

# *Application of LSTM Model Considering Temporal Dependency in Electric Vehicle Power Load Forecasting*

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**Abstract:** Power load forecasting is crucial for ensuring the safe and economical operation of modern power systems. Nowadays, a large number of electric vehicles (EVs) have been integrated into power systems, causing certain impacts on them. To address the issues of nonlinearity and temporal dependency in electric vehicle load data, this study proposes a short-term power load forecasting model based on Long Short-Term Memory (LSTM) neural networks. The model first performs data preprocessing, including missing value imputation and min-max normalization, and constructs 96-time-step sequences through feature engineering. It adopts a two-layer LSTM network combined with fully connected layers, with Mean Squared Error (MSE) as the loss function, and is trained for 30 epochs. Experimental results based on 2024 electric vehicle load data from a certain region in China show that the MSE of the training set and validation set drops to 0.00013 and 0.00009, respectively. The Mean Absolute Percentage Error (MAPE) between the predicted values and the actual values is only 0.91%, with a high degree of curve overlap. This indicates that the LSTM model can effectively capture the temporal dependency in power loads and provide an efficient and reliable solution for power systems.

**Keywords:** power load forecasting, electric vehicles, LSTM, short-term prediction, time series, neural network

## 1. Introduction

As a critical element of modern power systems, power load forecasting plays a vital role in ensuring the safe operation and cost-effective, efficient production of power systems. The outcomes of power load forecasting serve as key foundations for decisions such as future power infrastructure planning and power generation regulation within power systems. From a short-term viewpoint, the accurate prediction of power load curves is essential for enhancing the economic efficiency and reliability of power system operations. Power plants must formulate power generation plans based on prediction results and reasonably arrange power generation volumes and time allocations. Given the characteristic that electrical energy is challenging to store on a large scale, excessive power generation can cause abnormal increases in grid frequency, while insufficient power generation may result in power rationing or outages, exerting adverse effects on production and daily life. From a

long-term development perspective, it also holds significant guiding value for the overall construction planning of power systems.

Currently, the primary research methods for power load forecasting include traditional methods and artificial intelligence-based approaches. Traditional methods mainly encompass time series methods, regression analysis methods, and grey model methods. Reference [1] puts forward a global approach for long-term time series prediction, integrating a direct prediction strategy with three input selection criteria (k-nearest neighbors, mutual information, and nonparametric noise estimation) along with specific input selection strategies. Experiments conducted using the Poland electricity load dataset demonstrate the effectiveness of this method, with the direct prediction strategy proving to be superior.

With the advancement of artificial intelligence, researchers have gradually applied this technology to power load forecasting. In comparison to traditional methods, artificial intelligence methods are more adept at handling nonlinear data and possess greater advantages in power load forecasting. Reference [2] analyzes the factors influencing load fluctuations based on ANOVA and identifies that maximum, minimum, and average temperatures have a significant impact. Using this as a basis, the input for RNN is determined, and a load forecasting model is established. Example verification indicates that the prediction results of the model are close to the actual values, enabling effective prediction of the load for the next 24 hours and providing a viable method for power load forecasting. Reference [3] proposes a dual-channel short-term power load forecasting model named SSA-optimized CNN+BiLSTM-LSTM-Attention. This model employs grey correlation analysis to screen meteorological factors, constructs dual channels to enhance feature acquisition capabilities, and optimizes hyperparameters using SSA. Experiments reveal that, in comparison with other models, this model performs better in terms of error indicators and goodness-of-fit indicators, offering guiding significance for power system operation and dispatching. Both LSTM (Long Short-Term Memory neural network) and GRU (Gated Recurrent Unit) are variants of the RNN model, which effectively address the issue of gradient vanishing in the traditional recurrent neural network model RNN. Reference [4] presents an improved LSTM model, proposes a sequence-to-sequence (S2S) model structure based on LSTM, and conducts experimental comparisons with the standard LSTM. Reference [5] suggests a method combining CNN and LSTM for short-term power load forecasting, utilizing CNN to extract advanced features of power load, thereby improving prediction accuracy when the input to LSTM is excessively long.

## 2. Long short term memory

LSTM represents an improvement over ordinary neuron. It introduces memory units into each neuron of the hidden layer and employs three gating units, namely the forget gate, input gate, and output gate, to control the state of the memory units. This addresses the issue that ordinary RNNs struggle to learn long-distance temporal dependencies. The structure of LSTM is shown in Figure 1.

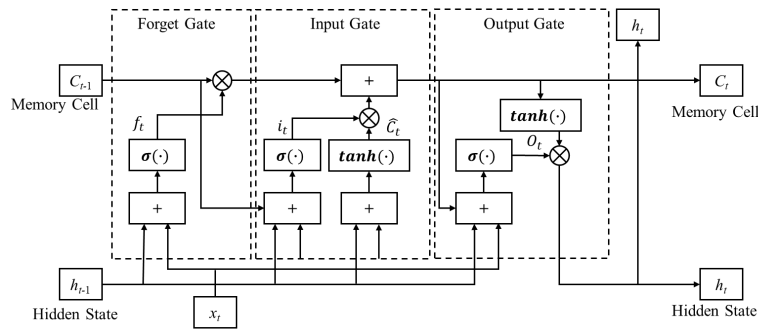


Figure 1. The structure of LSTM

The memory cell collaborates with the hidden state to store historical information of sequential data, with its internal information governed by three gating units. The forget gate deletes information from the memory cell based on relevant inputs and the hidden state. The input gate, in turn, adds new information to the memory cell based on relevant inputs and the hidden state, serving as the candidate memory cell for updating the memory cell. After completing the calculations of the forget gate and output gate, the memory cell is updated. The output gate then determines the output based on relevant inputs, the hidden state, and the state of the memory cell.

### 3. Load forecasting model based on LSTM

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#### 3.1. Model Building

Taking advantage of LSTM's capability to capture long-term temporal dependencies, this method takes into account both horizontal patterns (i.e., daily load fluctuations) and vertical patterns (i.e., hourly load trends within historical time windows) to predict the load on the target day. As illustrated in Figure 2, the LSTM network utilizes load curves and relevant influencing factors from the preceding  $n$  days to forecast the load for the target day. The model output, which denotes the predicted load, is formulated in Equation (5).

$$\widehat{L}_d = \{\widehat{l}_{0,d}, \widehat{l}_{1,d}, \dots, \widehat{l}_{t,d}, \dots, \widehat{l}_{T_d,d}\} \quad (1)$$

Where: When the sampling interval is 15 minutes, The historical load is:

$$L_{t,d-w} = \{l_{t,d-1}, l_{t,d-2}, \dots, l_{t,d-w}\} \quad (2)$$

In the established load forecasting model, the input at time step  $t$  consists of historical load data and can be represented as:  $I_{\text{input}} = \{L_{t,d-w}\}$ . The output is  $O_{\text{output}} = \widehat{l}_{t,d}$ .

#### 3.2. Model Training

For training the LSTM network designed for load forecasting, the BPTT (Back-Propagation Through Time) algorithm is employed. The core goal of training is to adjust the network parameters

in a way that makes the network's output as close as possible to the actual values. The specific training process is illustrated in Figure 2.

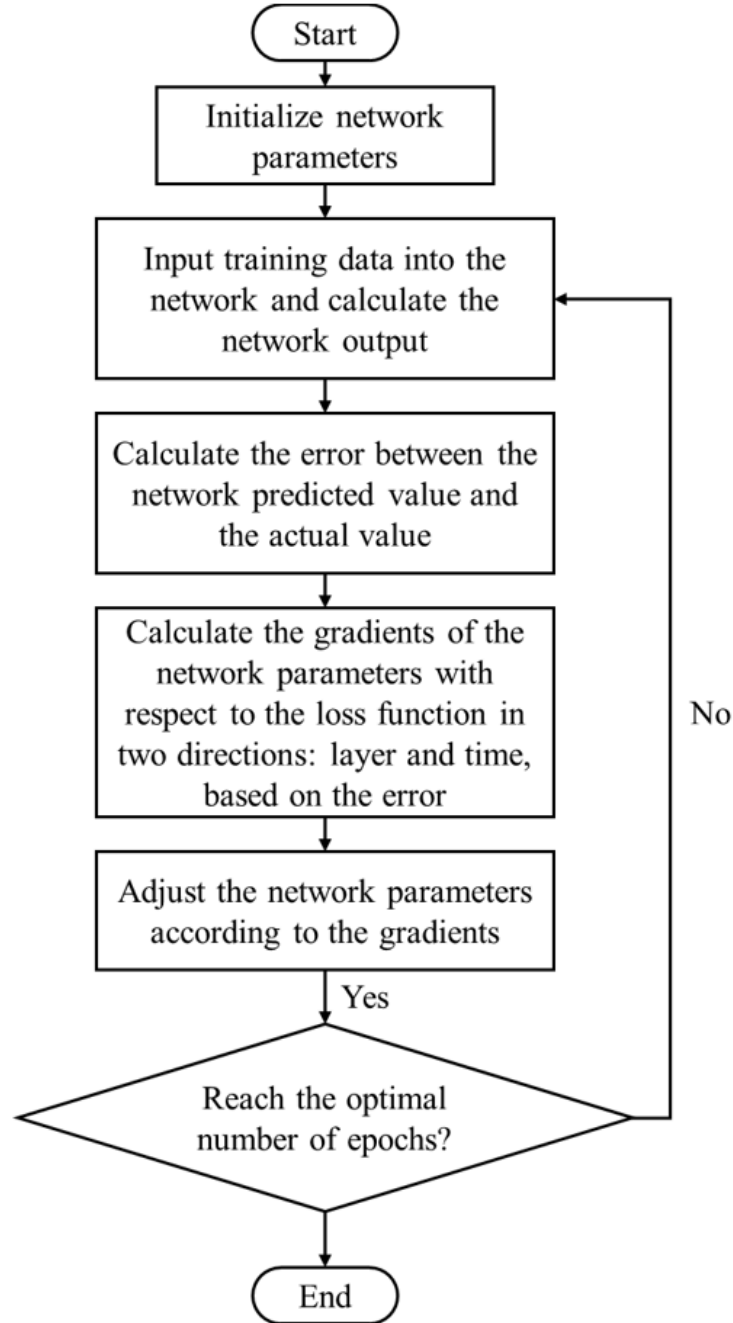


Figure 2. LSTM model training process

The loss functions include mean square error (MSE) loss, root mean square error (RMSE) loss, mean absolute error (MAE) loss, etc. In this paper, MSE is used as the loss function, which is expressed as:

$$L_{a,b} = \frac{1}{N} \sum_{i=1}^N \left( \hat{L}_i - L_i \right)^2 \quad (3)$$

As in (8):  $N$  is the total number of training samples;  $\hat{L}_i$  is the predicted load;  $L_i$  is the actual load;  $a$  and  $b$  are the model parameters.

#### 4. Case analysis with numerical examples

In this paper, the electric vehicle load values of a certain place in China in 2024 are selected. Each day is divided into 96 time periods, and the electric vehicle load values are shown in Fig. 3.

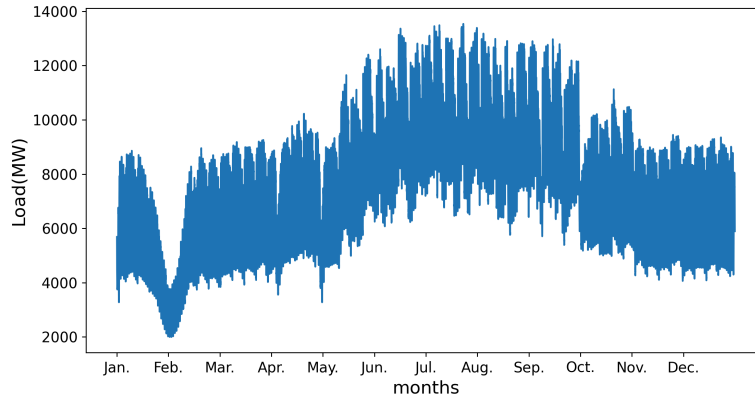


Figure 3. The annual electric load of this region

In this paper, the data from the first 329 days serve as the training set. The research process is as follows: first, data is imported and preprocessed, which involves handling missing values, dividing the data into training and validation sets, and conducting normalization. Subsequently, time-series features are constructed, and the data is transformed into an input format compatible with the LSTM model (specifically, sequences with a time step of 96). Then, a two-layer LSTM network structure is established, integrated with fully connected layers and utilizing the ReLU activation function, and it is compiled with mean squared error (MSE) as the loss function. Afterwards, 30 training epochs are carried out, and the model is assessed using the validation set. The evaluation results are visualized in Figure 4.

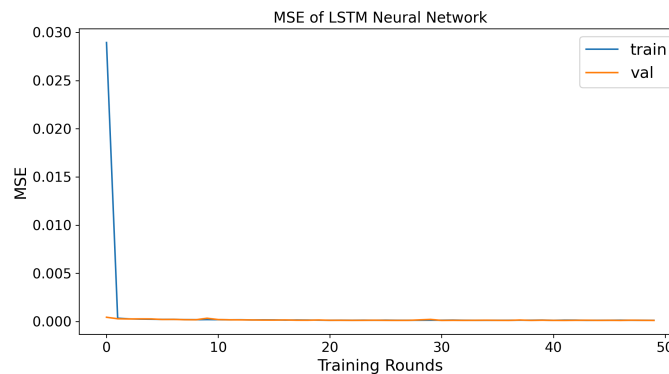


Figure 4. MSE of LSTM neural network

As can be seen from the results of the 30-round rolling calculation, the MSE values of both the training set and the validation set are less than 0.001, indicating that the training results are relatively favorable.

The trained LSTM model is loaded to predict the test data, and the predicted results and real values are inverse-normalized to restore the original data scale. Finally, matplotlib is used to plot the comparison curve between the predicted values and real values, intuitively demonstrating the prediction effect of the model as shown in Figure 5.

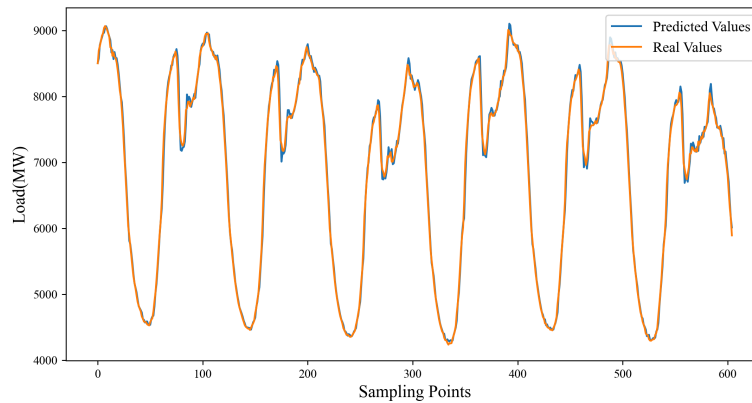


Figure 5. Comparison between predicted results and actual results

As shown in Figure 5, the predicted values from the LSTM neural network exhibit a high degree of overlap with the real values. Calculations indicate that the mean absolute percentage error (MAPE) between the two is only 0.91%. These results demonstrate that LSTM can accurately and efficiently predict short-term power loads.

## 5. Conclusion

This study addresses the problem of short-term electric vehicle load forecasting by constructing a neural network model based on LSTM. Through preprocessing of the power load data of a certain region in 2024 (missing value filling, normalization) and feature engineering (construction of 96-time step sequences), a two-layer LSTM network combined with fully connected layers was used for training. After 30 iterations with MSE as the loss function, the MSE of the training set and validation set dropped to 0.00013 and 0.00009 respectively. The test results show that the mean absolute percentage error (MAPE) between the predicted values and the real values is only 0.91%, and the curves have a high degree of overlap, confirming that the LSTM model can accurately capture the temporal dependency characteristics of power loads, providing an efficient and reliable prediction scheme for power system dispatching and planning.

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