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An ensemble model for short-term wind power prediction based on EEMD-GRU-MC

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As a kind of clean and renewable energy, wind power is of great significance for alleviating energy crisis and environmental pollution. However, the strong randomness and large volatility of wind power bring great challenges to the dispatching and safe operation of the power grid. Hence, accurate and reliable short-term prediction of wind power is crucial for the power grid dispatching department arranging reasonable day-ahead generation schedules. Targeting the problem of low model prediction accuracy caused by the strong intermittency and large volatility of wind power, this paper develops a novel ensemble model for short-term wind power prediction which integrates the ensemble empirical mode decomposition (EEMD) algorithm, the gated recurrent unit (GRU) model and the Markov chain (MC) technique. Firstly, the EEMD algorithm is used to decompose the historical wind power sequence into a group of relatively stationary subsequences to reduce the influence of random fluctuation components and noise. Then, the GRU model is employed to predict each subsequence, and the predicted values of each subsequence are aggregated to get the preliminary prediction results. Finally, to further enhance the prediction accuracy, the MC is used to modified the prediction results. A large number of numerical examples indicates that the proposed EEMD-GRU-MC model outperforms the six benchmark models (i.e., LSTM, GRU, EMD-LSTM, EMD-GRU, EEMD-LSTM and EEMD-GRU) in terms of multiple evaluation indicators. Taking the spring dataset of the ZMS wind farm, for example, the MAE, RMSE and MAPE of the EEMD-GRU-MC model is 1.37 MW, 1.97 MW, and from 1.76%, respectively. Moreover, the mean prediction error of the developed model in all scenarios is less than or close to 2%. After 30 iterations, the proposed model uses an average of about 35 min to accurately predict the wind power of the next day, proving its high computation efficiency. It can be concluded that the ensemble model based on EEMD-GRU-MC is a promising prospect for short-term wind power prediction.

KEYWORDS

ensemble empirical mode decomposition, gated recurrent unit, Markov chain, short-term wind power prediction, ensemble forecasting models

1 Introduction

In order to cope with the global energy crisis and climate change, renewable energy has become the focus of the development of countries around the world. As an important part of renewable energy, wind power has developed rapidly in recent years due to its low cost and mature technology (Chen et al., 2017; Yuan et al., 2022). According to statistics from the International Energy Agency, wind electricity generation reached 1,870 TWh in 2021 and it remains the leading non-hydro renewable technology. To achieve the goal of net-zero emissions by 2050, which is to generate around 7,900 TWh of wind power by 2030, it will be necessary to increase average annual electricity generation to almost 250 GW (International Energy Agency, 2021). However, with the increasing penetration of wind power into the power grids, the randomness, volatility and intermittency of wind power bring great challenges to the safe and stable operation of the power grids (Shafiullah et al., 2013; Dai et al., 2019). Accurate and reliable wind power forecasting is an effective way to cope with this problem and has therefore become quite a hot topic of research (Tascikaraoglu and Uzunoglu, 2014; Wang et al., 2021).

According to the length of the foresight period, wind power forecasting can be divided into: ultra-short-term forecasting (0–4 h) for real-time load balancing, short-term forecasting (4–72 h) for unit commitment and flexibility reserve, and medium and long-term forecasting (several days, weeks or months) for unit maintenance scheduling and generation capacity evaluation. This study only focuses on the short-term wind power prediction. In recent years, many short-term wind power forecasting methods have been proposed. These can be summarized into three categories: physical methods, statistical methods, and ensemble forecasting models.

Based on the meteorological conditions of the underlying surface of the wind farms and the output curve of the fans, the physical prediction methods can establish the mapping relationship between wind power output and meteorological information using micro-meteorology to realize the wind power prediction. Numerical weather prediction (NWP) is the most commonly used physical method. Charabi et al. (2011) evaluated the performance of NWP model data for wind energy applications in Oman and demonstrated that NWP data has better accuracy than satellite data compared to ground measurements. Liu et al. (2022) proposed a novel NWP-enhanced wind power prediction method based on rank ensemble and probabilistic fluctuation awareness. Prósper et al. (2019) focused on production prediction and validation of actual onshore wind farms using high horizontal and vertical resolution Weather Research and Prediction (WRF) model simulations. Ye et al. (2017) proposed a short-term wind power prediction model based on physical methods and spatial correlations to characterize the uncertainty and dependency structure of turbine's output in wind farms. However, physical methods rely on very precise meteorological and geographic data, which are sometimes difficult to obtain. In addition, the physical methods usually need significant computational time, making their application to short-term wind power forecasting difficult.

The statistical methods do not usually consider the complex physical mechanism of wind power generation, and only construct a statistical model based on the historical operational data of wind farms in order to achieve future wind power prediction. Compared with physical methods, the statistical methods have simpler calculation and can directly predict wind power by mapping the relationship between historical wind power data and the prediction target. Statistical models can be further divided into time series models, other machine learning models and deep learning models: 1) The typical time series models include the autoregressive moving average model (ARMA) (Torres et al., 2005), the autoregressive integrated moving average model (ARIMA) (Chen et al., 2010; Barbosa et al., 2017), the exponential smoothing method (Cadenas et al., 2010), and the generalized autoregressive conditional heteroscedasticity (GARCH) model (Jeon and Taylor, 2016). Nevertheless, time series models only analyze the potential relationship of time series variables, which makes it difficult for them to mine the nonlinear relationship between data, hence the prediction accuracy of this kind of model is poor. 2) Machine learning models can adaptively learn to make decisions and predict future data based on given historical data (Liu et al., 2019). Commonly used machine learning models, such as support vector machine (SVM) (Liu et al., 2017; Abedinia et al., 2022), random forest (RF) (Lahouar and Slama, 2017; Shi et al., 2018), and Bayesian additive regression tree (BART) (Chen et al., 2018), are widely used in wind power output prediction, wind speed prediction and other fields. However, the effect of SVM is closely related to the selection of kernel function and its parameters, which is strongly dependent on the user's experience. RF is prone to overfitting, and the BART method requires a long computation time. 3) With the rapid development of deep learning, artificial intelligence (AI) technology has also been applied to wind power prediction. The AI models, back-propagation (BP) neural network (Zhang et al., 2018), artificial neural network (ANN) (Carolin and Fernandez, 2008), convolution neural network (CNN) (Wang et al, 2017a; Afrasiabi et al., 2019) and recursive neural network (RNN) (Li et al., 2019) have been the focus of previous research on prediction models. These models have higher prediction accuracy than other machine learning models but have the same problem with difficulty in model training. Hence improved RNN and CNN models, such as long short-term memory (LSTM) (Zhang et al., 2019a; Zhang et al, 2019b; Wu et al., 2019), GRU (Ding et al., 2019; Chen et al., 2022), and temporal convolutional network (TCN) (Gan et al., 2021; He et al., 2022) have been widely used in wind power prediction. In recent years, the generative adversarial network (GAN) has attracted a lot of attention (Yuan et al., 2021; Zhou et al., 2021; Xia et al., 2022). Its generative model maps noise variables to multi-layer perceptron networks to make the generated data as close as possible to the distribution of training samples. In general, the AI models can better mine the hidden feature information of the wind power series, improve the overall prediction accuracy, and have strong learning ability and robustness.

Due to the high randomness and volatility of wind power, the prediction abilities of a single model often do not meet actual needs. In recent years, ensemble forecasting models which combine the advantages of multiple single models have become a popular direction for wind power prediction research. Current research on ensemble forecasting models can be summarized in four categories. 1) Ensemble forecasting models based on multi-model weighting. In these models, multiple single models, such as SVM and RNN (Yu et al., 2018), extreme learning machine (ELM), Elman neural network (ENN) and LSTM (Abedinia and Bagheri, 2022), least square SVM (LSSVM) and radial basis function neural network (RBFNN) (Shi et al., 2013), outlier robust ELM (ORELM), ENN, and bidirectional LSTM (BiLSTM) (Chen and Liu, 2020), are used to predict wind power series, and the prediction results are weighted to improve the prediction accuracy. 2) Ensemble forecasting models based on data preprocessing. To cope with the non-stationary wind power sequence, these methods use signal decomposition and denoising algorithms to decompose the original wind power data into multiple stationary subsequences, and use the prediction model to predict each subsequence separately. Commonly used mode decomposition algorithms include empirical mode decomposition (EMD) (Amjady and Abedinia, 2017; Abedinia et al., 2020), variational mode decomposition (VMD) (Yin et al., 2019; Duan et al., 2021), singular value decomposition (Wang et al., 2020), ensemble empirical mode decomposition (EEMD) (Wang et al, 2017b), wavelet transform (WT) (Zucatelli et al., 2021; Khazaei et al., 2022), and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) (Lu et al., 2020) Ensemble forecasting models based on optimization techniques. In order to improve the prediction accuracy, the parameters of the forecasting model are optimized by using optimization techniques. These models include the Multilayer Perceptron (MLP) neural network optimized by Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Khazaei et al., 2022), SVM optimized by cuckoo search algorithm (SVM-CSA) (Li et al., 2021), ENN optimized by multi-objective grey wolf optimization (ENN-MOGWO) (Wang et al., 2019a), ELM optimized by Particle Swarm Optimization (ELM-PSO) (Tian et al., 2019), Echo State Network optimized by MOGWO (ESN-MOGWO) (Wang et al., 2019b) Ensemble forecasting models based on error correction. In order to further reduce the prediction error, error correction technology has been widely used in wind power prediction, usually by predicting the error extracted from the initial prediction result as a secondary prediction. The Markov chain (MC) model (Zhang et al., 2014; Zhang et al., 2021), the GARCH (Jiang and Huang, 2017), the temporally local moving window technique (Yan et al., 2015), and machine learning methods (Liang et al., 2016) are commonly used to deal with the error component.

Although many advances have been made in wind power forecasting methods, wind power forecasting remains challenging due to the high instability of wind power output. Moreover, few prediction methods combine data decomposition, model prediction, and error correction techniques to further improve the prediction accuracy. Based on the above analysis, this research is driven by the following concepts: The EEMD method is an improved and robust decomposition technique, and can effectively discover the potential characteristics of wind power output; The GRU model shows good performance in extracting temporal correlation hidden features from time series, hence is making a figure in short-term power prediction of new energy sources; The MC approach is a very popular error correction technique because it is easy to understand and implement. Hence in this paper, following the concept of "data decomposition - model prediction - error correction", a novel ensemble forecasting model for short-term wind power sequences based on EEMD-GRU-MC is developed. The proposed model consists of three important steps: Firstly, the EEMD method is employed to decompose the original wind power output sequence into a set of relatively stationary subsequences and denoise the data sequence. Secondly, the GRU model is used to individually forecast each subsequence, and the predicted value of each subsequence is superimposed to obtain the predicted result of the original data. Finally, to further enhance the prediction accuracy, the MC is applied to correct the preliminary prediction results. Extensive numerical experiments are conducted to test the performance of the proposed forecasting model when applied to different wind farms and in different seasons. This testing indicates that the proposed hybrid model outperforms the benchmark models in terms of multiple evaluation indicators. Moreover, the mean prediction error of the developed model in all scenarios is less than or close to 2%, proving that it is a promising prospect for short-term wind power prediction.

The rest of this paper is structured as follows: Section 2 introduces the proposed ensemble forecasting method for short-term wind power sequences. Case studies are presented and discussed in Section 3. Finally, conclusions are drawn in Section 4.

2 Methodology

2.1 Data decomposition based on EEMD

EMD is a signal preprocessing analysis method proposed by Wu and Huang (2009), which is widely used in non-stationary and nonlinear signal processing. It progressively breaks down fluctuations or trends in different frequencies in the signal, and finally obtains a set of intrinsic mode functions (IMFs), where each decomposed IMF represents the characteristic signals of different frequencies in the original signal. However, mode mixing may occur in EMD signal processing, which prevents the IMFs from being separated effectively. The EEMD method introduces Gaussian white noise into the original signal and realizes the automatic distribution of the signal for the appropriate timescale after several averaging calculations, which effectively solves the mode mixing problem. Wind power output is easily affected by wind direction, wind speed and other factors, and presents large random fluctuations, which result in a large number of outliers in the wind power sequence. Therefore, the EEMD algorithm is applied to decompose and denoise the wind power sequence, extract the main trend component in the sequence, and eliminate the random fluctuation component. The decomposition of the wind power sequence by EEMD can be summarized as the following steps:

Step 1: The white noise signal $s_{k,t}$ is added to the original wind power sequence P_t, and the new power sequence $P_{k,t}$ is obtained using Eq. 1:

$$P_{k,t} = P_t + s_{k,t}, k = 1, \ldots, K \tag{1}$$

Step 2: The new sequence $P_{k,t}$ (see Eq. 2) is decomposed into a series of IMFs using the EMD algorithm (Naik et al., 2018):

$$P_{k,t} = \sum_{m=1}^{M} C_{k,t}^{m} + r_{k,t}^{M} \tag{2}$$

Step 3: Steps (1) and (2) are repeated K times, and white noise with different amplitude is added each time.

Step 4: Since the mean value of the white noise spectrum is 0, the mean value of all IMFs calculated for K iterations is the final IMF obtained by the EEMD method (see Eq. 3):

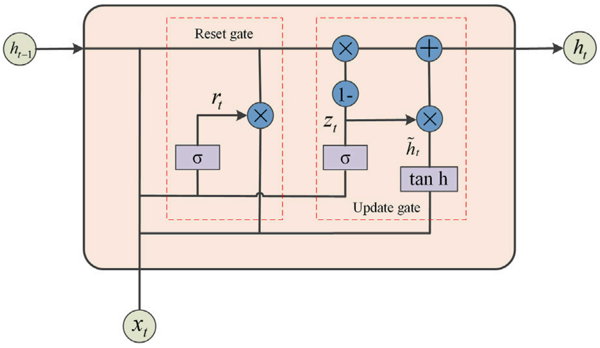

FIGURE 1
Structure of the GRU neuron.

$$C_t^m = \sum_{k=1}^{K} C_{k,t}^m / k \quad (3)$$

Step 5: The original wind power sequence can be reconstructed as Eq. 4:

$$P_t = \sum_{m=1}^{M} C_t^m + r_t^M \quad (4)$$

The amplitude of r_t^M is so small that it can be ignored in wind power prediction.

2.2 Model prediction based on GRU neural network

LSTM is an enhanced type of RNN, which effectively solves the problem of the vanishing collateral gradient of traditional RNNs. GRU is an improved version of LSTM, simplifying the number of gating units and improving the computational efficiency of the model while ensuring the output accuracy. The GRU neuron is the basic unit of the GRU neural network (GRUNN) model and its structure is shown in Figure 1. The GRU neuron includes reset gate r_t and update gate z_t. The update gate receives the current state x_t and the previously hidden state h_{t-1}. After receiving the input and the matrix operation, the sigmoid function σ determines whether the neuron is activated. The reset gate receives x_t and h_{t-1}, and the result determines how much past information needs to be forgotten. The current memory h_t is a summary of the input and output of the previous hidden layer. $\tilde{h}_t$ and h_{t-1} determine the final output h_t by dynamic control of the update gate and transmit h_t to the next GRU neuron. The mathematical model of GRU is shown as Eqs (5–8).

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \quad (5)$$

$$r_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \quad (6)$$

$$\tilde{h}_t = tanh(W_h \cdot [r_t \odot h_{t-1}, x_t]) \quad (7)$$

$$h_t = (1 - z_t) \odot h_{t-1} + \tilde{h}_t \odot z_t \quad (8)$$

Based on the GRU neuron, the time series prediction of GRUNN is shown in Figure 2.

2.3 Detailed description of error correlation based on MC

2.3.1 Basic theory of Markov chain

The Markov process is a typical stochastic process proposed by the famous mathematician Markov, which is applicable to both time series and interval sequences. The main content of the Markov process research is the state of a given stochastic process and its transition law. The MC refers to the Markov process with discrete time and state, and it can predict the changing trend of each state according to the initial probability of each state and the transition probability between each state. Hence the preliminary prediction results are corrected by MC to make up for the prediction error caused by the elimination of some components in the data decomposition process and the corrected wind power output is therefore closer to the actual value.

Assuming that $\{X_t, t = 1, 2, \ldots, T\}$ is a random sequence where t represents any time period, if for any state $i_0, i_1, \ldots, i_{t-1}$ state i and j satisfy Eq. 9, then $\{X_t, t = 1, 2, \ldots, T\}$ is a MC. i and j represent the possible states of the system at present and in future time, respectively:

$$p\left\{X_{t+1} = j \middle| X_t = i, X_{t-1} = i_{t-1}, \ldots, X_1 = i_0\right\} = p\left\{X_{t+1} = j \middle| X_t = i\right\} \quad (9)$$

Supposing there are n states in state space I and, since each state can turn to itself, each state has n turns. So, the one-step transition probability from state i to state j can be expressed as Eq. 10:

$$p_{ij}^{(1)} = M_{ij}^{(1)} \big/ M_j \quad (10)$$

The matrix composed of the one-step transition probability set of all states is called the one-step transition probability matrix, and is expressed as Eq. 11:

$$P^{(1)} = \begin{bmatrix} p_{11}^{(1)} & p_{12}^{(1)} & \cdots & p_{1n}^{(1)} \\ p_{21}^{(1)} & p_{22}^{(1)} & \cdots & p_{2n}^{(1)} \\ \vdots & \vdots & \cdots & \vdots \\ p_{n1}^{(1)} & p_{n2}^{(1)} & \cdots & p_{nn}^{(1)} \end{bmatrix} \quad (11)$$

Accordingly, the matrix composed of the k-step transition probabilities of all states is called the k-step transition probability matrix of the system. According to the homogeneity of MC, the k-step state transition probability matrix is expressed as Eq. 12:

$$P^{(k)} = \begin{bmatrix} p_{11}^{(k)} & p_{12}^{(k)} & \cdots & p_{1n}^{(k)} \\ p_{21}^{(k)} & p_{22}^{(k)} & \cdots & p_{2n}^{(k)} \\ \vdots & \vdots & \cdots & \vdots \\ p_{n1}^{(k)} & p_{n2}^{(k)} & \cdots & p_{nn}^{(k)} \end{bmatrix} = \left(P^{(1)}\right)^k \quad (12)$$

In the process of MC error correction, the classification of states is very important. In this paper, the mean-standard deviation classification method, which is simple in theory and widely used, is employed to divide the state space according to the mean and standard deviation of the samples. Let the sample sequence be $\{X_n, n = 1, 2, \ldots, N\}$, the sample mean is $\bar{x}$, and the standard deviation is δ. According to the central limit theorem in mathematical statistics, the sample sequence can be divided into five intervals: $H_1(\,min\{X_n, \forall n\}, \bar{x} - \delta]$, $H_2(\bar{x} - \delta, \bar{x} - 0.5\delta]$,

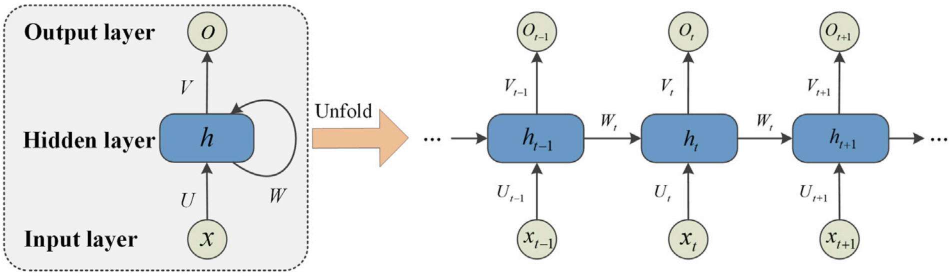

FIGURE 2
Schematic diagram of GRUNN prediction.

$H_3\,(\bar{x} - 0.5\delta, \bar{x} + 0.5\delta]$, $H_4\,(\bar{x} + 0.5\delta, \bar{x} + \delta]$, $H_5\,(\bar{x} + \delta, max\,\{X_n, \forall n\})$.

2.3.2 Basic theory of Markov chain

Based on the above analysis, the correction process for wind power prediction error is as follows:

Step 1: Calculate the historical wind power error sequence using Eq. 13:

$$e_s = p_s^h - p_s^{pf}, \forall s = 1, 2, \ldots, S \tag{13}$$

where p_s^h denotes the actual historical wind power output value of sample point s; p_s^{pf} denotes the predicted value of sample point s obtained by the EEMD-GRU model; S is the total number of sample points.

Step 2: Calculate the mean and standard deviation of the error sequence and divide the error sequence into five intervals H_1, H_2, H_3, H_4 and H_5 using the mean-standard deviation classification method.

Step 3: The number of sample points belonging to different intervals is counted, and then the one-step and k-step transition probability matrices of each error state are calculated by using Eqs. 11 and (2), respectively.

Step 4: The states of the error sequence 5 days before the forecast days are taken as the initial states. In the transition matrix $P^{(5)}$, the row vectors corresponding to each initial state $P_i^{(5)} = (P_{i1}^{(5)}, P_{i2}^{(5)}, \cdots, P_{i5}^{(5)}), i = 1, \ldots, 5$ are taken to form a new probability matrix (see Eq. 14):

$$R = \begin{bmatrix} p_{i1}^{(5)} & p_{i2}^{(5)} & \cdots & p_{i5}^{(5)} \\ p_{i1}^{(5)} & p_{i2}^{(5)} & \cdots & p_{i5}^{(5)} \\ \vdots & \vdots & \cdots & \vdots \\ p_{i1}^{(5)} & p_{i2}^{(5)} & \cdots & p_{i5}^{(5)} \end{bmatrix} \tag{14}$$

Step 5: The state corresponding to $max\left\{P_j = \sum_{i=1}^{5} p_{ij}^5, j \in [1, 5]\right\}$, i.e., the state to which the error is most likely to be transferred in the future, is taken as the state of the modified error. Thus the modified error $\tilde{e}_k = e_s + 0.5\,(H_{el} + H_{eu})$, where H_{el} and H_{eu} are the lower and upper bound of the state interval of the error to be modified.

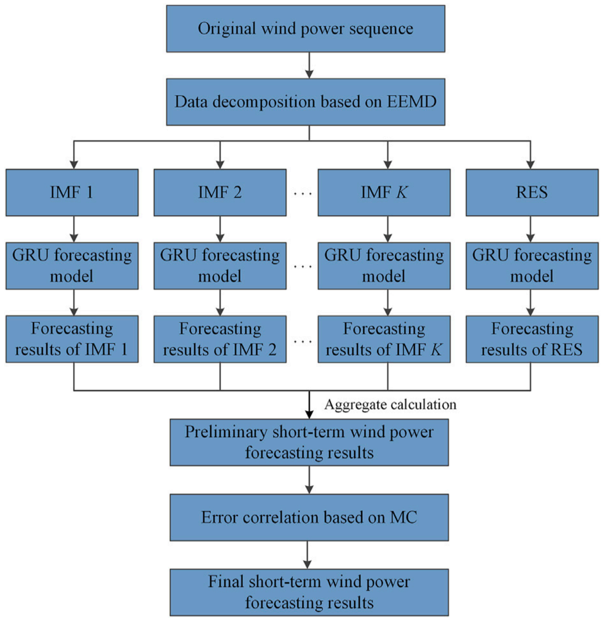

FIGURE 3
Flowchart of the proposed forecasting model.

Step 6: Correct the predicted wind power sequence on the forecast days using Eq. 15:

$$p_k^f = \tilde{e}_k + p_k^{pf} \tag{15}$$

2.4 Overall model prediction process

The overall flowchart of the proposed EEMD-GRU-MC model is depicted in Figure 3, and the main steps are as follows:

Step 1: Use the EEMD method to decompose the historical power data into K IMF components (subsequences) and one RES component.

Step 2: Divide each subsequence into a training set and a test set, and then use the GRU model to predict each component. The prediction results of each subsequence are aggregated as the preliminary prediction results of the EEMD-GRU model.

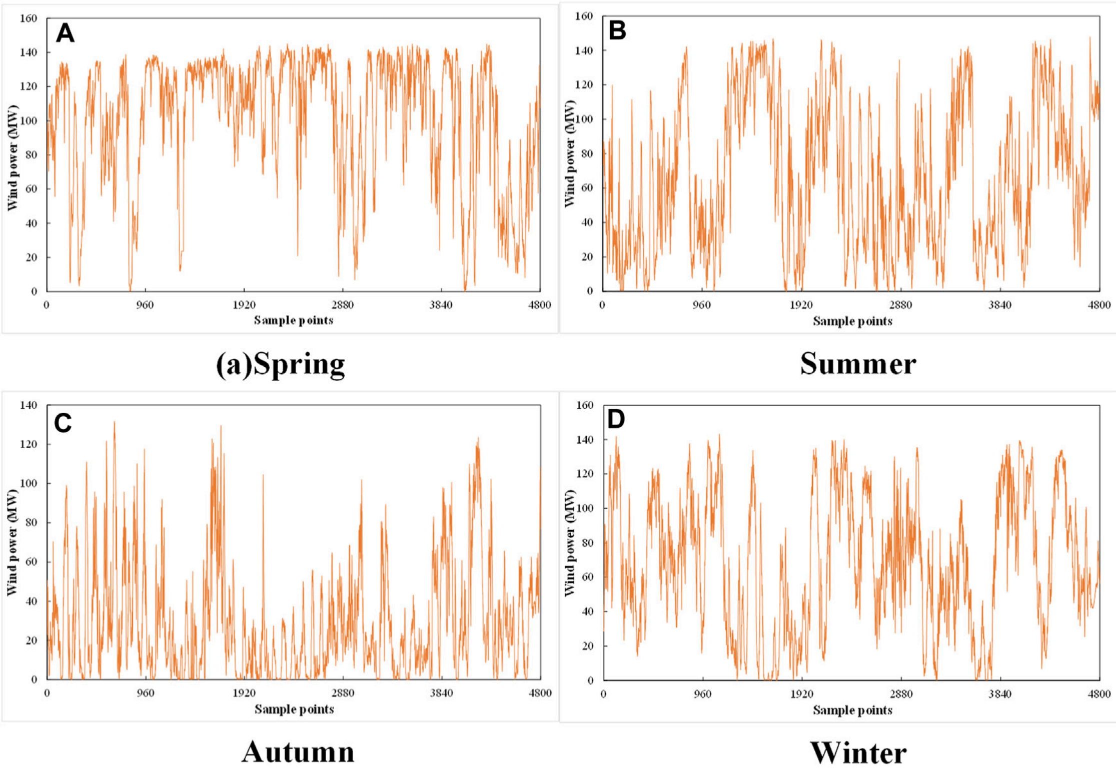

FIGURE 4
Wind power dataset for the ZMS wind farm.

Step 3: Calculate the prediction error between the historical wind power and the predicted power, then use the MC to correct the preliminary prediction results to get the final predicted wind power sequence.

3 Case studies

3.1 Data description

To verify the effectiveness and practicability of the EEMD-GRU-MC model, it was applied to the short-term wind power prediction of two wind farms, ZMS and YMC, which are located in Yunnan Province, China. For each wind farm, four datasets were collected to test the forecasting performance of the proposed model in different seasons. The datasets were collected from 1 February 2021 to 22 March 2021, from 1 June 2021 to 20 July 2021, from 1 September 2021 to 20 October 2021 and from 1 December 2021 to 19 January 2022, representing the wind power data in spring, summer, autumn and winter, respectively. Each dataset was recorded for a time period of 15 min. As shown in Figures 4, 5, there is a total of 50 days, representing 4800 sample points, included in each dataset. The first 3840 sample points are used for the training set, the middle 864 are used for the validation set to avoid modeling over fitting, and the last 96 are used for the test set. This study focuses on short-term wind power prediction 24 h in advance to assist day-ahead dispatching of power grids (Alham et al., 2016; Hu et al., 2019; Liu et al., 2021). Therefore, 96 sample points are selected as the test set in this study. The ratio of training set, verification set and test set is usually 6:2:2. In order to improve the prediction accuracy of the model, a longer training set and verification set were selected in this study, which made the data volume of the whole data set reach 4800. Table 1 lists the statistical information for the datasets, including the maximum, minimum, mean, median and standard deviation. It can be observed that the power variation of each wind farm in all seasons is close to the installed capacity, showing strong volatility and non-stationarity. The power output of all wind farms is larger in spring and winter, but smaller in summer.

The root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) are used as indexes to evaluate the predictive performance of the forecasting models (see Eqs 16–18). The smaller the RMSE, MAE and MAPE, the better the predictive performance of the models:

$$RMSE = \sqrt{\sum_{l=1}^{L}\left(p_l^a - p_l^f\right)^2/L} \tag{16}$$

$$MAE = \left(\sum_{l=1}^{L}\left|p_l^a - p_l^f\right|\right)/L \tag{17}$$

$$MAPE = \left(\sum_{l=1}^{L}\left|p_l^a - p_l^f\right|/p_l^a\right)/L \tag{18}$$

Where L is the number of sample points in the test set, which is 96 in this paper; p_l^a is the actual wind power value of sample point l; p_l^f is the predicted value.

The EEMD decomposition of the wind power sequence and MC error correction of the preliminary prediction results were realized

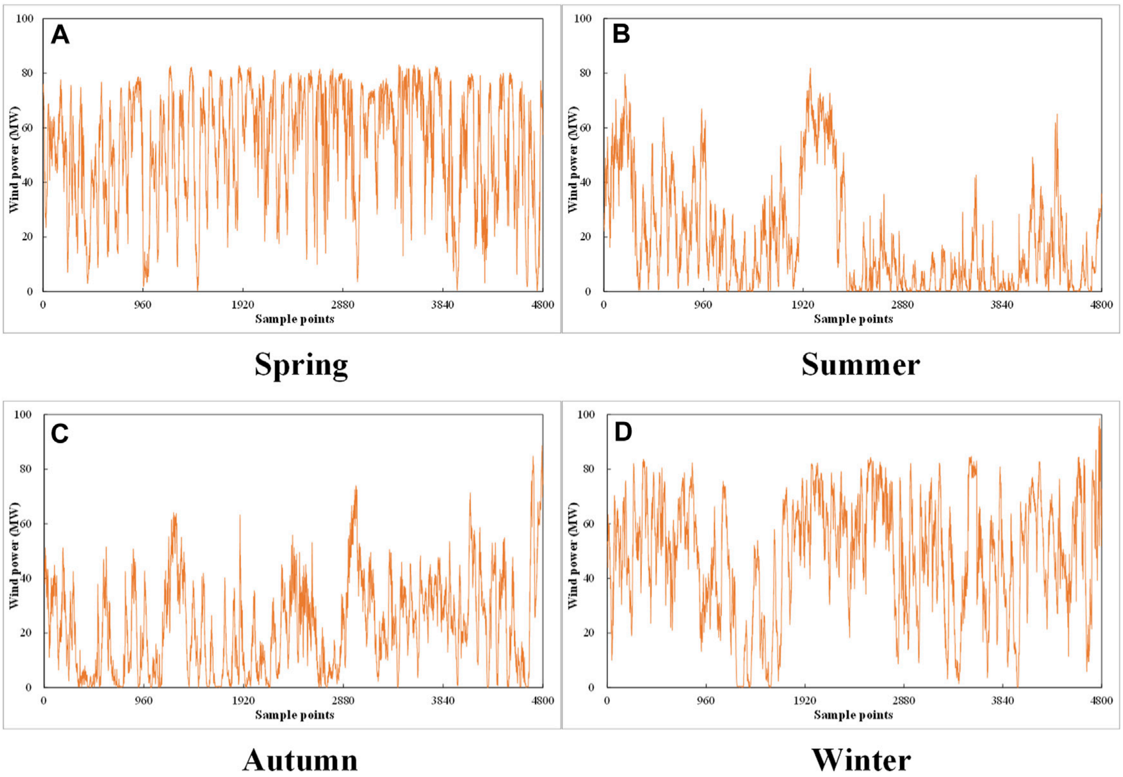

FIGURE 5
Wind power dataset for the YMS wind farm.

TABLE 1 Statistical information of the datasets used in this study.

Wind farm	Dataset	Maximum	Minimum	Range	Mean	Median	Std.
ZMS	Spring	145.2	0	145.2	101.4	114.4	37.2
	Summer	147.6	0	147.6	66.8	61.9	41.9
	Autumn	131.8	0	131.8	29.4	21.4	27.9
	Winter	143.3	0	143.3	68.5	67.3	38.7
YMS	Spring	83.0	0.1	82.9	53.7	58.5	20.9
	Summer	81.8	0	81.8	18.9	11.5	19.7
	Autumn	88.6	0	88.6	22.6	20.8	17.4
	Winter	98.5	0	98.5	48.5	51.7	21.6

by Matlab 2020a, and the training and prediction of the GRU model were realized by Python programming language. All numerical experiments were conducted on a Dell workstation equipped with an Intel Xeon Gold processor, with 20 cores and 40 threads, 2.1G main frequency and 64G memory.

3.2 Case 1: short-term wind power prediction for the ZMS wind farm

Aiming to solve the problem of poor model robustness caused by the randomicity and intermittent nature of wind power, the EEMD algorithm was introduced to decompose wind power data into a set of subsequences. Due to space limitations, Supplementary Figure S1 only displays the EEMD decomposition results of the spring dataset. It can be seen that EEMD decomposes the wind power sequence into seven IMF subsequences and one residual subsequence with different frequency characteristics, which facilitates the analysis of the hidden information in the data and overcomes the shortcomings of the original wind power sequence with its high volatility and non-stationarity.

In order to verify the superiority, reliability and stability of the proposed model, six other forecasting models based on LSTM, GRU, EMD-LSTM, EMD-GRU, EEMD-LSTM and EEMD-GRU were

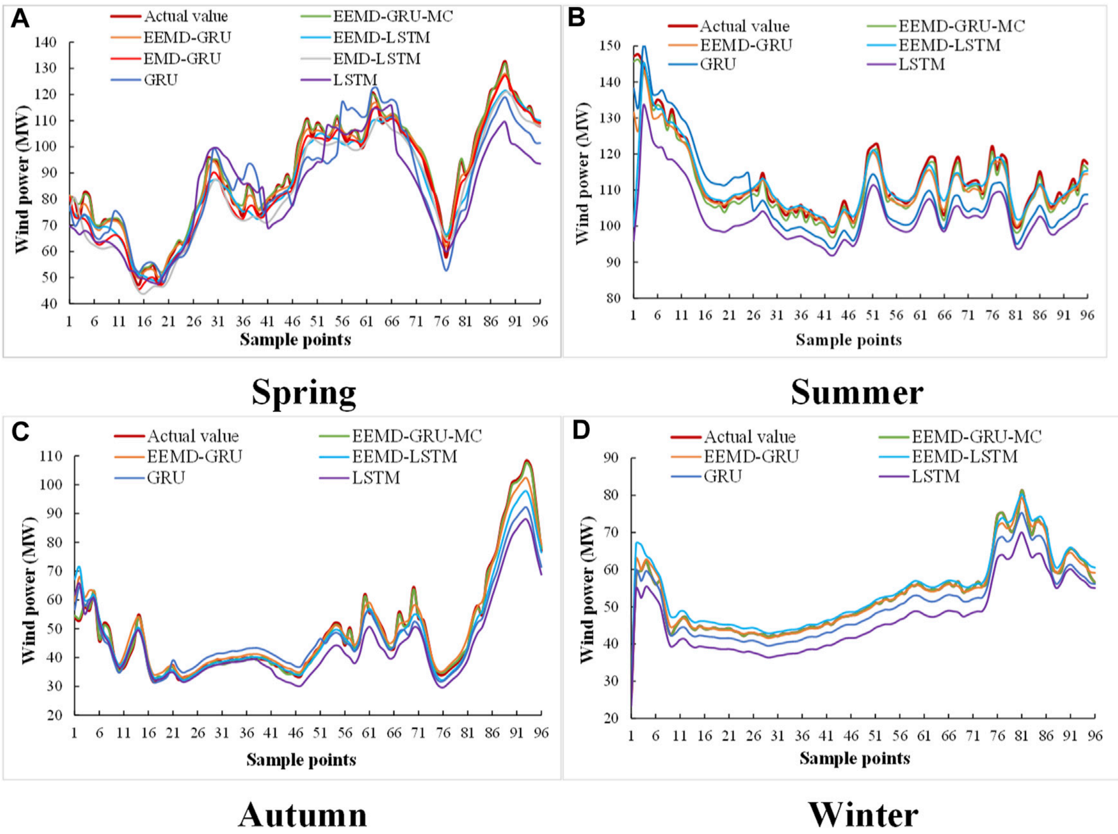

FIGURE 6
Short-term wind power forecasting results for the ZMS wind farm.

constructed as comparison models. It should be mentioned that the LSTM and GRU methods are adopted by (Duan et al., 2021; Chen et al., 2022), respectively. The prediction results of the seven models in different seasons are shown in Figure 6, and regression analysis of the prediction results for the ZMS wind farm using different models is presented in Figure 7. For further quantitative comparison, the evaluation indicators of various prediction models, including MAE, RMSE and MAPE are listed in Table 2. The detailed analyses are summarized as follows: (1) The predicted wind power curves of all models are generally consistent with the trend of the actual power curve. However, it is clear that the predicted wind power curve obtained by the proposed EEMD-GRU-MC model is very close to the actual power curve, and has the smallest RMSE, MAE and MAPE among the seven models for all seasons. In addition, the correlation between the observed data and the predicted data generated by the proposed model is greater than that of comparison models. Therefore, the proposed model connecting EEMD and MC to the GRU model has the ability to capture the dynamic characteristics of wind power output data series. (2) The LSTM has the largest prediction error and the prediction effect of EEMD-LSTM is also inferior to that of EEMD-GRU for different seasons, which proves that GRU has more advantages in predicting short-term wind power time series data compared to LSTM. (3) EEMD-LSTM and EEMD-GRU models are superior to LSTM and GRU respectively in various performance evaluation indexes. Taking the summer dataset with the strongest stochastic wind power volatility as an example, the MAE, RSME and MAPE of the EEMD-GRU model are 1.90 MW, 3.36 MW and 1.58%, which decreased by 69.3%, 48.7% and 71.2% compared with the GRU model. Similar results also appear in the comparison of the EEMD-LSTM and LSTM model, whose MAE, RMSE and MAPE decreased by 77.9%, 47.3% and 79.2%, respectively. This proves that EEMD can separate the noise information from the complex wind power data and facilitate the prediction model to extract the hidden information in the data. (4) Compared with EMD-LSTM and EMD-GRU, EEMD-LSTM and EEMD-GRU have better predictive performance, showing EEMD technique is more helpful for improving the prediction accuracy than EMD technique. (5) The prediction accuracy of the EEMD-GRU model can be further improved after MC error correlation. Taking the spring dataset, for example, after MC correction, the MAE, RMSE and MAPE of the EEMD-GRU model decreased from 1.87 MW to 1.37 MW, from 2.37 MW to 1.97 MW, and from 2.18% to 1.76%, respectively.

3.3 Case 2: Short-term wind power prediction of the YMS wind farm

In order to verify its robustness, the proposed model was applied to the short-term power prediction of the YMS wind farm, whose

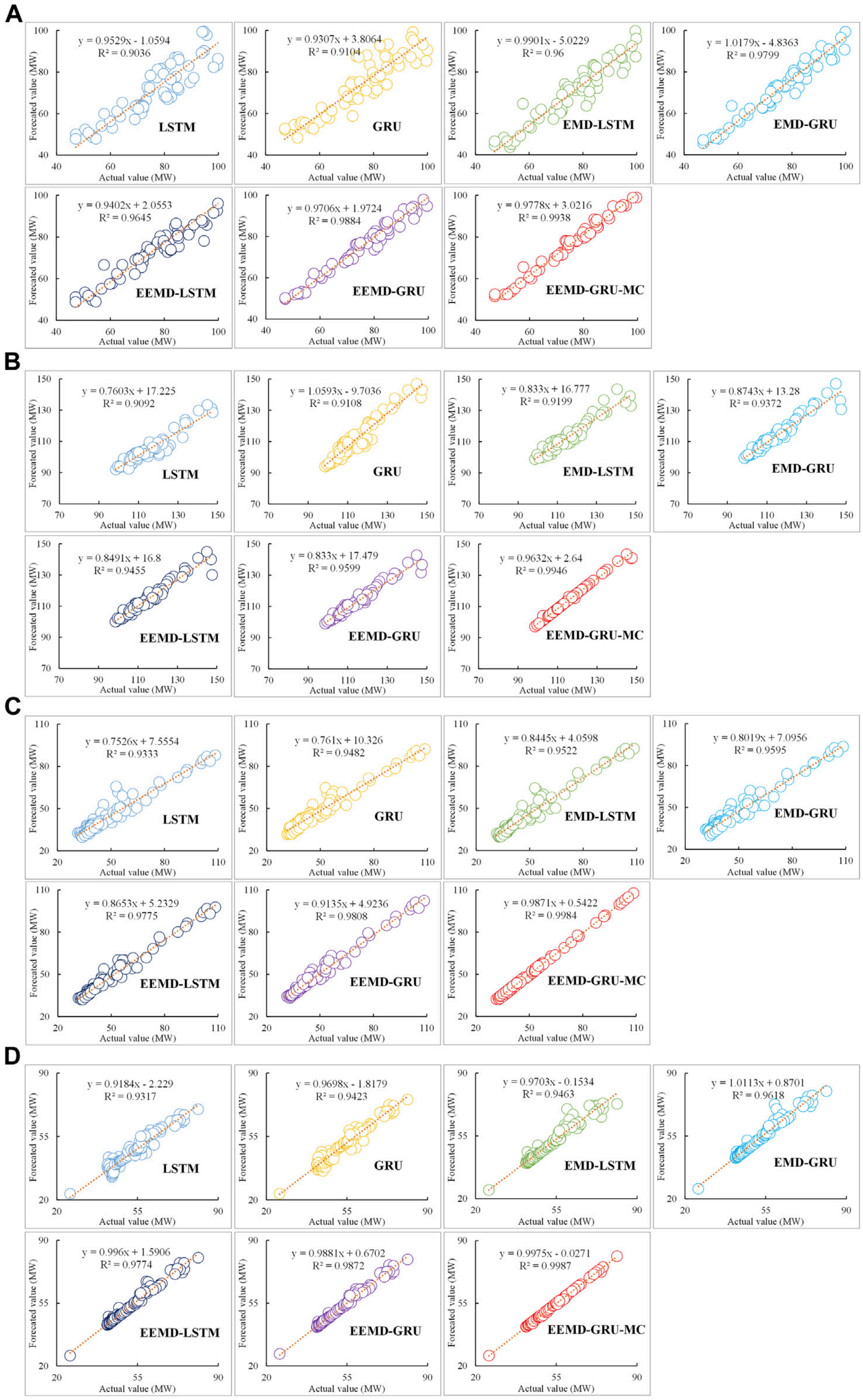

FIGURE 7
(A) Spring Regression analysis of prediction results for the ZMS wind farm using different models. **(B)** Summer Regression analysis of prediction results for the ZMS wind farm using different models. **(C)** Autumn Regression analysis of prediction results for the ZMS wind farm using different models. **(D)** Winter Regression analysis of prediction results for the ZMS wind farm using different models.

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TABLE 2 Statistical indexes of short-term power prediction for the ZMS wind farm using different models.

Dataset	Model	MAE(MW)	RMSE(MW)	MAPE (%)
Spring	LSTM	9.82	11.50	10.74
	GRU	7.49	8.61	8.32
	EMD-LSTM	6.13	7.26	7.27
	EMD-GRU	3.61	4.45	4.38
	EEMD-LSTM	4.03	5.15	4.59
	EEMD-GRU	1.87	2.37	2.18
	EEMD-GRU-MC	1.37	1.97	1.76
Summer	LSTM	9.62	11.11	8.35
	GRU	6.19	6.55	5.49
	EMD-LSTM	3.58	7.97	2.90
	EMD-GRU	2.27	6.03	1.84
	EEMD-LSTM	2.13	5.86	1.74
	EEMD-GRU	1.90	3.36	1.58
	EEMD-GRU-MC	1.43	1.41	1.28
Autumn	LSTM	5.45	7.41	9.69
	GRU	4.07	5.52	7.43
	EMD-LSTM	4.37	5.72	8.15
	EMD-GRU	3.95	5.67	7.00
	EEMD-LSTM	2.68	4.32	4.67
	EEMD-GRU	2.24	3.22	4.49
	EEMD-GRU-MC	0.76	0.84	1.69
Winter	LSTM	6.08	6.33	11.53
	GRU	2.64	2.90	4.94
	EMD-LSTM	2.48	3.01	4.62
	EMD-GRU	1.60	2.52	3.00
	EEMD-LSTM	1.50	2.07	2.85
	EEMD-GRU	0.75	1.15	1.33
	EEMD-GRU-MC	0.03	0.07	0.68

output characteristics are quite different from those of ZMS. The experiments were also conducted using six comparison models as mentioned in Section 3.1. The forecasting results from these models and regression analysis are shown in Figures 8, 9, while the evaluation indicators of the forecasting results are illustrated in Table 3. It can be found that the LSTM and GRU based models without data preprocessing fail to obtain satisfactory forecasting results. Especially in spring and summer, the MAPE values of both models exceed 10%. The proposed EEMD-GRU-MC model achieves the smallest MAE, RMSE and MAPE among the models for the four seasons, and the forecasted wind power curves closely match the trend of the actual power curves. Except for in spring, the MAPE values of the predicted results of the developed model are all within 2%. Although the developed model's prediction accuracy dropped slightly in the spring dataset where the wind power fluctuation is more severe, the proposed model performs best in the wind power prediction for the YMS wind farm. It can be concluded that the developed ensemble forecasting model has more outstanding potential and is better able to capture valuable information in complex and non-stationary wind power data.

3.3 Analysis of computational efficiency of the proposed model

Computational complexity is an important index to evaluate the efficiency of a wind power forecasting method, which describes how

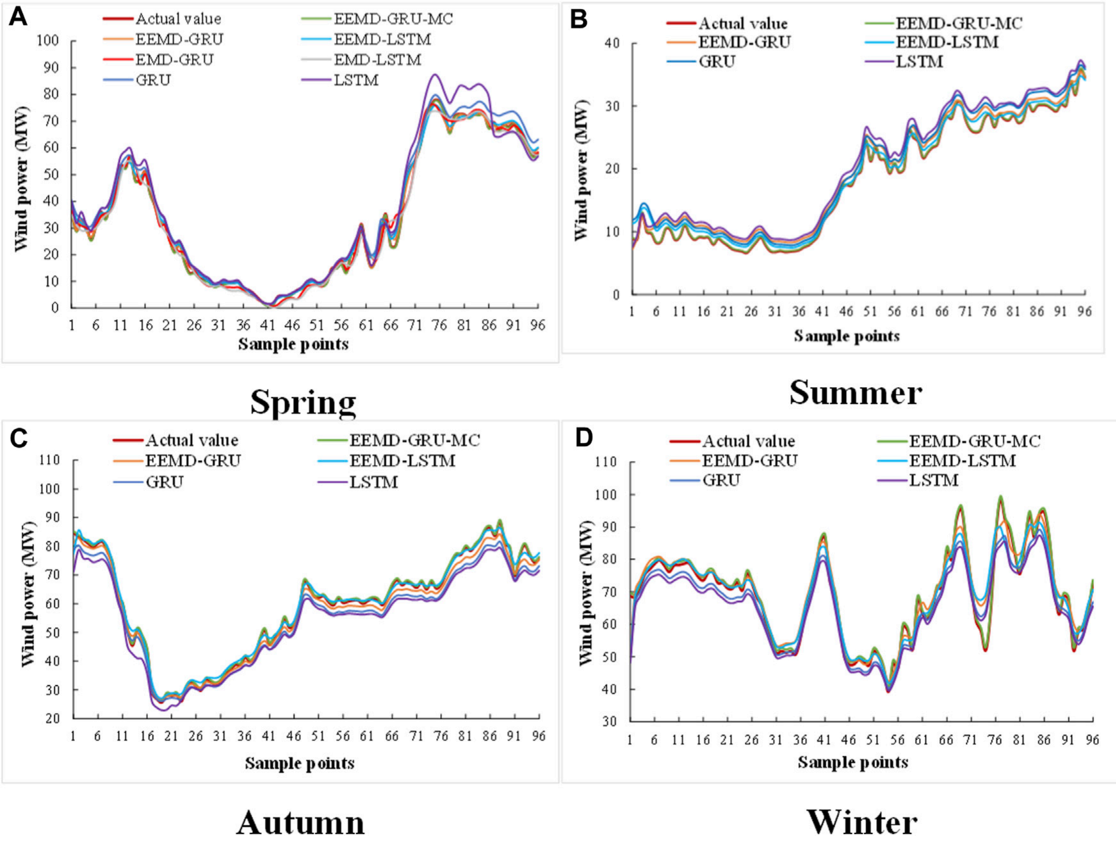

FIGURE 8
Short-term wind power forecasting results for the YMS wind farm.

the execution time of a method changes with the increase of the input size. The computational complexity of EEMD-GRU-MC model mainly depends on the respective complexity of EEMD, GRU and MC. EEMD is an adaptive signal processing method for nonlinear and non-stationary data. The time complexity of EEMD is actually equivalent to the time complexity of Fourier transform. This means that although EEMD is considered computationally intensive, it is actually a computationally efficient method. A GRU is a recurrent neural network used to process sequential data. The computational complexity of a GRU depends on several factors, including sequence length, number of network layers, and number of hidden units per layer. In general, the computational complexity of a GRU is proportional to these factors. An MC is a statistical model that describes random changes in the state of a system. The computational complexity of MC depends on the number of states. If the number of states is fixed, then the computational complexity of MC can be considered constant. In general, computational complexity is related to the parameters of the model and the amount of data.

In order to ensure that the proposed prediction model is realizable in practical applications, the prediction efficiency of the proposed model is analyzed, which is shown in Table 4. This model is designed to predict the day-ahead wind power output, rather than real-time prediction. After 30 iterations, the model uses an average of about 35 min to accurately predict the wind power of the next day. Considering that the accuracy of the model prediction is very high, the prediction time is completely acceptable and can meet the timeliness requirement of the short-term wind power prediction.

Few prediction methods combine data decomposition, model prediction, and error correction techniques to further improve the prediction accuracy. The EEMD-GRU-MC model proposed in this paper provides a novel method for wind power prediction. By integrating EEMD algorithm, GRU model and MC technology, this model effectively deals with the strong intermittency and large volatility of wind power, thus improving the accuracy of model prediction. This novel method provides a new perspective and idea for the theoretical research of wind power prediction. For the research community, the EEMD-GRU-MC model has enriched the theoretical research of wind power prediction, and provided a new reference and inspiration for the subsequent research. For practitioners, especially power grid dispatching departments, the research results of this paper can help them make more accurate and reliable short-term wind power forecasts, so as to arrange more reasonable day-ahead generation plans. Moreover, the wind farms' historical operation data and the source code of the proposed EEMD-GRU-MC model will be made available on request.

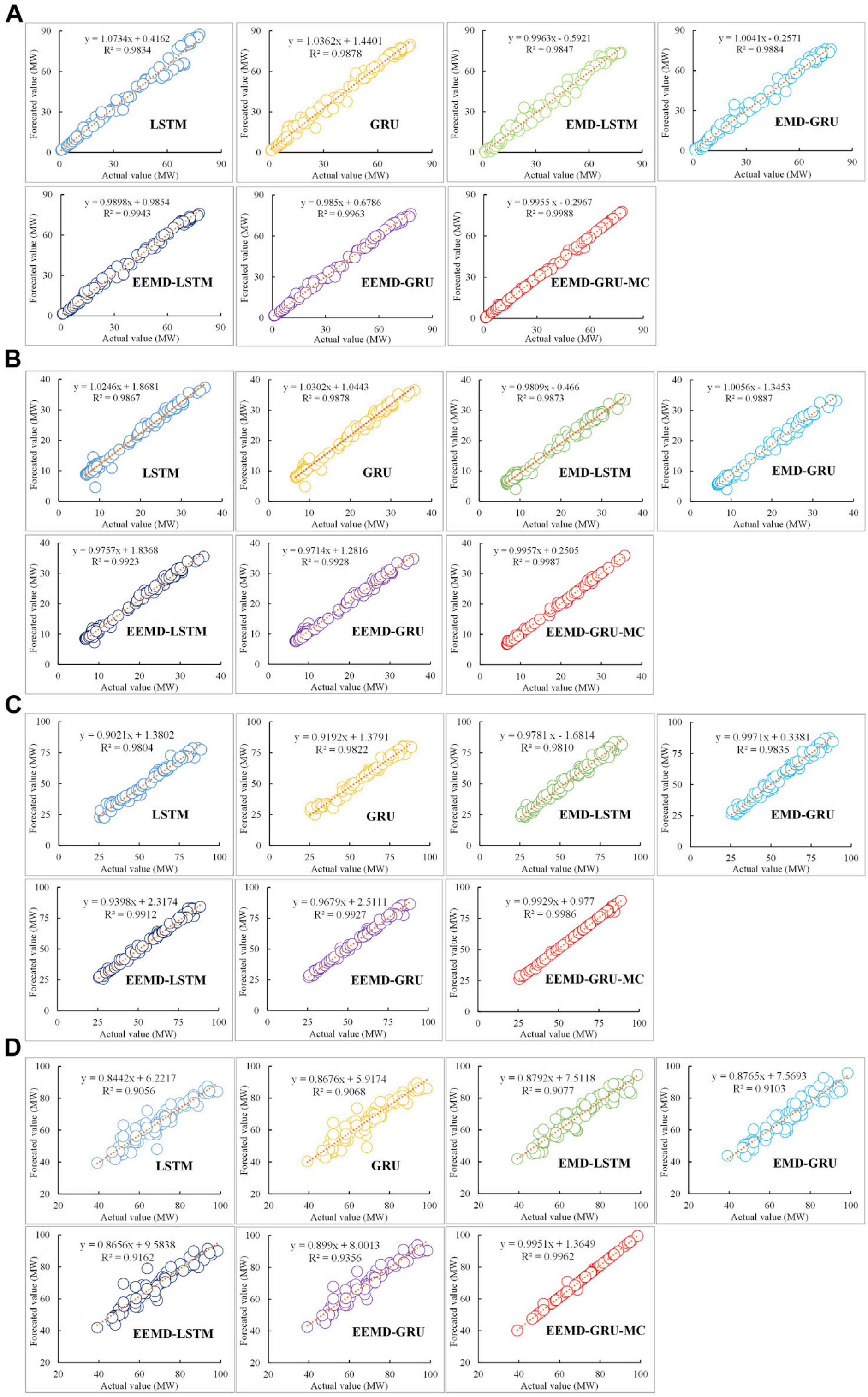

FIGURE 9
(A) Spring Regression analysis of prediction results for the YMS wind farm using different models. **(B)** Summer Regression analysis of prediction results for the YMS wind farm using different models. **(C)** Autumn Regression analysis of prediction results for the YMS wind farm using different models. **(D)** Winter Regression analysis of prediction results for the YMS wind farm using different models.

TABLE 3 Statistical indexes of short-term power prediction for YMS wind farm using different models.

Dataset	Model	MAE(MW)	RMSE(MW)	MAPE (%)
Spring	LSTM	3.59	4.87	11.58
	GRU	2.55	3.22	10.07
	EMD-LSTM	2.38	3.14	12.87
	EMD-GRU	1.95	2.68	10.61
	EEMD-LSTM	1.49	1.96	6.94
	EEMD-GRU	1.14	1.52	5.86
	EEMD-GRU-MC	0.32	0.39	2.55
Summer	LSTM	2.36	2.47	16.89
	GRU	1.71	1.90	12.05
	EMD-LSTM	1.34	1.60	9.90
	EMD-GRU	1.00	1.33	6.57
	EEMD-LSTM	1.41	1.57	11.55
	EEMD-GRU	0.92	1.12	7.29
	EEMD-GRU-MC	0.15	0.32	1.12
Autumn	LSTM	4.57	5.10	7.63
	GRU	3.20	3.61	5.16
	EMD-LSTM	3.31	3.86	6.14
	EMD-GRU	1.81	2.31	3.40
	EEMD-LSTM	1.68	2.03	2.78
	EEMD-GRU	1.26	1.70	2.47
	EEMD-GRU-MC	0.61	0.77	1.15
Winter	LSTM	4.52	5.57	6.35
	GRU	3.52	4.69	4.99
	EMD-LSTM	3.63	5.28	5.29
	EMD-GRU	2.85	5.06	4.11
	EEMD-LSTM	2.77	4.36	4.15
	EEMD-GRU	2.61	3.95	4.00
	EEMD-GRU-MC	0.98	1.15	1.44

TABLE 4 Prediction time for different wind farms in different seasons.

Wind farm	Dataset	Time (s)		
		Decomposition	Total prediction	Average
ZMS	Spring	10.135	2,135	2,140
	Summer	10.158	2,124	
	Autumn	10.206	2,138	
	Winter	10.319	2,162	
YMS	Spring	10.159	2,141	2,154
	Summer	10.171	2,136	
	Autumn	10.238	2,150	
	Winter	10.338	2,170	

4 Conclusion

Accurate and reliable short-term prediction of wind power is of important reference value for the power grid dispatching department to arrange reasonable day-ahead generation plans. This study innovatively combines a data decomposition technique, an AI-based prediction model and an error correction technique, and proposes a short-term wind power prediction method based on EMD-GRU-MC. Two case studies, including two wind farms and eight datasets, are used to verify the performance of the proposed forecasting model when applied to different wind farms and in different seasons. The conclusions can be summarized as follows:

(1) Compared with LSTM, GRU, EMD-LSTM, EMD-GRU, EEMD-LSTM and EEMD-GRU models, the proposed EEMD-GRU-MC model achieves the smallest MAE, RMSE and MAPE for all datasets, and the forecasted wind power curves very closely match the trend of the actual power curves. Taking the spring dataset of the ZMS wind farm for example, the MAE, RMSE and MAPE of the EEMD-GRU-MC model is 1.37 MW, 1.97 MW, and from 1.76%, respectively. Moreover, except for the YMS wind farm in spring, the mean forecasting error of the proposed model is always within 2%. This demonstrates that the proposed model has excellent forecasting performance and generalization ability, and can be used as an effective tool for short-term wind power prediction.
(2) After 30 iterations, the proposed model uses an average of about 35 min to accurately predict the wind power of the next day, proving its high computation efficiency.
(3) GRU has more advantages in predicting short-term wind power sequences than LSTM. EEMD-LSTM and EEMD-GRU models are also achieve better prediction performance than LSTM and GRU respectively in various scenarios, indicating that the EEMD algorithm can overcome the shortcomings of the original wind power sequence with its high volatility and non-stationarity and facilitate the prediction model to extract the hidden information in the data. Taking the summer dataset of the ZMS wind farm as an example, the MAE, RSME and MAPE of the EEMD-GRU model are 1.90 MW, 3.36 MW and 1.58%, which decreased by 69.3%, 48.7% and 71.2%, respectively, compared with the GRU model.
(4) For the spring dataset of the ZMS wind farm, the MAE, RMSE and MAPE of the EEMD-GRU model decreased by 26.73%, 16.88% and 19.27%, respectively, after MC correction. Similar results also appear in other datasets. This proves the effectiveness and applicability of the MC error correlation technique in short-term wind power forecasting.

The proposed EEMD-GRU-MC model is a deterministic wind power forecasting model, and does not take into account the complex meteorological factors. Moreover, the process of dissecting and projecting all of the data is not online forecasting, resulting in its temporary can not be applied to real-time forecasting. In future studies, the uncertainty of wind power prediction error will be considered and meteorological factors will be embedded to build a multi-feature interval prediction model, so as to obtain more comprehensive wind power prediction results. Moreover, the number of decomposed IMFs of EEMD and CEEMDAN, along with the standard EMD and its upgraded algorithms, is uncertain for different data characteristics. The developed model and the commercial solver Matlab 2020a can be integrated into the wind farm short-term power prediction support systems. In this case, the system program can automatically identify each IMF decomposed by the EEMD method, and then give it to the GRU model one by one for training and prediction. The support system would cope with the problem that the number of decomposed IMFs is uncertain for different data characteristics and realize online wind power forecasting. Hence, how to integrate the hybrid prediction model based on EEMD-GRU-MC into the decision support system for the short-term power prediction of wind farms to realize online and real-time prediction is our next research direction.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

PW: Software, Writing–Original Draft, Conceptualization. CS: Methodology, Writing–Review and Editing, Funding acquisition, Supervision. LL: Validation, Writing–Review and Editing. WY: Investigation, Validation. CG: Data Curation, Formal analysis. All authors contributed to manuscript revision, read, and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2023.1252067/full#supplementary-material

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Nomenclature

Sets and indices

K	Total number of times white noise is added
k	Index of times white noise is added
M	Total number of decomposed IMFs
m	Index of decomposed IMFs
t	Index of time periods
S	Total number of sample points
s	Index of sample points

Constants

P_t	Original wind power sequence
W_Z	Weight matrixes of the update gate
W_r	Weight matrixes of the reset gate
W_h	Weight matrixes of the intermediate state
p_s^h	Actual historical wind power output value of sample point s

Variables

$P_{k,t}$	Wind power sequence after adding white noise for the kth time
$C_{k,t}^m$	The mth IMF obtained by the EMD method for the kth time
C_t^m	The mth IMF obtained by the EEMD method
$r_{k,t}^M$	RES after EMD decomposition for the kth time
r_t^M	RES after EEMD decomposition
r_t	Reset gate
$s_{k,t}$	White noise signal added at the kth time
z_t	Update gate
x_t	hidden state and load data of GRU neuron at time t
$\tilde{h}_t$	Intermediate state
h_t	Output of GRU neuron
$M_{kij}^{(1)}$	Number of times state i turns into state j after one step
M_j	Total number of occurrences of state j
p_s^{pf}	Predicted value of sample point s obtained by the EEMD-GRU model

Functions

σ	Sigmoid function
$\odot$	Element-wise multiplication (Hadamard product)

Abbreviations

MC	Markov chain
GRU	Gated recurrent unit
EEMD	Ensemble empirical mode decomposition
NWP	Numerical weather prediction
WRF	Weather Research and Forecasting
ARMA	Autoregressive moving average model
ARIMA	Autoregressive integrated moving average model
GARCH	Generalized autoregressive conditional heteroscedasticity
SVM	Support vector machine
RF	Random forest
BART	Bayesian additive regression tree
AI	Artificial intelligence
BP	Back-propagation
CNN	Convolution neural network
RNN	Recursive neural network
LSTM	Long short-term memory
TCN	Temporal convolutional network
ELM	Extreme learning machine
ENN	Elman neural network
LSSVM	Least square SVM
RBFNN	Radial basis function neural network
ORELM	Outlier robust ELM
BiLSTM	Bidirectional LSTM
EMD	Empirical mode decomposition
VMD	Variational mode decomposition
WT	Wavelet transform
CEEMDAN	Complete ensemble empirical mode decomposition with adaptive noise
MLP	Multilayer Perceptron
NSGA- II	Non-dominated Sorting Genetic Algorithm II
MOGWO	Multi-objective grey wolf optimization
PSO	Particle Swarm Optimization
ESN	Echo State Network
IMF	Intrinsic mode function
RES	Residual
GRUNN	GRU neural network
RMSE	Root mean square error
MAE	Mean absolute error
MAPE	Mean absolute percentage error