Wind Speed Prediction Model Based on Deep Learning

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Abstract. This article selects hourly wind speed data recorded by meteorological monitoring stations as the dataset, and conducts in-depth analysis on the preprocessing methods of wind speed data in response to the nonlinearity and instability of wind speed time series. At the same time, the algorithm principles and steps of empirical mode decomposition, comprehensive empirical mode decomposition, and complementary ensemble empirical mode decomposition were introduced, and the decomposition results of different methods were compared. In addition, in the selection of prediction algorithms for wind speed prediction models, the theoretical basis and algorithm steps of backpropagation neural networks, deep confidence networks, and long-term and short-term memory neural networks were studied, and a single model prediction performance comparison was conducted on three time series short-term prediction models. Compared with the LSTM model, the RMSE of the model established in this article decreased by 0.9422, MAE decreased by 0.6789, and MAPE decreased by 7.23%.

1 Introduction

Among many renewable energy sources, wind energy has attracted much attention due to its many advantages. For many years, in order to improve the accuracy of wind speed prediction, researchers have continuously proposed and improved wind speed prediction models. Common wind speed prediction models can be divided into sustained models, physical models, statistical models, and machine learning models. However, traditional wind speed prediction models have certain limitations, such as excessive reliance on physical models, which cannot fully consider the complex factors that affect wind speed. These limits the widespread application and accuracy of traditional models in wind speed prediction. In order to overcome limitations, we need to seek more advanced methods to improve the accuracy and reliability of predictions[1].

Deep learning technology has made significant progress in wind speed prediction, with models that can automatically learn and extract features from a large amount of data, and have stronger pattern recognition and prediction capabilities. By utilizing deep learning models, we can better capture potential patterns and long-term correlations in wind speed data, thereby improving the accuracy and stability of predictions. So, introducing deep learning models into wind speed prediction research is of great significance. Through in-depth research and improvement, we can further improve the performance of wind speed prediction models, providing guarantees for efficient utilization of wind energy, promoting technology promotion, and meeting energy needs[2,3].

The main research content of this article can be divided into three parts: comparative selection of data decomposition techniques, experimental comparison of single prediction models, and design experiments of combination models. In terms of experimental data selection, measured data from wind farms and monitoring data from meteorological stations were selected as samples for wind speed data. Then, methods such as empirical mode decomposition (EMD), integrated empirical mode decomposition (EEMD), and complementary set empirical mode decomposition (CEEMD) were used to extract eigenvalues from the original wind speed set, and the advantages, disadvantages, and application effects of various methods were analyzed. In terms of single prediction model experiments, we used BP inverse neural network prediction model, DBN deep confidence network model, and LSTM long-term and short-term memory network model to analyze the experimental samples and improve the problems of single wind speed prediction model when dealing with nonlinear time series, thereby improving the accuracy of the prediction model. In the aspect of combined model design experiment, we combined a variety of prediction algorithms, and compared with other kinds of experimental models for research and analysis, to obtain a better CEEMD-LSTM wind speed prediction model, which ultimately proved that the combined model can achieve more accurate results than a single model, and carried out in-depth analysis and discussion on the prediction experiment.

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2 A Wind Speed Prediction Model Based on CEEMD and LSTM

2.1 Signal decomposition technology

Signal decomposition technology is a processing method that can decompose the original signal into multiple sub signals to gain a more comprehensive understanding of signal features and extract effective information. The use of signal decomposition technology in wind speed prediction can effectively improve model accuracy and optimize prediction results. The original wind speed data usually has obvious nonlinear, periodic, and noise characteristics, which are difficult to directly describe and analyze using traditional mathematical models. Therefore, using traditional modeling methods may encounter many problems, such as low model accuracy, poor model robustness, and unstable prediction results. For the processing of the original wind speed signal, signal decomposition technology can be used to decompose the signal into multiple sub signals with different scales and frequencies. This can make the signal easier to describe and analyze, and can model and predict sub signals with different scales and frequencies separately. Meanwhile, signal decomposition can effectively remove noise from the original signal, reduce errors, and improve the accuracy and robustness of the model[3,4].

2.2 Long Short Term Memory Neural Network

LSTM is a specific loop neural network suitable for processing information such as time series and sequence. Compared to conventional RNN, this method has strong memory capacity and can better capture long-term related information. In response to the problems of "gradient loss" and "gradient explosion" in conventional recurrent neural networks, LSTM proposes a new control strategy in recurrent neural networks. LSTM is a cellular state with three gates, namely forgetting gate, input gate, and output gate. These gates use nonlinear activation functions and learnable weights to control information flow. In the LSTM unit, the forgetting gate determines which information needs to be discarded based on the current input and the hidden state of the previous time step. The input gate calculates new candidate values for updating the cell state. The cell state is updated based on the results of the forgetting gate and input gate, and the output of the output gate is controlled based on the hidden state of the current input and current time step. The key to LSTM lies in its cellular state, which allows the network to retain and update information in long sequences. Through the gating mechanism, LSTM can selectively remember and forget information, thus effectively handling long-term dependency relationships. During the training process, LSTM gradually learns the patterns and features of the input sequence using backpropagation algorithm and gradient descent method. In the application phase, LSTM can predict future outputs based on past input sequences[5].

2.3 Raw Dataset Analysis

This article selects the actual wind speed data of a domestic wind farm as the research object to systematically verify the reliability and applicability of the proposed model. By using real wind speed data, we can better evaluate the performance and effectiveness of the model in practical applications.

This study selected wind speed data from 00:00 on May 1, 2016 to 23:00 on May 31, and from 00:00 on December 1 to 23:00 on December 31 as the research subjects. The collection frequency was once an hour, and each data group contained 724 records. Before modeling, we divide the dataset into training and testing sets. Among them, the first 70% of the data is used for model training, and the remaining 30% is used as the test set to verify the predictive performance of the model. In this way, we can evaluate the model's generalization ability to new data. The wind speed dataset from 00:00 on May 1, 2016 to 23:00 on May 31 is dataset A, and the wind speed dataset from 00:00 on December 1, 2016 to 23:00 on December 31 is dataset B. The distribution of two wind speed datasets is shown in Figures 1 to 2.

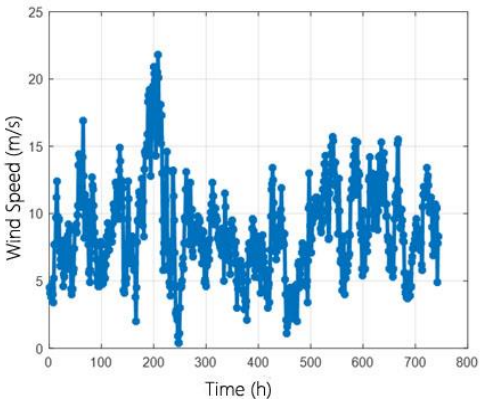


Fig.1 Wind speed line chart for dataset A

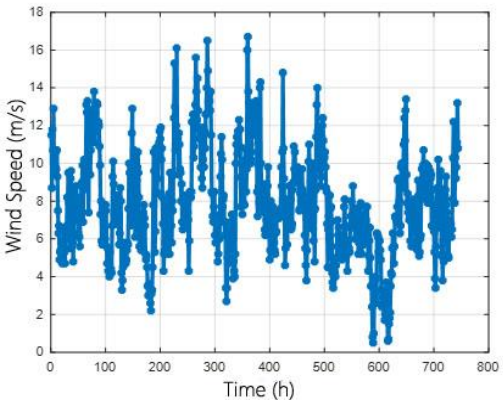


Fig.2 Wind speed line chart for dataset B

2.4 Parameter Setting of CEEMD-LSTM Model

When using the CEEMD method for feature value extraction, the multiple of noise standard deviation is set to 0.02, which affects the degree of separation between signal and noise in CEEMD decomposition. Smaller values can enhance the retention of the signal, but may

not effectively remove noise. Setting the number of iterations for a CEEMD decomposition to 200 can improve the accuracy of the decomposition results, but it also increases the computational complexity. The maximum number of iterations for CEEMD decomposition is set to 200. Normalize the data after feature value extraction and map its value range to between [0,1]. Meanwhile, determine the look_ The back value is 24 and the dataset is divided, with a ratio of 7:3 for the training and testing sets. For regression prediction, set the number of individual output responses to 1 and the number of hidden layer units to 200. The gradient threshold is 1, the initial learning rate is 0.005, and the piecewise method is used for learning rate scheduling. That is, every 125 iterations, the learning rate will decrease to 0.2 times the original. Reverse normalize the predicted and actual results, and map the data back to the original range, as shown in Figures 3 to 4.

2.5 Analysis of Prediction Results of Wind Speed Series

2.5.1 Prediction Performance Analysis of LSTM Models Based on Different Decomposition Methods

Based on the error indicators provided in Tables 1 and 2, we summarized and compared the MAPE, MAE, and RMSE of dataset A and dataset B. The results showed that the CEEMD-LSTM model performed the best among these three error indicators, while the LSTM model performed the worst. This trend has been validated in both datasets. In dataset A, the CEEMD-LSTM model exhibits the smallest MAPE, MAE, and RMSE values, indicating that this model can more accurately predict wind speed data compared to other models. In contrast, the LSTM model has the largest error indicator, indicating that it is relatively inaccurate in predicting wind speed. Similar results were also observed in dataset B, indicating better predictive performance than other models on this dataset.

The analysis results for dataset A show that the CEEMD-LSTM model has made significant improvements in three error indicators. Its MAPE is 0.0830, MAE is 0.1706, and RMSE is 0.3107. Compared with the LSTM model, the RMSE of the CEEMD-LSTM model decreased by 0.9422, MAE decreased by 0.6789, and MAPE decreased by 7.23%. This indicates that by adding the feature value extraction process, the predictive performance of the wind speed prediction model has been significantly improved. Compared with the EMD-LSTM model, the improvement of the CEEMD-LSTM model is also significant. Its RMSE decreased by 0.2855, MAE decreased by 0.2176, and MAPE decreased by 1.06%. Compared to the EEMD-LSTM model, the improvement of the CEEMD-LSTM model is greater, with a reduction of 0.1737 in RMSE, 0.0427 in MAE, and 0.66% in MAPE.

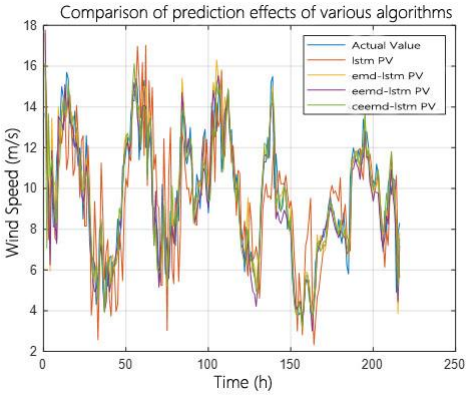


Fig.3 Several decomposition methods of Dataset A combine LSTM modeling prediction results

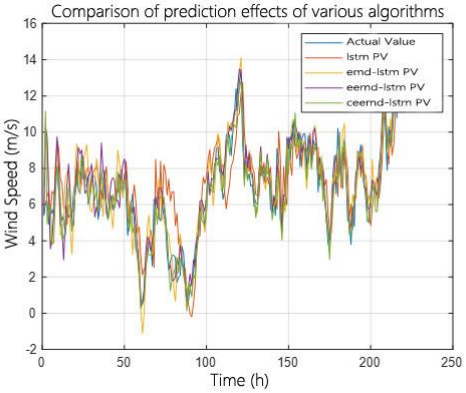


Fig.4 Several decomposition methods of Dataset B combine LSTM modeling prediction results

Tab.1 Several decomposition methods of Dataset A are combined with predictive performance metrics of the LSTM model

Model	RMSE	MAE	MAPE
LSTM	1.2529	0.8495	0.1553
EMD-LSTM	0.5962	0.3882	0.0936
EEMD-LSTM	0.4844	0.2133	0.0896
CEEMD-LSTM	0.3107	0.1706	0.0830

Tab.2 Several decomposition methods of Dataset B are combined with predictive performance metrics of the LSTM model

Model	RMSE	MAE	MAPE
LSTM	1.3077	0.9802	0.1638
EMD-LSTM	0.9840	0.6324	0.1204
EEMD-LSTM	0.7589	0.5201	0.1088
CEEMD-LSTM	0.6326	0.4220	0.0981

Using the piecewise method for learning rate scheduling, the analysis results for dataset B show that the CEEMD-LSTM model has also made significant improvements in three error indicators after every 125 iterations. Its MAPE is 0.0981, MAE is 0.4220, and RMSE is 0.6326. Compared with the LSTM model, the RMSE of the CEEMD-LSTM model decreased by 0.6751, MAE decreased by 0.5582, and MAPE

decreased by 6.57%. This once again indicates that the performance of the wind speed prediction model has been significantly improved by adding the feature value extraction process. Compared with the EMD-LSTM model, the improvement of the CEEMD-LSTM model is equally significant. Its RMSE decreased by 0.3514, MAE decreased by 0.2104, and MAPE decreased by 2.23%. Compared to the EEMD-LSTM model, the improvement amplitude of the CEEMD-LSTM model is 0.1263 reduction in RMSE, 0.0981 reduction in MAE, and 1.07% reduction in MAPE.

In summary, the CEEMD-LSTM model has shown significant advantages in both dataset A and dataset B. By adding a feature value extraction process, this model can significantly improve the performance of wind speed prediction, and compared to LSTM and EMD-LSTM models, it has achieved significant improvements in all three error indicators. The CEEMD-LSTM model improves the performance of wind speed prediction models by introducing the CEEMD feature value extraction method. Compared to the traditional LSTM model and EMD-LSTM model, the CEEMD-LSTM model exhibits better prediction accuracy on both dataset A and dataset B, demonstrating its reliability and applicability in wind speed prediction.

2.5.2 Comparative analysis of the predictive performance between the combination model and other models in this article

In order to comprehensively evaluate the predictive performance of the CEEMD-LSTM model proposed in this article, we conducted comparative studies with other models. These comparison objects include DBN, BP, EMD-BP, EEMD-BP, and CEEMD-BP models, and were compared on dataset A and dataset B.

According to the prediction results in Figure 5 and Figure 6, a single model such as LSTM, BP and DBN can only roughly predict the trend of the wind speed series, and cannot well fit the behavior of the wind speed series at the break point. In contrast, other models have significantly lower prediction accuracy and cannot achieve ideal results. However, combination models, especially the CEEMD-LSTM model, exhibit better predictive ability. The CEEMD-LSTM model exhibits better predictive ability. The closer proximity between the actual and predicted values indicates that these combined models perform better in predicting wind speed. On this basis, this article will make a detailed comparison of the predictive performance of the two models mentioned above, and link them with Tables 3 and 4. From the error indices listed in the table, it can be seen that the CEEMD-LSTM model has a good effect on both sets of data. Compared with other models, it has smaller MAPE, MAE, and RMSE values, indicating higher accuracy and reliability in wind speed prediction. In summary, compared to other models, the CEEMD-LSTM model performs better in predicting both dataset A and dataset B. Compared with single model and other combined models, CEEMD-LSTM model shows better wind speed prediction ability, which provides strong support for decision-making and application in wind farm and other fields.

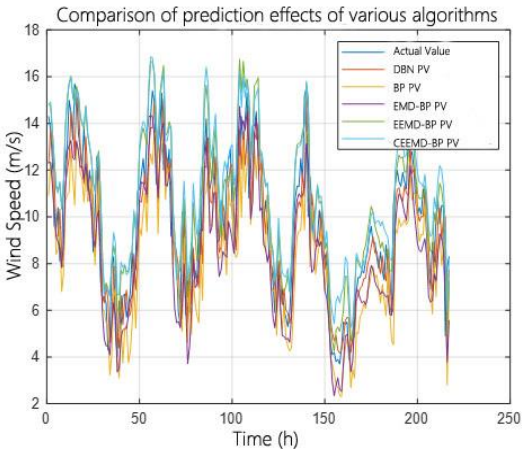


Fig.5 Dataset A predicts the results of several models

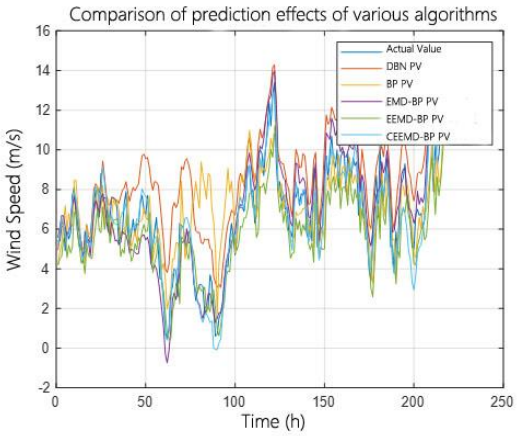


Fig.6 Dataset A predicts the results of several models

Based on the data in Tables 3 and 4, we can observe the differences in error indicators between various models in dataset A and dataset B. Among these models, the CEEMD-LSTM model achieved the lowest level of wind speed prediction error indicators (MAPE, MAE, and RMSE) on datasets A and B. Compared to the DBN, BP, EMD-BP, EEMD-BP, and CEEMD-BP models, the three error indicators of the CEEMD-LSTM model exhibit lower values. At the same time, it can be seen that the three error indicators of LSTM model are significantly better than the other two single models. This clearly demonstrates the strong ability of the LSTM model in learning nonlinear time series. The CEEMD-LSTM wind speed prediction model combines the advantages of CEEMD and LSTM, successfully handling the nonlinear and non-stationary characteristics of wind speed data, and generating highly accurate prediction results. The model also has the characteristics of adapting to multi-scale features and strong interpretability. This result fully verifies the high prediction accuracy of the prediction model proposed in this article, and brings new insights into the field of wind speed prediction.

Tab.3 Predictive performance indicators for other models in Dataset A

Model	RMSE	MAE	MAPE
DBN	1.3047	0.9627	0.1915
BP	1.2597	0.9452	0.1721
EMD-BP	0.8298	0.6305	0.1253
EEMD-BP	0.7713	0.5125	0.1098
CEEMD-BP	0.6169	0.4095	0.0944
CEEMD-LSTM	0.3107	0.1706	0.0830

Tab.4 Predictive performance indicators for other models in Dataset B

Model	RMSE	MAE	MAPE
DBN	1.5433	1.2108	0.1748
BP	1.2729	1.0313	0.1645
EMD-BP	1.0816	0.7526	0.1382
EEMD-BP	0.9690	0.6600	0.1253
CEEMD-BP	0.7713	0.5225	0.1098
CEEMD-LSTM	0.6326	0.4220	0.0981

3 Conclusion

This article proposes a CEEMD-LSTM combination model for predicting short-term wind speed sequences. Firstly, CEEMD is used to decompose the wind speed sequence into multiple sub sequences with different frequency characteristics to better capture the non-stationary and nonlinear characteristics of the wind speed sequence. Then, LSTM networks are used to model and predict each subsequence, improving the accuracy and stability of the prediction by learning long-term correlations within the sequence. Through experimental verification, this article found that using EMD, EEMD, and CEEMD decomposition methods can obtain a series of more stable subsequences, among which CEEMD exhibits better performance. Compared with single model and other combined models, CEEMD-LSTM combined model performs better in wind speed prediction and has higher prediction accuracy. This model can effectively reduce the interference of nonlinearity, volatility, and intermittency of wind speed series on the prediction model, and improve the accuracy of the prediction results. Compared with the LSTM model, the RMSE of the model established in this article decreased by 0.9422, MAE decreased by 0.6789, and MAPE decreased by 7.23%.

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