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RENEWABLE ENERGY OUTPUT FORECASTING BASED ON DEEP LEARNING

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Abstract: To address the challenge of decreased prediction accuracy caused by the significant uncertainty and volatility of renewable energy sources, this paper proposes a data-driven forecasting model that leverages an improved deep learning algorithm to enhance accuracy. First, data mining techniques are used to preprocess collected data, minimizing the impact of poor-quality data on forecasting outcomes. Then, Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is applied to separate the data into high- and low-frequency components. A Gated Recurrent Unit (GRU) model is employed for predicting high-frequency data to capture short-term fluctuations, while a Kalman Filter (KF) model is used for low-frequency data to extract long-term trends. The final forecast is obtained by combining the high- and low-frequency predictions. Simulation results demonstrate that the proposed data preprocessing effectively removes poor-quality data, improving subsequent forecast accuracy. Additionally, the combined forecasting approach effectively captures both high-frequency fluctuations and low-frequency trends, meeting the accuracy requirements for renewable energy forecasting.
Keywords: Deep Learning; Forecast; Load; Complete Ensemble Empirical Mode Decomposition with Adaptive Noise

1 INTRODUCTION

Accurate forecasting of renewable energy output has become increasingly critical for the reliable operation and planning of modern power systems. As countries transition towards greener energy sources, the integration of intermittent renewable energy like wind and solar power has accelerated significantly. Unlike traditional energy sources, renewable generation is inherently variable and influenced by numerous environmental factors, making it difficult to predict with precision [1]. These fluctuations can destabilize the grid, posing challenges to maintaining a consistent balance between supply and demand. For instance, unexpected weather changes can lead to sudden decreases in renewable generation, necessitating costly compensatory actions through conventional power sources, which are often less environmentally friendly [2]. Therefore, effective forecasting is essential for reducing the costs associated with these measures and optimizing grid stability and efficiency. Accurate predictions enable grid operators to better manage reserve power allocations, avoid over-reliance on fossil fuels, and minimize environmental impact. Additionally, improved forecasting supports better scheduling and dispatch of energy resources and enhances demand response mechanisms [3]. In the broader context of sustainable development, advancements in renewable energy forecasting play a pivotal role in achieving carbon reduction goals and building a resilient, low-carbon energy infrastructure for the future.

Traditional forecasting methods for renewable energy can be broadly divided into two main categories: model-based approaches and data-driven approaches. Model-based methods rely heavily on physical models and domain-specific knowledge, incorporating factors such as meteorological inputs, power generation characteristics, and system constraints to generate predictions [4]. These methods often use deterministic or stochastic models based on physical laws and engineering principles. For instance, PVs [5] forecasting might rely on models of solar radiation that take cloud cover, atmospheric conditions, and solar angle into account, while WTs [6] forecasting may depend on models that simulate wind flow and turbine dynamics. The first group references [5]-[8] show how to improve the model of the WTs, PVs, and other renewable energy. Model-based approaches are generally effective when environmental conditions are relatively stable and predictable, allowing them to produce accurate results by simulating the underlying physical processes [9]. However, they are limited in their ability to handle the high uncertainty and variability inherent in renewable energy sources, which are highly sensitive to rapid and unpredictable changes in weather patterns and environmental conditions.

In contrast, data-driven approaches have gained popularity for renewable energy forecasting due to their ability to analyze large datasets and automatically extract patterns. These methods employ machine learning or data mining algorithms that analyze historical data without requiring detailed knowledge of the physical processes involved. Instead of relying on deterministic models, data-driven methods identify statistical relationships and trends within the data [10], making them particularly useful for capturing complex, nonlinear dynamics in renewable energy output. Techniques such as neural networks [11], decision trees [12], and clustering algorithms [13] allow data-driven models to adapt to new information, effectively learning from recent observations. Unlike model-based methods, data-driven approaches can automatically adjust to emerging patterns and anomalies, making them highly adaptable to the rapidly fluctuating nature of renewable energy sources [14]. This flexibility makes data-driven forecasting particularly advantageous for managing the intermittency and variability of renewable energy, as it can more readily capture short-term fluctuations and seasonal patterns. As a result, data-driven forecasting is increasingly viewed as a future trend in the field, offering a promising alternative to traditional methods and paving the way for more accurate and resilient renewable energy integration into the grid.

Although data-driven methods provide advantages like capturing nonlinear relationships and adapting to changing conditions, they face significant challenges due to the high uncertainty and short-term fluctuations in renewable energy generation. Sudden weather changes, equipment malfunctions, and fluctuating energy demand complicate accurate forecasting. While data-driven approaches can learn from historical patterns, they often struggle with the dynamic nature of renewable sources, particularly during peak load times or extreme weather events when precise predictions are critical for grid stability. To address these issues, researchers have focused on algorithmic improvements, as highlighted in Reference [15], which discusses enhancements such as hybrid models, ensemble learning, and advanced neural networks. Techniques like ensemble learning combine multiple models to reduce individual biases, while recurrent neural networks and long short-term memory networks (LSTMs) are effective for time-series predictions [16]. Despite these advancements detailed in References [17]-[20], there remains a crucial need for further improvements in prediction accuracy. Enhanced models are vital for optimizing power system operations and facilitating the integration of renewable energy sources into the grid, thereby supporting the transition to a sustainable energy future.

This paper introduces a novel forecasting approach that combines data preprocessing with a frequency decomposition model. First, data preprocessing removes poor-quality data, minimizing their impact on the model. Second, the proposed method utilizes a hybrid frequency-combination approach that separately models high-frequency and low-frequency components to effectively capture both short-term fluctuations and long-term trends in renewable energy data. This dual approach demonstrates the potential to significantly improve forecast accuracy by addressing both data quality and frequency-specific modeling challenges.

2 DATA PREPROCESSING

The chapter begins by using Graph Neural Networks (GNNs) to detect and filter abnormal data, ensuring data quality for subsequent processing. Then, the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) is applied to separate the data into high- and low-frequency components, providing a foundation for further analysis and prediction across different frequency bands.

2.1 Abnormal Data Detection Using

Graph Neural Networks (GNNs) [21] have recently gained prominence in anomaly detection, particularly in datasets with complex interdependencies, such as social networks and power system sensor networks. In such datasets, traditional anomaly detection methods may fall short as they often ignore the relationships between data points. GNNs, however, excel at modeling these relationships by constructing a graph structure where nodes represent data points, and edges represent relationships. This makes GNNs highly effective in detecting anomalies that deviate from expected patterns, especially those related to the network's structural properties.

In a GNN model, data is often represented as a graph $G=(V,E)$, where V is the set of nodes and E is the set of edges. Each node $v\in V$ represents a data point, and each edge $(u,v)\in E$ represents a relationship between nodes u and v. GNNs update the features of each node by aggregating information from its neighbors. A common update formula is:

$$h_v^{(k)}=\sigma(W^{(k)}\cdot AGG(\{h_u^{(k-1)}:u\epsilon N(v)\}\cup h_v^{(k-1)})) \quad (1)$$

where $h_v^{(k)}$ is the feature vector of node v at layer k,$N(v)$ denotes the neighbors of node v,W^k is the weight matrix at layer k,$\sigma$is an activation function, and $AGG$is an aggregation function (such as mean or weighted average).

After training, the GNN model assigns anomaly scores to nodes, based on how much a node's behavior or connections deviate from the learned patterns. Nodes with high anomaly scores are considered outliers or "bad data." By removing these high-scoring nodes, it is possible to eliminate erroneous or unrepresentative data from the dataset, which improves data quality and enhances the accuracy of downstream tasks, such as predictive modeling or pattern recognition.

2.2 Steps in Data Frequency Division Preprocessing

After processing with the GNN, clearly abnormal data is removed to prevent common interference. Next, the CEEMDAN method is applied to perform frequency division on the GNN-processed data. The steps are as Figure 1 shows.

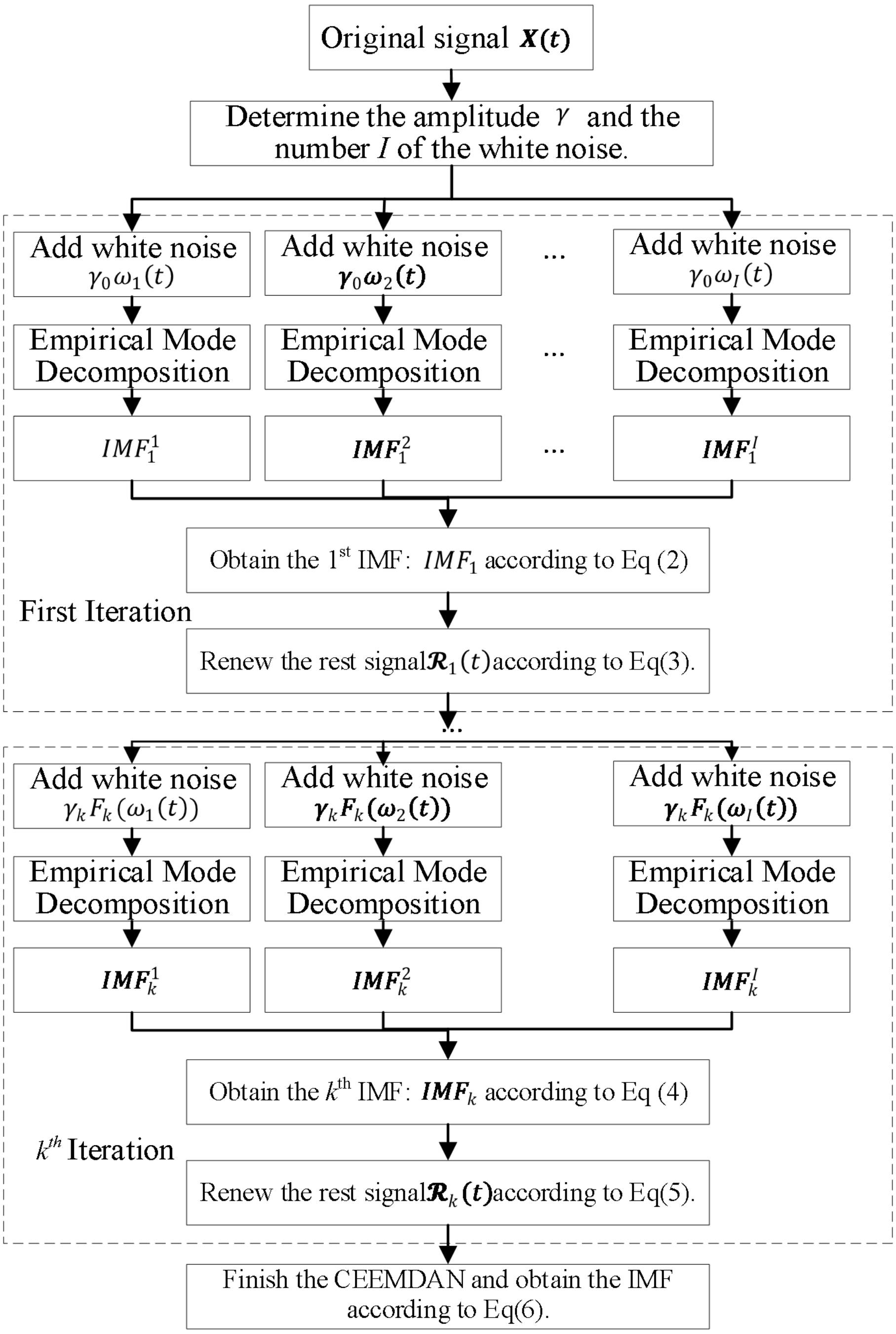

Figure 1 Flow Chat of the CEEMDAN

1. Generate the *i*-th signal sequences:

$$\boldsymbol{X}_{new}(t) = \boldsymbol{X}(t) + \gamma_0\omega_i(t), (i = 1,2, ..., N) \tag{1}$$

2. Extract the first IMF and the residual signal using the CEEMDAN method:

$$IMF_1 = \frac{1}{N}\sum_{i=1}^{N} IMF_1^i \tag{2}$$

$$\mathcal{R}_1(t) = \boldsymbol{X}(t) - IMF_1 \tag{3}$$

3. Extract the (*k*+1)-th IMF after adding white noise $\omega_i(t)$ to the residual signal:

$$IMF_{k+1} = \frac{1}{N}\sum_{i=1}^{N} F_1[\mathcal{R}_k(t) + \gamma_k F_k(\omega_i(t))] \tag{4}$$

$$\mathcal{R}_k(t) = \mathcal{R}_{k-1}(t) - IMF_k \tag{5}$$

4. Continue with step 3 until $r_k(t)$ becomes either a monotonic function or a constant. At this stage, the signal is represented by Equation (6), assuming that there are *m* IMF after step 3.

$$\boldsymbol{X}(t) = \sum_{k=1}^{m} IMF_k + \mathcal{R}_m(t) \tag{6}$$

The IMF components decomposed by CEEMDAN exhibit varied characteristics, including components that capture instantaneous fluctuations and others that represent tends. Using a single prediction model for all components is neither specific nor efficient in terms of computational resources. Therefore, the IMF components are classified and reorganized into high- and low-frequency components, each assigned to an appropriate prediction model. The classification process uses sample entropy to assess the complexity of each IMF, as shown in reference [22].

3 DIFFERENT FORECASTING MODEL FOR DIFFERENT FREQUENCE COMPONENTS

This chapter forecasts the preprocessed high- and low-frequency data. The Gated Recurrent Unit (GRU) is applied to predict the high-frequency data, while the Kalman Filter (KF) is used for the low-frequency data. Finally, the predictions are combined to produce the final forecast.

3.1 High- frequency Data Forecasting Based on GRU

The framework of the GRU is as Figure 2 shows.

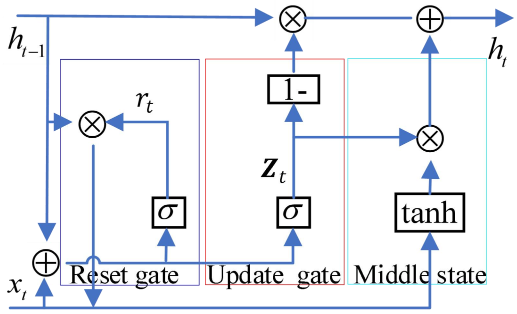

Figure 2 Structure of GRU

As shown in Figure 2, using GRU (Gated Recurrent Unit) to predict high-frequency data can capture short-term and long-term dependencies in sequence data. GRU is an improved version of recurrent neural network (RNN), which controls the transmission of information through "reset gate" and "update gate", which helps solve the gradient disappearance problem of traditional RNN.
The "reset gate" controls whether the state of the previous time step has an impact on the current state as follow:

$$\boldsymbol{r}_t = \sigma(\mathbf{W}_t \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \mathbf{b}_t) \tag{7}$$

The "update gate" is the update $\mathbf{z}_t$ that calculates the current time t:

$$\mathbf{z}_t = \sigma(\mathbf{W}_z \cdot [\boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \mathbf{b}_z) \tag{8}$$

The candidate hidden state $\widetilde{\boldsymbol{h}}_t$ is calculated as follows:

$$\widetilde{\boldsymbol{h}}_t = \tanh\left(\mathbf{W} \cdot [\boldsymbol{r}_t * \boldsymbol{h}_{t-1}, \boldsymbol{x}_t] + \mathbf{b}\right) \tag{9}$$

The hide state $\boldsymbol{h}_t$ renew as follows:

$$\boldsymbol{h}_t = \boldsymbol{z}_t * \boldsymbol{h}_{t-1} + (1 - \boldsymbol{z}_t) * \widetilde{\boldsymbol{h}}_t \tag{10}$$

Through the above GRU, the high-frequency data can be forecasted accurately.

3.2 Low- frequency Data Forecasting Based on KF

The low-frequency data can be predicted by the KF, which is an optimal state estimation method for linear dynamic systems. KF estimates the optimal value of state variables through iteration based on the dynamic system model and observation data and it is divided into a prediction step and an update step.
Assume that the state $\boldsymbol{x}_k$ is as follows:

$$\boldsymbol{x}_k = \boldsymbol{A}\boldsymbol{x}_{k-1} + \boldsymbol{w}_{k-1} \tag{11}$$

Where $\boldsymbol{x}_k$ is the hidden true state at time *t*. $\boldsymbol{A}$ is the state transfer matrix. $\boldsymbol{w}_{k-1}$ is the noise.
Thus, the low-frequency data $\boldsymbol{X}_{low}$ is as follows:

$$\boldsymbol{X}_{low} = \mathbf{H}\boldsymbol{x}_k + \mathbf{v}_k \tag{12}$$

Where $\mathbf{H}$ is the observation matrix, that influence the state to observation. $\mathbf{v}_k$ is the observation noise.
1. Prediction Step
State prediction is as follows:

$$\widehat{\boldsymbol{x}}_{k|k-1} = \boldsymbol{A}\widehat{\boldsymbol{x}}_{k-1|k-1} \tag{13}$$

Covariance prediction is as follows:

$$\mathbf{P}_{k|k-1} = \boldsymbol{A}\mathbf{P}_{k-1|k-1}\boldsymbol{A}^T + Q \tag{14}$$

2. Update Step
After receiving a new observation $\boldsymbol{z}_t$, the KF updates its state estimate and error covariance.
Kalman Gain Calculation is as follows:

$$\mathbf{K}_T = \mathbf{P}_{k|k-1}\mathbf{H}^T(\mathbf{H}\mathbf{P}_{k|k-1}\mathbf{H}^T + \mathbf{R})^{-1} \tag{15}$$

Where $\mathbf{K}_T$ is the Kalman Gain, which determines the weight given to the observation vs. the prediction.
State Update is as follows:

$$\widehat{\boldsymbol{x}}_{k|k} = \widehat{\boldsymbol{x}}_{k|k-1} + \mathbf{K}_k(\boldsymbol{z}_t - \mathbf{H}\widehat{\boldsymbol{x}}_{k|k-1}) \tag{16}$$

Where $\widehat{\boldsymbol{x}}_{k|k}$ is the updated state estimate after incorporating the new observation $\boldsymbol{z}_t$.
Covariance Update is as follows:

$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k\mathbf{H})\mathbf{P}_{k|k-1} \tag{17}$$

Where $\mathbf{P}_{k|k}$ is the updated error covariance matrix.

4 SIMULATION

The article employs data from January 1 to December 31, 2019, collected from a specific region in Xinjiang, to make predictions. It utilizes a sliding window approach for single-point forecasting, as illustrated in Figure 3.

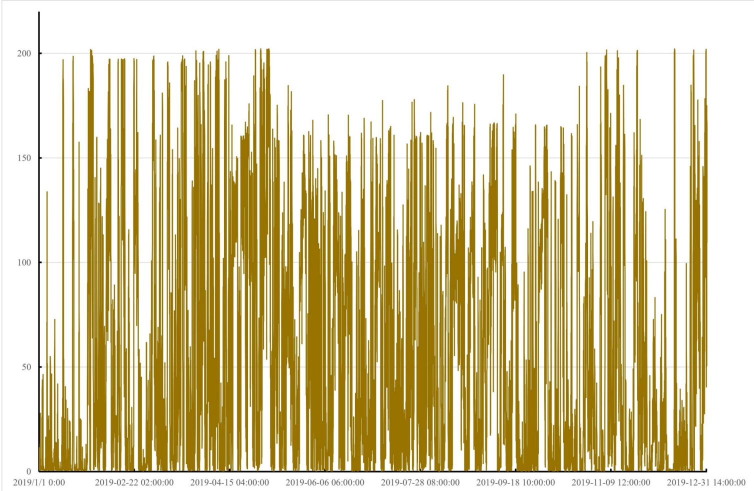

Figure 3 The Output of the WTs in Xinjiang Province

The data was decomposed using CEEMDAN, resulting in 11 IMF values, which were grouped into high- and low-frequency bands. Various models, as discussed in the article, were applied to these bands for prediction. The forecast results were then recombined, yielding the outcomes displayed in Figure 4, which also includes comparisons with other standard algorithms. The statistical comparison of these results is presented in Table 1.

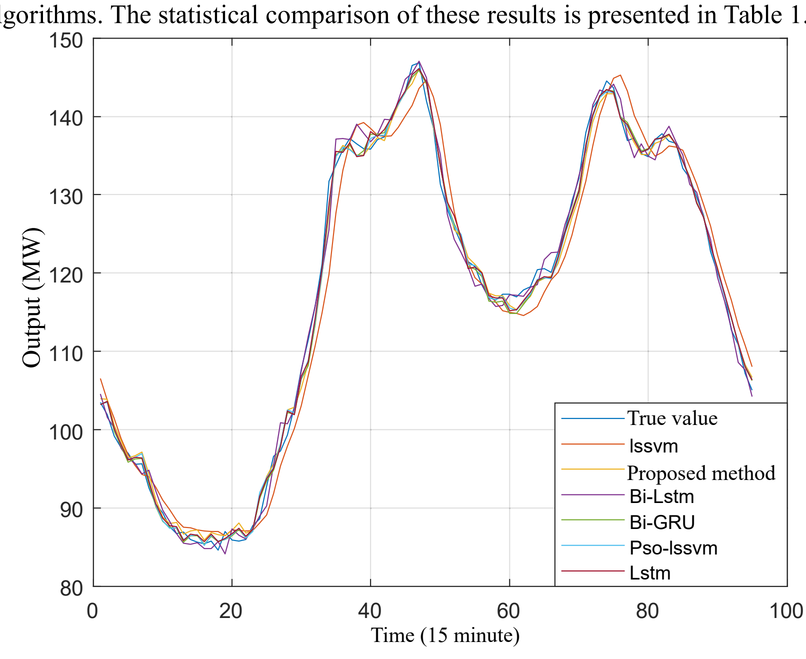

Figure 4 The Forecast Results in Different Methods

Table 1 Statistics in Different Methods

	RMSE	MAE	MAPE

Proposed method	1.0817	0.8097	0.80503%
Lssvm	1.5355	1.1235	0.96216%
Bi-lstm	1.1785	0.91779	0.8066%
Bi-GRU	1.1777	0.92081	0.8161%
Pso-lssvm	1.171	0.93537	0.82399%
Lstm	3.1757	2.5535	2.1448%

The analysis results indicate that the prediction method outlined in the article achieves the highest accuracy, effectively forecasting the output trend of wind turbines (WTs) with greater precision than existing algorithms. This superior performance can be attributed to the use of CEEMDAN for frequency division processing, which allows for separate consideration of short-term fluctuations and long-term trends. The GRU algorithm excels in capturing the accuracy of short-term fluctuations, while the KF algorithm effectively extracts long-term trends. By combining the strengths of both algorithms, the prediction accuracy achieved is significantly superior to that of other methods.

5 CONCLUSION

This paper presents a data-driven prediction model that utilizes frequency division techniques to separate short-term fluctuations from long-term trends in wind turbine (WT) output. The model employs the GRU algorithm to predict short-term fluctuations and the Kalman Filter (KF) algorithm to capture periodic changes in long-term trends. This approach effectively avoids the mutual interference of multimodal data, leading to improved prediction accuracy. Simulation results demonstrate that the proposed prediction model performs well, showcasing its potential for further development and broader application.

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COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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