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Research on medium-term electric power load forecasting based on SSAD-CEEMDAN

Qiaoli Li

Shanghai Maritime University, 1550 Haigang Avenue, Pudong New Area, Shanghai, 201306

chloe5572@163.com

Abstract. To fully enhance the accuracy of electric power load forecasting, a medium-term electric power load forecasting model based on secondary decomposition (predicted model of power load based on secondary decomposition, PMPL-SD) is proposed. In the PMPL-SD algorithm, the original load data are first decomposed and reconstructed using the singular spectrum analysis decomposition method; then, the data after denoising are further decomposed and reconstructed using the noise-assisted complete ensemble empirical mode decomposition to obtain three components: high frequency, medium frequency, and trend. At the same time, a combined network model consisting of convolutional neural networks and bidirectional long short-term memory networks is used to predict the three components separately. The component results are integrated to obtain the final forecasting result. To verify the performance of the PMPL-SD algorithm, three models are selected for comparison. The experimental results show that the proposed algorithm has higher forecasting accuracy in medium-term electric power load forecasting.

Keywords: Electric power load forecasting; Long Short-Term Memory networks; Secondary decomposition

1. Introduction

1.1. Research Background

To improve the accuracy of electric power load forecasting, scholars from both domestic and international communities have proposed numerous methods [1]. These can mainly be divided into time series analysis methods and machine learning methods [2]. Among them, machine learning methods include support vector machines [3], random forests [4], etc. Compared to the former, machine learning methods are better at capturing hidden relationships within electric power load sequences, effectively modeling the non-linear power load sequences, and thus achieving higher forecasting accuracy [5].

However, as electric power load data becomes increasingly complex, single models are no longer adaptable to the varied types of data, and more scholars are adopting hybrid model approaches to enhance forecasting accuracy [6]. For instance, Wan and others [7] proposed a short-term electric power load forecasting model based on Convolutional Neural Network (CNN) and Long Short Term Memory Neural Network (LSTM), also incorporating an attention mechanism (Attention) to optimize the output

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weights of LSTM. Experiments have shown that the CNN-LSTM-Attention model can fully mine data features, and its power load forecasting accuracy is superior to traditional LSTM models.

At the same time, considering the strong volatility and non-linearity of electric power load data, signal decomposition techniques have attracted the attention of many scholars [8]. In particular, the secondary decomposition technique can more effectively extract data features and reduce the impact of noise on forecasting accuracy. Xiang Ling proposed a multi-step wind speed forecasting method, initially using variational mode decomposition to decompose wind speed data, followed by a secondary decomposition using Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) on the decomposed residual components, then inputting the subsequences into the LSTM model for forecasting. Experimental results indicate that the multi-step wind speed forecasting algorithm has good forecasting effects and is practically applicable [9].

To further enhance the effectiveness of medium-term electric power load forecasting, this paper proposes a medium-term electric power load forecasting model based on secondary decomposition. It first decomposes and reconstructs the original electric power load data using Singular Spectrum Analysis Decomposition (SSAD), obtaining a denoised dataset. Then, it employs CEEMDAN for a further decomposition of the denoised data and uses Permutation Entropy (PE) for signal reconstruction, obtaining three components: high frequency, medium frequency, and trend. A CNN-BiLSTM hybrid network model is constructed by combining CNN with these components, introducing Attention to automatically allocate weights to hidden layers, highlighting key features of the input. By comparing with other algorithms using a power load dataset from a region in Australia and selecting mean squared error, mean absolute error, and mean absolute percentage error as the error evaluation metrics, experimental results show that the evaluation metrics for the PMPL-SD model are: 0.9723, 156.096, 1.963, respectively, significantly outperforming other comparison models and verifying the effectiveness of the proposed forecasting algorithm.

1.2. CNN

The main structure of a CNN consists of an input layer, convolutional layer, pooling layer, fully connected layer, and output layer [10]. The convolutional layer extracts spatial features of electric power load data through convolution kernels, while the pooling layer uses operations such as max pooling and average pooling to implement the down sampling process of data features [11]. Due to its excellent capability in high-dimensional space extraction, CNNs have shown significant effects in the field of time series forecasting [12].

1.3. BiLSTM

Compared to traditional recurrent neural networks, LSTM adds input gates, forget gates, and output gates, possessing the capability for long-term memory and effectively avoiding issues such as gradient explosion and gradient vanishing [13]. The basic structure of an LSTM is shown in Figure 1 [14].

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{1}$$

$$u_t = \sigma(W_u[h_{t-1}, x_t] + b_u) \tag{2}$$

$$\tilde{c}_t = tanh(W_c[h_{t-1}, x_t] + b_c) \tag{3}$$

$$c_t = f_t \odot C_{t-1} + u_t \odot \tilde{c}_t \tag{4}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t \odot tanh(C_t) \tag{6}$$

In the formulas: f_t represents the forget gate; σ is the Sigmoid function; h_{t-1}denotes the hidden state from the previous moment; $x_t$represents the input sequence at the current moment *t*; u_t is the input gate; $\tilde{c}_t$ denotes the candidate value for the cell state at time t; W_f, W_u, W_c, and W_o respectively represent the weight matrices for the forget gate, input gate, cell unit, and output gate; b_f, b_u, b_c, and b_o respectively stand for the bias vectors for the forget gate, input gate, cell unit, and output gate; tanh is the hyperbolic tangent activation function; c_t is the cell state at the current moment *t*; $\odot$ represents the Hadamard product, i.e., the product of corresponding elements of two vectors. o_t is the output gate; h_t denotes the output at the current moment *t*.

BiLSTM is an improvement over LSTM, capable of extracting features from both forward and backward directions, mining the intrinsic connections of the current moment's data with the past and the future, and further enhancing the model's forecasting accuracy [15]. Its network result is shown in Figure 2, where y_t denotes the output sequence at time t.

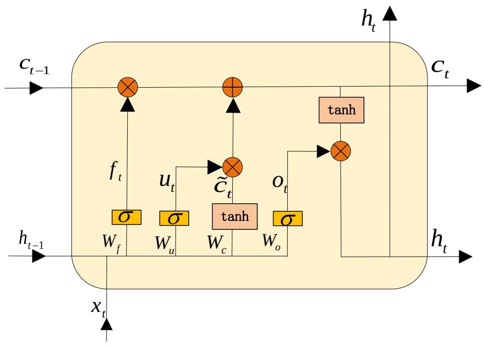

Figure 1. Structure of LSTM

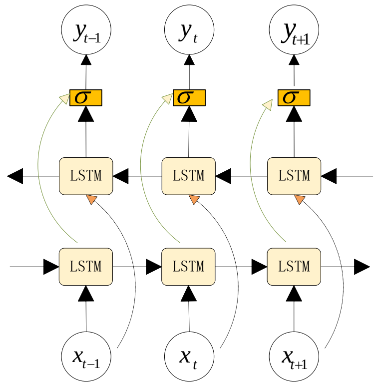

Figure 2. Network Structure of BiLSTM

1.4. Singular Spectrum Analysis Decomposition Method

SSAD is a method for processing non-linear time series signals, capable of denoising, dynamic reconstruction, and feature extraction of signals [16]. SSAD can decompose the original signal into trend, oscillatory, and noise components based on the magnitude of the singular values. Due to its advantages such as not requiring prior information and assumptions, SSAD is widely applied in the field of time series forecasting research.

1.5. CEEMDAN

CEEMDAN is a signal decomposition method improved from EMD, which effectively mitigates issues like mode mixing by repeatedly adding adaptive white noise during the decomposition process [17]. The IMF components obtained from CEEMDAN decomposition are relatively simple, effectively reducing the difficulty of forecasting.

2. PMPL-SD Model

Electric power load data is a type of non-stationary time series data, and without appropriate preprocessing, direct forecasting can lead to significant error [18]. CNNs can effectively extract hidden features of the data to improve forecasting results, and BiLSTMs can consider both past and future information [19]. This paper utilizes a secondary decomposition technique combining SSAD and CEEMDAN to process the original data and combines CNN with BiLSTM to propose a medium-term electric power load forecasting model based on secondary decomposition. The specific steps of the PMPL-SD model are as follows:

（1）Use SSAD to decompose and reconstruct the original data to obtain a denoised dataset;

（2）Use CEEMDAN to further decompose the denoised dataset and use PE for reconstruction to obtain three components: high frequency, medium frequency, and trend;

（3）Employ a hybrid network model of CNN-BiLSTM to model the three components, adding Attention to differentiate the importance of information in the hidden layers, constructing a CNN-

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BiLSTM-Attention hybrid network model (abbreviated as AC-BiLSTM), whose structure is shown in Figure 3;

（4）Integrate the forecast values of each component to obtain the final forecasting result.

（5）The structure of the PMPL-SD model is shown in Figure 4.

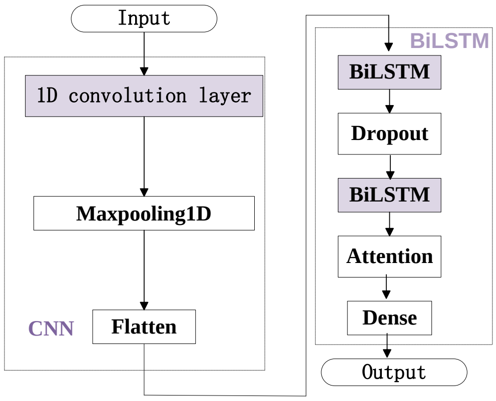

Figure 3. Structure of the AC-BiLSTM Model

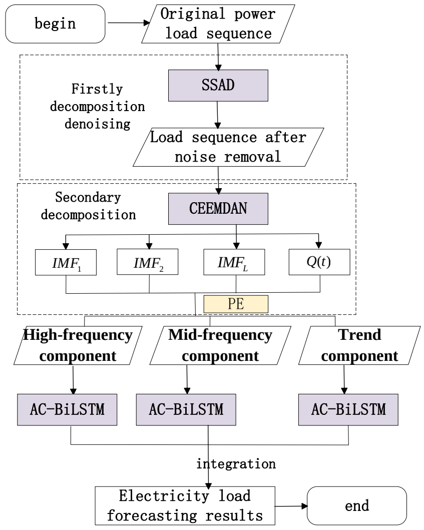

Figure 4. Flowchart of the PMPL-SD Model

3. Experimental Results and Analysis

3.1. Data Source and Data Preprocessing

To verify the effectiveness of the proposed algorithm, a simulation analysis was conducted using an electric power load dataset from a region in Australia [20]. The dataset from January 2, 2006, to April 2, 2006, was selected for the experiment, with the first 80% as training data and the remaining 20% as testing data. The dataset was normalized using min-max standardization, as shown in equation (7).

$$\bar{X}_i = \frac{X_i - X_{min}}{Xmin_{max}} \tag{7}$$

Where X_i and $\bar{X}_i$ represent the value of the i-th sample before and after normalization, respectively; X_{max} and X_{min} respectively represent the maximum and minimum values of the data.

The dataset was decomposed and reconstructed using a secondary decomposition technique combining SSAD and CEEMDAN. Figure 5 shows the load sequence after SSAD denoising of the original data. CEEMDAN was used to further decompose the denoised electric power load data into various components, including 1 original sequence, 8 IMF components, and 1 residual component. Figure 6 displays some of the components, showing that the volatility of the subsequences generated by CEEMDAN decomposition decreases, with simple curve characteristics, and the components are independent of each other without any modal mixing issues. The results of the three components - high frequency, medium frequency, and trend items, reconstructed from the components, are shown in Figure 7.

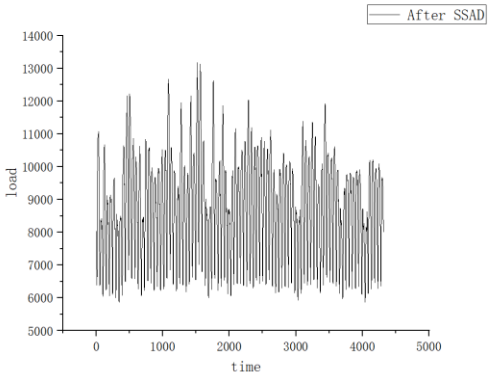

Figure 5. Electric Power Load Sequence After SSAD Denoising

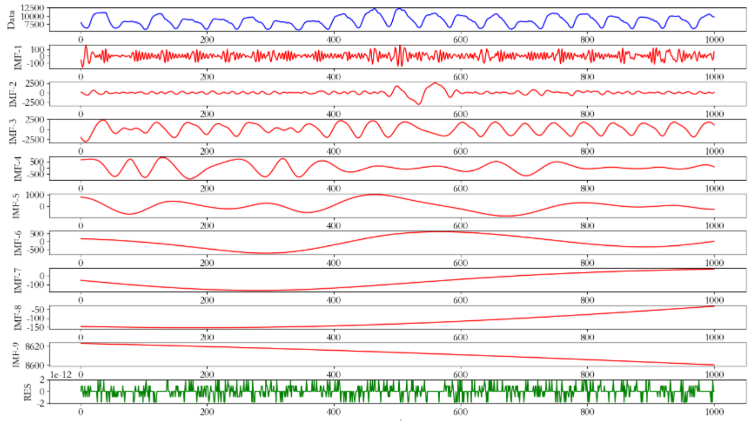

Figure 6. Subsequence Components Generated by CEEMDAN Decomposition (Partial)

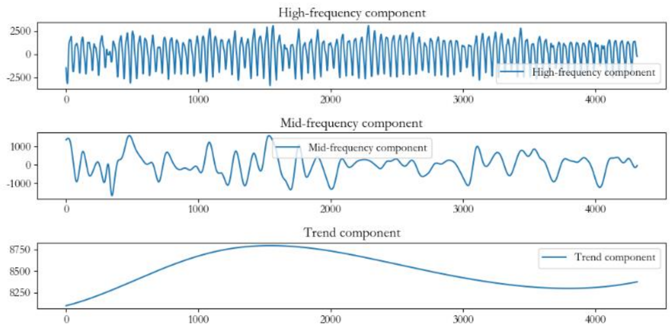

Figure 7. Components of High Frequency, Medium Frequency, and Trend Items After Secondary Decomposition

3.2. Evaluation Metrics and Parameter Settings

The experiments in this paper were all conducted on the Python 3.9 platform, with models built and trained using the Keras framework. In this experiment, the CNN uses a one-dimensional convolutional layer to extract effective local features of the data, with the number of convolutional kernels set to filters=64 and the kernel size set to 3; the pooling layer uses a max pooling method to compress data features, in order to obtain more crucial information. Furthermore, the model's error function uses the mean squared error, the optimization method uses the Adam optimizer, and the learning rate is set to 0.001.

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To comprehensively evaluate the performance of the medium-term electric power load forecasting model, this paper selects the Mean Square Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) as evaluation metrics [21]. The calculation formulas are shown in equations (8)-(10).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \tag{8}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{9}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y}_i - y_i}{y_i}\right| \tag{10}$$

Where $\hat{y}_i$ represents the forecasted value, y_i represents the actual value of the load data, and $\bar{y}$ represents the average value of the actual load data.

3.3. PMPL-SD Model Prediction Results

This paper focuses on the research and development of the secondary decomposition model. Therefore, to verify the superiority of the proposed algorithm, various single decomposition prediction models (CEEMDAN-AC-BiLSTM [22], SSAD-AC- BiLSTM [16]) as well as a single model (BiLSTM [23]) were used for comparison experiments. The prediction effects of each model on the test set are shown in Table 1.

(1) Compared to the single model (BiLSTM), the PMPL-SD algorithm has significantly improved predictive performance. It shows reductions of 80.1%, 55.8%, and 55.6% in MSE, MAE, and MAPE, respectively, thus proving the feasibility and superiority of the proposed algorithm in mid-term electric power load forecasting.

(2) Compared to single decomposition models (SSAD-AC-BiLSTM, CEEMDAN-AC-BiLSTM), the SSAD-CEEMDAN secondary decomposition strategy significantly enhanced the predictive effect of the AC-BiLSTM model, with noticeable reductions in all metrics. This indicates that secondary decomposition can more fully extract data features, greatly improving the algorithm's prediction accuracy.

Table 1. Prediction Results of Different Algorithms

Model	MSE	MAE	MAPE(%)
PMPL-SD	**44119.12**	**156.096**	**1.963**
SSAD-AC-BiLSTM	68787.24	191.416	2.334
CEEMDAN-AC-BiLSTM	58526.78	182.259	2.275
BiLSTM	221521.06	353.478	4.425

3.4. Permutation Entropy Complexity Analysis

PE is a method for detecting the randomness of time series, widely used in fields such as signal analysis [24]. This paper conducts a complexity analysis of various components using PE, with the PE values of each component shown in Figure 9. Higher PE values indicate higher complexity and stronger volatility of the sequence, whereas lower values suggest more regular sequences with less volatility. Therefore, IMF-1, IMF-2, and IMF-3 are selected as high-frequency reconstruction components, IMF-4, IMF-5, IMF-6, and IMF-7 as low-frequency reconstruction components, and IMF-8 as the trend reconstruction component.

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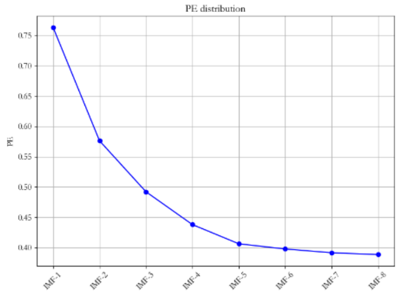

Figure 9. Distribution of PE Values

4. Conclusion

This paper proposes a mid-term electric power load forecasting algorithm based on SSAD-CEEMDAN, demonstrating the effectiveness and superiority of the proposed algorithm through comparative experimental analysis in the electric power load dataset. The complexity of components is determined based on PE values, which allows for the reconstruction of various components, effectively reducing the difficulty of modeling for electric power load forecasting. The SSAD-CEEMDAN secondary decomposition technique positively affects the predictive performance of the model. In summary, the algorithm presented in this paper shows good performance in the study of mid-term electric power load forecasting.

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