Original Research Article

Application of WOA-based LSSVM model for wind speed prediction in Mianyang

ABSTRACT

In recent years, countries have vigorously developed renewable energy resources to alleviate energy shortages and improve the environment. Wind energy, as a clean and renewable new energy source, has been increasing its power generation capacity, but the wind power generation itself has the characteristics of volatility and instability which makes wind power generation more difficult. Therefore, a novel prediction model based on the least squares support vector machine (LSSVM) with whale optimization algorithm (WOA) is proposed in the paper to improve the prediction accuracy and applied to the wind speed prediction in Mianyang. The prediction results are then evaluated quantitatively using the mean absolute percentage error, and the proposed model results are compared with XGBoost, SVR, and Random Forest models. Further, the MAPE of the prediction results of the proposed model is about 4.7%-5.5%, which can be 6.3% higher than other models at best. The results show that the proposed prediction model can have good prediction accuracy and generalization performance and can be applied to other fields in the future.

Keywords: Wind speed prediction; least squares support vector machine; whale optimization algorithm; multi-step ahead forecasting

1. INTRODUCTION

1.1 Background

In recent years, with the economic growth of many countries, the pace of urbanization and industrialization accelerated, fossil fuels have been unable to meet the huge, growing consumption and global energy tension, and wind energy as a clean renewable energy, with a huge amount of content, and non-polluting characteristics, can meet the needs of human sustainable development. Vigorous development of wind power can reduce the consumption of thermal power, coal power, and other disposable energy and emissions of polluting gases, thus effectively alleviating the increasingly serious environmental problems, and can reasonably adjust the structure of power resources. 2022 In August, the eastern part of Sichuan Province, known as the "province of a thousand rivers", experienced power shortages due to extreme heat. Many places experience water shortages during the flood season. In the difficult situation of increased demand for electricity, the government calls on companies to "provide electricity to the residents". In this case, wind power may become a more critical way to supply electricity.

According to the "China Wind Power Development Roadmap 2050" plan, by 2020, 2030, and 2050, installed wind power capacity will reach 200 million, 400 million, and 1 billion kilowatts, respectively, becoming one of China's top five power sources and meeting 17 percent of electricity demand by 2050. Despite the increasing research on wind power-related issues at home and abroad in recent years, wind energy prediction is still a challenging issue in large-scale wind power grid management due to the instability of wind speed which makes wind power systems less stable. Accurate prediction results can effectively improve the utilization of wind energy resources and reduce the impact of wind power fluctuations on grid stability, thus maximizing the economy of wind farms and achieving efficient and stable operation. Therefore, it is crucial to improve the accuracy of wind speed prediction, analysis, and wind speed information mining.

1.2 Related work

The most commonly used methods for forecasting wind speed are physical methods, statistical methods, artificial intelligence-based methods, and hybrid model methods. Physical methods can be divided into numerical weather prediction (NWP) [1]-[3]and spatial correlation methods. NWP is currently used for weather forecasting, but it requires consideration of many other factors, including topography, temperature, etc., so the forecasting process is more complicated. The physical method has a relatively complex computing process, requires considerable running time and computational resources, has relatively high operating costs, and tends to be more suitable for long-term wind speed forecasting.

Statistical methods are based on the premise that the statistical patterns of future weather evolution should be the same as those in the sample window. They rely on many historical statistics and require high data integrity, so they are generally used for short-term wind speed forecasting. Commonly used statistical methods include the Kalman filter, Auto Regressive (AR) mode [4], Autoregressive Moving Average (ARMA) model, Differential Autoregressive Sliding Average (ARIMA) model, Autoregressive Integrated Moving Average Model (ARIMA) [5]. Hui Liu et al. proposed an improved recursive autoregressive integrated moving average model (RARIMA) [6] and applied the model to short-term wind speed prediction of Qinghai-Tibet Railway, and their prediction results were satisfactory in terms of accuracy and time performance.

With the development of artificial intelligence, support vector machine (SVM) [7][8], artificial neural network (ANN) [9], and tree mode [10] were applied to wind speed prediction. J Zhou et al. first systematically investigated the fine-tuning of LS-SVM model parameters for single-step ahead wind speed prediction in 2011 [11]. In recent years, hybrid models [12]-[16] have been widely used in several fields and have shown excellent performance.

Based on the results of the literature review, it can be seen that machine learning and deep learning models are widely used in the field of wind speed forecasting.Most scholars currently use neural networks and support vector machines for wind speed prediction, but because the wind speed is highly stochastic and influenced by many factors with strong nonlinear relationships, the prediction accuracy of neural network models is low and slow in short-term prediction. Therefore, in this study, we propose a hybrid model based on LSSVM and WOA, which combines the advantages of the model and algorithm and uses a multi-step prediction strategy to improve the prediction accuracy of the model and effectively improve the prediction performance and generalization ability.

1.3 Motivation and article structure

Wind power output and wind speed are related, both of them have strong random and non-smooth characteristics and are difficult to predict. Accurate wind speed prediction can optimize the grid dispatch, reduce the rotating reserve flow, save resources, and ensure the safe, stable, and economical operation of the grid. Therefore, it is important to provide data to the relevant authorities through multivariate prediction of short-term wind speeds to make reasonable decisions to ensure maximum benefits.

Therefore, in our study, we will analyze and predict the wind speed of Mianyang. To avoid the limitations of a single model, a hybrid prediction model is used in the paper, and a multi-step prediction model based on the least squares support vector machine, whale optimization algorithm, and NAR is proposed and applied to the wind speed prediction of Mianyang. The remainder of this paper is as follows: Section 2 focuses on the principles of the main models in this paper, Section 3 shows the experimental design process of this paper, the prediction results and the analysis, and Section 4 summarizes the whole paper and gives the main conclusions.

2. METHODOLOGY (ARIAL, BOLD, 11 FONT, LEFT ALIGNED, CAPS)

2.1 Least Squares Support Vector Machine (LSSVM)

LSSVM is a machine learning algorithm proposed by Suykens et a[16].LSSVM, as an improved support vector machine based on a statistical theory with an advanced and complete theoretical system, can simplify the solution of quadratic optimization problems by transforming them into the solution of a system of linear equations. It has been successfully applied to many fields, including data regression, pattern recognition, time series prediction, etc.

For a given training data (x_i, y_i), where $x_i = (x_i^1, x_i^2, \cdots x_i^d)^T$ is the d-dimensional input vector, y_i is the corresponding output data, and N is the total number of training data. To map the input space to the feature space, a nonlinear function $\phi(x_i)$ is used, and the nonlinear function estimation modeling takes the following form:

$$f(x) = b + \langle \phi(x), w \rangle \tag{1}$$

where w is the weight vector, b is the bias term and the symbol $\langle \cdot \rangle$ refers to the inner product operation.

Based on the structured risk minimization principle, the evaluation problem is described as an optimization problem:

$$\begin{gathered} \min J(w,e) = \min(1/2\|w\|^2 + 1/2\gamma\sum_{i=1} e_i^2) \\ s.t. \quad y_i = \langle w, \phi(x_i) \rangle + b + e_i \quad i = 1, 2, \ldots, N \\ \gamma > 0 \end{gathered} \tag{2}$$

γ is the regularization parameter used to determine the trade-off between model complexity and accuracy, and e_i represents the regression error between the actual and predicted values of the output.

To solve the above optimization problem, the corresponding Lagrangian functions are constructed:

$$L_{LSSVM} = 1/2\|w\|^2 + 1/2\gamma\sum_{i=1} e_i^2 - \sum_{i=1}\alpha_i\left\{\langle w, \phi(x_i)\rangle + b + e_i - y_i\right\} \tag{3}$$

α_i is the Lagrangian multiplier.

By setting the derivatives of w, b, e_i, α_i to zero, the conditions for the optimal solution of the problem can be obtained. By eliminating w and e_i , the four linear problems can be simplified to:

$$\begin{bmatrix} 0 & E^T \\ E & \Omega + 1/\gamma \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{4}$$

where $y = \left[y_1, \cdots, y_N\right]^T$, $\alpha = [\alpha_1, \cdots, \alpha_N]^T$, $E = \left[1, \cdots, 1\right]^T$, and Ω are symmetric matrices of $N \times N$ kernel function:

$$\Omega_{ij} = K(x_i, x_j) = \phi(x_i)^T \phi(x_j) \quad i, j = 1, 2, \ldots, N \tag{5}$$

where $K(x_i, x_j)$ is the kernel function, which satisfies Meser's condition. The kernel function has the ability to reduce the computational complexity of high-dimensional spaces and plays an important role in constructing high-performance least-squares support vector machines.

Then the LSSVM model can be expressed as:

$$\begin{aligned} y_i &= \langle w, \phi(x_i)\rangle + b \\ &= \sum_{i=1} \alpha_i \phi(x_i) \cdot \phi(x_i) + b \\ &= \sum_{i=1} \alpha_i K(x_i, x) + b \end{aligned} \tag{6}$$

The radial basis function (RBF) kernel is a widely adopted kernel function as follows:

$$K(x_i, x_j) = \exp(-\left\|x_i - x_j\right\|^2 / 2\sigma^2), \sigma > 0 \tag{7}$$

σ is the bandwidth of the kernel function. Two of the hyperparameters, γ as well as σ , are parameters that have a significant impact on the performance of the LSSVM model and need to be carefully determined.

2.2 Whale Optimization Algorithm (WOA)

The whale Optimization Algorithm (WOA) is a metaheuristic optimization algorithm that simulates the hunting behavior of humpback whales. The main difference in the current work compared to other swarm optimization algorithms is the use of random or optimal search agents to simulate hunting behavior and the use of spirals to simulate the bubble net attack mechanism of humpback whales. The algorithm has the advantages of a simple mechanism, few parameters, and strong search ability, and has been widely used in economic scheduling, optimal control, photovoltaic systems, and image segmentation. The humpback whale optimization algorithm mainly consists of the following steps:

Step 1: Initialize the data

The formula for initializing the whale population location is as follows:

$$X_i = lb + rand \times (ub - lb) \tag{8}$$

where X_i is the location of individual i, lb and ub are the lower and upper bounds of the search space, and $rand()$ is a random number between 0 and 1.

Step 2: Prey encirclement

Calculate the fitness of each whale, find the current optimal whale position, and keep it. After the target prey location is defined, other whales will make attempts to encircle the target prey location. The formula for this process is as follows:

$$X(t+1) = X^*(t) - A \times D \tag{9}$$

$$\begin{cases} A = 2 \times a \times \text{rand}() - a \\ D = |C \times X^*(t) - X(t)| \\ C = 2 \times \text{rand}() \end{cases} \tag{10}$$

where t is the current number of iterations, A and C are the coefficients, X is the current solution position, X^* is the position of the current optimal solution, and a gradually decreases from 2 to 0 during the iterations.

Step 3: Predation phase

Firstly, we calculate the distance between to and then use the spiral update formula to simulate the spiral advance of the whale.

$$\begin{aligned} X(t+1) &= X^*(t) - A \times D \quad ,if\ rand < 0.5 \\ &= D^* \times e^{bl} \times \cos(2\pi l) + X^*(t)\ ,\text{other} \end{aligned} \tag{11}$$

The WOA algorithm first initializes a random set of solutions, and in each iteration, the search agents update their positions according to the randomly selected search agent or the optimal solution obtained so far. The a parameter is reduced from 2 to 0 with the number of iterations, thus moving gradually from exploration to exploitation. The random search agent is selected when $|A| > 1$ and the optimal solution is selected to update the search agent positions when $|A| < 1$. Depending on the value of p, the WOA can switch between spiral and circular motions. Finally, the WOA algorithm is terminated by satisfying the termination criterion.

2.3 Multi-step forecasting strategy

The multi-step forecasting method uses the step-by-step prediction of future time series values based on the historical values of the time series as a way to reduce the error and improve the prediction accuracy. Firstly, the test set is divided into an equal number of subseries, and then the optimal model obtained by the algorithm is predicated on the corresponding test set separately, and the next value is predicted by the previous lag( ) value in each prediction, and finally, the results of multi-step prediction of each optimal model are reconstructed by wavelets to obtain the final short-term wind speed prediction results.

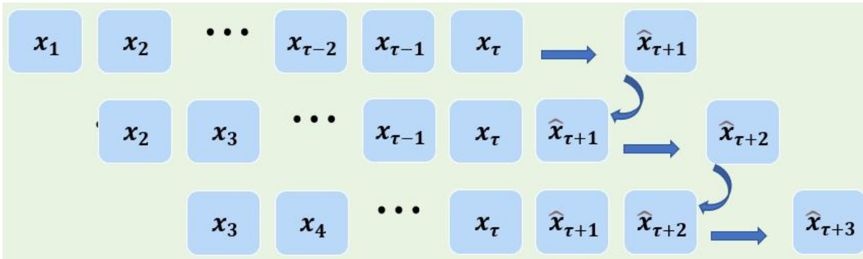

Fig. 1. Multi-step forecasting

3. RESULTS AND DISCUSSION

3.1 Data description

The wind speed data of Mianyang used in this study were obtained from the website of Xiaomaiya[1], and the monthly average wind speed of 20 years was collected. Firstly, the correlation trend plot and the autocorrelation plot of the data were plotted based on the original data, and it can be seen from Fig.2 that the data set has strong volatility and certain periodicity.

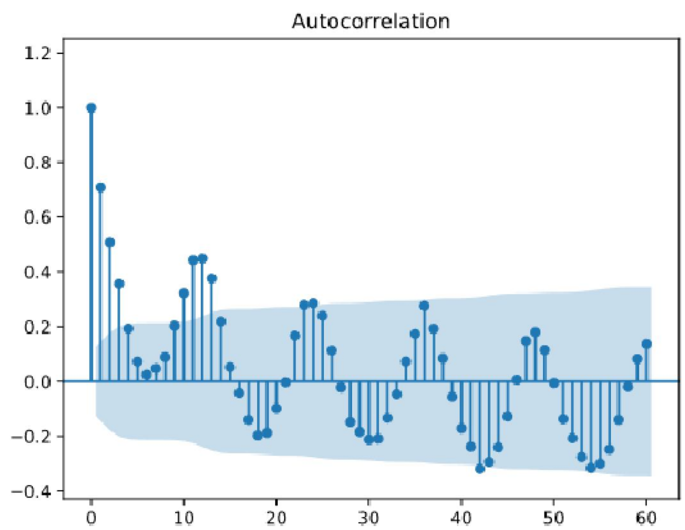

Fig. 2. Autocorrelation graph

The original data were then subjected to data reconstruction and the data were divided into datasets according to 8:1:1. In addition, we made calculations and statistics on the relevant properties of the datasets, and the following table shows some of the statistical characteristics of the two different datasets:

Table 1. Selected features of the dataset

Data sets	lag=9					
	Data volume	Max	Min	Mean	Std	Var

[1] http://www.wheata.cn/

Training	184	4.89	1.65	3.53	0.55	0.30
Validation	23	4.35	2.96	3.72	0.37	0.13
Testing	24	4.62	2.86	3.78	0.46	0.21

3.2 Evaluation metrics

To quantitatively evaluate the prediction performance of the models, the mean absolute percentage error (MAPE) is introduced in this study to evaluate the prediction performance of the models. In addition, to highlight the enhancement effect of the proposed hybrid model, we also compare the results of XGBoost, CAT, MLP, RF, SVR, and LSTM models with those of the WOA-based LSSVM model for analysis.

3.3 Forecasting result

In this subsection, we will show the prediction results of the WOA-based LSSVM model (WOA-LSSVM) and compare them for analysis and discussion. In this study, we use a multi-step prediction strategy to model and optimize the model based on the data of the past 20 years, and then predict the monthly mean wind speed for the next five months, and the results of each step of the prediction indicate the prediction of the monthly mean wind speed value for the next month.

The prediction results of all models are shown in Table 2, and it can be seen from the table that WOA-LSSVM has the best prediction results with the highest MAPE values for each step ahead of the prediction in this case, which can indicate that WOA-LSSVM has a strong prediction capability. the MAPE values of the WOA-LSSVM model from one to five steps of prediction at lag=5 are: 5.3689%, 5.1288%, 5.2651%, 5.4896%, and 4.7251%, all between 4.7% and 5.5%, and the MAPE can be as low as 4.7% at the best, while the MAPE values of XGBoost, CAT, MLP, RF, and LSTM are between 5.3% and 10.4%, which is nearly double the difference with the proposed model. In addition to this, it is worth noting that the SVR model exhibits an overfitting situation in this case, which can be attributed to the small amount of data and other circumstances. This can indicate that WOA-LSSVM has superior prediction performance and the whale optimization algorithm can effectively improve the prediction accuracy of the model.

Table 2. MAPE values of prediction results for LSSVM, XGBoost, CAT, MLP, RF, SVR, and LSTM models (%)

Data sets	Steps / Model	1-step	2-step	3-step	4-step	5-step
Wind speed	LSSVM	**5.3689**	**5.1288**	**5.2651**	**5.4896**	**4.7251**
	XGBoost	7.4695	8.0939	8.2126	9.0654	8.4584
	CAT	6.1300	5.9568	5.3306	6.4032	7.0707
	MLP	8.6904	9.0267	10.1849	10.3625	9.5969
	RF	5.8693	5.9189	6.0458	5.8052	5.6551
	SVR	11.1812	11.1873	11.4399	11.5879	11.0017
	LSTM	7.0277	8.2803	9.1025	9.6001	9.4577

Meanwhile, the trend of the prediction error between WOA-LSSVM and other models can be seen in Fig.3. It is easy to know from the figure that RF has close prediction accuracy with the proposed model, and all other models have a large gap, and this gap gradually increases with the increase of prediction steps, and the proposed model has strong stability.

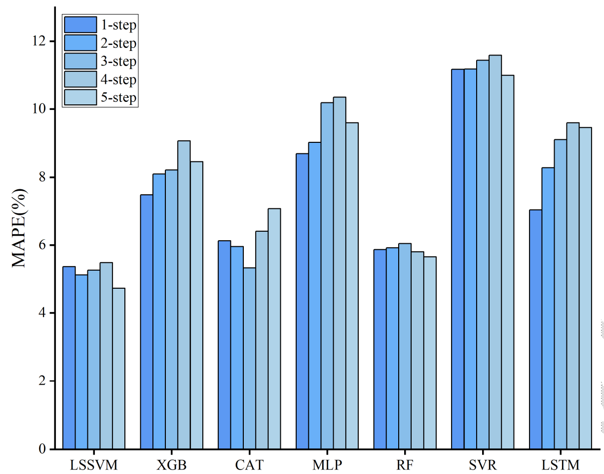

Fig. 3. Prediction error variation of LSSVM, XGBoost, CAT, MLP, RF, SVR, LSTM models

The prediction step size and the prediction accuracy of the model are discussed next. It is clear that the prediction error of most of the models tends to increase and then decrease when the prediction step size increases, so it can indicate that the models have better prediction accuracy in multi-step prediction. The prediction errors of MLP and RF are similar to those of WOA-LSSVM in one-step ahead prediction, but the difference gradually increases as the number of prediction steps increases, and the advantages of this model gradually appear.

4. CONCLUSION

In order to effectively improve the utilization of wind energy resources, reduce the impact of wind power fluctuations on grid stability, and provide timely and reliable information to relevant departments so as to maximize the economy of wind farms and achieve efficient and stable operation, this study establishes a hybrid model based on metaheuristic algorithm (WOA) and machine learning model (LSSVM) and predicts the wind speed in Mianyang.

Based on the analysis of the results in Section 3 of the article, we can obtain the following conclusions: 1) the WOA-LSSVM model has strong prediction performance and prediction accuracy, and can be widely used in the field of wind speed prediction, and also has strong potential in other prediction fields; 2) the WOA algorithm can effectively improve the prediction accuracy of the model, and it can be subsequently combined with other models to improve the performance of the model; 3) in multi-step prediction, the prediction error may decrease as the prediction step length increases, and the proposed WOA-LSSVM has better stability and prediction accuracy in multi-step prediction compared with other comparison models.

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