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Short-Term Combination Prediction of Wind Power Considering Meteorological Complexity and Wind Power Volatility

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ABSTRACT

Wind power is a significant part of renewable energy and plays a crucial role in modern power networks. Precise wind power prediction is essential for grid scheduling. Numerous studies have been undertaken to forecast wind energy. The traditional single prediction model is limited as it fails to consider the complexity of meteorological data, specifically the correlation between meteorological data and wind energy. Additionally, it overlooks the volatility of wind power. As a result, there is a decrease in prediction accuracy. This study introduces a novel model for prediction short-term wind power combinations, incorporating meteorological feature selection and signal decomposition to overcome current model constraints. Firstly, maximal information coefficient (MIC) is used for meteorological feature selection. Secondly, for the volatility of wind power, complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) is used to decompose the wind power time series data. Subsequently, the meteorological data that underwent feature selection, along with the two frequency signals, were fed into the sample convolution and interaction network (SCINet), bidirectional long short-term memory (BiLSTM), and gated recurrent unit (GRU) models via three separate channels for prediction. The weight coefficients for the meteorological data prediction results and the signal decomposition prediction results were determined using sequential least squares programming (SLSQP). These weight coefficients were then used to get the final prediction results through a weighted combination. The experimental results show that the prediction accuracy of the model proposed in this study is significantly improved compared to the traditional single prediction model.

Keywords: wind power prediction, renewable energy, feature selection, signal decomposition, SCINet

NONMENCLATURE

Abbreviations	
CEEMDAN	Complete ensemble empirical mode decomposition with adaptive noise
BiLSTM	Bidirectional long short-term memory
GRU	Gated recurrent unit
SCINet	Sample convolution and interaction network
SLSQP	Sequential least squares programming
MIC	Maximal information coefficient
ANN	Artificial neural network
MLP	Multilayer perceptron
SVM	Support vector machine
BPNN	Back propagation neural network
LSTM	Long short-term memory
RNN	Recurrent neural network
IMF	Intrinsic mode function
RMSE	Root mean square error
MAE	Mean absolute error
Symbols	
$B(n)$	Network size
n	Number of samples
x	Normalized value
x_0	Original value
y_{it}	Actual value of wind power
y_{ip}	Predicted value of wind power

1. INTRODUCTION

Wind energy, as a renewable energy source, is an important component of the future energy structure [1]. However, wind power generation is inherently volatile and intermittent. Hence, the development of a more precise wind power prediction model is crucial for enhancing the accuracy of wind power forecasting, optimizing resource allocation, and mitigating the adverse effects of wind power volatility on grid stability. The field of wind power prediction has extensively

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utilized various models such as artificial neural network (ANN) [2], multilayer perceptron (MLP) [3], support vector machine (SVM) [4], back propagation neural network (BPNN) [5], and recurrent neural network (RNN) [6] due to the advancements in artificial intelligence technology. Long short-term memory (LSTM) [7] and gated recurrent unit (GRU) [8], two types of recurrent neural networks (RNN), have superior performance in predicting time series data and are more adept at handling the nonlinear relationships within the time series. Nevertheless, LSTM solely considers the past data of the time series and disregards any future information. To address this limitation, BiLSTM was devised to capture both forward and backward information in the wind power time series [9]. Nevertheless, a solitary model frequently proves inadequate in effectively capturing the intricate patterns of internal fluctuations in wind power. Therefore, several studies have proposed the use of combined models to predict wind power, which includes optimizing LSTMs for prediction via genetic algorithms [10]. Existing research has not fully explored the complexity of meteorological data and the volatility of original wind power data.

To address the issues, this work presents a model for predicting short-term wind power mix. The approach is based on the selection of meteorological features and signal decomposition. Initially, the MIC approach is employed to do feature selection. Next, the original wind power data undergoes CEEMDAN signal decomposition. Next, the SCINet model, BiLSTM model, and GRU model are used to predict the input meteorological data and decomposed high-frequency and low-frequency signals. Ultimately, the weighting coefficients are determined using the SLSQP method, and the proportion of the prediction results of the above models is determined according to the weighting coefficients to achieve the final prediction. The experimental results demonstrate that the prediction model provided in this study achieves a reduction of 55.31% in the root mean square error (RMSE) and a reduction of 38.71% in the mean absolute error (MAE) compared to the single LSTM model without feature selection and signal decomposition.

2. METHODOLOGY

Due to the nonlinear nature and high volatility of wind power time series, the CEEMDAN approach can be employed to deconstruct the time series into various intrinsic modal functions. This decomposition allows for more accurate prediction of different frequency signals.

The wind power time series data undergoes CEEMDAN decomposition, resulting in high-frequency signals with nonlinear characteristics. The BiLSTM structure can accommodate this complex nonlinear relationship. Additionally, the BiLSTM structure considers both past and future data, enabling better capture of the high-frequency signal characteristics and improving prediction accuracy. Hence, the disintegrated high-frequency wind power signal is employed for short-term forecasting by the utilization of a BiLSTM model. The architecture of the BiLSTM model is depicted in Figure 1 [11].

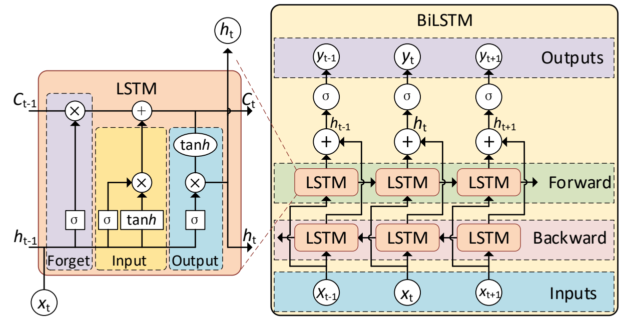

Fig. 1 BiLSTM's structural diagram

GRU can reduce the risk of overfitting and higher computational efficiency when dealing with low-frequency signals, so it is used for short-term prediction of low-frequency signals of wind power time series. GRU mainly solves the problem of not being able to memorize for a long period in RNN and the gradient problem in backpropagation [12]. Its structure is shown in Figure 2.

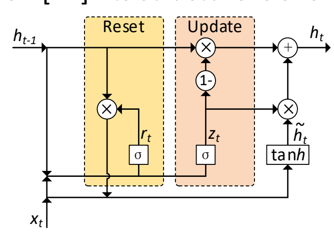

Fig. 2 GRU's structural diagram

When there is a large variety of data in the dataset, MIC can capture all the functional relationships and can give similar coefficients for the correlations of different types of data of similar degree. The calculation of MIC is shown in Equation (1):

$$MIC(D) = \max_{xy < B(n)} \{M(D)_{x,y}\} \tag{1}$$

where $B(n)$ is the network size and n is the number of samples in the dataset, which is generally taken as $B(n) = n^{0.6}$ [13]. In this study, meteorological data with a strong correlation with wind power are screened by MIC.

SCINet can accurately simulate the complex dynamics in a time series by extracting different temporal features from the downsampled subsequence using multiple convolution filters and combining these features efficiently. The overall architecture of SCINet is

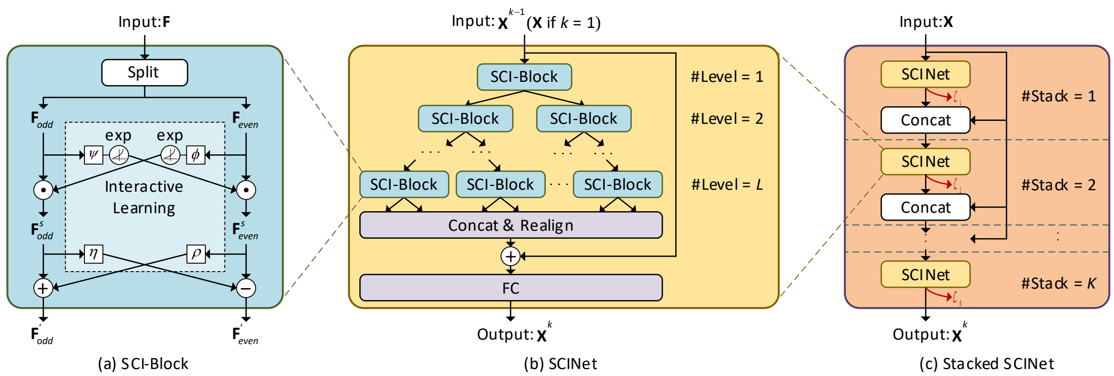

Fig. 3 SCINet's overall architecture

shown in Figure 3.

SLSQP is an optimization technique that uses gradients to solve nonlinear optimization problems with constraints [14]. The SLSQP technique is highly efficient in addressing nonlinear restricted situations. This work utilizes the SLSQP technique to ascertain the weights for model combination.

3. WIND POWER PREDICTION MODEL

3.1 Combination prediction process

The flowchart of the short-term wind power combination prediction considering meteorological complexity and wind power volatility is shown in Figure 4.

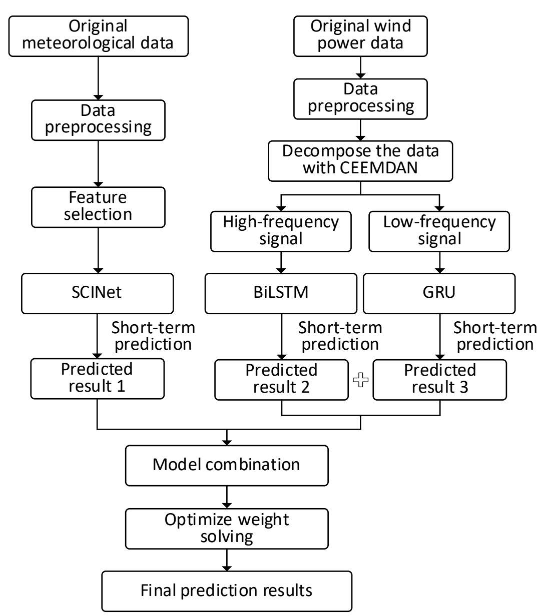

Fig.4 Flow chart for short-term wind power prediction

Step 1: Preprocess the original meteorological data and original wind data. Then, apply feature selection to the meteorological data. Next, perform CEEMDAN signal decomposition on the wind power data. Finally, use the t-test to determine the high-frequency and low-frequency signals.

Step 2: The feature-selected meteorological data, high-frequency signals, and low-frequency signals of wind power from the three-channel inputs are predicted using the SCINet model, BiLSTM model, and GRU model, respectively.

Step 3: Utilize the SLSQP method to calculate the weight coefficients for combining the meteorological data prediction results and the wind power prediction results, resulting in the final prediction results.

3.2 Data preprocessing and model evaluation indicators

This study analyzes meteorological data and measured wind power data from a wind farm in Jiangsu Province, China. The data spans a period of 50 days, from 1 January to 19 February 2020. The objective is to estimate the wind power for the following day. The experimental simulation was conducted utilizing Python 3.7. Table 1 displays the configurations for each model parameter.

Tab.1 Model parameter configuration

Model	Parametric	Value
SCINet	Hidden size	64
	Kernel size	5
	Learning rate	0.001
BiLSTM	Number of iterations	50
	Batch size	16
	Number of recurrent layers	2
GRU	Hidden size	64
	Number of recurrent layers	1

3.2.1 Data normalization

To account for the varying dimensions of different datasets, it is essential to normalize the meteorological data and wind power data. This research employs the maximum and minimum values for normalization, as indicated in Equation (2):

$$x = \frac{x_0 - \min(x_0)}{\max(x_0) - \min(x_0)} \tag{2}$$

where x is the normalized value and x_0 is the original data value; $\min(x_0)$ and $\max(x_0)$ denote the minimum and maximum values in the data set respectively.

3.2.2 Evaluation indicators

To assess the effectiveness of the combination model proposed in this study, we use RMSE and MAE as the evaluation metrics of the prediction model. The calculated values of RMSE and MAE are shown in Equation (3) and Equation (4), respectively.

$$E_{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{it} - y_{ip})^2} \tag{3}$$

$$E_{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_{it} - y_{ip}\right| \tag{4}$$

where y_{it} is the actual value of wind power, y_{ip} is the predicted value of wind power and n is the number of samples.

4. EXPERIMENTAL VALIDATION

4.1 Feature selection

Traditional models ignore the complexity of meteorological data, and too many inputs of meteorological features increase the prediction error. In this study, six groups of data with high correlation with the wind power data are selected by the MIC, including surface pressure, mean sea level pressure, temperature at 2m, wind speed at 10m, relative humidity at 2m, and wind direction at 10m as shown in Figure 5 shown.

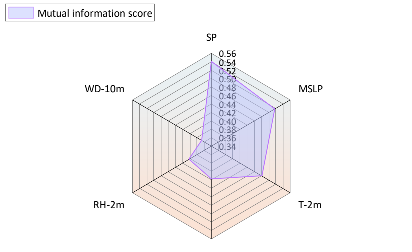

Fig.5 The outcomes of MIC's feature selection

4.2 Signal decomposition

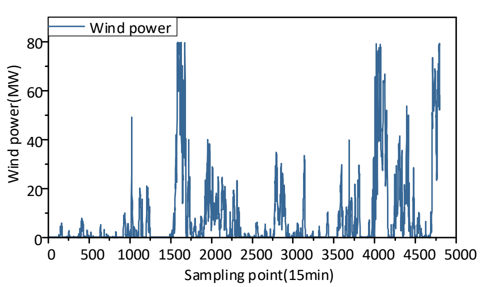

Fig.6 The original wind power data

The original wind power data exhibits significant volatility, as depicted in Figure 6.

Direct prediction of it will produce a large error, this study uses CEEMDAN to decompose it and reduce its volatility. Following the decomposition, a total of 11 intrinsic mode function (IMF) modal components and one residual Res are acquired. Subsequently, the t-test successfully identifies IMF1-IMF6 as high-frequency signals, while IMF7-IMF11 are recognized as low-frequency signals. Figure 7 displays the sequence that follows the CEEMDAN decomposition.

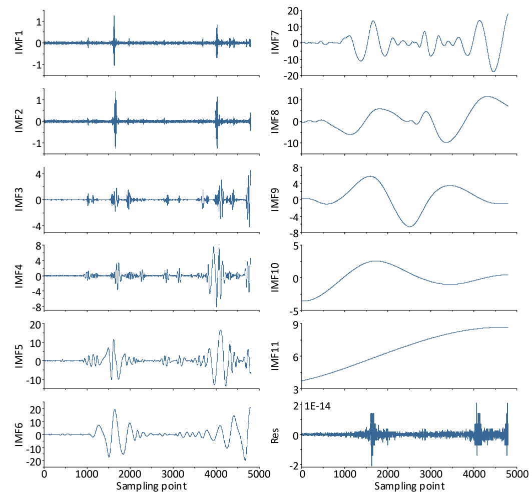

Fig.7 Sequence after signal decomposition

4.3 Analysis of projected results

4.3.1 Prediction results with initial weights set

The decomposed high-frequency wind power signals are individually forecasted using BiLSTM. The predictions of these signals are then combined to derive the final prediction of the high-frequency signal, as illustrated in Figure 8.

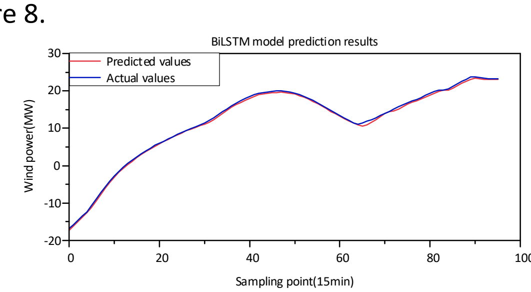

Fig.8 BiLSTM model prediction results

The decomposed low-frequency signals are individually forecasted using GRU. The resulting signal forecasts are then combined to derive the ultimate forecast of the low-frequency signal, as depicted in Figure 9.

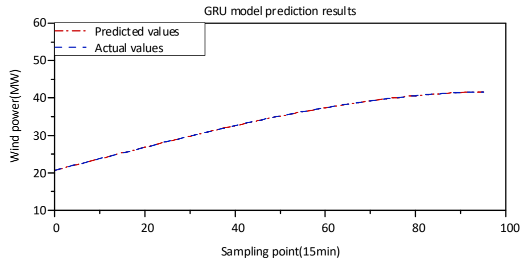

Fig.9 GRU model prediction results

The final prediction result after the decomposition of the original wind power signal is obtained by adding the high-frequency signal and low-frequency signal prediction results, as shown in Figure 10.

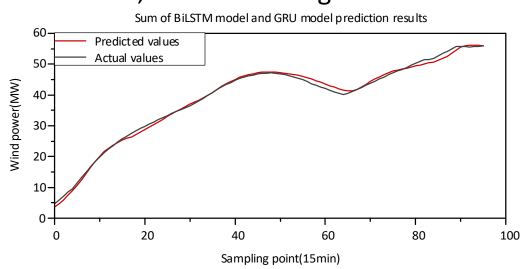

Fig.10 Sum of BiLSTM model and GRU model prediction results

Figure 11 illustrates the regression of the six sets of meteorological data, which have undergone feature selection, using SCINet to forecast future wind power generation.

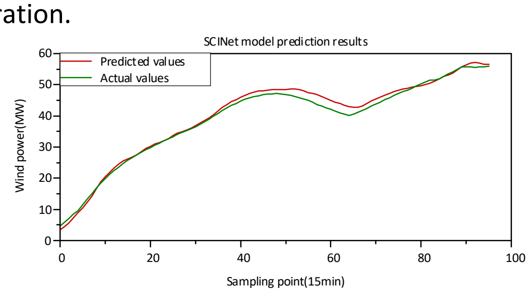

Fig.11 SCINet model prediction results

The forecasts of the aforementioned three models are combined based on the predetermined weights, and the resultant forecasts are displayed in Figure 12.

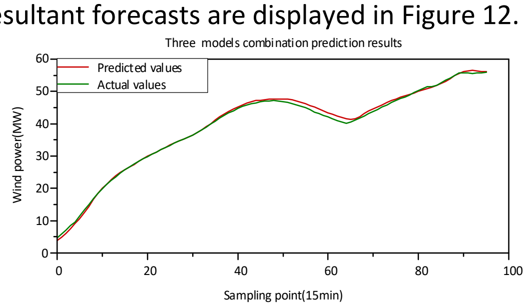

Fig.12 Three models combination prediction results

Currently, the RMSE of the prediction result is 0.6789, while the MAE stands at 0.5263. The starting weights are directly set as follows: 0.5 for the SCINet prediction result and 0.5 for the sum of the prediction results of the high-frequency signal and the low-frequency signal.

4.3.2 Predictions after optimizing weights using SLSQP

The SLSQP algorithm is employed to determine the weights that minimize the root mean square error. The resulting projected values are displayed in Figure 13.

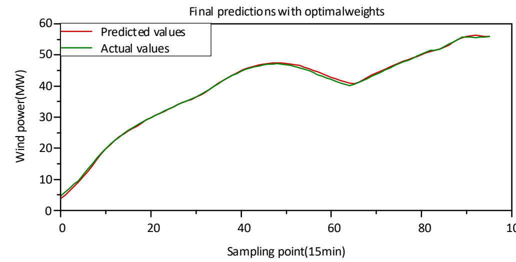

Fig.13 Final predicted values based on SLSQP

The optimal solution yields weights of 0.2 for SCINet prediction and 0.8 for the sum of high-frequency signal and low-frequency signal prediction. With these weights, the RMSE and the MAE are reduced by 38.49% and 39.59% respectively, compared to when the weights were not solved by the SLSQP algorithm.

4.4 Comparative experiments

To authenticate the precision and soundness of the combinatorial model put out in this research, we devised a comparative experiment. The initial comparative experiment employs a solitary LSTM, GRU, and SCINet to forecast forthcoming wind power based on past wind power data. In the second comparative experiment, a single LSTM, GRU, and SCINet model are employed to perform regression on meteorological data to forecast future wind power. Table 2 displays the forecast inaccuracies of several models.

Tab.2 Prediction error values for various models

Model	RMSE	MAE
LSTM	0.9344	0.5187
GRU	0.8041	0.7091
SCINet	10.0085	6.2756
Regression prediction-LSTM	1.3483	1.1625
Regression prediction-GRU	5.4833	4.7669
Regression prediction-SCINet	6.7187	5.2380
MIC-CEEMDAN-SCINet-BiLSTM-GRU-SLSQP	0.4176	0.3179

Based on the error values in Table 2, the proposed method has higher prediction accuracy than other models. In the prediction based on historical wind power data, compared with a single LSTM model without feature selection and signal decomposition, the RMSE of the proposed model is reduced by 55.31% and the MAE is reduced by 38.71%. In the regression prediction based on meteorological data, compared with the single LSTM model without feature selection and signal decomposition, the RMSE of the proposed model is reduced by 69.03% and the MAE is reduced by 72.65%. It is concluded that the model proposed in this paper fits better with the real data.

5. CONCLUSIONS

The wind power combination prediction model, known as SCINet-BiLSTM-GRU-SLSQP, presented in this research, enhances the accuracy of short-term wind power forecast by incorporating meteorological feature selection and signal decomposition. The following deductions can be derived from experiments:

1) The use of MIC can accurately screen out meteorological data types with high correlation with wind power and reduce the complexity of the prediction model.

2) The CEEMDAN approach mitigates the influence of wind power data volatility on prediction accuracy.

3) The SCINet-BiLSTM-GRU-SLSQP combined model takes into account both meteorological data complexity and wind power volatility, combines meteorological feature selection and signal decomposition, and improves the overall prediction accuracy by efficiently assigning weights. This approach provides additional advantages over the use of traditional single prediction models.

ACKNOWLEDGEMENT

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