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Wind Speed Prediction Based on Improved VMD-BP-CNN-LSTM Model

Chaoming Shu[1], Bin Qin[2], Xin Wang[2*]

[1]College of Railway Transportation, Hunan University of Technology, Zhuzhou, China
[2]College of Electrical and Information Engineering, Hunan University of Technology, Zhuzhou, China
Email: *wangxin97p@163.com

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Abstract

Amid the randomness and volatility of wind speed, an improved VMD-BP-CNN-LSTM model for short-term wind speed prediction was proposed to assist in power system planning and operation in this paper. Firstly, the wind speed time series data was processed using Variational Mode Decomposition (VMD) to obtain multiple frequency components. Then, each individual frequency component was channeled into a combined prediction framework consisting of BP neural network (BPNN), Convolutional Neural Network (CNN) and Long Short-Term Memory Network (LSTM) after the execution of differential and normalization operations. Thereafter, the predictive outputs for each component underwent integration through a fully-connected neural architecture for data fusion processing, resulting in the final prediction. The VMD decomposition technique was introduced in a generalized CNN-LSTM prediction model; a BPNN model was utilized to predict high-frequency components obtained from VMD, and incorporated a fully connected neural network for data fusion of individual component predictions. Experimental results demonstrated that the proposed improved VMD-BP-CNN-LSTM model outperformed other combined prediction models in terms of prediction accuracy, providing a solid foundation for optimizing the safe operation of wind farms.

Keywords

Wind Speed Forecast, Long Short-Term Memory Network, BP Neural Network, Variational Mode Decomposition, Data Fusion

1. Introduction

Wind energy, as a new and clean energy source with abundant reserves, has attracted widespread attention worldwide. The introduction of the “peak carbon emissions and carbon neutrality" goal has provided a boost to China's wind power industry, which is currently experiencing stable growth.

For large-scale wind farms, the randomness and volatility of wind speed can pose threats to the reliability and economic efficiency of power system operations, leading to significant social and economic losses [1]. In order to address the issues caused by this uncertainty, scholars have continuously proposed methods to estimate and predict wind speed for a future period, aiming to optimize and plan the operation of wind power generation systems [2]. Accurate wind speed forecasting is crucial for the operation and scheduling of wind farms. For example, it can help optimize the power generation plan to ensure a stable power supply, as well as adjust the operating status of wind turbines to avoid turbine damage or safety issues caused by excessively high or low wind speeds.

In terms of wind speed prediction, physical methods typically rely on weather systems, requiring the collection of various geographical and meteorological data. This method involves significant computational complexity and faces challenges in data collection. On the other hand, statistical methods struggle to ensure accuracy when dealing with nonlinear data [3]. With the advancement of computer technology, prediction models based on Artificial Neural Networks (ANN) have gained widespread application. Compared to traditional physical and statistical methods, ANN-based wind speed prediction models offer higher prediction accuracy [4]. Within neural network prediction models, LSTM were introduced to handle long-term dependencies and time sequence information in the data. LSTM has shown better performance in time series forecasting compared to traditional neural networks [5]. To extract spatial features from wind speed, Cuixian Lu [6] and Ran Li [7] utilized a combination model called CNN-LSTM. The CNN module extracts spatial features from the data while the LSTM module captures temporal features, further improving prediction accuracy. Wang Yuxuan [8] proposed a method for ultra-short-term wind power prediction based on a combination of CNN-LSTM and Light Gradient Boosting Machine (Light GBM). This method solves the problem of inconsistent error magnitudes in single prediction models at different prediction points. It achieves this by mathematically combining the predictions and assigning larger weights to models with smaller prediction errors, thereby further improving the overall prediction accuracy. Currently, CNN-LSTM prediction models are widely used in short-term wind power prediction. However, wind speed sequences exhibit characteristics such as volatility and non-stationarity, which can lead to significant errors when directly predicting the raw wind speed sequence.

VMD technique can decompose non-stationary signals into different Intrinsic Mode Functions (IMFs). It is commonly used for noise reduction and multi-scale feature extraction. Compared to Wavelet Decomposition (WD) and Empirical Mode Decomposition (EMD), VMD decomposition has two major advantages: it is less prone to mode mixing and allows for autonomous selection of the number of decomposition sub-sequences. Therefore, VMD is often used in time series prediction. Gang Zhang [9] applied the VMD technique to wind power prediction and proposed a wind power prediction model that combines multi-frequency combination and feature selection. By using the VMD technique to reduce the volatility of the original sequence, the model effectively improves the prediction accuracy. Bin Qin *et al.* [10] combined WD, VMD, and Least Squares Support Vector Machine (LSSVM) prediction models, and proposed the WD-VMD-LSSVM model. Through comparative experiments, they demonstrated that WD and VMD decomposition techniques significantly improve prediction accuracy. In recent years, researchers have started to combine VMD with CNN-LSTM. Tiantian Wang [11], in the context of storm prediction, first decomposed the data using VMD into multiple modes, then input them into CNN-LSTM for prediction, and aggregated the individual predictions to obtain the final prediction result. This method effectively improves prediction accuracy. The above-mentioned methods have achieved good prediction results while leaving room for improvement. For example, they did not consider that different frequency components obtained from decomposition have different characteristics, and not all frequency components are suitable for a single prediction model. LSTM models are more suitable for capturing long-term dependencies and slow changes, but their accuracy may be lower for high-frequency components. The proposed improved VMD-BP-CNN-LSTM method in this paper uses a BPNN model to predict the high-frequency components obtained from VMD, while the remaining components are predicted using the CNN-LSTM model. Previously, researchers simply added the prediction results obtained from each mode together. However, each component's prediction result has its own limitations and uncertainties, and the simple summation still resulted in significant errors. In order to maximize the complementary nature of the predicted results from multiple components and improve the overall prediction performance, this paper introduces a fully connected neural network after the prediction results of each mode component. The prediction results from each mode are input into the neural network for data fusion processing to obtain the final output prediction result, thereby further reducing the prediction error.

The rest of the paper is organized as follows: Section 2 presents the overall framework of the improved VMD-BP-CNN-LSTM model and introduces the relevant principles; Section 3 provides an experimental comparative analysis of the proposed prediction model; Section 4 concludes the paper.

2. Improved Wind Speed Prediction Model Based on VMD-BP-CNN-LSTM

2.1. Wind Speed Prediction Model Framework

Based on the "Decompose-Predict-Fuse" concept [11], in this paper a combined prediction model is constructed. The model consists of BP+CNN-LSTM, incorporating VMD decomposition. The framework of the improved VMD-BP-CNN-LSTM wind speed prediction model is illustrated in **Figure 1**.

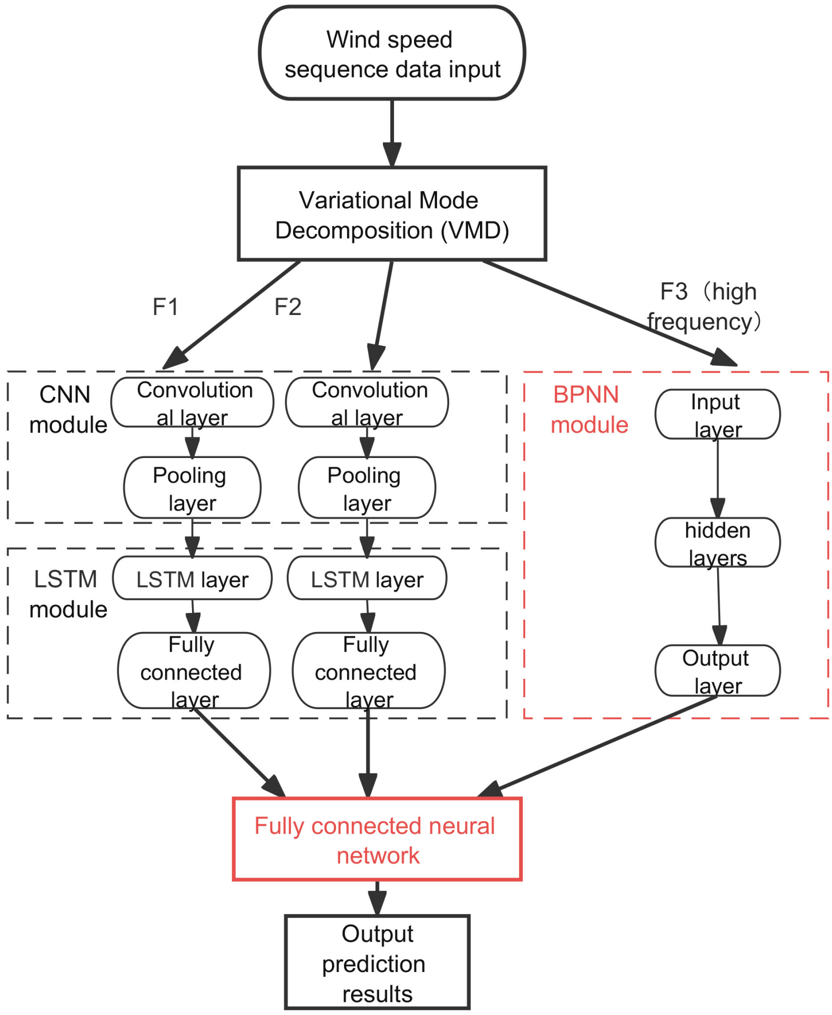


Figure 1. Prediction model framework.

The framework is mainly divided into three parts:

1) VMD decomposition: The wind speed sequence is decomposed using VMD, resulting in three modal components.

2) BP+CNN-LSTM model for prediction: The high-frequency modal component undergoes differencing and normalization operations before being input into the BPNN model for prediction. The remaining frequency components are input into the CNN-LSTM model for prediction.

3) Fully connected neural network for data fusion of each component: The predicted results from each component are restored and then fed into a fully connected neural network for data fusion. Finally, the prediction result is obtained.

2.2. VMD

VMD is a signal processing technique that has wide applications in signal denoising, feature extraction, data compression, and time series analysis. The characteristics of wind speed sequences, such as volatility and non-stationarity, pose challenges to prediction accuracy. VMD can decompose the original complex data into multiple simpler sequences, thereby reducing the difficulty of prediction and improving prediction accuracy [12]. In this paper, the wind speed signal is decomposed into several intrinsic mode functions, and each IMF is then subjected to the Hilbert transform. Gaussian smoothing is applied to estimate the bandwidth of each component, resulting in a minimization problem for obtaining the total sum of modal bandwidths [13].

$$\begin{aligned} &\min\left\{\sum_{k=1}^{k}\left\|a\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)\cdot u_k(t)\right]\mathrm{e}^{-j\omega_k t}\right\|_2^2\right\} \\ &\text{s.t}\sum_{k=1}^{k}u_k = f \end{aligned} \tag{1}$$

In the Equations (1) and (2), K represents the number of modal components to be decomposed; u_k represents the k-th decomposed modal component; ω_k represents the central frequency of modal component u_k; f represents the original signal.

Then, by introducing a quadratic penalty factor α and a Lagrange multiplier operator $\lambda(t)$, the problem is transformed into an unconstrained variational problem for further solving.

$$\begin{aligned} L(\{u_k\},\{\omega_k\},\lambda) = \alpha\sum\nolimits_{k=1}^{K}&\left[\left(\delta(t)+\frac{j}{\pi t}\right)^2 * u_t(t)\right]\mathrm{e}^{-j\omega_k t} \\ &+\left\|tf(t)-\sum_{k=1}^{K}u_k(t)\right\|_2^2+\left\langle\lambda(t), f(t)-\sum_{k=1}^{K}u_k(t)\right\rangle \end{aligned} \tag{2}$$

The wind speed data is decomposed using VMD in this paper. The VMD algorithm is implemented using the vmdpy package in Python. VMD requires a predefined number of modes K. When the number of modes K is small, VMD tends to filter out some important information in the wind speed sequence, which can affect the performance of the prediction model. Conversely, when the central frequencies of some Intrinsic Mode Functions are close, it can lead to mode mixing or the generation of additional noise [14]. Additionally, larger values of K may increase the computational complexity and runtime of subsequent predictions. Based on reference wind speed prediction experiences, K values are generally chosen between 3 and 6. To further determine the number of modes K, this paper analyzes the correlation between adjacent decomposed mode components, as shown in **Table 1**.

In **Table 1**, C_{nm} represents the Pearson correlation coefficient between the nth and mth decomposed modes. From **Table 1**, it can be observed that when K is less than 5, the correlation coefficients are all less than 0.1, indicating normal decomposition of each mode. However, when the correlation coefficient is greater than 0.1 (indicating $K \geq 5$), the paper considers the occurrence of mode mixing in the mode components, leading to excessive decomposition of the wind speed signal. Taking into account the computational complexity, the paper selects $K = 3$.

Table 1. Pearson correlation coefficient between adjacent modes.

K	C_{12}	C_{23}	C_{34}	C_{45}	C_{56}
2	0.08974966				
3	0.08545569	0.07960345			
4	0.0842692	0.08263681	0.09491308		
5	0.08363256	0.08473537	0.10278227	0.08692165	
6	0.08325264	0.08599266	0.10910449	0.1015569	0.054154

The number of decomposed modes for VMD is chosen as $K = 3$, and the decomposition results are shown in **Figure 2**.

2.3. CNN-LSTM Prediction Model

The CNN-LSTM prediction model is a deep learning model that combines the capabilities of CNN and LSTM. This model is commonly used for processing time series and spatial data, and it demonstrates strong performance in multi-step prediction tasks [15]. A typical CNN consists of convolutional layers, pooling layers, hidden layers, and fully connected layers. It can effectively extract spatial features from input data by sliding convolutional kernels and computing weighted sums to capture different features. The introduction of LSTM units addresses the vanishing and exploding gradient problems observed in general Recurrent Neural Networks (RNNs). LSTM units utilize input gates, output gates, and forget gates to control the modification, access, and storage of internal states, enabling them to capture long-term temporal relationships within input sequences [16]. The combination of CNN and LSTM can handle both the spatial correlation of data and the long-term dependency in time series, and has been widely used in wind speed prediction. To reduce overfitting, improve model generalization, and enhance robustness, the CNN-LSTM combination model incorporates dropout layers.

Given wind velocity data deconstructed via VMD into tripartite components (high, medium, and low frequencies), the predictive structure of the CNN-LSTM for the medium and low-frequency components encapsulates two one-dimensional convolutional layers (Conv1D), a duo of pooling layers, an LSTM layer, quartet of dropout layers, and three fully connected layers (FC). The network parameters and architecture of the CNN-LSTM model are shown in **Table 2**. The CNN layers are used to extract spatial features from the data, followed by the LSTM layer for modeling the temporal information. The output is then transformed into the predicted result for each component using fully connected layers.

2.4. BPNN Prediction Model and Fully Connected Neural Network

BP Neural Network, also known as Backpropagation Neural Network, is a common type of feedforward artificial neural network. It updates the weights and biases of the network through error backpropagation during the learning process,

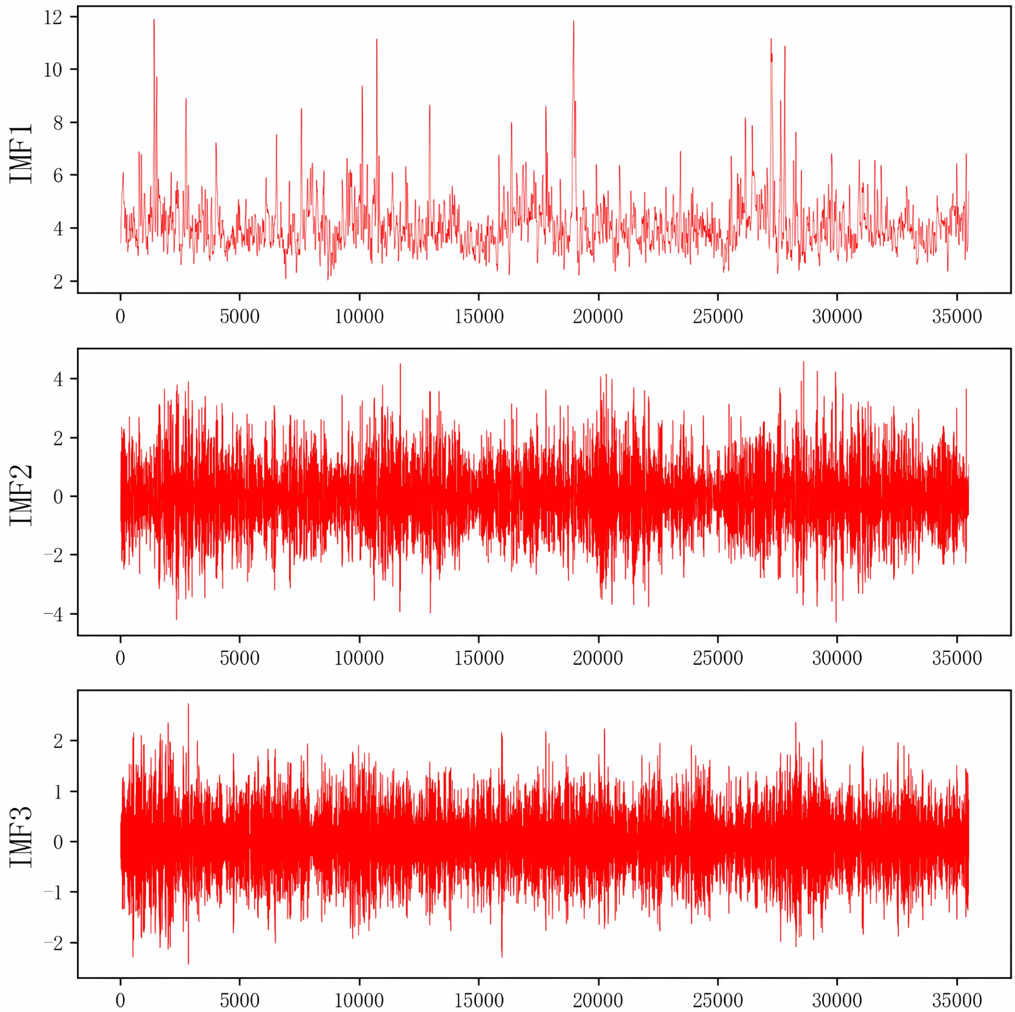


Figure 2. Decomposition results graph.

Table 2. CNN-LSTM model structure and parameter table.

Network architecture	Parameters
Conv1d layer	Number of neurons: 128 Filters: 3
Pooling layer	
Dropout layer	Dropout rate: 0.5
Conv1d layer	Number of neurons: 64 Filters: 3
Pooling layer	
LSTM layer	Number of neurons: 64
Dropout layer	Dropout rate: 0.2
Fully connected layer	Number of neurons: 64
Fully connected layer	Number of neurons: 64
Dropout layer	Dropout rate: 0.2
Fully connected layer	Number of neurons: 4

enabling model training and prediction [17]. A BP Neural Network consists of multiple layers, typically including an input layer, several hidden layers, and an output layer. The network structure is shown in **Figure 3**.

The output of the *i*th neuron in the hidden layer can be written as:

$$y_{ij} = \varphi\left(\sum w_{ij} + b_j\right) \tag{3}$$

Equation (3), where w_{ij} represents the weight between the *i*th and (i − 1)th layers of the neural network, b_j represents the bias of the *j*th neuron in the *i*th layer, φ represents the activation function. In this paper, the output layer uses a linear activation function, and the hidden layer uses the rule activation function.

Considering that high-frequency components exhibit rapid changes, LSTM models are better at capturing long-term dependencies and slow changes. However, they may not perform well for high-frequency components. In this paper, the high-frequency components obtained from VMD decomposition are predicted using the BPNN model, whilst retaining components are predicted using the CNN-LSTM model. Compared to predicting all components using the CNN-LSTM model, this improved approach considers the impact of the characteristics of different frequency components on prediction accuracy. Each component is assigned an appropriate prediction model, thereby improving overall prediction accuracy. The BPNN prediction model used for high-frequency components in the paper consists of one input layer, one hidden layer (with 64 neurons), and one output layer. The remaining frequency components are input into the CNN-LSTM model for prediction.

Data fusion processing is the process of integrating and merging data from different sources or modalities. In the data fusion process, noise can be eliminated, accuracy can be improved, and robustness can be enhanced by automatically detecting, correlating, and combining different data sources. Currently, data fusion

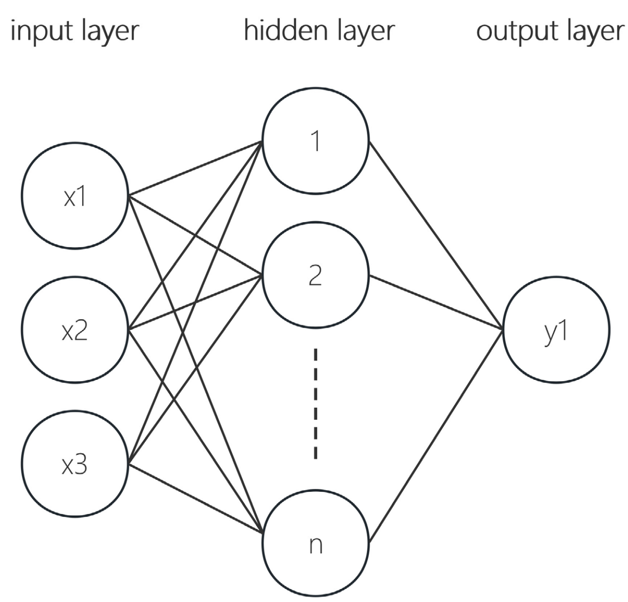


Figure 3. Multilayer perceptron of BP Neural Network.

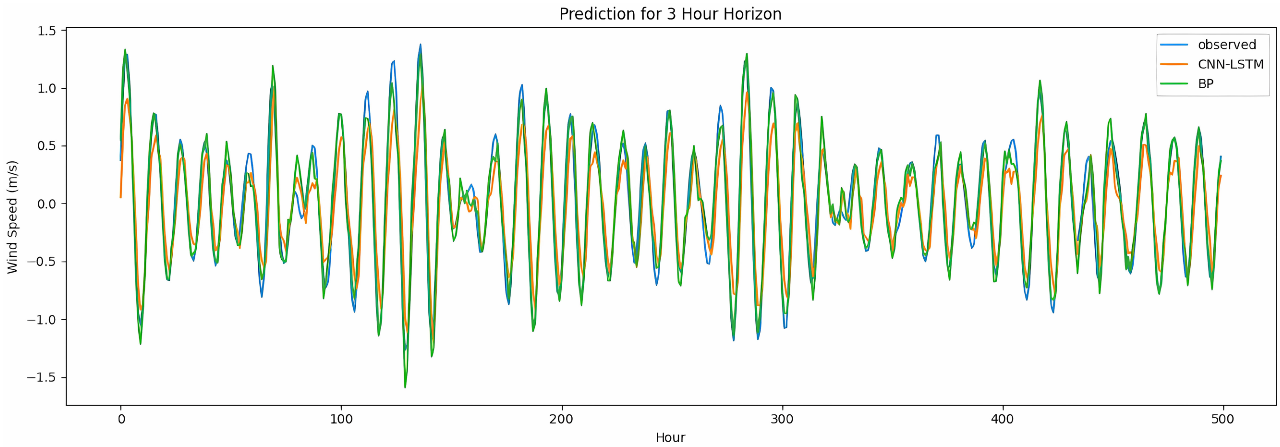
processing techniques are mostly based on machine learning and deep learning models, and they have been widely applied in various fields. Full-connected neural networks are widely used for data fusion and have achieved good results. For example, Yu Qian [18] applied a fully connected neural network to fuse the extracted features in short-term passenger flow prediction for urban rail transit, improving the prediction performance. In order to maximize the complementary nature of the predicted results from multiple components and further reduce prediction errors, another improvement proposed in the paper's prediction model is the addition of a fully connected neural network for data fusion processing after the BPNN and CNN-LSTM prediction models. The fully connected neural network consists of two hidden layers and one fully connected layer, with each hidden layer containing 64 neurons. The predictions from both BPNN and CNN-LSTM, representing each modal component, are subsequently channeled into the fully connected neural network, yielding the comprehensive prediction.

3. Experimental Results and Analysis

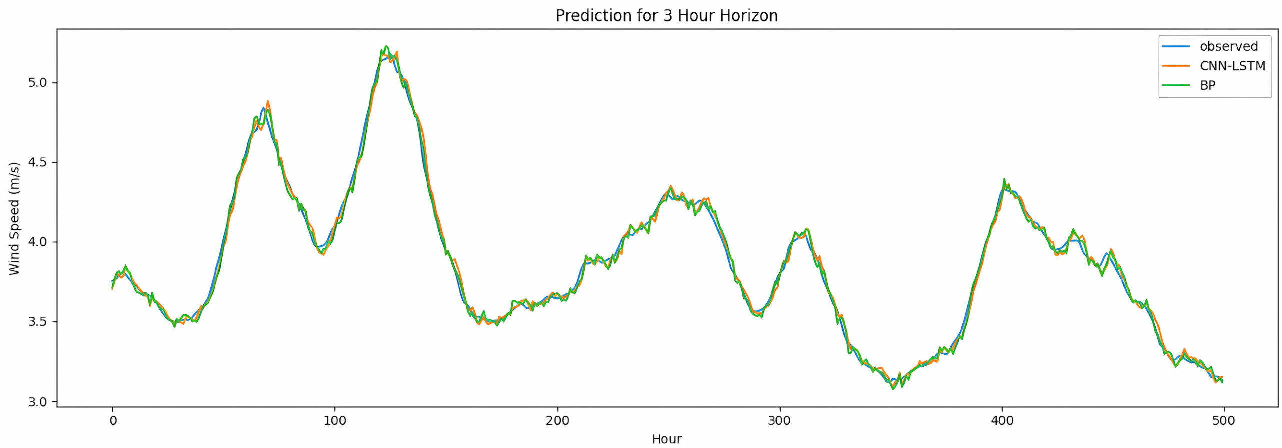
To evaluate the performance of the improved VMD-BP-CNN-LSTM prediction model, the paper compares it with the CNN-LSTM model and the recently proposed VMD-CNN-LSTM prediction model. The input data for all models is the same, collected from several years of historical data from the meteorological bureau, obtained from
https://github.com/fengjiqiang/LSTM-Wind-Speed-Forecasting. To conduct the experiments, the pre-training samples are decomposed using VMD, and 80% of the data is used as the training set, while the remaining 20% is used as the test set. The prediction time scale is set to 3 hours. Prior to predicting the data, the paper preprocesses the VMD-decomposed data to improve the performance of the prediction model. The paper applies differential operations to eliminate trends and seasonal variations, resulting in stationary time series data. Additionally, scaling operations are performed on the differentially transformed data to map the data range to a smaller interval. This helps eliminate differences in scales between different features, allowing neural networks to learn the weights of each feature more stably and improving the convergence speed of the model.

After decomposing the wind speed data using VMD, different frequency components are obtained. In order to test the prediction performance of the BPNN model and CNN-LSTM model on high and low-frequency components, we conducted comparative testing and calculated the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) between the predicted results of each model and the actual data. These metrics were used as performance evaluation indicators for the prediction models. The results are shown in **Figure 4** and **Table 3**.

From **Figure 4** and **Table 3**, it can be observed that on the high-frequency component, the CNN-LSTM model has significantly lower MAE and RMSE values compared to the BPNN model, indicating higher prediction accuracy.



(a)



(b)

Figure 4. Comparison chart of the prediction performance between BPNN and CNN-LSTM models. (a) high-frequency component. (a) low-frequency component.

Table 3. Performance metrics of the prediction for high-frequency and low-frequency component BPNN and CNN-LSTM models.

component	Prediction model	MAE	RMSE	Training time
High-frequency component	CNN-LSTM	0.184	0.235	1720s
	BPNN	0.106	0.137	141s
Low-frequency component	CNN-LSTM	0.035	0.046	1213s
	BPNN	0.032	0.042	120s

However, due to the complex structure of LSTM, the training time for the CNN-LSTM model is much higher than that of the BPNN model. Therefore, in the case of high-frequency components, the paper adopts the BPNN model for prediction. Compared to the VMD+CNN-LSTM prediction model where all components are predicted using the CNN-LSTM model after VMD decomposition, the VMD+BP+CNN-LSTM prediction model, which predicts the high-frequency component using the BPNN model and the low-frequency component using the CNN-LSTM model, shows its prediction results as shown in **Figure 5**.

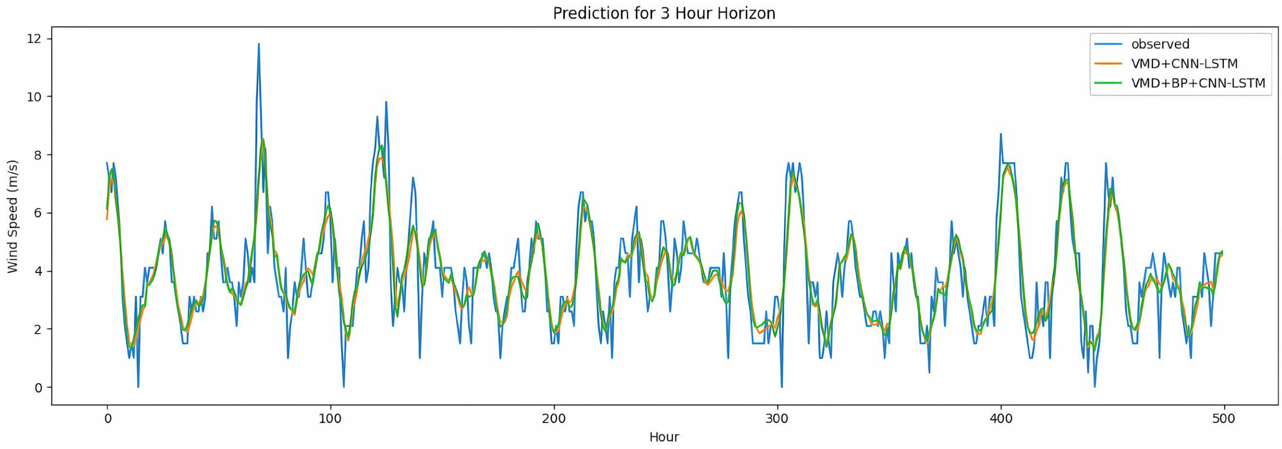


Figure 5. Prediction results of two models.

The computed MAE and RMSE values for the VMD+CNN-LSTM model are 0.733 and 0.975, respectively, while for the VMD+BP+CNN-LSTM model, the MAE and RMSE values are 0.701 and 0.932, respectively. The MAE and RMSE values of the VMD+BP+CNN-LSTM model are lower than those of the VMD+CNN-LSTM model. Additionally, from Figure 5, it can be observed that the prediction curve of the VMD+BP+CNN-LSTM model is closer to the actual values. Therefore, it can be concluded that predicting the high-frequency component using the BPNN model improves the final wind speed prediction accuracy, demonstrating the effectiveness of the proposed improvement. To further improve the prediction accuracy, the proposed improved VMD-BP-CNN-LSTM model takes the predicted results of each component from the BPNN model and CNN-LSTM model and inputs them into a fully connected neural network for data fusion processing to obtain the final prediction result. Compared to the VMD+BP+CNN-LSTM model where the predicted results of each component are simply added together, the comparison of prediction results is shown in Figure 6.

The VMD+BP+CNN-LSTM model, where the predicted results of each component are simply added together, has MAE and RMSE values of 0.695 and 0.926, respectively. In contrast, the improved VMD-BP-CNN-LSTM model, which uses a fully connected neural network for data fusion processing, has MAE and RMSE values of 0.681 and 0.899, respectively. The use of data fusion processing techniques can reduce the MAE and RMSE values of the prediction results. Combined with Figure 6, it can be observed that the prediction curve of the improved VMD-BP-CNN-LSTM model is closer to the actual values. Therefore, it can be concluded that utilizing a fully connected neural network for data fusion processing of the predicted results from each component can further improve the final prediction accuracy, demonstrating the effectiveness of the improvement.

To further validate the performance of the proposed improved VMD-BP-CNN-LSTM prediction model, a comparison is made with the widely-used basic

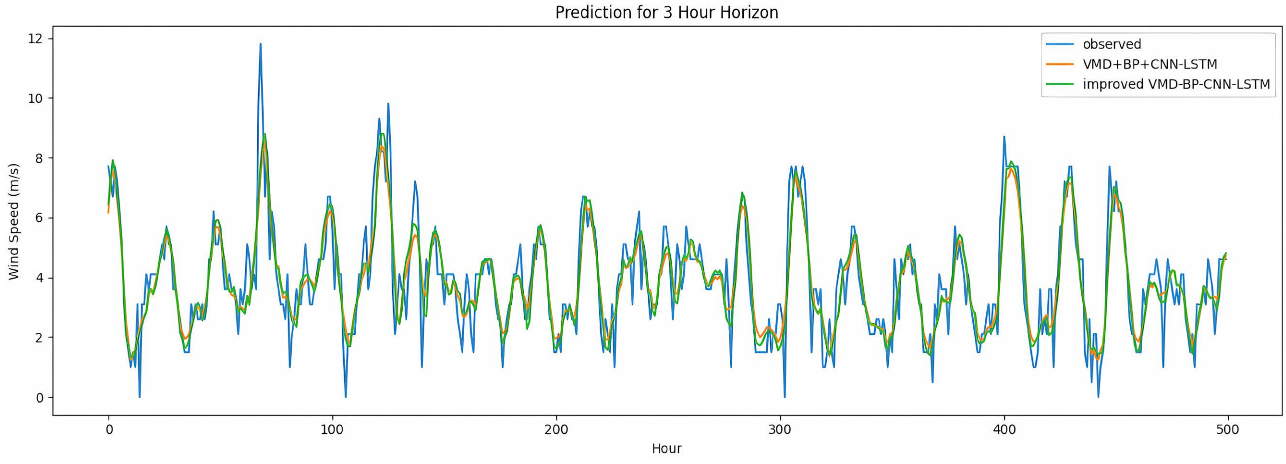


Figure 6. Comparison chart of the model's prediction results before and after introducing a fully connected neural network for data fusion processing.

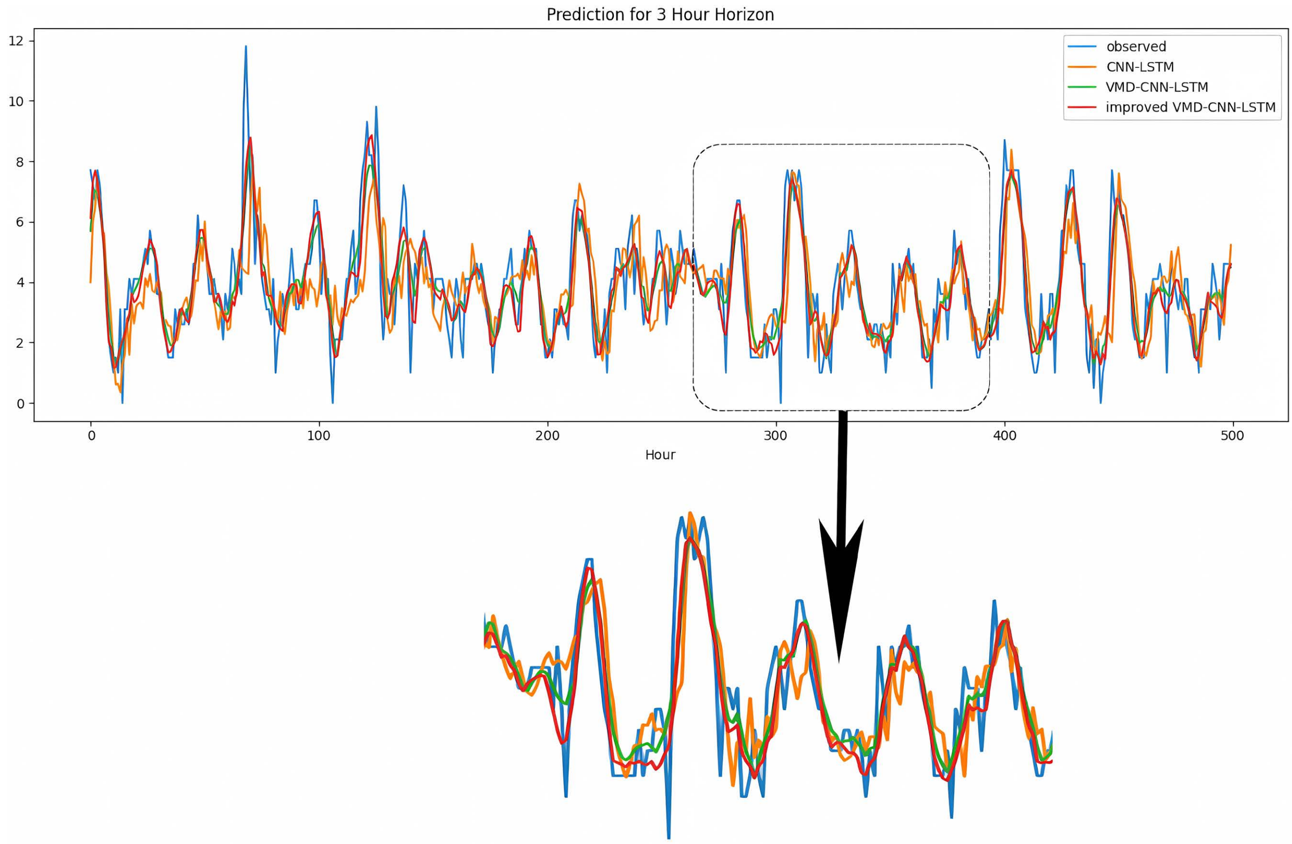


Figure 7. Prediction results of different models.

model CNN-LSTM and the recently proposed VMD-CNN-LSTM prediction model, which are commonly used in wind speed prediction. The prediction results of different models are shown in Figure 7 and Table 4.

From Figure 7, it can be observed that the improved VMD-BP-CNN-LSTM prediction model is closer to the actual values and performs better in capturing peaks and valleys compared to the other two prediction models. Table 4 shows

Table 4. Performance indicators of each predictive model.

Prediction model	MAE	RMSE
CNN-LSTM	1.103	1.493
VMD-CNN-LSTM	0.734	0.978
Improved VMD-BP-CNN-LSTM	0.678	0.894

that the MAE and RMSE values of the VMD-CNN-LSTM prediction model are lower than those of the CNN-LSTM model, indicating that incorporating VMD decomposition technique effectively reduces the MAE and RMSE values. The proposed improved VMD-BP-CNN-LSTM prediction model, which predicts the high-frequency component using the BPNN model and applies data fusion processing using a fully connected neural network on the predicted results of each component, further reduces the MAE and RMSE values compared to the previously proposed VMD-CNN-LSTM prediction model. This demonstrates that the improved VMD-BP-CNN-LSTM model achieves the highest prediction accuracy, indicating the effectiveness of the improvement.

4. Conclusions

In response to the randomness and volatility of wind speed in wind farms, accurate wind speed prediction is crucial for power system planning and operation. In this paper, an improved VMD-BP-CNN-LSTM prediction model is proposed. By introducing VMD decomposition into the conventional CNN-LSTM prediction model, the high-frequency component obtained from VMD is predicted using the BPNN model, and a fully connected neural network is added to fuse the predicted results from each component. Compared to previous models, this approach achieves better prediction accuracy in short-term wind speed forecasting.

The combination of decomposition techniques and neural network models opens up new possibilities for wind speed prediction in wind farms. Additionally, we found that different frequency components exhibit varying temporal characteristics. By using suitable models for each component, prediction accuracy can be further improved. Future research can explore the use of more models and different model parameters for testing purposes.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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