EAI Endorsed Transactions
on Energy Web
Research Article EAI.EU

Research on Wind Power Prediction Model Based on Random Forest and SVR

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Abstract

Wind power generation is random and easily affected by external factors. In order to construct an effective prediction model based on wind power generation, a wind power prediction model based on principal component analysis (PCA) noise reduction, feature selection based on random forest model and support vector regression (SVR) algorithm is proposed. First, in the data preprocessing stage, PCA is used for sample data denoising; then the random forest model is used to calculate the importance evaluation value of each feature to optimize the selection of feature parameters; finally, The SVR algorithm is applied for training and prediction. Experiments show that the prediction effect of the model based on random forest and SVR is excellent, the root mean square error(RMSE) is 0.086, the average absolute percentage error(MAPE) is 23.47%, and the coefficient of determination(R^2) is 0.991. Compared with the traditional SVR model, the root mean square error of the method proposed in this paper is reduced by 95.9%, and the prediction accuracy and the fit of the prediction curve are significantly improved.

Keywords: PCA; random forest; SVR; wind power; prediction

Received on 18 November 2023, accepted on 6 April 2024, published on 12 April 2024

doi: 10.4108/ew.5758

1. Introduction

Wind power can reduce greenhouse gas emissions and help alleviate the current energy crisis [1,2]. The use of new energy to replace traditional thermal power and coal power will become an inevitable trend. Wind energy resources are widely distributed, clean and zero-emissions, etc., which have attracted the attention of all countries. There are many large-capacity wind farms in China, and wind power instability characteristics can affect the power output of wind turbine generation, making the grid unstable after wind power is connected to the grid. There is a need to construct a model that can accurately predict the wind power generation power [3-4]. This has important applications in grid-connected wind power [5], which can ensure stable operation of the power system [6].

Currently, wind power forecasting studies mainly includes probabilistic statistical methods, machine learning methods and deep learning methods. This paper discusses the application of machine learning methods in wind power forecasting. Machine learning methods can be divided into single prediction models and composite models. However, the single model is less sensitive to the sample data, which affects the final prediction accuracy. In response to the above problems, some scholars have proposed the use of combined forecasting models for wind power forecasting. For example, the literature [7] combined time series and neural networks, and wind speed data with time-series characteristics were fed into the neural network for training, achieving better prediction results [8]. The literature [9], on the other hand, combined statistical and machine learning models with better results than the time-series and RBF models. Literature[10] proposed a wind power signal prediction method based on improved empirical mode decomposition and SVM, this method is an improved method for the abatement of undershoot phenomena. Taking the wind power data of a wind farm as a training sample, firstly, the wind power signal is decomposed into a set of relatively stable sub-sequence components by IEMD, which is effective in reducing the number of undershoot points. Then, the IEMD-SVM combined prediction model of wind power signal intermediate frequency component is constructed based on SVM, the experiments illustrate the model's high prediction

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accuracy and greater stability. A wind power prediction model based on MEEMD-KELM is proposed[11], where the wind power signal decomposition uses MEEMD and is combined with the KELM model, and the results showed that the MEEMD-KELM model has a good forecasting effect. Literature[12] uses the particle swarm optimization algorithm PSO-GA to optimize the SVM model, the genetic algorithm (GA) with local optimization is used to optimize the parameters such as the kernel function of the support vector machine. Considering the limitations of a single optimization method, the particle swarm optimization (PSO) with global optimization is proposed for parameter optimization of the GA-SVM prediction model, the experiments show that the PSO-GA-SVM model has higher prediction accuracy. Literature[13] proposed a predictive model of PSO-SVM based on Variational Model Decomposition (VMD). Firstly, VMD was used to decompose the original wind power sequence, and PSO was used to optimize the SVM parameters. A good prediction effect has been achieved.

The combined wind power forecasting model proposed in the above research either performs smooth processing of wind power signals and then predicts, or optimizes the forecasting model itself. Although certain effects have been achieved, the noise in the data samples and the irrelevant features in the samples will also affect the To predict the effect, this requires the introduction of methods in the two links of data preprocessing and feature selection. Based on the characteristics of short-term wind power data that are inherently unstable and have many influencing factors, a combination model combining principal component analysis, random forest and support vector regression is proposed. First, PCA is used to filter data noise, and then feature selection is performed based on random forest. Finally, SVR is used for training and testing, and a reliable wind power prediction model is obtained.

2. Related work

This section will introduce the technologies related to the work of this article, including PCA-based noise reduction processing of sample data, random forest-based feature selection methods, and SVR regression algorithm models.

2.1. Noise filtering based on PCA

PCA is an effective data dimensionality reduction algorithm, in other words, mapping high-dimensional features to low-dimensional features, that is, use orthogonal transformation to convert a high-dimensional vector group into a set of linearly uncorrelated vectors. After the change, the main components in the original data are retained, which can be effective To eliminate redundant information in the original data, the new low-dimensional orthogonal features are called principal components. Assuming that there are mxn-dimensional data samples, there are a total of m samples, and each row is n-dimensional, the main steps of the PCA algorithm[14-16] are as follows:

1) First, center the sample data matrix $y_{(n\times m)}=\{y_1,y_2...y_m\}$ to get the centered matrix y'

2) Decompose the eigenvalues of the covariance matrix of y'

3) The eigenvectors are calculated for the first t maximum eigenvalues, and after normalization, they form the eigenmatrix $W=\{W_1,W_2...W_t\}$

4) The final data after dimensionality reduction is $y_{new}=W^T y'$, $y_{new}\in R_{(t\times m)}$

In addition to dimensionality reduction, PCA can also perform noise filtering on sample data, because the influence of any component in the principal component is far greater than the influence of noise, and each component is relatively unaffected. The principal components can be used to reconstruct the noisy original sample data. The main idea is to reduce the dimensionality of the data set on the premise of retaining the main information of the original data set, and then upgrade the low-dimensional data to high-dimensional data, that is, to restore to the original data set's dimensionality. The upgrade steps are as follows:

1) First, take the transposed matrix WT of the matrix W containing the t largest eigenvalues

2) Then multiply the dimensionality-reduced matrix y_{new} and WT to increase the dimensionality-reduced matrix to the original dimension, and the resulting matrix is denoted as y_r

3) Find the mean value of each column of the matrix to get the n-dimensional vector V

4) Add the matrix y_r and the mean vector V to deconstruct the original dimension data matrix

2.2. Feature extraction method based on random forest

The wind power output is influenced by a large number of factors, that is, there are many feature parameters in the sample data, which will affect the performance and speed of model training, and the existence of some features that are not related to the label feature or have a low degree of correlation will also influence the accuracy of the model. So, feature dimensionality reduction is required. Feature dimensionality reduction is divided into two types, feature transformation and feature selection[17]. Feature transformation is an elimination strategy for redundancy between features, such as principal component analysis (PCA), etc.[18]. Feature transformation retains the main information of the sample data features and expresses it in low-dimensional form. However, after the high-dimensional becomes low-dimensional, it also loses the physical meaning of the original feature, and it is impossible to judge the relationship between the feature and the category by dimensionality reduction alone.

The key to feature selection is to calculate features with high correlation between statistics and marked features to construct effective feature subset evaluation indicators, including evaluation indicators based on classification performance and evaluation indicators based on the statistical characteristics of the data itself. According to this, Feature selection mainly includes: encapsulation model, embedded model and filtering model [19].

Common methods for measuring the correlation between each characteristic variable and the dependent variable include linear correlation coefficient, mutual information, random forest, etc. Among them, the correlation coefficient method is used to express the closeness of the correlation between two variables. As a statistical indicator, it has been widely used in many application fields. Pearson coefficient belongs to one of them. It mainly reflects the linear correlation of the two variables. The mutual information method can be used to calculate the correlation between two non-linear characteristics, but it is only suitable for measuring the difference between discrete variables relation. In this paper, there is no obvious linear relationship between the characteristics of wind power generation and the characteristics of the data samples, and all the characteristics and the value of the labeling characteristics are quantitative and continuous. Therefore, this paper uses random forest to evaluate the importance of each sample feature.

The random forest(RF) model is developed from decision regression[20]. The model first generates a certain number of decision trees. The data of each tree is defined by the self-sampling method from the definition set B. The remaining data not in the training sample is called OOB, the data set is defined as B, C is defined as the set of B, and □C is the set of □B. Suppose that the X matrix has n measured data and P features, and y is an n-dimensional label vector, and each value corresponds to a category of the sample data. The RF algorithm calculates the importance of the feature by rearranging the classification errors before and after the feature. The importance of the feature mainly includes the Gini index (Gini index) or the out-of-bag data (OOB) error rate. This article uses the OOB-based approach to calculate. The steps to calculate feature importance are as follows:

1. The out-of-bag data error is calculated from the OOB data of each decision tree and represented by the variable errOOB1.

2. Noise is randomly added to feature X of the OOB data and the out-of-bag data error is calculated and represented by the variable errOOB2.

3. If the number of decision trees in the random forest is M,the importance of feature X(denoted as VIM) is calculated as follows:

$$\mathrm{VIM} = \sum(errOOB2 - errOOB1)/M \tag{1}$$

Add random noise to a feature, if the out-of-bag accuracy is significantly reduced, it indicates that the feature is more important for the classification results.

2.3.SVR Algorithm Model

Support Vector Regression (SVR) is a regression analysis using SVM. The difference between SVR and SVM is that the optimal hyperplane sought by SVR is not to divide the two types of samples into the "most open", but to ensure that the "total deviation" of all samples from the hyperplane is minimized.

Support vector regression is suitable for solving small sample data. It has the characteristics of high prediction accuracy and strong generalization ability. It has various types of kernel functions to deal with various regression problems. The goal of support vector regression model[21,22] is different from that of support vector machine. The goal of SVR is to fit all points in the training set to a linear model. Set each point of the sample to (x_i, y_i), then linear The form of the model is as follows:

$$f(x_i) = \omega \times \varphi(x_i) + b \tag{2}$$

Where $\varphi(x_i)$ is a nonlinear mapping of the vector x_i to a high-dimensional feature space, and ω and b represent the vector and the offset, respectively. If there is a constant ∂>0, suppose the value of $|f(x_i) - y_i|$ is G, if a certain point (x_i, y_i), if G<=∂, the loss is 0, otherwise, the corresponding loss is |G -∂|, record the loss as err(x_i, y_i). Suppose the optimization objective function of the regression model is $(1/2)||w||^2$. According to the set loss degree, the final loss function formula is:

$$S = C \times \frac{1}{n} \times \sum_{i=1}^{n} err(x_i, y_i) + \frac{1}{2}||w||^2 \tag{3}$$

The parameter C in formula(3) is the penalty factor, which indicates the tolerance for misclassification in the classification results. C indicates the degree of emphasis on outliers. The larger the C, the penalty for misclassification increases, and the penalty for error classification decreases when the C value is small. Too large C value may lead to over-fitting, while too small C value may easily lead to under-fitting.

This paper proposes a forecasting model based on PCA-RF-SVR. The specific prediction process is shown in Figure 1:

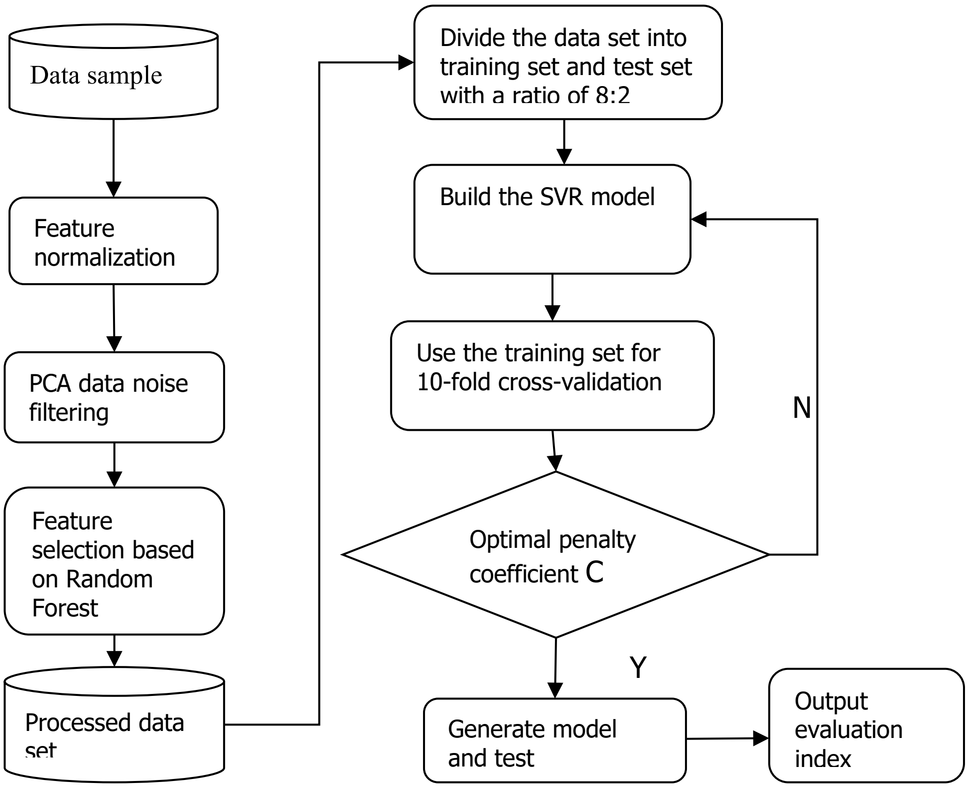

Figure 1. Flow chart of PCA-RF-SVR prediction model

3. Wind power forecasting model construction

3.1. Determination of data samples

The data sample used in this paper is a public dataset, which is the measurement data of an anemometer tower. The data sample features include: 10m, 30m, 50m, 70m wind speed, 30m, 50m, 70m wind direction, and temperature, barometric pressure, humidity, and power generation. Power generation is the target feature of the forecast. The data samples were collected every 15 minutes. The descriptive information for the sample data is shown in Table 1:

Table 1. Samples description information

	WS10(m/s)	DIR10(degree)	WS30 (m/s)	DIR30(degree)	WS50 (m/s)	DIR50(degree)	WS70 (m/s)	DIR70(degree)	WSHUB(m/s)	DIRHUB (degree)	TEMP(°C)	PRESSURE(KPa)	RH%	POWER(MW)
mean	8.75	207.31	5.87	198.45	6.11	190.48	5.95	191.82	5.95	191.82	32.88	967.19	87.95	5.7
max	28.92	359.89	13.92	359.09	12.84	356.89	11.28	359.79	11.28	359.79	39.1	974.77	100.0	26.11
min	0.84	0.6	0.24	0.5	0.84	0.8	1.44	0.6	1.44	0.6	26.2	961.77	48.6	-0.48
standard deviation	5.09	69.51	2.7	70.14	2.47	68.96	2.2	69.19	2.2	69.19	2.26	3.8	14.23	6.7
coefficient of variat	58.17	33.53	46	35.34	40.43	36.2	36.97	36.07	36.97	36.07	6.87	0.39	16.18	117.54

ion (%)

From Table 1 we can notice that all wind direction and wind speed related features have a large range, especially the wind direction feature range reaches about 360 degrees, which also indicates that the wind direction and wind speed features have great instability, which indicates that a specific prediction model is needed to predict the value of wind power. In terms of the coefficient of variation, the coefficient of variation of the power generation feature reaches 117.54%, indicating that the power generation data is discrete and highly volatile, which poses difficulties for the effective prediction of this target feature, and also indicates that outliers and noise may exist in the sample data corresponding to this feature, which requires outlier detection and processing, as well as the necessary noise reduction processing of the sample data.

3.2. Data preprocessing

Data preprocessing includes two parts: normalization of sample feature data and data denoising processing.

(1) Data normalization processing. Due to the large difference in the value range of each feature index of the selected wind power generation samples, each sample feature has a different dimension. To eliminate the impact of the sample feature units and scale differences, regarding the features of each dimension equally, the features are normalized. Here, the maximum and minimum normalization method is used to convert all the feature values to the interval [0,1] . The formula is shown in (4):

$$x'_t = (x_t - x_{min})/(x_{max} - x_{min}) \tag{4}$$

Among them, the maximum value of the sample data is denoted as x_{max} and the minimum value is denoted as x_{min}, x_t represents the original data, x'_t represents the normalized value.

(2) Data denoising with PCA

Noise in sample data can affect model prediction performance. The sample data collected by the wind tower may be polluted by noise. Therefore, it is necessary to perform data denoising. PCA dimensionality reduction algorithm is used. Under the premise of retaining the effective information in the sample, the sample data set is first reduced in dimensionality and then raised to the original dimension to achieve the effect of reducing noise. Because the proportion of data collected by the device is not large, the PCA algorithm is set to retain 98% of the sample information.

From the sample statistics in Table 2, it can be seen that the wind speed-related features are highly volatile and have a high coefficient of variation, indicating the instability and randomness of wind speed itself. Noise reduction can smooth the data curves of features with high fluctuations and high variability, which will reduce noise data interference and thus improve the prediction effect. The noise reduction comparison effect for the three features corresponding to WS10, WS30 and WS50 is shown in Figure 2:

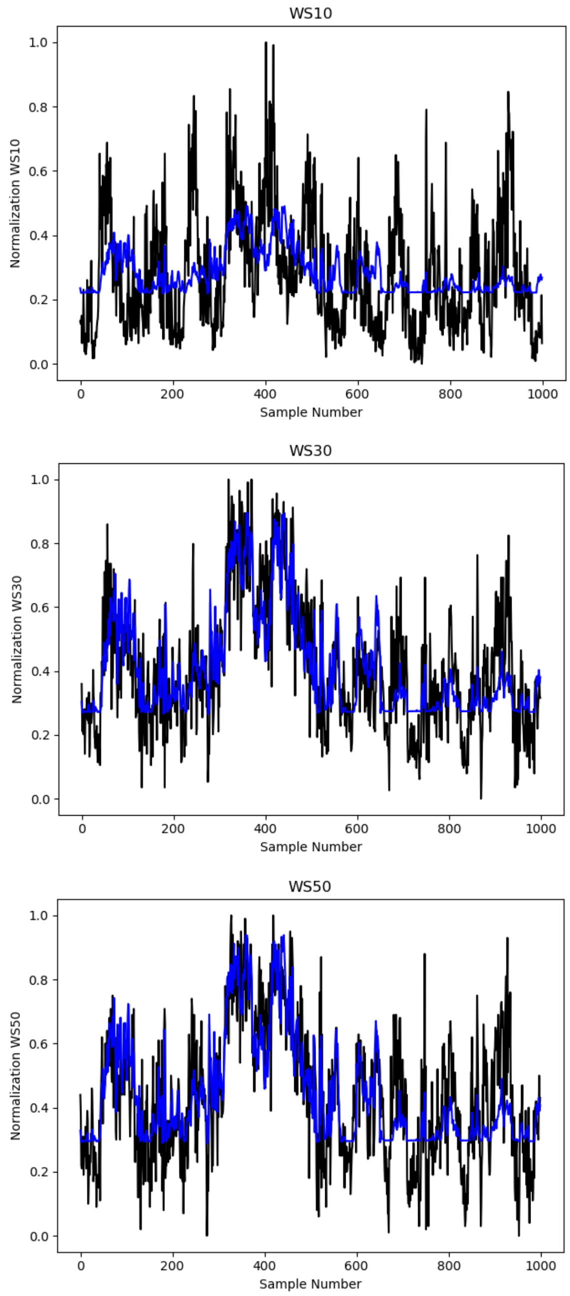

Figure 2. Comparison of data for each feature before and after PCA noise reduction

It can be seen from the Fig.2 that after PCA noise reduction, the fluctuation of the new sample data is significantly reduced, the plotted curve is smoother, and the trend of data change is basically the same as the trend of data change before noise reduction.

3.3. Selection of characteristic parameters

In this paper, there is not necessarily a linear relationship between sample characteristics and power generation, and the values of all statistical index characteristics are quantitative and continuous, so the RF model is used to evaluate the importance of each feature, and finally selected features with a high degree of relevance are used as input of the SVR .

After removing the generated power, there are 13 features, the size of the dataset is 1000 and the ratio of the training set to the test set is 7:3., and then train through the RF model. The importance evaluation results of each feature are shown in Table 2:

Table 2. The importance of each feature

Characteristic index	Importance
PRESSURE	0.084203
WS10	0.083974
WS30	0.082554
TEMP	0.081623
WS50	0.081540
DIR10	0.080331
WSHUB	0.075142
DIR30	0.075011
WS70	0.074219
DIR50	0.073440
DIR70	0.071961
DIRHUB	0.071939
RH	0.064061

Table 2 shows that atmospheric pressure has the greatest effect on power generation, and RH has the least effect on power generation, and this paper sets the relevant importance threshold to 0.08. The features finally selected for model training according to the results shown in Table 2 are: PRESSURE, WS10, WS30, TEMP, WS50 and DIR10. This reduces the complexity of the SVR model and improves its generalization capabilities.

3.4. SVR algorithm and evaluation index descriptions

The SVR algorithm is adopted, and the kernel function adopts the RBF kernel. The RBF kernel, also known as Gaussian kernel. It will map the input samples to a high-dimensional space in a non-linear manner, so it can handle the non-linear relationship between class labels and sample attributes. The feature parameters after feature selection are used for model training, 10-fold cross-validation is used for model verification, then test set is used to fit the prediction effect.

This paper uses the RMSE to evaluate the performance of wind power forecasting, which is the square root of the mean square error(MSE). The calculation formula for the MSE is shown in (5), where y_i refers to the actual value and p_i refers to the prediction value.

$$\mathrm{MSE} = \frac{1}{\mathrm{N}}\sum_{i=1}^{\mathrm{N}}(\mathrm{y_i} - \mathrm{p_i})^2 \tag{5}$$

In addition to considering the error, MAPE also considers the ratio between the error and the actual value, which is of more reference value. The calculation formula of MAPE is shown in (6):

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|y_i - \hat{y}_i|}{|y_i|} \tag{6}$$

Among them, y_i denotes the actual value, and $\hat{y}_i$ refers to the predicted value.

R2 reflects the degree of explanation of the dependent variable by the independent variable, and reflects the goodness of fit of the model. The formula is shown in (7):

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \overline{y}_i)^2} \tag{7}$$

Among them, y_i and $\overline{y}_i$ represents the sample true value and the mean value respectively.

4. Experiment and discussion

This section will show the experimental results of this method. First, Section 4.1 will introduce some of the parameters used in the experiment of this method and the data set used in this experiment. Section 4.2 will show the comparative experimental data of this method and other algorithms.

4.1. Experimental parameter settings

The experiment in this paper is based on the measurement data in a certain wind measurement tower, including 13 characteristics such as wind force, wind direction, humidity, etc. The target characteristic is power generation. First, the data is processed by PCA noise reduction, and then after feature selection based on the random forest model, finally the index feature greater than 0.08 is selected for the training prediction of wind power generation, that is, as the input of the SVR model. The parameters of the SVR model are configured as follows: The SVR algorithm selects the RBF function as the kernel function, gamma=0.01, and the penalty coefficient C is obtained by setting a numerical range for optimization, and setting C∈[1,1000]. 80% of the collected data samples are used as training data and 20% of the sample data are used as test data.

4.2. Comparative Experiment

The method proposed in this paper, which is based on PCA noise reduction processing, random forest feature selection combined with SVR, is labeled as M3, the traditional SVR prediction method is labeled as M1, and the PCA+SVR combined method is labeled as M2. Among them, the SVR algorithm of the three methods uses the same parameter settings. The penalty factor C is obtained by optimizing for each method from a certain range, and the optimizing range of C is [0,500]. Choosing different penalty factors corresponds to the variation curve of the determination coefficient of the M1 model as shown in Figure 3:

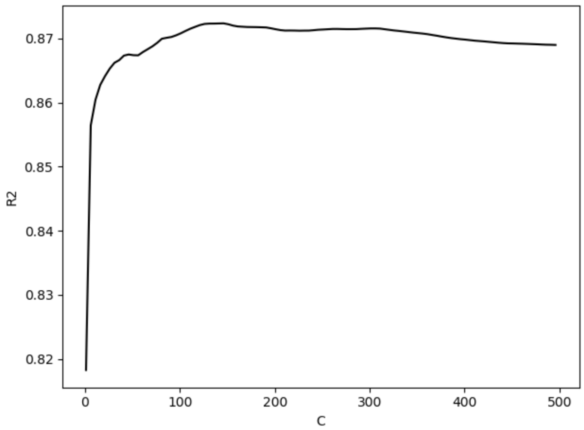

Figure 3. The variation curve of the coefficient of determination of the M1 model

Finally choose C=146. The three methods all select the same parameters, and the performance metrics for each model are shown in Table 3:

Table 3. Performance metrics for each model

Method	RMSE	MAPE%	R2
M1	2.475	238%	0.88
M2	0.101	23.93%	0.96
M3	0.086	23.474%	0.99

From the RMSE index, the RMSE of M2 is reduced by 2.374 compared with M1, that is, the prediction accuracy is improved by an average of 95.9%, indicating that prediction performance of the algorithm using PCA noise reduction processing combined with SVR is better than the traditional SVR algorithm, the prediction effect has improved significantly. Compared with M2, the RMSE of M3 is decreased by 0.015, that is, the prediction accuracy of wind power is increased by an average of 14.85%, indicating that the random forest-based feature selection has a certain effect on the improvement of prediction accuracy.

From the perspective of R2 index, the values of M1, M2, and M3 increase in order, indicating that the PCA-RF-SVR prediction model is relatively optimal.

A scatter plot is drawn to observe the model fit based on the true and predicted values of the test samples, with the horizontal axis indicating the serial numbers of the samples and the vertical axis indicating the wind power values. The fitting effect of the M1 model is as follows:

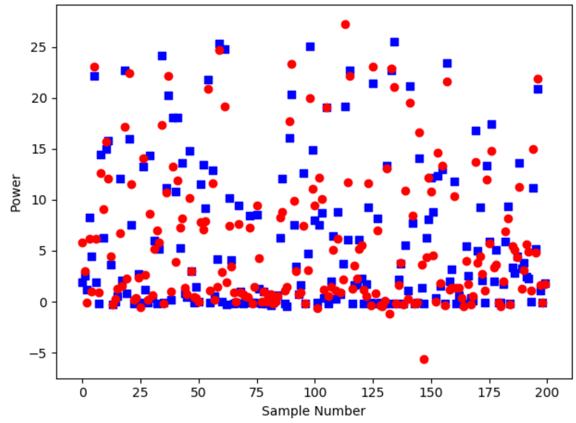

Figure 4. SVR wind power forecasted value and true value fitting effect

The fitting effect of the SVR model after using RF for feature selection and PCA noise reduction processing is as follows:

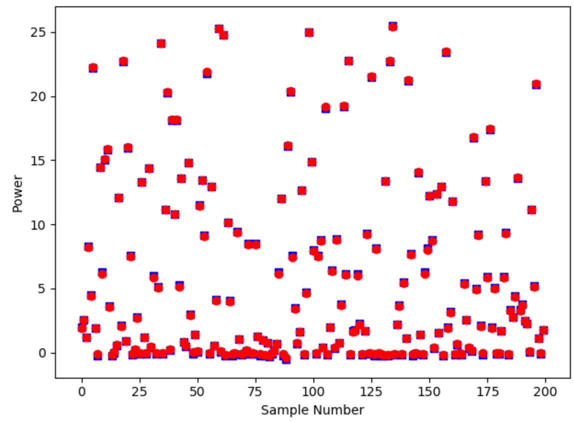

Figure 5. PCA-RF-SVR wind power forecasted value and true value fitting effect

It is easy to see from the comparison of Figure 4 and Figure 5 that the PCA-RF-SVR model has a better fit than the traditional SVR model, and the fitting accuracy is significantly improved.

5. Conclusion

We propose a prediction model based on random forest and SVR in view of the diverse influencing factors of wind power generation and the characteristic that the characteristic value itself is a continuous attribute. First, in view of the noise data that may exist in the statistical data of a certain wind measurement tower, a noise reduction process based on the PCA algorithm is proposed. Then, the RF model is used to calculate the importance evaluation of each sample feature, and some features with a higher degree of correlation with the power generation are selected as the training feature parameters. Finally, the selected characteristic parameters are passed to the SVR model as input. SVR and PCA+SVR are compared with the proposed model. The experimental results directly illustrate that the proposed model has better prediction. PCA denoising and feature extraction based on RF can significantly improve the prediction accuracy of the model.

Acknowledgements.
The authors would like to thank Dr. Xinping Wang for his suggestions on model evaluation indicators.

References

[1] Ma,W.Z.; Cheng, R.L.; Shi, J.;Hua, D.; Sun, G.S.; Zhang, C. Imitation interval tide calculation considering wind farm model[J]. Guangdong Electric Power, 2019, 32(11): 10.
[2] Han, Z.F.; Jing, Q.M.; Zhang, Y.K. Overview of wind power forecasting methods and new trends[J]. Power System Protection and Control, 2019, 47(24):10.
[3] Ma, T.T.; Wang, C.; Peng, L.L. Power system short-term load forecasting considering demand response and deep structure multi-task learning[J]. Electrical Measurement and Instrumentation, 2019,56(16):50-60.
[4]Wang,Y.Q.; Wang, Y.L.; Wang, L.B. An improved fruit fly algorithm optimizes the neural network short-term load forecasting model[J]. Electrical Measurement & Instrumentation, 2018, 55(22):7.
[5] Ge, W.C.; Sun, P.; Li, J.J.; Hui, X.; Kong, X. Robust estimation model of wind power prediction confidence under different scenarios during peak load hours of power grid[J]. High Voltage Technology,2019,45(04):1281-1288.
[6] Liu, X.J. Wind power output prediction methods and systems [D]. North China University of Electric Power, 2011.
[7] Zhang, K.; Qu, Z.; Wang, J.; Zhang, W.; Yang, F. A novel hybrid approach based on cuckoo search optimization algorithm for short-term wind speed forecasting[J]. ENVIRONMENTAL PROGRESS & SUSTAINABLE ENERGY, 2017, 36(2):943-952.
[8] Zhang, H.C. Research on short-term power prediction method for wind farms based on neural network combination model[D]. Hunan University of Technology,2019.
[9] Li, L.L.;Xu,Y.H.; Tian, X.Y.; Niu,Y.T. Short-term prediction of wind power based on combined model[J]. Journal of Electrical Engineering Technology,2014,29(S1):475-480.
[10] Wang, T.; Gao, J.; Wang, Y.Y. Research on wind power power prediction based on improved empirical mode decomposition and support vector machine [J/OL]. Electrical Measurement and Instrumentation: 1-6 [2020-9-24]
[11] Zhao, R.Z.; Ding, Y.F. Short-term wind power prediction based on MEEMD-KELM[J]. Electrical Measurement & Instrumentation, 2020, 57(21):7.
[12] Huang, X.X.; Yu, H.J.; Gong, X.Y. Short-term prediction of wind power based on PSO-GA-SVM[J]. Electrical Engineering Technology, 2020(6): 4.
[13] Huang, F.; Xiang, X.C.; Wang, R.; Jia, R.Y, You, H. A Short-Term Wind Power Prediction Algorithm Based on VMD-PSO-SVM [J]. Journal of Hunan Institute of Engineering (Natural Science Edition), 2022, 32(02):7-12.
[14] Zhao, X.; Wang, W.J.; Zeng, Y.Y. Improved modular PCA new algorithm for face recognition [J]. Computer Engineering and Applications, 2015, 51(2):161-164, 175.
[15] Dong, E.Z.;Wei, K.X.;Yu, X. A car model recognition algorithm incorporating PCA with LBP feature reduction [J]. Computer Engineering and Science, 2017, 39(2): 359-363.
[16] Dong, H. Non-convex compressed sensing reconstruction based on PCA dictionary and two-stage optimization [D]. Xi'an: Xidian University, 2013.
[17] Huang, R.J.;Sun, W.D.; Guang, L.Manifold-based constraint Laplacian score for multi-label feature selection.[J].Pattern Recognition Letters,2018.112346-352.
[18] Cai. J.; Luo, J.W.;Yang, S..Feature selection in machine learning: A new perspective[J].Neurocomputing,2018,300(Jul.26).70-79.
[19] Mursalin Md,Chen Yuehui,Chawla Nitesh V.,et al.Automated epileptic seizure detection using improved correlation-based feature selection with random forest classifier[J].Neurocomputing,2017,241(Jun.7).204-214 .
[20] Lin, C.D.; Peng, G.L. Application of Random Forest in the Determination of Enterprise Credit Evaluation Index System[J]. Journal of Xiamen University: Natural Science Edition, 2007, 46(2): 5.
[21] Zhang, H.L.; Gao, X.L.; Liu, Y.Q. Comparative study on the adaptability of three mainstream wind farm power measurement algorithms [J]. Modern Electric Power, 2015, 32(6): 15-20.
[22] Zhou, Q.; Mou,C.; Yang, D. Overview of the Research Progress of Educational Data Mining[J]. Journal of Software, 2015, 26(11): 3026-3042.