A design of power prediction algorithm based on health assessment optimized neural network

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Abstract

Wind power prediction holds significant value for the stability of the electrical grid when wind power is connected to the grid. Using neural networks for wind power prediction may have some limitations, such as slow speed and low accuracy. This paper proposes to enhance the power prediction accuracy and speed by optimizing the neural network through health assessment wind turbines. Firstly, based on wind turbine actual operating data, a health assessment is conducted to obtain a health matrix of wind turbine. Then, by calculating the weights of the matrix, the power prediction strategy of the network is optimized. Following that, matrix approximation hyperparameters are utilized to expedite the optimization process. Finally, some tests are conducted on neural network power prediction, act as optimized back propagation (BP) neural network and whale swarm algorithm–support vector regression (WSA-SVR) neural networks are employed for wind power prediction. Results show noticeable optimization: after optimizing the BP network, power prediction accuracy increased by about 40%, and prediction speed rose by about 20%; after optimizing the WSA-SVR network, power prediction accuracy improved by 10%, and prediction speed surged by about 45%. Further analysis shows that this method can improve the accuracy and speed of most neural network wind power prediction algorithms.

Keywords: Wind power prediction, Health assessment, Health matrix, BP neural network, Whale swarm algorithm, Prediction optimization

Introduction

The fluctuation of wind energy may lead to the instability of wind electricity [1], affecting the operation of the electrical grid once connected. To ensure the safety of the electrical grid, it is essential to predict wind power and adjust it in a timely manner. Hunan Province in China has a requirement for grid connected voltage of wind farms, with a monthly compliance rate of 98% for voltage control curves. The accuracy of short-term wind power prediction should not be less than 83%, and the accuracy of ultra short-term power prediction should not be less than 87%.

Early wind power predictions often employed some traditional methods such as numerical weather prediction (NWP), power curve graphs, and so on. Due to the low

measurement accuracy and significant transmission delay of NWP, the power prediction accuracy of this method is not high. Power curve graphs, derived from turbine conditions, also see reduced power prediction accuracy when environmental changes affect wind turbine operation and actual power deviates from rated power [2, 3].

In fact, the impact of weather and terrain conditions in areas where the climate was changeable and the terrain was complex led to significant errors in NWP, resulting in a lot of forecasting errors. In recent years, with the development of artificial intelligence technology, many new neural network algorithms have emerged. To improve accuracy, neural networks are often used for data processing, such as power predictions. Neural networks can train network models using historical data to predict wind power. Compared to similar methods, its predictive performance is significantly improved. Moreira et al. [4] used artificial neural networks (ANN) to establish forecasting models for photovoltaic generation that improve the information exchange capabilities and consequently enhancing the forecasting determination. Zhu et al. [5] established forecasting models based on the support vector machines (SVM) and Kalman filtering method that showed some efficacy in handling noise in wind power data. Sompop and Nawinda [6] design a modification of multivariable gray prediction model and states and parameters are sequentially estimated by means of the traditional Kalman filtering. But issues like slow prediction speed and high data costs persist. Thus, finding efficient optimization methods to enhance the predictive performance of neural networks has become a research hotspot in recent years.

Optimization algorithms can enhance network capabilities while improving prediction speed and accuracy. Wang et al. [7] proposed a short-term wind power prediction method combining variational mode decomposition (VMD) and hybrid kernel extreme learning machine (HKELM) which enhanced neuron communication capabilities to reduce optimization time and speed up predictions. Moreira et al. [8] explored how to use cluster analysis to select the ANNs and how to combine them in in the ensemble. Zhang et al. [9] improved Bayesian parameter optimization machine learning algorithms for wind turbine fault diagnosis. Shi et al. [10] proposed wind power operation uncertainty risk assessment based on sensitivity-layer hidden Markov model (HMM) which increased sampling tolerance to reduce data collection time, thereby increasing prediction speed. Yang et al. [11] designed a convolutional neural networks–bidirectional long short-term memory (CNN-BiLSTM) wind power prediction method which adjusted the network weight allocation method to reduce rounding errors and improve prediction accuracy. Korprasertsak and Leephakpreeda [12] designed a weighting method combine the predicted values of the autoregressive moving average model, the artificial neural network model, and the gray prediction model for the wind power generation. Ye et al. [13] established the wind power reference and loss prediction models based on XGBoost and Transformer algorithms to quantify theoretical output and power shortage in cold weather. They adopted seasonal models to reduce modeling errors, improving prediction accuracy. Chenniappan et al. [14] used the autoregressive integrated moving average (ARIMA) model for forecasting the future requirements of water supply. Lee and Park [15] forecasted housing submarkets trading volumes with the ARIMA model and the recurrent neural network (RNN). The trading volumes in adjacent areas are utilized as covariates and an ensemble prediction. They added a buffer module to improve gradient

smoothness, ensuring predictive accuracy. Zhang et al. [16] adopted the temporal convolutional network for wind power prediction. Liu Ying, et al. [17] propose a knowledge-embedded graph neural network (K-GNN) model based on the general framework of multivariate time series graph neural network (MT-GNN) to predict the multivariate time series state data of wind turbines. Liu et al. [18] introduced attention mechanisms to reduce latency errors. However, currently, most optimization algorithms can only improve either accuracy or speed independently, and the outcomes are not ideal.

This paper improves wind turbine power weight calculation methods and adjusts prediction strategies by employing health assessment to derive a wind turbine health matrix, thereby enhancing both the accuracy and speed of neural network predictions.

The first part of the paper introduces the health assessment algorithm and analyzes neural network algorithms. In the third part, a new optimization scheme is introduced to optimize the hyperparameter of two neural networks, and the fourth part simulation tests the algorithms.

Methods

The concept of health assessment was proposed by Lars Landberg in 2011 [19]. It leverages the characteristics of the statistical probability distribution of model outputs, transforming a two-dimensional multivariate probability density function into a health matrix.

Wind speed and power generation efficiency are positively correlated. As wind speed decreases, the wind turbine rotates slower, resulting in lower power generation efficiency. Conversely, as wind speed increases, the wind turbine rotates faster, leading to higher power generation efficiency. By applying a multivariate Gaussian distribution model to compute power generation efficiency, we can derive the health matrix. The specific process is illustrated in Fig. 1:

(1) Data collection: Collect data on wind speed, temperature, pressure, rotational speed, and power [20], among other metrics, via sensors and the SCADA system.
(2) Data cleaning: Address missing values, anomalies, and noise in the data to enhance its reliability [21].

To mitigate the order error of data at different magnitudes, a normalization process is first carried out. Given that some types of data can have negative values, the min–max normalization algorithm is as follows:

$$\dot{x}_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x_i represents the current data, x_{min} denotes the minimum data value, and x_{max} represents the maximum data value.

(3) Feature selection: From the cleaned data, select feature data to determine the dimensions of the health matrix [22], as well as the approximation hyperparameters for the neural network.
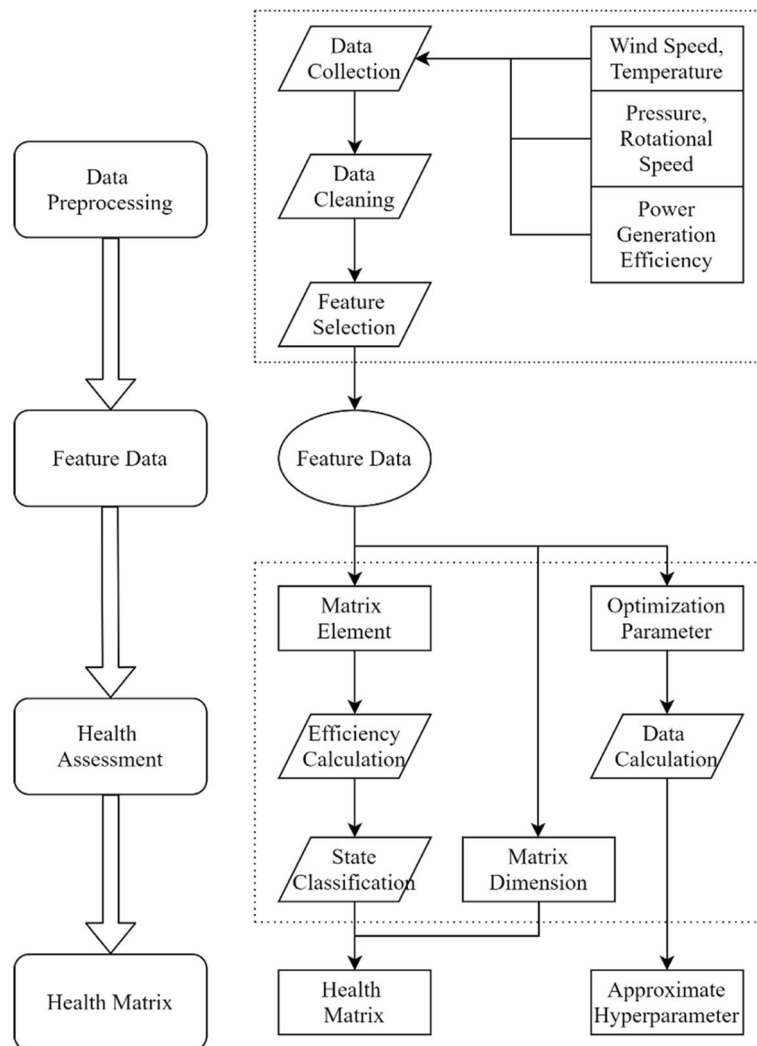
Fig. 1 Health assessment process diagram

(4) State classification: Based on the feature data, calculate the power generation efficiency and categorize the wind turbine statuses into categories such as normal, minor fault, and major fault [23]. The power generation efficiency is defined as:

$$f(x; \mu, \Sigma) = \frac{1}{(2\pi)^{\frac{i}{2}} |\Sigma|^{\frac{1}{2}}} \exp[\frac{1}{2}(x - \mu)^T \Sigma^{-1} (x - \mu)] \tag{2}$$

where i is the feature identifier, ranging from 1 to n, μ is the mean vector, and Σ is the covariance matrix.

(6) Matrix generation: Arrange the power generation efficiencies of the same status categories in order of value to form a matrix. Each matrix element represents the power generation efficiency of the wind turbine in that specific state [24].

Arrange the computed power generation efficiencies in order of feature to get the efficiency matrix $Q_{n \times 1}$.

By applying factor analysis to the measurement data, we can obtain the power feature correlation matrix $V_{1 \times n}$. After arranging it using Q^T, multiplying Q with V yields the health matrix A, defined as:

$$A_{n \times n} = Q_{n \times 1} V_{1 \times n} \qquad (3)$$

where n is the dimension of the health matrix, typically ranging from 6 to 12. When n exceeds 12, dimensionality reduction is required.

The existing health assessment algorithm has two shortcomings:

1. High data costs: To calculate power generation efficiency, various wind turbine data are required, increasing the cost of data collection, processing, and analysis [25].
2. High complexity: To enhance assessment reliability, the feature selection module is introduced, increasing the algorithmic complexity [26].

To reduce complexity, simplify the health matrix, and lower assessment costs, the factor analysis method is first used to simplify the feature selection module and reduce matrix complexity. Then, dimensionality reduction and decoupling are performed on the feature data to reduce data processing costs.

Analysis of neural network algorithm

There are shortcomings in the current optimization neural network algorithms: firstly, the improvement in prediction speed after optimization is not significant; secondly, there is not much change in accuracy after optimization. Li et al. [27] optimized the BP neural network for wind power prediction, enhancing the network's adaptability, nonlinear mapping, and parallel processing capabilities. However, the quality of power weight was not improved, resulting in limited enhancement in prediction accuracy. Heidari [28] used the optimized SVR network for photovoltaic power prediction, strengthening SVR's mutation handling capability. However, the optimization process was not improved, and the prediction speed remains slow.

Power weight has a significant impact on BP's prediction accuracy [29]. Using the health matrix to improve power weight calculation can enhance BP prediction accuracy. The prediction speed of SVR is significantly affected by parameter optimization [30]. To accelerate the optimization process, WSA is introduced as SVR's optimization algorithm.

WSA is a new group intelligence algorithm [31] which is used to solve the merit-seeking problem by imitating behaviors such as searching and hunting among whale populations using ultrasonic waves as information carrier. The position iterative formula of the whale swarm algorithm is:

$$\begin{cases} x_i^{t+1} = x_i^t + \beta \left(y_i^t - x_i^t \right) \\ \beta = rand \left(0, \rho_0 e^{-\eta d_{X,Y}} \right) \end{cases} \qquad (4)$$

where η is the ultrasonic attenuation factor; d_{xy} is the distance between X and Y; ρ_0 represents the initial ultrasonic intensity; y_i^t indicates the position of whale y_i at step t; x_i^t and x_i^{t+1} are the position of whale x_i at step t and $t+1$, respectively; and β is a random number of $[0, \rho_0 e^{-\eta d_{X,Y}}]$.

The approximate hyperparameters of the health matrix are used as the starting value for WSA, accelerating the SVR optimization process and improving prediction speed.

New optimization scheme

Through health assessment, the health matrix is obtained. After calculating the improved power weight, the power is predicted using the neural network output. Without increasing data processing costs, the prediction error is reduced, and the accuracy and speed of network prediction are enhanced.

The neural network optimization scheme is shown in Fig. 2.

1. Health assessment: Based on feature data, perform health assessment to obtain the health matrix and neural network approximate hyperparameters.
2. Power prediction: Using matrix approximate hyperparameters and speeding up the optimization process, the neural network is used for power prediction, obtaining the original predicted power.

From Eqs. (2) and (3), we know that n features correspond to health matrix $A_{n \times n}$. Arrange the current time data according to the order of matrix Q into feature matrix $B_{n \times 1}$.

Firstly, matrices A and B are multiplied to get the weight matrix $C_{n \times 1}$, i.e.:

$$C_{n \times 1} = A_{n \times n} B_{n \times 1} \tag{5}$$

Then, the original predicted power P_i is expanded into power matrix $D_{1 \times n}$. All elements in D are the original predicted power P_i.

Next, matrices D and C are multiplied, the result is multiplied by the correction factor λ, and added to P_i, obtaining the reconstructed predicted power $\overline{P_i}$, i.e.:

$$\overline{P_i} = \lambda \cdot |D \times C| + P_i \tag{6}$$

where λ is related to the feature data and turbine operating conditions, with values ranging from 0.01 to 0.1.

The optimization process of BP network is as follows:

For the BP network, the hidden layer error can be represented as:

$$\delta_h = f'(x) \times \Sigma(\omega \times \delta_o) \tag{7}$$

where δ_h represents the hidden layer error; δ_o represents the estimated system error, a given value; $f\prime$ is the derivative of the activation function; x is the hidden layer input; ω is the power weight, identical to the elements of weight matrix C; and Σ denotes summation over the output layer nodes.

The update calculation of BP power weight is as follows:

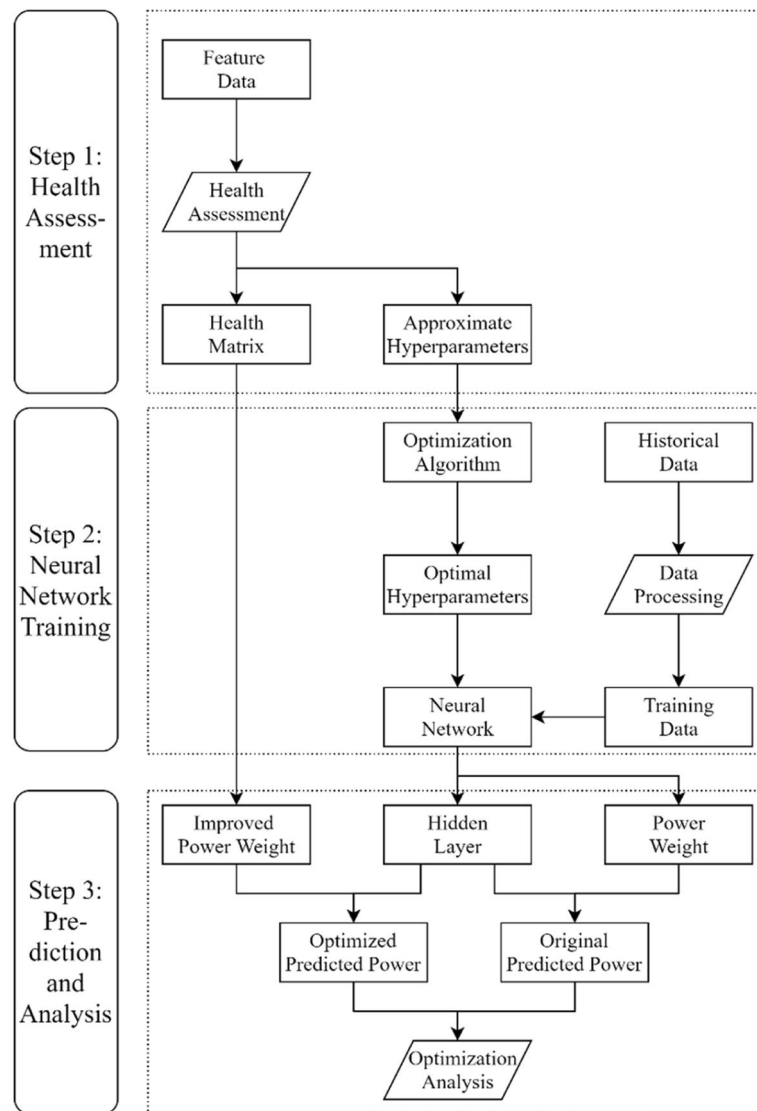$$\Delta\omega = \alpha \times \delta \times x_i \tag{8}$$

Fig. 2 Neural network optimization scheme based on the health matrix

where $\Delta\omega$ represents the change in weight, α is the learning rate, δ is the error of the current node, and x_i is the input of the current node.

In Eq. (7), ω is calculated using the health matrix to reduce interference in ω, making the value of $\omega \times \delta_o$ significantly reduced, lowering δ_h, reducing prediction error, and enhancing BP prediction accuracy.

Using the health matrix as x_i, Eq. (8) can reduce the update calculation amount and accelerate weight convergence to obtain an approximate optimal learning rate. After optimization, the prediction time of the BP network is significantly reduced.

The optimization process of SVR is as follows:

Suppose the input of the ith data is x_i, the output is y_i, and the predicted value is $f(x_i)$. Define the error variable e_i to represent the gap between the actual value and the predicted value, which is:

$$e_i = f(x_i) - y_i \tag{9}$$

During the optimization process, while minimizing the sum of squares of errors, limit each e_i to not exceed the given threshold ε, resulting in Eqs. (10) and (11):

$$\text{minimize} : 0.5 \times \omega^T \times \omega + T_1 \times \Sigma e_i \tag{10}$$

$$\text{subject} : |e_i| \leq \varepsilon, i = 1, 2, \ldots, n \tag{11}$$

wherein, ω is the power weight, the same as the elements of weight matrix C. T_1 is a regularization parameter, and ω^T is the transpose of ω. The WSA algorithm is used to optimize T_1.

The calculation of SVR predicted values is:

$$f(x_i) = \Sigma \alpha_i \times K(x_i, x) + e_i \tag{12}$$

where α_i is the Lagrangian multiplier, obtained by solving the Lagrangian function equation of SVR; $K(x_i, x)$ represents the inner product kernel function; and e_i is the error variable.

The approximate regularization parameter of the health matrix allows WSA to start optimization near the global optimum, reducing the optimization time, accelerating the prediction process, and improving the prediction speed of SVR.

Simulation tests and optimization analysis

Error metrics

Three types of error metrics are used: coefficient of determination (R^2), mean squared error (MSE), and mean absolute error (MAE), as given in Eqs. (13, 14, and 15):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(\widehat{y_i} - y_i \right)^2}{\sum_{i=1}^{n} \left(\overline{y_i} - y_i \right)^2} \tag{13}$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} \left(\widehat{y_i} - y_i \right)^2 \tag{14}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| \overline{y_i} - y_i \right| \tag{15}$$

where y_i is the actual value, $\widehat{y_i}$ is the predicted value, and $\overline{y_i}$ is the average of the actual values. R^2 indicates prediction accuracy; the closer the value is to 1, the higher the prediction accuracy. MSE and MAE represent the degree of error dispersion; the smaller the value, the smaller the prediction error.

Simulation tests

Using Baidu KDD CUP 2022, test data set 1# unit for a total of 40 days [32]. BP and WSA-SVR networks were selected for optimization testing. Data preprocessing uses forward and backward interpolation to ensure input data consistency.
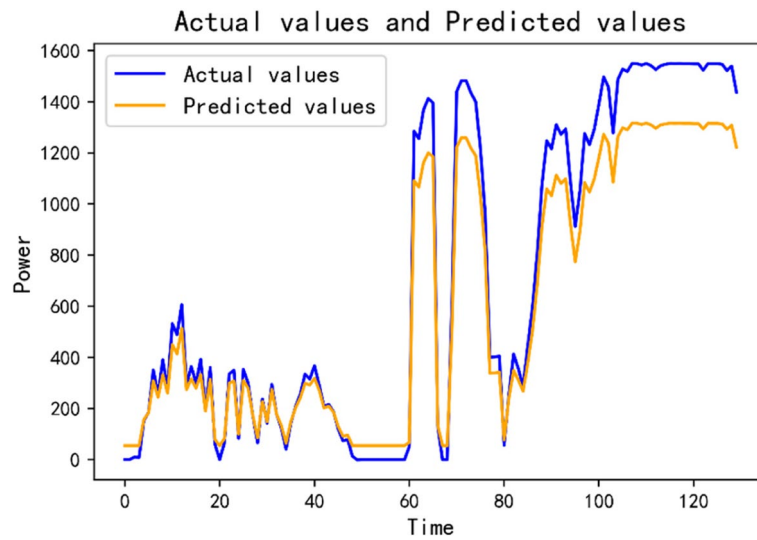
Fig. 3 BP prediction effect without optimization
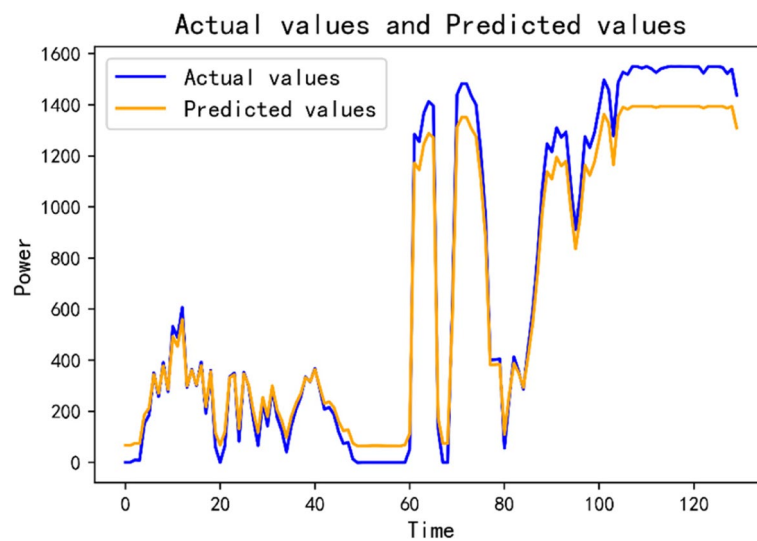

Fig. 4 BP prediction effect after optimization

The BP network's pre-optimization and post-optimization prediction effects are shown in Figs. 3 and 4.

The pre-prediction and post-optimization prediction effects of the WSA-SVR network are shown in Figs. 5 and 6.

The comparison of prediction errors before and after optimization is shown in Table 1.

From Table 1 and Figs. 3 and 4, it can be seen that after optimizing the BP network, the prediction accuracy increased by about 40%, and the prediction time was reduced by about 20%. From Table 1 and Figs. 5 and 6, after optimizing the WSA-SVR network, the prediction accuracy increased by about 10%, and the prediction time was reduced by about 45%.
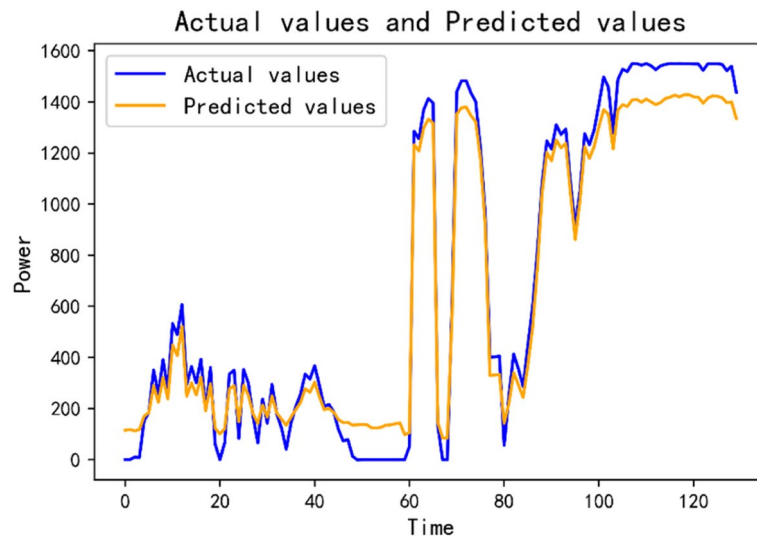
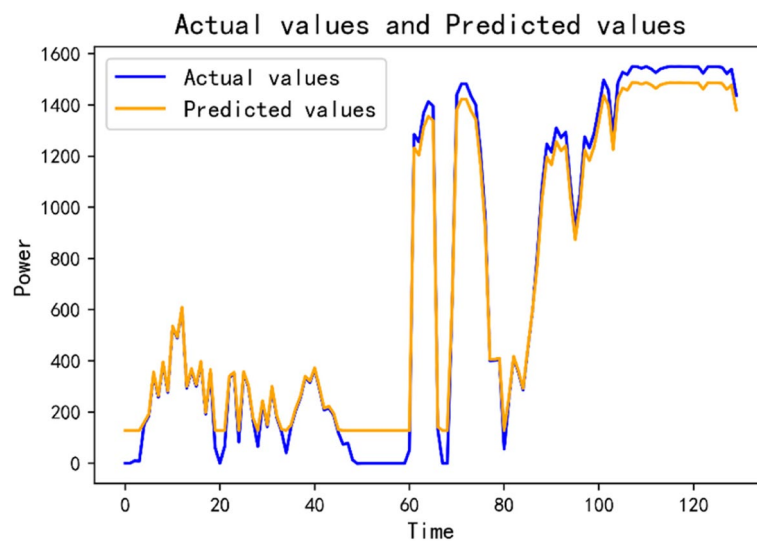**Fig. 5** WSA-SVR prediction effect without optimization

Fig. 6 WSA-SVR prediction effect after optimization

Table 1 Neural network prediction error comparison

	R^2	MSE	MAE	Time
BP network	0.9510	0.0054	0.0627	60.02 s
Optimized BP network	0.9732	0.0030	0.0496	48.02 s
WSA-SVR	0.9685	0.0035	0.0536	108.9 s
Optimized WSA-SVR	0.9729	0.0031	0.0503	58.4 s

Results and discussion

The optimization algorithm significantly improved the lag of the prediction and enhanced the quality of the BP network's power weight. After optimization, the

BP network's prediction accuracy noticeably improved. Simultaneously, using the matrix's approximate regularization parameter as the starting value for optimization can improve the optimization efficiency and reduce the prediction time of BP.

Hyperparameter optimization accounts for about 70% of the total SVR prediction time [33]. In the WSA-SVR optimization process, by passing the approximate regularization parameter of the health matrix to the WSA-SVR network and allowing WSA to start optimization from an approximate global optimum, the WSA-SVR prediction time can be reduced. After optimization, the accuracy of WSA-SVR significantly improved.

Conclusions

Here it employed health assessment to derive a wind turbine health matrix, thereby enhancing both the accuracy and speed of neural network predictions. The optimization algorithm designed based on health assessment can simultaneously improve the wind power prediction accuracy and speed of neural networks. Compared with existing optimization algorithms, the neural network optimization algorithm based on the health matrix has a smaller data cost and better prediction performance. From the principle and process of the algorithm, it can be concluded that it can improve the accuracy and speed of most neural network wind power prediction algorithms.

Abbreviations
BP	Back propagation
WSA	Whale swarm algorithm
SVR	Support vector regression
NWP	Numerical weather prediction
ANN	Artificial neural networks
SVM	Support vector machines
HKELM	Hybrid kernel extreme learning machine
HMM	Hidden Markov model
CNN-BiLSTM	Convolutional neural networks–bidirectional long short-term memory
ARIMA	Autoregressive integrated moving average
RNN	Recurrent neural network
K-GNN	Knowledge-embedded graph neural network
MT-GNN	Multivariate time series graph neural network
MAE	Mean absolute error
RMSE	Root mean square error
MAPE	Mean absolute percentage error

Declarations

Competing interests
No conflict of interests in this paper.

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