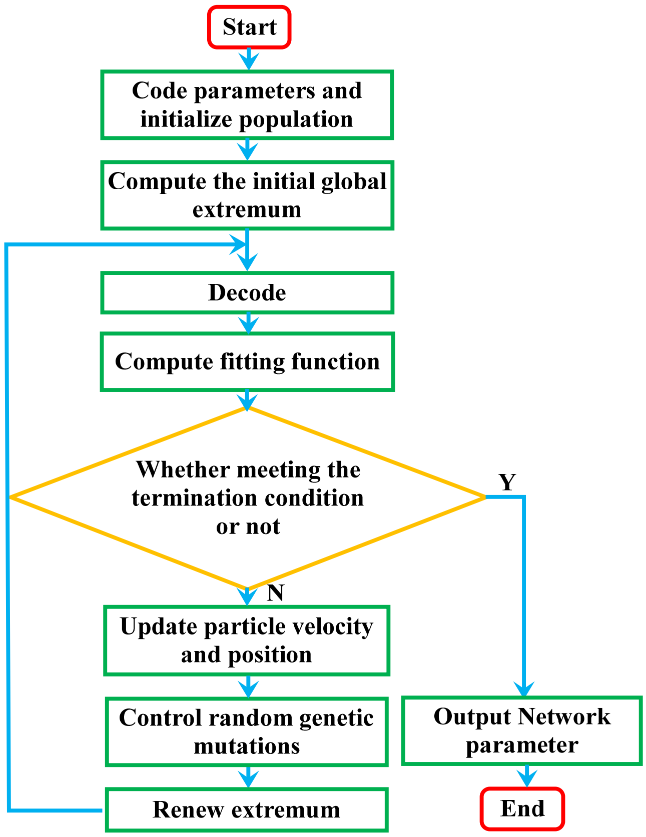


Figure 3. Flow chart of the IPSO-BP model.

The IPSO-BP model improves the speed update formula on the original basis, and it can be written as:

$$V_{id}(t+1) = wV_{id}(t) + c_1r_1[P_{id}(t) - X_{id}(t)] + c_2r_2[P_{id} - X_{id}(t)] \quad (4)$$

where w is the inertia weight; c_1, c_2 are the learning factors; r_1, r_2 are the random numbers; $P_{id}(t)$ is the individual extremum; P_{id} is the global extremum; $X_{id}(t)$ is the weight vector.

In Equation (4), first and foremost, the first term is related to the particle's last modified increment, which can balance the global search and the local search. In addition, the second term is the part that the particle learns from its own optimal value, called the self-learning part, which can keep particles with a strong global search ability and avoid falling into the local minima. Finally, the third term is the part that the particles learn from the global optimal value, called the mutual learning part, which can speed up the search.

The proposed algorithm tends to solve the global search problem when the inertia weight is high and the particle velocity is fast. When the weight value is small, the speed of the particles is low, which is conducive to the local search. When evaluating the wind resources of the wind farms in this study, the fitting accuracy of the overall data needs to be considered, so the inertia weight w is set as a large constant.

2.5. Accuracy Assessment Method

In order to assess the accuracy of the IPSO-BP model in predicting the wind resources of wind farms, the assessment indexes, such as the absolute error (AE), mean square error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE) and goodness of fit (R), are introduced, and the quantitative statistics and analysis of the wind speed simulation effect is carried out.

The AE is defined as:

$$\mathrm{AE} = |y_i - \hat{y}| \quad (5)$$

where y_i indicates the predicted value; $\hat{y}$ is the measured value.

The MSE is defined as:

$$\text{MSE} = \sum_{i=1}^{N} (y_i - \hat{y})^2 / N \tag{6}$$

where N is the sample size.

The formulas of RMSE, MAPE and R are respectively expressed as:

$$\text{RMSE} = \sqrt{\sum_{i=1}^{N} (y_i - \hat{y})^2 / N} \tag{7}$$

$$\text{MAPE} = \frac{|y_i - \hat{y}|}{\hat{y}} \times 100\% \tag{8}$$

$$\text{R} = \sum_{N}^{i} (y_i - \overline{y}) / \sqrt{\sum_{N}^{i} (y_i - \overline{y})^2} \tag{9}$$

where $\overline{y}$ is the average value.

3. Performance Analysis of the Offshore Wind Resources in the Luchao Port Area

Located on the west coast of the Pacific Ocean, Luchao Port is at the intersection of the East Sea and Hangzhou Bay in China. Sailing southward, one can reach Putuo Mountain, Shengsi Mountain, Dayang and Xiaoyang Mountains, etc. Furthermore, sailing northward, one can arrive at the Yangtze River estuary. Therefore, Luchao Port is close to the sea on three sides and has rich wind resources. Its regional profile is shown in Figure 4.

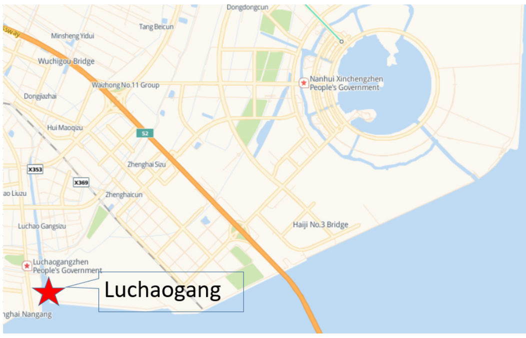
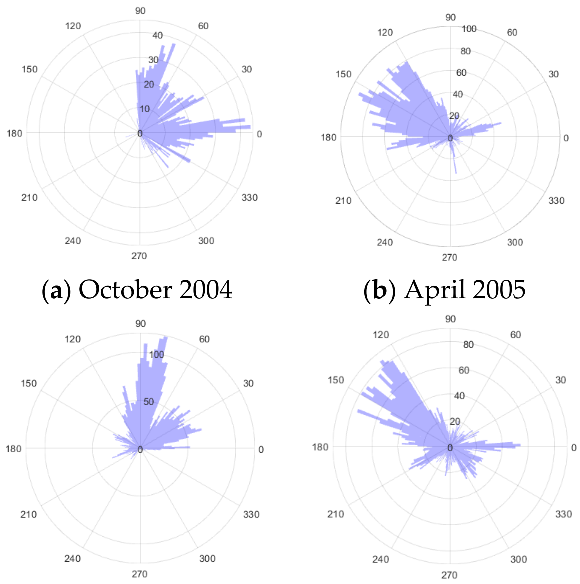


Figure 4. Geomorphic map of Luchao Port.

3.1. Wind Direction Rose Map

The wind directions in the different months and years are recorded at 10-min intervals. What is more, the wind directions measured in October 2004, April 2005, October 2005 and April 2006 are shown in Figure 5.

From the perspective of the wind direction distribution: the main wind direction in October is northeast, as shown in Figure 5a,c, while the one in April is northwest, as shown in Figure 5b,d. In October 2004, there were two prevailing wind directions, the easterly and northerly winds. In April 2005, there was a prevailing wind direction north-westerly. In October 2005, the prevailing wind direction was north by east. In April 2006, its prevailing wind direction was northwesterly. It can be seen that the wind direction distribution in Luchao Port is relatively stable at the same time every year, which has a reference value for the design of the impeller orientation and yaw range in this region.



(**a**) October 2004 (**b**) April 2005

(**c**) October 2005 (**d**) April 2006

Figure 5. Wind direction rose map at different time periods.

3.2. Wind Energy Parameter Analysis

The wind speed data of six time periods, including 1 October, 2 October, 27 October in 2005 and 1 April, 8 April and 20 April in 2006, are separately selected in this study for research. The corresponding wind power density is calculated, according to Equation (1) and listed in Tables 1 and 2, respectively. It is not difficult to know that to obtain following information:

(1) The monthly average wind speed in Luchao Port is generally about 6~7 m/s, but the maximum daily one can exceed 10 m/s;

(2) The standard deviation of the monthly wind speed is maintained at about 3 m/s, and that of the short-term wind speed changes from 1 m/s to 3 m/s;

(3) The monthly wind power density is about 300 W/m^2, but the instantaneous one is also less than 100 W/m^2;

(4) The effective hours of wind energy in Luchao Port account for about 92% of the whole month.

Table 1. Wind parameters of each month.

Time	Average	Standard Deviation of the Wind Speed	Wind Power Density	Percentage of Wind Energy Effective Hours
October 2004	6.59	2.44	253.28	92.80%
October 2005	6.46	2.56	249.19	92.95%
April 2006	7.41	3.49	425.45	91.42%

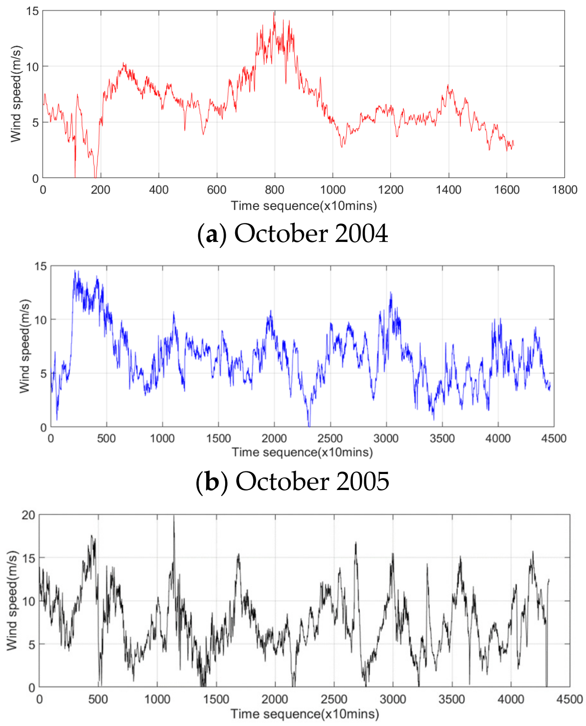
Table 2. Wind parameters of each sample group.

Time	Average	Standard Deviation of the Wind Speed	Wind Power Density
1 October 2005	4.01	1.35	35.95
2 October 2005	12.27	1.90	828.68
27 October 2005	4.34	1.08	41.21
1 April 2006	8.84	1.67	247.35
8 April 2006	11.00	3.18	699.10
20 April 2006	3.55	1.10	56.50

4. Prediction Results and Precision Analysis of the Wind Speed

4.1. Measuring Wind Data

The measuring wind tower measures the long-term wind resource data in Luchao Port at 10-min intervals. Figure 6a–c exhibits the wind speed data in late October 2004, October 2005 and April 2006, respectively, with the geographic coordinates (30°51.696′ N, 121°55.001′ E).



(**a**) October 2004

(**b**) October 2005

(**c**) April 2006

Figure 6. Time series distribution of the wind speed in different periods.

It is found that, by comparing with the time series distribution of the wind speed in Figure 6a–c, that the wind speed in October 2004 was relatively stable, and only once, the wind speed is close to 15 m/s. In October 2005, the wind speed rose sharply at the initial stage, then gradually decreased and the fluctuation tended to be stable. In addition, the wind speed in October 2006 fluctuated more frequently than the ones in 2004 and 2005, and there were seven times in both years, when it exceeded 15 m/s or equals to 0 m/s.

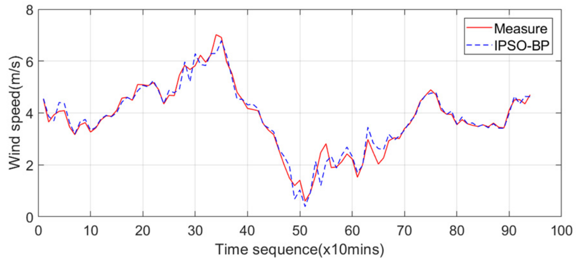
Based on the above wind speed data, the IPSO-BP hybrid intelligent algorithm model can be trained so as to predict the wind speed.

4.2. Training and Simulation

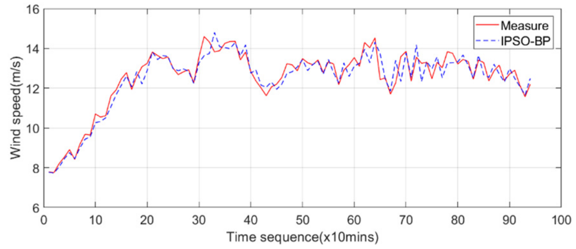
According to the IPSO-BP model, taking the wind speed data of Luchao Port in 2004 as the training object, one can predict the three time periods in 2005, as shown in Figure 7. It is necessary to explain that the BP in Figures 7–9 actually represents the BPNN, to simplify the description.

The wind speed changes slowly in Figure 7a, while in Figure 7b, the wind speed increases significantly and fluctuates sharply within a short period of time, and the prediction curve appears as a small deviation, at this time. In Figure 7c, the wind speed also rises sharply, but it is relatively stable in the range of 5~6 m/s, and the IPSO-BP model maintains an accurate prediction performance at this moment.

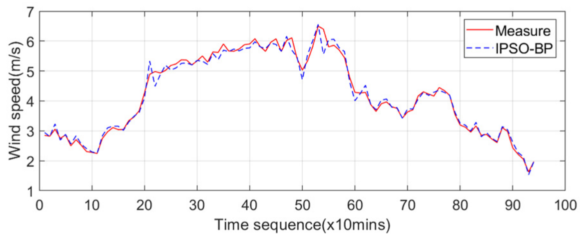
It can be observed from Figure 7d,e that the error is relatively large on 27 October, but the overall AE of the IPSO-BP model is small and its maximum does not exceed 1.4 m/s. It is clear that the IPSO-BP model is very accurate in predicting the wind speed with little fluctuations, in a short period of time. However, if the wind speed fluctuates sharply or suddenly in a very short time range (such as 1~2 h), the IPSO-BP model will have a prediction deviation, but the change trend of the corresponding wind speed is more accurate.



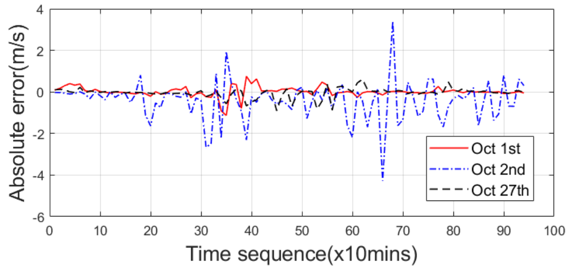
(**a**) 1 October



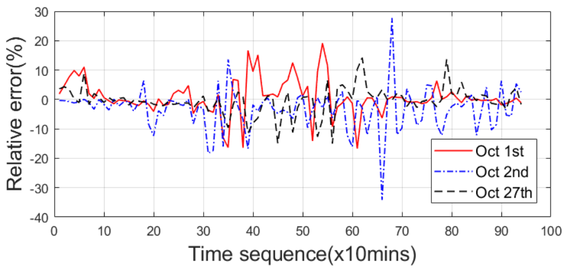
(**b**) 2 October



(**c**) 27 October



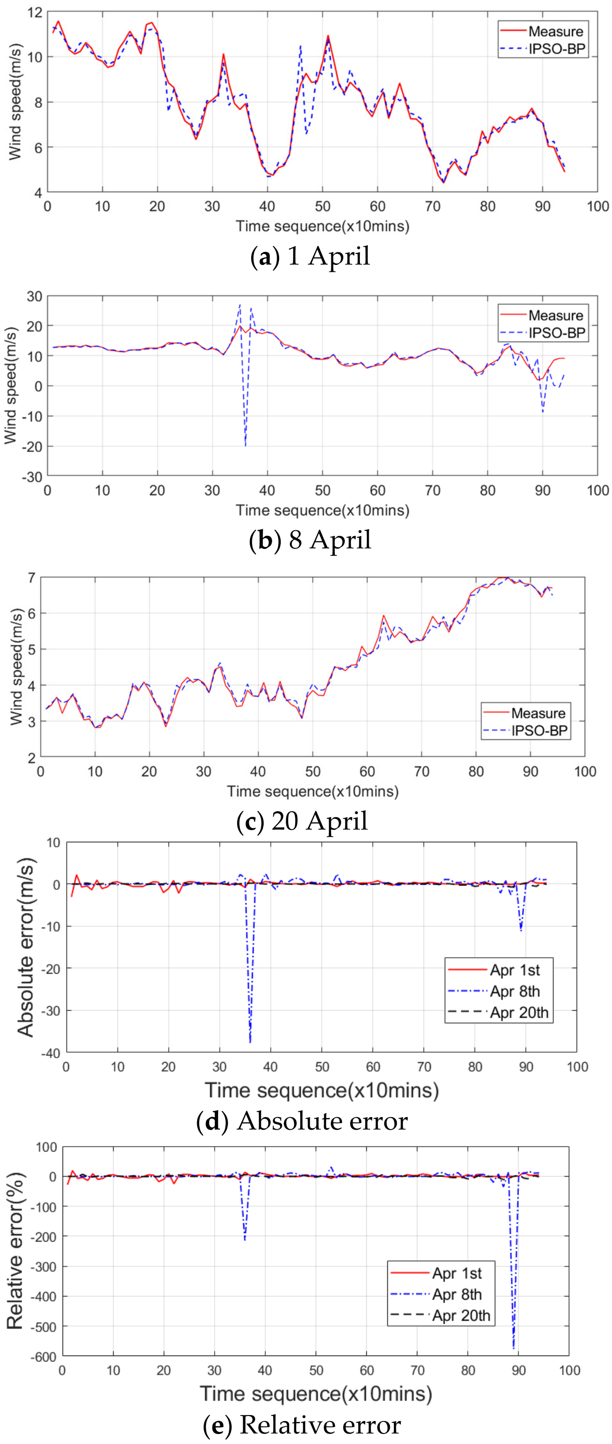
(**d**) Absolute error



(**e**) Relative error

Figure 7. Prediction results for 2005 based on the training set in 2004.

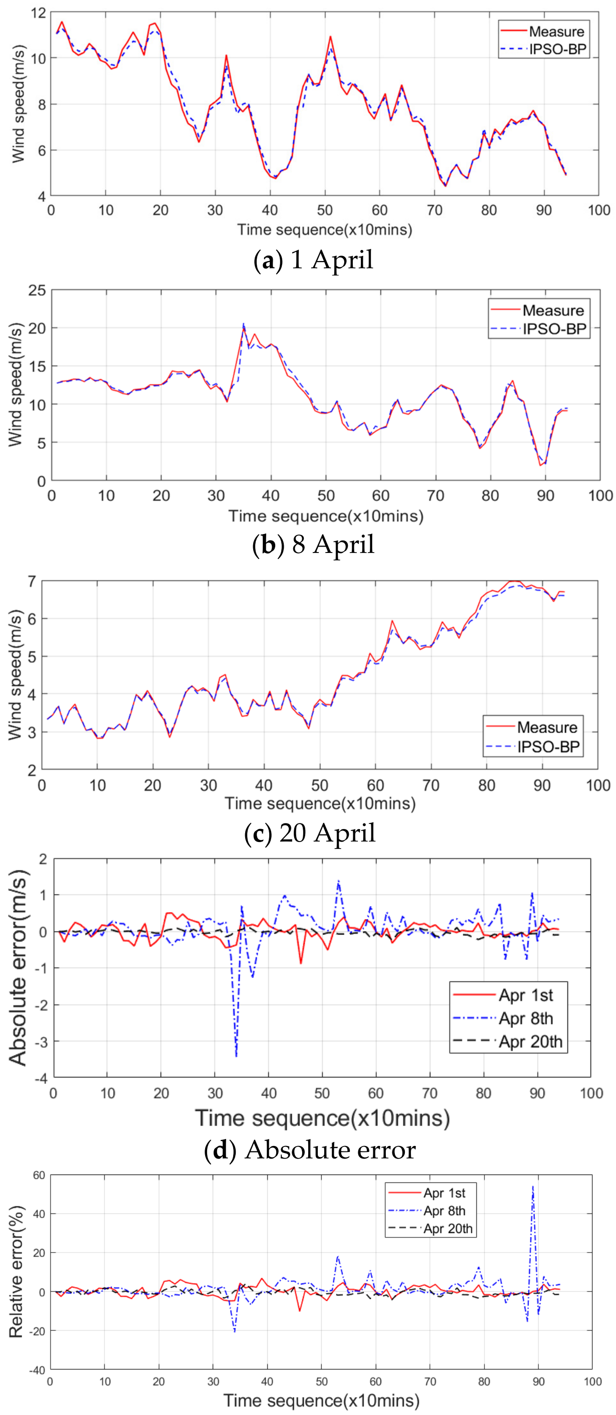
In order to further verify the accuracy of the model, the data from 2004 is still used as the training object to predict the three time periods in 2006, and the corresponding results are shown in Figure 8.



(**a**) 1 April
(**b**) 8 April
(**c**) 20 April
(**d**) Absolute error
(**e**) Relative error

Figure 8. Prediction results for 2006 based on training set in 2004.

The wind speed in Figure 8a varies greatly, the difference between the maximum wind speed and minimum one is about 6 m/s, and the prediction curve will have a small deviation when the wind speed sharply increases or decreases. The wind speed in Figure 8b ascends evidently and fluctuates violently in a short time, and at this time, there is a certain deviation in the prediction curve, especially near the 37th and 90th time series point. The sharp change of wind speed in a short period indicates that the measured value may be wrong or extreme weather may occur. Here are the 33rd to 38th values and the 85th to 95th values, where the wind speed fluctuates violently, rather than some value, and this is abnormal. Therefore, it can be ruled out that it is a measurement problem. The wind speed rises slowly in Figure 8c, and the IPSO-BP model presents a relatively accurate prediction performance. It can be seen from Figure 8d,e that the error of the other time periods is controlled within 5%, except that of the prediction value is relatively large, due to the sudden change of wind speed on 8 April.



(**a**) 1 April

(**b**) 8 April

(**c**) 20 April

(**d**) Absolute error

(**e**) Relative error

Figure 9. Prediction results for 2006, based on training set in 2005.

Finally, the wind speed of the three time periods in 2006 is predicted by taking the data of 2005 as the training object, as shown in Figure 9.

The results reflect the fact that the prediction errors of the 46th and 47th time points in Figure 9a, the 36th, 37th and 90th time points in Figure 9b, and the 46th and 47th time points in Figure 9c, are visibly reduced. The maximum AE of the IPSO-BP model drops by about 35 m/s, in comparison with Figures 8d and 9d. Nevertheless, since the wind speed rose sharply from the 32nd to the 35th points on 8 April, and dropped sharply from the 85th to the 90th points and then rose rapidly, these two places have large errors. Therefore, the selection of the training data has a certain impact on the precision of the IPSO-BP model, multiple groups of data should be trained and tested before determining the model parameters, and a group of data with the smallest MAPE are ultimately selected as the benchmark training data applied to the prediction model.4.3.

The above nine groups of prediction results, based on the IPSO-BP model, are listed in Tables 3–5.

Table 3. Average error of the IPSO-BP model (2004 →2005).

Prediction Time	AE	MSE	RMSE	MAPE	R
1 October 2005	0.38	0.23	0.48	13.46%	0.93
2 October 2005	0.78	1.07	1.04	6.02%	0.83
27 October 2005	0.27	0.13	0.36	6.88%	0.96

Table 4. Average error of the IPSO-BP model (2004 →2006).

Prediction Time	AE	MSE	RMSE	MAPE	R
1 April 2006	0.74	0.92	0.96	9.53%	0.87
8 April 2006	1.17	2.70	1.64	15.51%	0.90
20 April 2006	0.28	0.12	0.34	6.28%	0.97

Table 5. Average error of the IPSO-BP model (2005 → 2006).

Prediction Time	AE	MSE	RMSE	MAPE	R
1 April 2006	0.60	0.53	0.73	7.98%	0.93
8 April 2006	0.40	0.46	0.68	4.94%	0.98
20 April 2006	0.24	0.08	0.29	5.63%	0.98

It is found that the prediction accuracy of the wind speed on 27 October 2005 is the highest (See Table 3); the prediction error on 8 April 2006 is the biggest (See Table 4) and the one on 20 April 2006 is the smallest (See Table 5); the error in Table 5 is relatively the minimum, compared with Tables 3 and 4, that is, the overall prediction effect, at this time, is the best. Therefore, through the analysis and research in this study, it is concluded that the error of the IPSO-BP model is smaller when the time of the training data is closer to the target time.

In the future, it is possible to study the range of sharp rises or falls in wind speed in the short term, because some data ranges fluctuate violently, which will affect the overall prediction performance of the model. Moreover, when determining the parameters of the final prediction model, it is necessary to complete more experiments to determine the best parameters, which can improve the accuracy. It is also a good idea to divide the data according to the fluctuation degree of the wind speed, so as to avoid some abnormal points. On the whole, the AE, MSE and RMSE errors of the IPSO-BP model are less than 1 m/s, except on 8 April 2006, because the wind speed fluctuated more violently on that day. In addition, the goodness of fit is basically above 0.9 and the value of the MAPE is also relatively stable. These results further show that the IPSO-BP model performs well, in relation to the wind prediction.

5. Conclusions

To accurately evaluate the offshore wind resources, an IPSO-BP hybrid intelligent algorithm model is established, and its short-term prediction accuracy is explored. The following conclusions are drawn:

(1) In the Luchao Port of China, the wind power densities under different time spans are approximately 300 W/m^2. Meanwhile, the effective wind energy hours take up about 92%, and the wind direction distribution is stable. The average wind speed is basically greater than 2 m/s, and the maximum one can reach nearly 20 m/s, so there is a better wind energy resource reserve;

(2) Due to the effects of climate change and pollution, the characteristics of wind speed in a place can change. Specifically, the goodness of fit in 2006 is greater than that in 2005, and the AE, MSE, RMSE and MAPE in 2006 are all less than those in 2005. This indicates that the prediction error of the IPSO-BP model is smaller when the time of training data is closer to the target time. In the future, wind resource assessments can go further in studying how long the time interval between the training set and the testing set is, so as to predict the most accurate effect;

(3) The percentage of wind energy effective hours in 2005 was the highest, compared to 0.15% and 1.53% higher than that in 2004 and 2006, respectively. As a result, the IPSO-BP model trained using the 2005 data has a better tracking performance for the prediction of the gentle wind speed, and greatly reduces the AE of the extreme value in the prediction of the wind speed.

(4) The IPSO-BP model provides significant guidelines for researchers and manufacturers in the aspect of wind speed prediction, for its development. Meanwhile, the progress of wind energy resource assessment can effectively accelerate the development of low-carbon energy and promote the improvement of energy policy.

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