Real-time wind power prediction based on WD-GA-SVM combined model

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Abstract. In recent years, the development of the wind power industry has been particularly rapid. The research of wind power forecasting technology is of great significance for ensuring the stability of the entire power system and improving the competitiveness of wind power in the power industry. In this paper, the wavelet denoising WD algorithm has good applicability in signal denoising, and a wind power prediction model based on WD-GA-SVM is established for a single wind turbine. Firstly, preprocess the related data to get the initial historical sequence, and then use the wavelet denoising method to reduce the noise of the historical data, and the revised historical data is closer to the actual data. Finally, the automatic optimization feature of the GA algorithm is used to complete the parameter optimization of the support vector machine, and the SVM model is optimized. The research results show that the method described in this paper effectively improves the accuracy of the real-time wind power prediction model.

1. Introduction
The development and utilization of wind energy plays an irreplaceable role in optimizing the production capacity structure and adhering to the implementation of sustainable development strategies. However, wind power has the characteristics of interval, randomness and volatility, which poses serious challenges to the safe and stable operation of the entire power system, which directly affects the competitiveness of wind power in the entire power industry.

At present, most of the research on wind power forecasting technology is focused on short-term and ultra-short-term forecasting with a single wind field or a certain area as the research object. There are not many studies on real-time wind power prediction for a single wind turbine, and the prediction time scale of the study is relatively large. The two important reasons are that the resolution of NWP in time and space is not high, and the real-time data transmission rate is not fast enough. With the development of communication technology and the improvement of weather forecast technology, the real-time output prediction technology of a single wind turbine is also more necessary and feasible.

The real-time wind energy prediction in this paper can start from the current moment, with 7 seconds as the node, and predict the output of the wind turbine within 7 minutes. This lays the foundation for further research on real-time wind power prediction technology in terms of reducing the time scale and improving the model prediction rate, which is of great significance for optimizing the wind turbine control system and improving wind power stability.
2. Data preprocessing
The authenticity and objectivity of the experimental data directly affect the accuracy of the real-time wind power prediction model. The historical data collected from the SCADA system often has some invalid values, such as the lack of data and the appearance of outliers, which must be pre-processed before model training.

2.1. Processing of abnormal data
The output of the fan is closely related to wind speed, wind direction and other factors, and the abnormal condition of historical data can be judged according to this characteristic.

The wind speed and wind direction remain stable but the power is abrupt or the wind speed is less than 3m/s but the wind power is not zero, which indicates the appearance of abnormal data. In addition, the inherent characteristics such as the maximum output power of the fan and the cut-out wind speed are also the basis for judging the occurrence of abnormal values. In order to improve the accuracy of the real-time wind power prediction model, abnormal data in historical data must be eliminated. The main elimination steps are as follows:

(1) When the power value is continuously zero but the wind speed is large, the relevant data needs to be eliminated as a whole;
(2) Set all negative power to zero;
(3) When the wind speed is lower than 3m/s, the output power is set to 0;
(4) The data of the fan output exceeding 1.5MW is uniformly set to 1.5MW;
(5) Exclude historical data that exceeds the cut-out wind speed.

2.2. Processing of missing data
The historical power data exported from the SCADA system has some missing values. In order to ensure the authenticity and continuity of the data, this article deals with the missing data. details as follows:

(1) The wind power time series rarely has sudden changes. For some sporadic missing points, the average of the data before and after the missing point can be used as the missing point data value.
(2) As a simple and commonly used interpolation method, linear interpolation method is widely used in statistics, computer science and other fields. For a small number of missing points in the collected data, we choose this method to fill in the data. The formula is as follows:

\[ P_{n+x} = P_n + x \frac{P_{n+y} - P_n}{y}, 0 < x < y \]  

Occasionally, there are a large number of missing points in the data exported from the SCADA system, which may be caused by power curtailment plans, wind turbine maintenance, etc. Since the historical data is relatively sufficient, the historical data with a large amount of missing data can be considered discarded as invalid data.

3. Prediction model building

3.1. Wavelet denoising
Due to the influence of the collection environment and other factors, the experimental data collected by the system, such as wind speed and power, are all mixed with noise. The presence of noise seriously reduces the accuracy of the data. In order to obtain more original and accurate data, it is necessary to perform noise reduction processing on the collected historical data.

Wavelet denoising(WD) has been widely used in various fields such as electrical, communications, computer technology, etc., with different methods such as median denoising, wavelet denoising has a variety of low entropy and multi-resolution Features. now hard threshold denoising and soft threshold denoising are widely used in signal processing. However, the hard threshold function has a discontinuous characteristic, which makes it difficult to avoid the Pseudo-Gibbs phenomenon. In view of the good continuity and certain smoothness of the wind speed and power data in the experiment, the
wavelet soft threshold denoising method is used to reduce the noise. When the absolute value of the wavelet coefficient is less than the given threshold, let it be 0; when it is greater than the threshold, make the wavelet coefficient minus the threshold, as follows:

$$\omega_{\lambda} = \begin{cases} 
\text{sgn}(\omega)\lvert \omega \rvert - \lambda & \lvert \omega \rvert \geq \lambda \\
0 & \lvert \omega \rvert < \lambda 
\end{cases}$$  \hspace{1cm} (2)

The main idea of wavelet denoising is that after the experimental data is wavelet transformed, the wavelet coefficients of the original signal are greater than the wavelet coefficients of the noise. Choosing the appropriate threshold value can separate the signal and the noise to achieve the effect of noise reduction. The main process of wavelet soft threshold denoising method is as follows:

1. Select the appropriate wavelet basis function (sym5), and the number of decomposed layers is 3 layers.
2. Threshold value processing for each detail coefficient.
3. The denoised signal is obtained through data reconstruction.

### 3.2. Support Vector Machine Theory

The main idea of support vector machine (SVM) is to establish a classification hyperplane as a decision surface, so that the isolated edges of the positive and reverse columns are maximized.

The support vector regression machine is essentially not different from the support vector classification machine, only in the output range. The classification machine requires us to finally divide the experimental data into two or more categories, and the regression machine requires the final output of a real value. Support vector regression machine also transforms nonlinear problems into high-dimensional linear solvable problems through the mapping of kernel functions. When the parameters are found so that the error between the objective function and the actual value is within the acceptable range, the task of the return machine is completed.

The SVM principle model is as follows:

**Known training set:**

$$T = \{(x_1, y_1), \ldots, (x_l, y_l)\} \in (X \ast Y)^l$$  \hspace{1cm} (3)

Among them, \( x_i \in X = \mathbb{R}^n \), \( y_i \in Y = \{1, -1\} \); \( i = 1, 2, \ldots, l \); \( x_i \) is the feature vector.

Select the appropriate kernel function \( K(x, x') \) and the appropriate parameter \( C \) to construct and solve the optimization problem:

$$\min_{\alpha} \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} y_i y_j a_i a_j K(x_i, x_j) - \sum_{j=1}^{l} a_j$$  \hspace{1cm} (4)

$$s.t. \sum_{i=1}^{l} y_i a_i = 0, 0 \leq a_i \leq C, i = 1, \ldots, l$$  \hspace{1cm} (5)

Get the optimal solution: \( \alpha^* = (a_1^*, \ldots, a_l^*)^T \).

**Calculation threshold:**

$$b^* = y_j - \sum_{i=1}^{l} y_i a_i^* K(x_i, x_j)$$  \hspace{1cm} (6)

**Construct the decision function:**

$$f(x) = \text{sgn}\left( \sum_{i=1}^{l} a_i^* y_i K(x, x_i) + b^* \right)$$  \hspace{1cm} (7)
There are many types of kernel functions $K(x, x')$, and radial basis kernel functions are used in this paper.

### 3.3. Genetic Algorithm Theory

Genetic algorithm originated from the computer simulation study of biological systems. Compared with the traditional optimization algorithm, this adaptive probability optimization algorithm does not rely on gradient information and is not subject to the continuous and differentiable constraint of the objective function. At the same time, it can realize the arbitrary setting of the definition domain through coding. This makes it widely used in research fields such as statistics, computer science, and life sciences.

The method of genetic algorithm to search for the optimal solution is to imitate the evolutionary process of organisms, simulating the phenomena of duplication, crossover and mutation occurring in natural selection and genetics. This algorithm is used to optimize the kernel parameters and penalty factors of the support vector machine model, which greatly improves the efficiency of the prediction model and the accuracy of prediction.

The main steps of GA to optimize SVM are as follows:

1. Pre-process data related to wind speed, power, etc.
2. Determine the value range of the nuclear parameters and penalty factors.
3. Binary coding the penalty factor and kernel parameters to generate the initial population.
4. The objective function is transformed into the fitness function, and the fitness function is used as the basis for optimization of the genetic algorithm.
5. If the optimization condition is satisfied, the optimal solution is decoded and output.
6. If the optimization condition is not satisfied, a new progeny population is generated through genetic operations, and the fourth step is continued until it is satisfied.
7. According to the relevant parameters obtained by GA optimization, an SVM model is established to make predictions.

The flow chart of WD-GA-SVM prediction model is shown in Figure 1.

![Flow chart of wind power prediction based on WD-GA-SVM](image)

**Figure 1.** Flow chart of wind power prediction based on WD-GA-SVM
4. Experimental results and analysis
The SCADA system is widely used in China's power industry. It can efficiently and accurately monitor the operating status of the power system. When the system fails, it can quickly and accurately display the system's fault status. The many advantages of this system make it play an irreplaceable role in ensuring the stable operation of the power system and realizing power dispatch automation. Based on the data in the SCADA system, this paper studies the real-time wind power forecasting work.

4.1. Wavelet denoising results
In order to obtain more original and accurate data, it is necessary to perform noise reduction processing on the collected historical data. Denoising historical wind speed data, intercepting the de-noised signal to 1500 sampling points for display, where the abscissa is time and the ordinate is wind speed. It can be seen from Figure 2 that the denoising method has a good denoising effect on wind speed data, ensuring the accuracy of real-time wind power prediction. Using the same method, the temperature, power and wind direction information are all processed for noise reduction.

![Original data vs. Data after noise reduction](image_url)

**Figure 2.** Noise reduction effect comparison chart

4.2. GA parameter optimization results
Now take 350 sets of continuous data from 0:00 on October 16, 2018. Each set includes four items: wind speed, wind direction, temperature, and power. Wind speed, wind direction, and temperature are inputs, and power is output. The first 290 sets are the training set, and the last 60 sets are the prediction set for real-time wind power rate prediction.

The genetic algorithm is used to optimize the parameters, and the penalty factor is 3.1113 and the kernel parameter is 1.7595. Figure 3 shows the results of genetic algorithm parameter optimization. It can be found that after GA optimization of the most traditional SVM model, the tedious and time-consuming trial and error process can be avoided, and the efficiency of the prediction model is greatly improved.
4.3. Combined model wind power prediction results

The WD-GA-SVM model is built on the basis of wavelet denoising, and the same sample set is trained and analyzed to predict the effect.

It can be seen intuitively from Figure 4 that the prediction curve of the GA-SVM model based on wavelet denoising is closer to the original output curve, and the prediction accuracy of the WD-GA-SVM model has also been greatly improved compared to the other two prediction models. The GA algorithm's automatic optimization feature replaces the traditional low efficiency and high error parameter determination work, which improves the performance of the model. The wavelet denoising method restores the authenticity of historical data and improves the accuracy of the model.

In order to further verify the applicability of the WD-GA-SVM forecasting model in real-time wind power forecasting, based on the three forecasting models, a total of 120 sample sets of ten days of historical data were subjected to prediction experiments, and the obtained prediction errors were averaged. In this paper, the root mean square error (RMSE) and the average percentage error (MAPE)
are used as the evaluation indicators of the real-time wind power prediction model. The final prediction error is shown in Table 1.

| Prediction model | RMSE(%) | MAPE(%) |
|------------------|---------|---------|
| SVM              | 15.69   | 17.83   |
| GA-SVM           | 11.23   | 13.56   |
| WD-GA-SVM        | 8.16    | 9.29    |

It can be seen that the prediction model based on WD-GA-SVM has the highest prediction accuracy, RMSE and MAPE are 8.16% and 9.29%, respectively, and the accuracy is improved compared with the other two methods.

5. Conclusion

The wavelet denoising method makes the historical data more reliable. After solving the parameter optimization problem of the support vector machine based on genetic algorithm, the efficiency and accuracy of the real-time wind power prediction model are greatly improved. It is fully proved that the WD-GA-SVM combined model has higher prediction accuracy and more applicability than the single model in real-time wind power prediction, which laid the foundation for further research on real-time wind power prediction technology in terms of reducing the time scale and improving model prediction accuracy. At the same time, the research is of great significance for improving the stability of the power system.

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