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EDITED BY

Kaiping Qu,
China University of Mining and
Technology, China

REVIEWED BY

Li Wang,
Changsha University of Science and
Technology, China
Wentao Sun,
State Grid Jiangsu Electric Power Co.,
Ltd., China

*CORRESPONDENCE

Zhenshan Zhu,
✉ zszhu@whu.edu.cn

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Electric vehicle charging load prediction based on variational mode decomposition and Prophet-LSTM

Nuo Cheng¹, Peng Zheng², Xiaofei Ruan¹ and Zhenshan Zhu^{3*}

¹State Grid Fujian Economic Research Institute, Fuzhou, China, ²State Grid Fujian Electric Power, Fuzhou, China, ³College of Electrical Engineering and Automation, Fuzhou University, Fuzhou, China

With the large-scale development of electric vehicles, the accuracy of electric vehicle charging load prediction is increasingly important for electric power system. Accurate EV charging load prediction is essential for the efficiency of electric system planning and economic operation of electric system. This paper proposes an electric vehicle charging load predicting method based on variational mode decomposition and Prophet-LSTM. Firstly, the variational mode decomposition algorithm is used to decompose the charging load into several intrinsic mode functions in order to explore the characteristics of EV charging load data. Secondly, in order to make full use of the advantages of various forecasting methods, the intrinsic mode functions are classified into low and high frequency sequences based on their over-zero rates. The high and low frequency sequences are reconstructed to obtain two frequency sequences. Then the LSTM neural network and Prophet model are used to predict the high and low frequency sequences, respectively. Finally, the prediction results obtained from the prediction of high frequency and low frequency sequences are combined to obtain the final prediction result. The assessment of the prediction results shows that the prediction accuracy of the prediction method proposed in this paper is improved compared to the traditional prediction methods, and the average absolute error is lower than that of ARIMA, LSTM and Prophet respectively by 7.57%, 8.73%, and 46.02%. The results show that the prediction method proposed in this paper has higher prediction accuracy than the traditional methods, and is effective in predicting EV charging load.

KEYWORDS

electric vehicles charging load, prophet prediction model, neural network, variational mode decomposition, time series prediction

1 Introduction

At present, the problems of environmental pollution and energy resource crisis are becoming more and more serious. Oil-fueled automobiles are causing serious environmental pollution and high energy consumption. Electric vehicles (EVs) offer cleaner energy and environmental advantages over petrol vehicles, effectively alleviating problems such as energy resource shortages and severe air pollution (Wu and Zhang, 2017). Consequently, EVs have been widely promoted globally, and in China, the government has vigorously advanced the construction of public and private EV charging stations (Gao and Zhang, 2011). However, a significant number of EVs connecting to the power grid can also have an impact on the power grid. According to (Das et al., 2020), EV charging equipment may cause

harmonic pollution to the grid, and the clustering effect of EV charging will have a significant impact on distribution networks. Chen and Huang (2019) demonstrates that the disordered charging of huge numbers of EVs will have impact on the safety and reliability of electric power system. At the same time, since the effective prediction of EV charging load is a prerequisite for the analysis of the impact of EV charging on the power grid, it is of great significance to conduct accurate EV charging load prediction (Yin et al., 2023).

Significant progress has been made in research on EV charging load predicting all over the world. EV charging load predicting can be divided into two categories: statistical model-based predicting methods and deep learning-based predicting methods (Yin et al., 2023). The methods based on statistical models are relatively simple, computationally efficient, and have faster prediction speeds (Luo et al., 2019). Selvi and Mishra (2021) utilizes a functional linear regression model to predict the day-ahead power load. Bahrami et al. (2014) employs a short-term power load prediction model that combines wavelet transform with grey model, and the high frequency component of the load is effectively eliminated, and the prediction accuracy is improved. de Oliveria and Oliveria (2018) forecasts medium-term electricity load using an autoregressive integrated moving average model (ARIMA) with a seasonal trend decomposition model combining weighted regression. Luzia et al. (2023) forecasts Brazilian electricity demand with ARIMA combined with Wavelet Transform and Fourier Transform. Wang (2022) utilizes ARIMA combined with BP neural network to predict *per capita* coal consumption of China. The above-mentioned models can achieve rapid predictions for simple time series with high accuracy. However, these models have poor robustness and perform less effectively in predicting power loads with abrupt variations.

Deep learning-based prediction methods can overcome the limitations of statistical model-based methods in predicting complex sequences. Nikolaev et al. (2019) predicts wind power generation using recurrent neural network (RNN). However, RNN may encounter issues such as vanishing or exploding gradients during the training process, which can affect the prediction accuracy. Bouktif et al. (2018) predicts electricity consumption in a particular city with Long Short-Term Memory (LSTM) neural networks. They further optimized the time lag features of the LSTM network using genetic algorithms (GAs). LSTM networks address the problems of vanishing and exploding gradients that occur in RNNs. Liu et al. (2019) utilizes support vector machines (SVMs) to predict electricity load and employs empirical mode decomposition (EMD) for denoising the power load data. Wang et al. (2021) proposes a short-term electricity load predicting model based on a locally random sensitivity deep autoencoder (D-LiSSA). The model utilizes a nonlinear fully connected feedforward neural network as the regression layer and utilizes the learned hidden representations from D-LiSSA to enhance the generalization ability of the model.

While deep learning-based prediction methods are effective in handling nonlinear problems, their performance is influenced by the quality of input data. In real-world scenarios, EV charging loads are affected by many factors like electricity prices, temperature, date and so on. Forecasting using only a single forecasting method can have an impact on forecasting effectiveness (Luo et al., 2019). Therefore, it

is necessary to preprocess the data using appropriate methods and employ ensemble prediction models for forecasting the preprocessed data. To address this, Lu et al. (2019) utilizes convolutional neural networks (CNNs) to extract feature vectors from a massive amount of electricity load data and uses them as inputs to an LSTM neural network to obtain load predictions. However, this approach only utilizes superficial features of the data and does not perform deep analysis. Time series data can be divided into components with different characteristics using certain methods. The effect of disjoint features on prediction can be avoided by predicting the partitioned components. Therefore, Yang et al. (2021) decomposes the photovoltaic power output into components with different frequencies with Variational Mode Decomposition (VMD) and uses LSTM to predict them, then, integrates predicting results to get the final predicting result. In a similar manner, Wang et al. (2020) uses a deep echo state network (DESN) to establish prediction models for each component obtained through VMD, and the predicting results are integrated to get the result. However, these methods do not consider the characteristics of each component during the predicting process and solely used a single model to predict each component. In order to get better predicting result, researchers have divided the components obtained through VMD decomposition of electricity load data into high-frequency and low-frequency sequences (Cai et al., 2022; Yu et al., 2022). Cai et al. (2022) employs gate recurrent units (GRUs) and temporal convolutional networks (TCNs) to predict the high-frequency and low-frequency sequences, respectively. Then reconstructs the final predicting result. Similarly, Yu et al. (2022) utilizes GRUs and ARIMA models to predict the high-frequency and low-frequency sequences separately and combines the predicting results to obtain the result. These ensemble prediction methods consider the characteristics of each component, leveraging the advantages of different prediction models for high and low frequency sequences. Compared to utilizing a single prediction model, these approaches enhance the prediction accuracy. However, the ARIMA algorithm requires more background knowledge and parameter tuning, making it more complex. Moreover, when dealing with missing data, manual imputation and handling are necessary for the ARIMA algorithm. On the other hand, the Prophet algorithm overcomes these drawbacks of the ARIMA algorithm and is better suited for medium-scale time series data forecasting.

Based on the above analysis, an EV charging load predicting method based on VMD and Prophet-LSTM is proposed in this paper to improve the prediction accuracy of EV charging loads. Firstly, for mining the characteristics of EV charging load data, the load data is decomposed into several intrinsic mode functions (IMFs) using VMD algorithm. Secondly, to fully leverage the superiorities of each prediction model, the IMFs are divided into high and low frequency sequences using zero-crossing rates, and each sequence is reconstructed individually. Then the high and low frequency sequences are predicted using LSTM neural networks and the Prophet model, respectively. Finally, the predicting results for high and low frequency sequences are combined to get the final predicting result. Evaluation of the predicting results shows that the predicting method proposed in this paper achieves improved prediction accuracy compared to traditional methods. The average absolute error of the proposed method is lower than ARIMA,

LSTM, and Prophet prediction models by 7.57%, 8.73%, and 46.02%, respectively.

2 Decomposition of EV charging load

2.1 VMD

The VMD method is a technique for estimating individual signal components by solving a variational optimization problem in frequency domain (Dragomiretskiy and Zosso, 2014). This method can decompose complex unstable sequences into IMFs with finite bandwidths, denoted as $u_i(t)$, where $i = 1, 2, 3, \dots, k$, and the central frequencies ω_i of each IMF are determined during the decomposition process, the parameter k above denotes the number of IMFs after decomposition.

The principle of the variational problem is that the decomposed sequence is a finite bandwidth modal component with a central frequency. The original sequence is decomposed into k sub-sequences, and the sum of all sub-sequences is guaranteed to be the original sequence, while the sum of the estimated bandwidths of the sub-sequences is minimum. The constrained variational problem is shown as follows:

$$\begin{cases} \min_{\{u_i\}, \{\omega_i\}} \left\{ \sum_{i=1}^k \left\| \partial_t \left[\left(\delta(t) + j/\pi t \right) * u_i(t) \right] e^{-j\omega_i t} \right\|_2^2 \right. \\ \left. s.t. \sum_{i=1}^k u_i - f \right. \end{cases} \quad (1)$$

where k represents the number of desired mode components to be decomposed; $\{\omega_i\}$ and $\{u_i\}$ represent the central frequency of the i -th decomposed mode component and i -th component after decomposition, respectively; $\delta(t)$ denotes the Dirac function, and $*$ represents the convolution operator. The selection of k is typically done using optimization algorithms, based on central frequencies, or through specific formulas. In this study, a criterion is used to obtain the value of i (Zhang et al., 2021), and the criterion is expressed as follows:

$$E_k = \sum_{i=1}^k \sqrt{\frac{\sum_{j=1}^{len} I_i^2(j)}{len}} \quad (2)$$

$$\theta_k = \frac{|E_{k+1} - E_k|}{E_k} \quad (3)$$

where len represents the length of the time series; I_i represents the i -th IMF, and E_k represents the energy of each intrinsic mode function. When the θ_k suddenly increases after a certain value of k , it is considered as the optimal value of k for that moment.

The constrained variational problem can be transformed into an unconstrained variational problem by introducing the Lagrange multiplier operator and the augmented Lagrange expression is as:

$$\begin{aligned} L(\{u_k\}, \{\omega_k\}, \lambda) = & \alpha \sum_{i=1}^k \left\| \partial_t \left[\left(\delta(t) + j/\pi t \right) * u_i(t) \right] e^{-j\omega_i t} \right\|_2^2 \\ & + \left\| f(t) - \sum_{i=1}^k u_i(t) \right\|_2^2 + \langle \lambda(t), f(t) - \sum_{i=1}^k u_i(t) \rangle \end{aligned} \quad (4)$$

where α is the quadratic penalty factor, which is used to decrease the disturbance of Gaussian noise. The optimal modal component and

center frequency can be obtained by the alternating direction multiplier (ADMM) iterative algorithm combined with Fourier iso-distance transform and Parseval/Plancherel, and the saddle point of augmented Lagrange function can be obtained. The process of alternating optimization iteration for u_k , ω_k and λ is as follows:

$$\hat{u}_k^{n+1}(\omega) \leftarrow \frac{\hat{f}(\omega) - \sum_{i \neq k} \hat{u}_i(\omega) + \hat{\lambda}(\omega)/2}{1 + 2\alpha(\omega - \omega_k)^2} \quad (5)$$

$$\omega_k^{n+1} \leftarrow \frac{\int_0^\infty \omega |\hat{u}_k^{n+1}(\omega)|^2 d\omega}{\int_0^\infty |\hat{u}_k^{n+1}(\omega)|^2 d\omega} \quad (6)$$

$$\hat{\lambda}^{n+1}(\omega) \leftarrow \hat{\lambda}^n(\omega) + \gamma(\hat{f}(\omega) - \sum_k \hat{u}_k^{n+1}(\omega)) \quad (7)$$

where γ represents the noise margin, which meets the fidelity requirement of decomposition of signal; $\hat{u}_k^{n+1}(\omega)$, $\hat{u}_i(\omega)$, $\hat{f}(\omega)$, and $\hat{\lambda}(\omega)$ correspond to the Fourier transforms of $u_k^{n+1}(t)$, $u_i(t)$, $f(t)$, and $\lambda(t)$.

2.2 Division of high and low frequency sequences

Sequences with high frequency that possess poor stationarity and complexity are predicted by LSTM neural network. This paper uses the Prophet model to predict sequences with low frequency that are stable and periodic. Therefore, it is necessary to divide the intrinsic mode functions obtained by VMD processing into sequences with high and low frequencies.

This paper primarily utilizes the over zero rate of a sequence to divide the high and low frequency sequences. The over zero rate of a sequence is defined by the following equation:

$$P_{zfc} = \frac{n_{zfc}}{N} \quad (8)$$

where n_{zfc} represents the number of passing zero in the sequence; N represents the length of the sequence.

3 Predicting method of EV charging load based on Prophet-LSTM

3.1 Prophet model

The Prophet model is a time series forecasting model developed by the Facebook team (Taylor and Letham, 2018). This model fits the time series by considering trend components, seasonal components, holiday effects, periodic components, and error terms. The prediction results are obtained by combining these fitted components. The Prophet model can be represented by the following equation:

$$y(t) = g(t) + h(t) + s(t) + \varepsilon(t) \quad (9)$$

where $g(t)$ represents the trend term, which captures the non-cyclical trends in the time series; $h(t)$ represents the holiday term, accounting for the impact of holidays on the time series; $s(t)$ represents the seasonal term, typically defined at the weekly or yearly level; $\varepsilon(t)$ represents the error term, which captures the unexpected fluctuations of the time series.

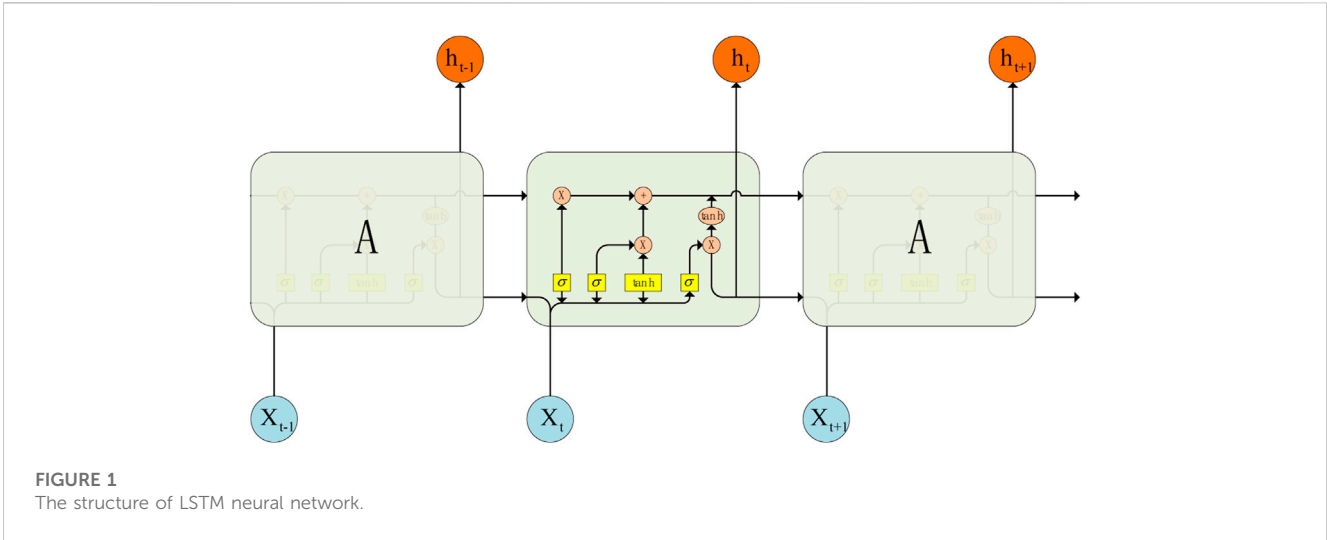


FIGURE 1
The structure of LSTM neural network.

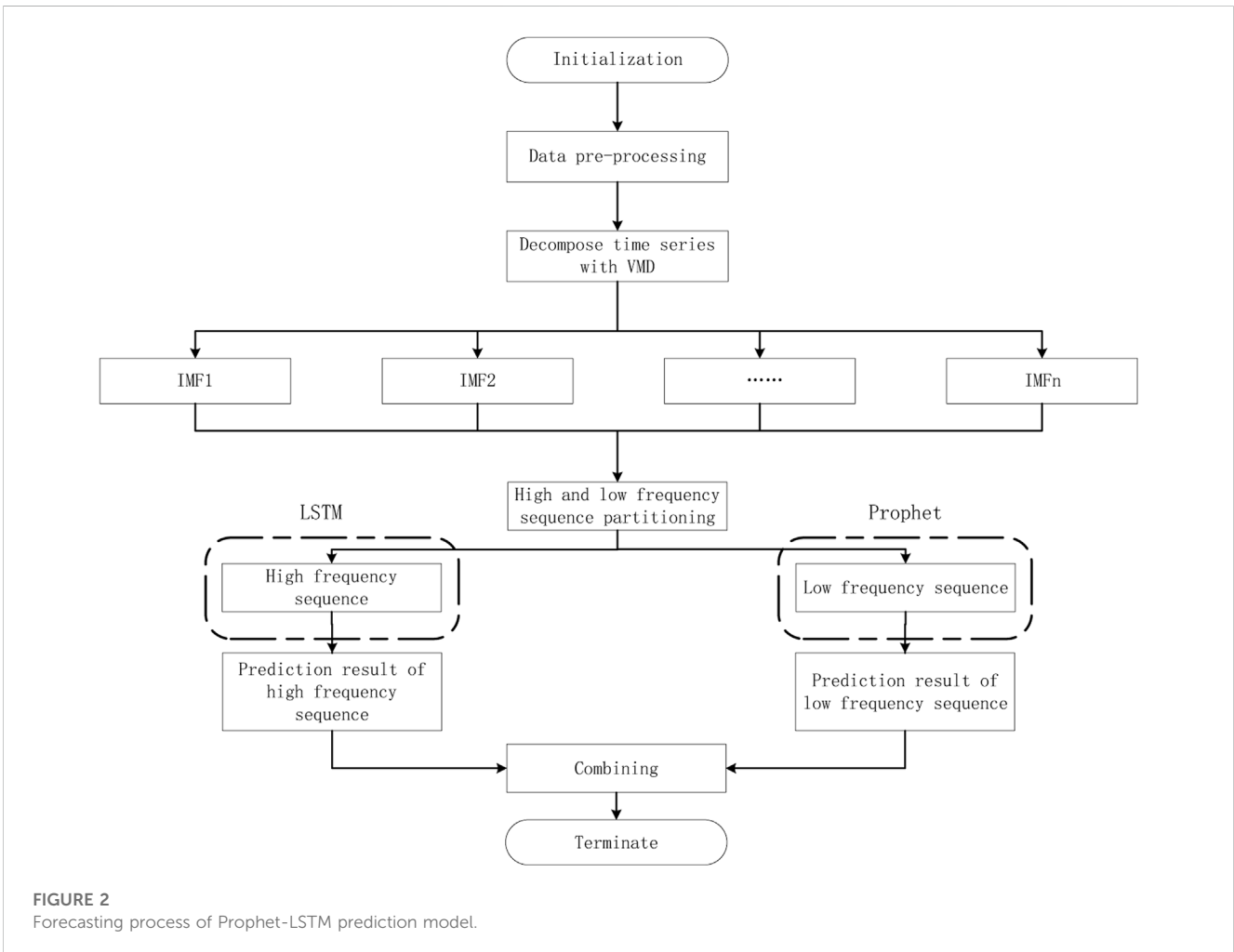


FIGURE 2
Forecasting process of Prophet-LSTM prediction model.

The trend term can be expressed as:

$$g(t) = \frac{C}{1 + e^{-(k(t-m))}} \quad (10)$$

where C represents the load capacity; k represents the rate of increase; m represents the deviation parameter.

The holiday effect can be represented by the following equation:

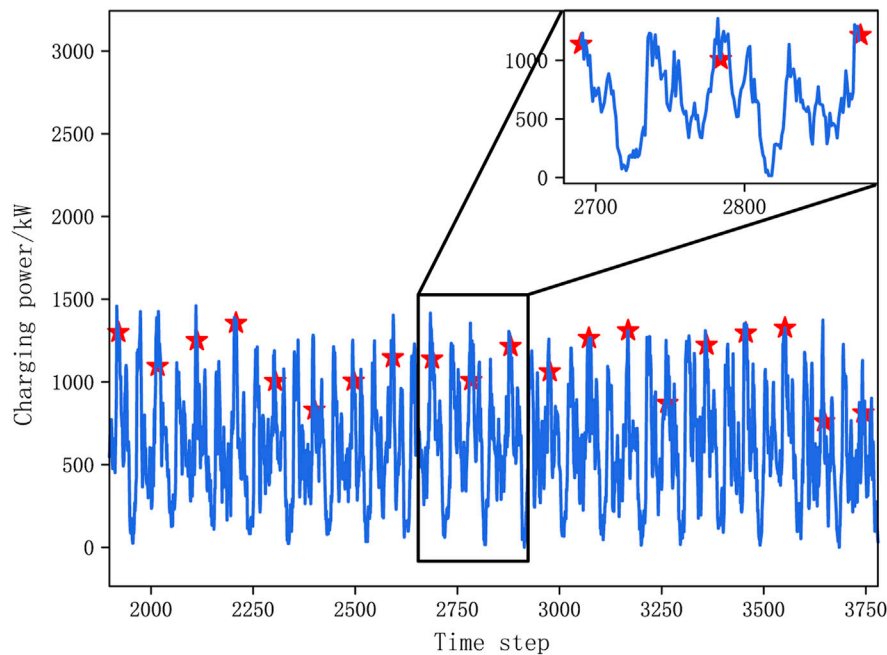


FIGURE 3 Charging power diagram of EV charging station.

TABLE 1 VMD algorithm parameters.

Parameters	Value of parameters
Data fidelity constrains balance parameters α	8,000
Double ascending time step tau	0
Label value of whether the first mode is DC	False
Center frequency label value init	0
Convergence criterion tolerance tol	1e-7

$$\begin{aligned}
 \mathbf{h}(t) &= \mathbf{Z}(t)\boldsymbol{\kappa} \\
 \mathbf{Z}(t) &= [1(T \in D_1), \dots, 1(T \in D_L)] \\
 \boldsymbol{\kappa} &\sim \text{Normal}(\mathbf{0}, \mathbf{v}^2)
 \end{aligned}
 \tag{11}$$

where D_i represents the set of the past and future dates of holiday i .

The Prophet model is a model-based forecasting method. Currently, another popular model-based forecasting method is the ARIMA model. The Prophet model incorporates the advantages of the ARIMA model while avoiding its disadvantages such as limited robustness and the inability to consider external factors that influence time series changes. Therefore, this paper chooses the Prophet model to predict stationary low-frequency sequences.

3.2 LSTM neural network

LSTM neural networks are a variant of recurrent neural networks (RNNs) that were primarily developed to address the issue of vanishing and exploding gradients that can occur in RNNs

during long sequence predictions (Li et al., 2018). Compared to traditional RNNs, LSTM neural networks have improved performance in long sequence predictions.

LSTM networks extend the basic structure of RNNs by introducing additional components such as input gates, forget gates, output gates, and a concept known as the cell state. These additions allow LSTMs to selectively retain and discard information over time, enabling them to capture long-term dependencies more effectively. The architecture of an LSTM network is illustrated in Figure 1.

LSTM neural network has a more complex structure compared to traditional RNNs, as shown in Figure 1. LSTM introduces the concept of a cell state and utilizes input, output and forget gates to control and retain information. The calculation for LSTM at time step t is as follows:

$$\begin{cases}
 f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\
 i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\
 \tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \\
 c_t = f_t * c_{t-1} + i_t * \tilde{c}_t \\
 o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\
 h_t = o_t * \tanh(c_t)
 \end{cases}
 \tag{12}$$

where $f_t, i_t,$ and o_t denotes the forget, input, and output gate layer, respectively; c_t denotes the cell state; \tilde{c}_t denotes the cell state candidate value; h_t represents the hidden state; W and b denotes the weights and biases.

The forget gate combines the foregoing hidden state with the present input, and utilizes the sigmoid function to determine which information to discard. The sigmoid function outputs values between 0 and 1. It discards part of the information when its value is approaching to 0 and keeps the information when its value is nearly 1.

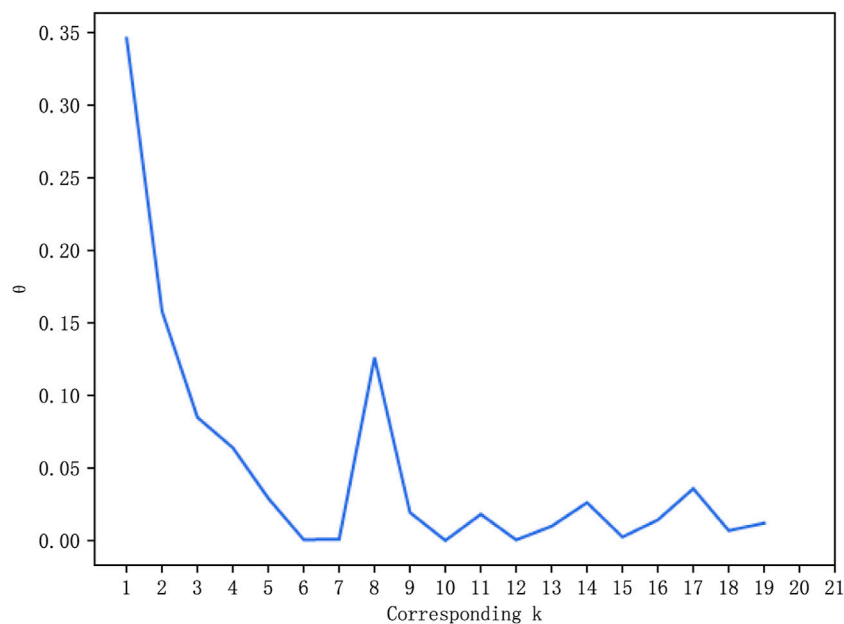


FIGURE 4
Changing map of θ_k .

The input gate and the tanh function determine which new information to incorporate from the foregoing hidden state and the present input, resulting in a candidate value \tilde{c}_t . Then, the forget and input gates are combined to discard or retain information, resulting in the current cell state c_t . Finally, the output gate combines with the tanh function to determine which information from h_{t-1} , x_t and c_t to output as the current hidden state h_t at the current time step.

The LSTM neural network constructed in this study consists of a 96-dimensional input layer, a 1-dimensional output layer, two LSTM layers, and four fully connected layers. The number of neurons in these layers is 128, 64, 32, and 16, respectively. The activation function chosen for the LSTM layers is the hyperbolic tangent (tanh) function. The Adam optimization algorithm is used to minimize the error during training. This LSTM neural network is utilized for predicting high-frequency sequences with significant variations. Through multiple iterations and training, an effective LSTM prediction model is obtained, which is capable of capturing complex temporal dependencies and making accurate predictions.

3.3 Prophet-LSTM combination model

Since the EV charging load time series is highly influenced by real-world factors, the time series exhibits pronounced variations. Predicting such time series using a single forecasting method without considering the relevant factors often results in poor prediction performance and large errors. Therefore, it is necessary to utilize a combination forecasting model. In this study, a Prophet-LSTM prediction model is established. The proposed model takes the advantages and disadvantages of both the Prophet and LSTM model into account. The Prophet model is employed to predict low-frequency sequences with relatively smooth variations, while the LSTM neural network is used to predict

sequences with high frequency with more pronounced variations. By dividing the original complex time series prediction problem into two relatively simpler time series prediction problems, better prediction results can be achieved. The overall prediction process is illustrated in Figure 2.

3.4 Error evaluation index selection

To assess the prediction performance of the Prophet-LSTM model, this study uses the mean absolute error (MAE) as well as the goodness-of-fit to evaluate (R-squared) the prediction results. The calculation methods for MAE and R-squared are as follows:

$$X_{MAE} = \sum_{n=1}^l \left| \frac{\hat{y}_n - y_n}{\hat{y}_n} \right| \quad (13)$$

$$R^2 = 1 - \frac{\sum_{n=1}^l (\hat{y}_n - y_n)^2}{\sum_{n=1}^l (\bar{y} - y_n)^2} \quad (14)$$

where l represents the length of the sequence; \hat{y}_n denotes the predicted value of the model for the n th data in the sequence; \bar{y} denotes the mean of the sample.

4 Results

The hardware environment for the experiments includes an Intel i5 8300H 2.3 GHz CPU and an NVIDIA GTX 1050Ti graphics card, with 16 GB of memory. The model was implemented using Python 3.9 as the programming language, utilizing software architectures such as TensorFlow, Keras, and the Prophet algorithm framework for power load forecasting.

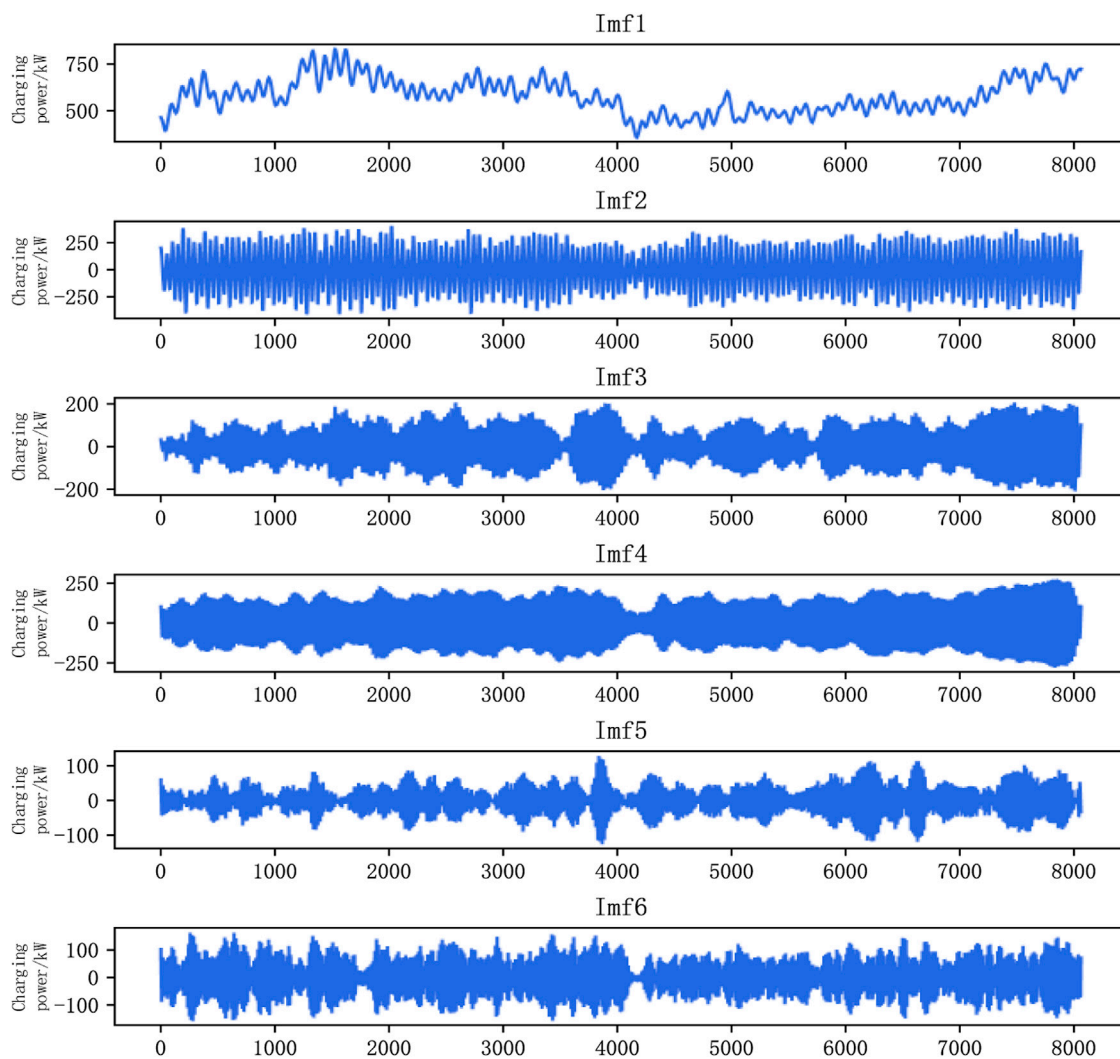


FIGURE 5
Sequence diagram after VMD decomposition.

TABLE 2 Over zero rate of each IMF.

IMF	Zero-crossing rate
IMF1	0
IMF2	0.041
IMF3	0.063
IMF4	0.083
IMF5	0.106
IMF6	0.125

Based on the threshold of 0.05 for the zero-crossing rate, the division between high-frequency and low-frequency sequences can be defined as follows: when the zero-crossing rate of an intrinsic mode function is greater than 0.05, it is considered as a high-frequency sequence, and when the zero-crossing rate is less than 0.05, it is considered as a low-frequency sequence.

4.1 Data processing

This study utilizes EV charging data from a charging station in Fujian Province, China, spanning from January to April 2022. The

sample time of the data is 15 min. The EV charging power curve is depicted in Figure 3.

Each red “☆” in Figure 3 represents 24:00 of the previous day and 0:00 of the next day. The power data between two consecutive

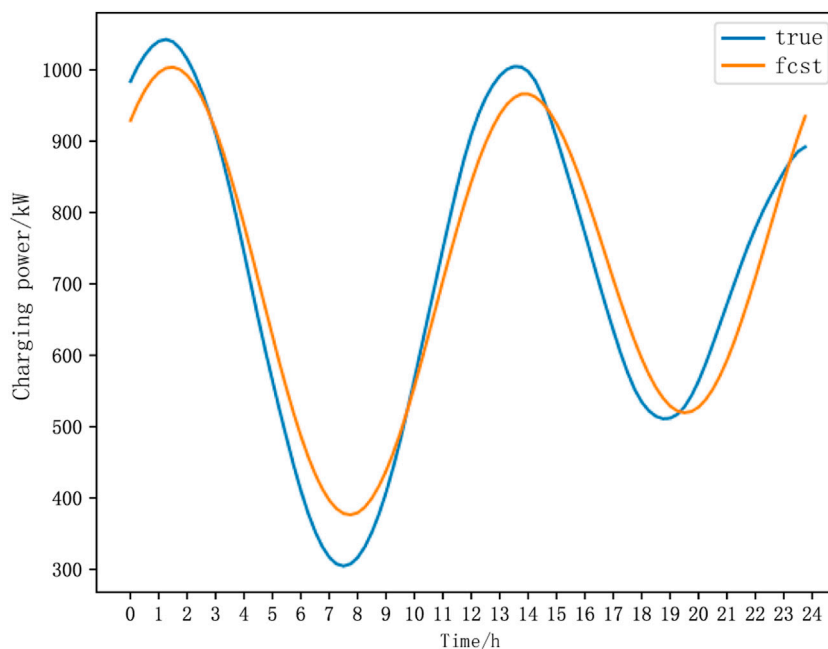


FIGURE 6
Predicting result of low frequency sequence.

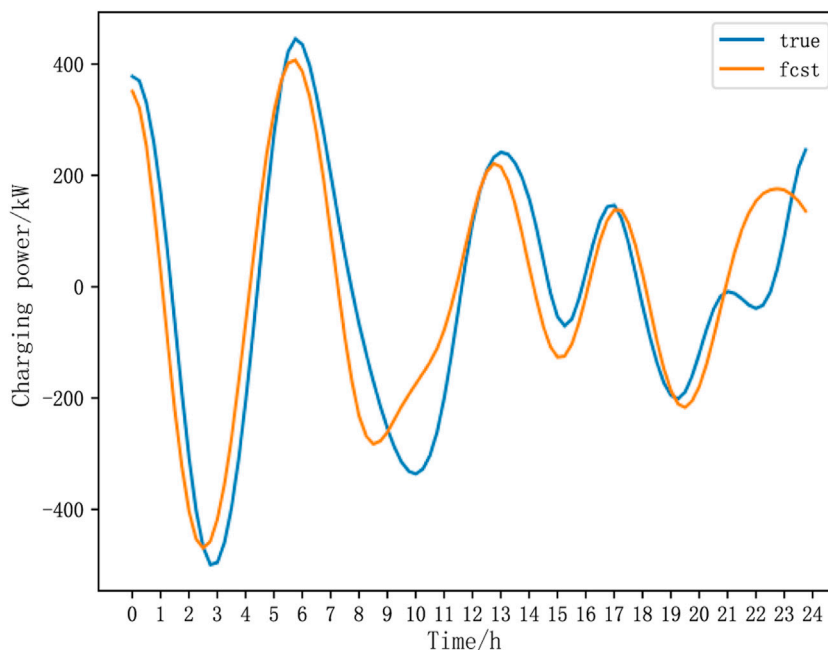


FIGURE 7
Predicting result of high frequency sequence.

“☆” markers is complete data set for each day. From Figure 3, it can be observed that the raw data has a certain periodicity. Given the 15-min data granularity, this study defines 96 time steps as 1 week. However, the daily variation of the charging load is quite volatile, and the sequence is not sufficiently stationary. Using a

single forecasting method for prediction would result in poor performance. Therefore, this paper employs the VMD algorithm to partition the time series into components with high and low frequency. The parameters for the VMD algorithm are shown in Table 1.

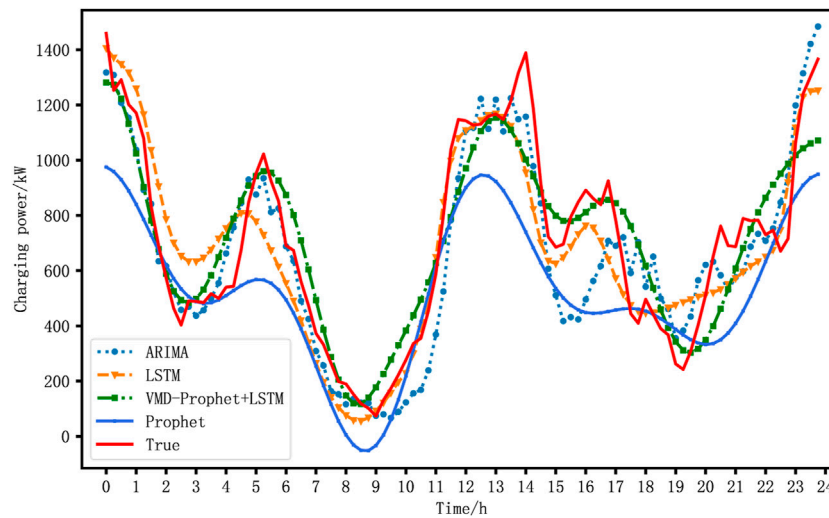


FIGURE 8
Comparison of prediction results.

TABLE 3 Evaluation value of different model predicting results.

Forecasting methods	MAE/kW	R ²
Prophet-LSTM	109.22	0.8411
ARIMA	118.16	0.8227
LSTM	119.67	0.8202
Prophet	202.32	0.4936

First, the value of k in the VMD algorithm needs to be determined using Eqs 2, 3. The variation of θ_k with the value of k is illustrated in Figure 4.

From Figure 4, it can be observed that θ_k reaches its minimum value during a decreasing process when k is equal to 7. However, when k is equal to 8, θ_k increases dramatically. Additionally, since the values of θ_k are close when k equals 6 and k equals 7. Based on the selection rule mentioned above, it can be considered that an appropriate value for k is 6. By applying the VMD algorithm with $k = 6$, the sequence is divided into six IMFs by the VMD algorithm, and the individual IMFs are illustrated in Figure 5.

Based on Figure 5, it can be observed that the magnitude of fluctuations increases from IMF1 to IMF6. In this paper, the zero-crossing rate is used to divide the decomposed IMFs into sequences with high and low frequency. The zero-crossing rates of the obtained intrinsic mode functions are provided in Table 2.

4.2 Results analysis

Through the application of the VMD algorithm, the data was processed and divided into the high-frequency sequence with more pronounced variations and the low-frequency sequence with relatively stable variations. The low-frequency sequence was then predicted using the Prophet model, while the sequence with high

frequency was predicted using LSTM neural network. The resulting predictions for sequences with high and low frequency are shown in Figures 6, 7, respectively.

Finally, the predicting results for the sequences with high and low frequency are combined to obtain the final prediction result. The comparison between the predicting result of the Prophet-LSTM method and other predicting methods is illustrated in Figure 8.

As can be seen from Figure 8, compared with several other predicting methods, the predicting method proposed in this paper has a better performance. The predicting results are better fitted to the real data curve. Additionally, the error values and R-squared values for each model's predicting results are summarized in Table 3.

Table 3 presents the assessed values of predicting results of each method. According to Table 3, the VMD-Prophet-LSTM prediction method proposed in this study exhibits the highest accuracy. The average absolute errors of the VMD-Prophet-LSTM model are 7.57% lower than those of the ARIMA model, 8.73% lower than those of the LSTM model, and 46.02% lower than those of the Prophet model. This indicates that the VMD technique utilized in the proposed model enables the Prophet model to be applied for predicting sequences with pronounced variations and improves its performance in predicting sequences with high volatility. Moreover, it ensures the predicting performance of the LSTM model.

Additionally, the coefficient of determination (R-squared) value achieved by the proposed prediction model is 0.8411. Generally, a value of 0.8 or higher indicates a good fit. Therefore, the prediction performance of the proposed method is satisfactory, and it demonstrates improvements compared to current prediction methods.

5 Conclusion

This paper proposes a combined forecasting method for EV charging load predicting. The proposed method is based on the VMD technique and integrates the advantages of the Prophet model and LSTM neural network. Through the application of the VMD

algorithm, the EV charging load time series is divided into sequences with high and low frequency, allowing the Prophet model and LSTM neural network to leverage their advantages for prediction. The conclusions drawn from the case analysis are as follows:

- (1) Compared to using a single method to predict the EV charging load time series, the proposed combined forecasting method demonstrates better prediction performance.
- (2) By employing the VMD technique and zero-crossing rate, the EV charging load time series is effectively partitioned into a relatively stable sequence with low frequency and a highly volatile sequence with high frequency. The Prophet model and LSTM neural network are then applied to predict the sequences with low and high frequency, respectively. The case analysis demonstrates that this partitioning approach helps overcome the limitations of the Prophet model in predicting sequences with high volatility, thereby reducing the errors in the combined forecasting results.

Overall, the proposed method proves effective in improving the EV charging load prediction accuracy by leveraging the advantages of both the Prophet model and LSTM neural network, while addressing the challenges posed by highly volatile sequences through the utilization of the VMD technique.

In the future research, the combined prediction method proposed in this paper will be applied to different fields (such as photovoltaic power prediction) to further verify the prediction performance and generalization ability of this method.

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.

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Author contributions

NC: Conceptualization, Writing—original draft. PZ: Data curation, Investigation, Methodology, Writing—review and editing. XR: Formal Analysis, Resources, Writing—review and editing. ZZ: Methodology, Writing—review and editing.

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Conflict of interest

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