Energy Proceedings
Vol 36, 2023
ISSN 2004-2965

Research on Optimization Method of Short-Term Load Forecasting Model Based on CNN-LSTM

Xueyuan Zhao[1], Xiaoyu Ying [1*],Tingting Xu[2],Yang Tan[1]

1 Institute of Land and Space Planning, Hangzhou City University, Hangzhou, 310015, China

2 Institute of Mechanical Engineering, Tongji University, Siping Road, Shanghai, 1239, China
(*Corresponding Author: zhaoxy@zucc.edu.cn)

ABSTRACT

Accurate power load forecasting can significantly reduce the operating costs of the power grid and is an important guarantee for the stable and efficient operation of the power system. However, the randomness and volatility of short-term power loads are strong, and traditional load forecasting methods are difficult to grasp the patterns of short-term load changes. In order to predict short-term power load more accurately, this paper proposes a short-term power load prediction method based on convolutional neural networks and short-term memory networks (CNN-LSTM), and combines down-sampling processing and time features to extract features from the dataset. The prediction results are compared to improve prediction accuracy. By comparing and analyzing the prediction accuracy of the model based on measured data of public buildings, the reliability of the proposed model was verified, and it was confirmed that its application effect in the field of short-term power load forecasting is good, which can provide theoretical basis and technical support for power planning in the power supply department.

Keywords: load forecasting, long-short-term memory, convolutional neural network, optimization method

1. INTRODUCTION

With the increasingly close relationship between electricity and residents' lives, industrial and agricultural production, and social development, it is increasingly important for electricity customers whether safe, high-quality, and economically reliable electricity can be met. Electric energy itself is difficult to store in large quantities and needs to go through multiple stages such as transmission, transformation, and distribution to meet user requirements, resulting in unavoidable losses in each stage. Therefore, in order to effectively reduce losses and improve the utilization rate of primary energy, formulating accurate power generation plans and reasonable scheduling plans in advance is an important means to improve the stability and economy of the power grid. Accurate load forecasting provides a reasonable reference basis for the formulation of plans and the proposal of plans.

The short-term power load forecasting problem has always been a focus of attention for scholars both at home and abroad due to its important significance in the power system. Especially in the current environment of the new electricity market, in order to adapt to the more flexible and ever-changing pace of the times, many scholars have done a lot of work in the research of method theory and the proposal and improvement of prediction models, and have also achieved many results.

In the field of power load forecasting, scholars classify forecasting methods, including physical model method, statistical method, and artificial intelligence method. The physical model method can predict power loads, but its prediction accuracy is low and is rarely applied; Statistical laws excessively rely on the periodicity and outliers of historical data, making it difficult to obtain accurate prediction results in the face of complex and nonlinear power load data. Therefore, more and more scholars are using artificial neural networks in the field of load forecasting. The self-learning function of artificial neural networks can adjust model parameters at any time according to the data situation, thereby making the prediction results closer to the true value. Reference [1] established two improved autoregressive moving average models for residential load forecasting, which have high prediction accuracy under specific conditions. However, when faced with nonlinear time series, the prediction results of both models are not ideal. Reference [2] uses lifting wavelets to decompose load data, and models and trains each layer of signal obtained through decomposition using least squares support vector machines. Finally, an error correction model is established to correct prediction points with larger errors. But the predictive performance of the model overly relies on kernel functions. Reference

This is a paper for the 9th Applied Energy Symposium: Low Carbon Cities and Urban Energy Systems (CUE2023), Sep. 2-7, 2023, Matsue & Tokyo, Japan.

[3] established a quantile regression equation using the previous day's electricity consumption and the highest temperature of the day as prediction factors, but the prediction effect is poor on a large time scale.

With the continuous innovation of artificial intelligence technology, a third type of method that comprehensively considers the temporal and nonlinear characteristics of load data has emerged, with long-term and short-term memory network algorithm as the main algorithm. LSTM is a variant of recurrent neural networks with the ability to simultaneously process time series and nonlinear data. Reference [4] used LSTM for short-term power load forecasting, while reference [5] combined support vector machine and LSTM for power load forecasting. The study in reference [6] showed that the proposed LSTM method outperforms other listed competitive algorithms in short-term load forecasting tasks for single residential households.

In view of the randomness and volatility of power load data and the fact that a single model cannot accurately predict short-term power load, this paper proposes a method based on CNN-LSTM combined model to predict short-term power load. At the same time, the raw data is preprocessed by down-sampling before prediction, and temporal features are added to improve prediction accuracy.

2. RESEARCH OBJECT AND METHODOLOGY

2.1 Research object

This study selected an office building located in Hangzhou, China as the research object to monitor the electricity load of the power system in normal operation. Fig. 1 shows an overview of the historical electricity load data of the research object for three months, including January, February, and March. Its main operating equipment includes air conditioning, lighting sockets, etc. Through Fig. 1, it was found that due to the office nature of the research object, personnel and electricity consumption are relatively stable and have a certain periodicity. Therefore, this study chose the monitored historical electricity load of these three months as the prediction dataset.

2.2 Methodology

The Convolutional Neural Network (CNN) model is a network model first proposed by LeCun in 1998. This model has good performance in feature extraction and can compensate for the shortcomings of other network models in feature extraction. The accuracy of data feature extraction directly affects the accuracy of prediction. The CNN model consists of five functional modules: the input layer is responsible for inputting the original data; The convolutional layer is responsible for extracting important features, and it is also the most important component of the model; The pooling layer is responsible for reducing data dimensions; The fully connected layer is responsible for classifying the processed data; Finally, output the results to the next network model.

After feature extraction and flattening by CNN, the load data is fed into the LSTM model for load prediction. LSTM can extract complex feature relationships from long and short time series, and has good performance in processing time series. This is because LSTM introduces a "gate mechanism" to address the long-term memory of time series information. By controlling the input gate, forgetting gate, and output gate, LSTM adds or removes current and past time state information to the storage unit.

This article uses the CNN−LSTM combination model to predict the power load of the system. Compared with single CNN and single LSTM, this model has strong ability to extract data features and handle time series well, making it more suitable for load forecasting scenarios. In the combination model, a CNN network is first used to process the historical data of the load, and the feature extracted by CNN is converted into a time series. Secondly, important information in power load data is extracted using convolutional layers, and output data is obtained through dimensionality reduction through pooling layers; Then, the output data enters the LSTM layer for training; Finally, the trained output data enters the output layer to obtain the output value. The structure of the CNN−LSTM combination model is shown in Fig. 2.

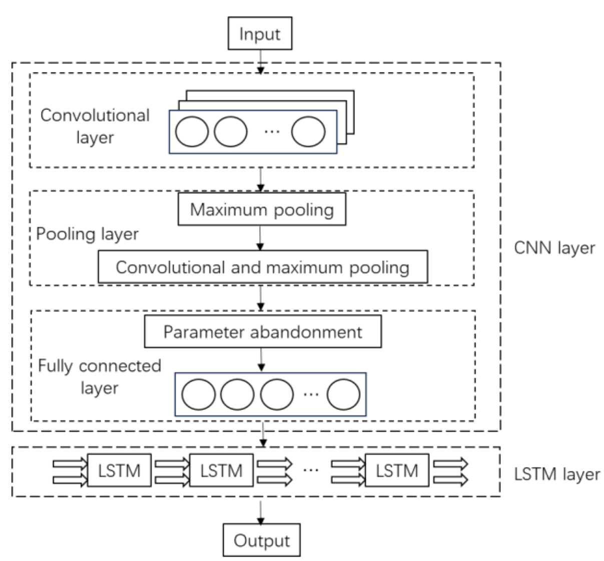

Fig. 2 Schematic diagram of CNN-LSTM model structure

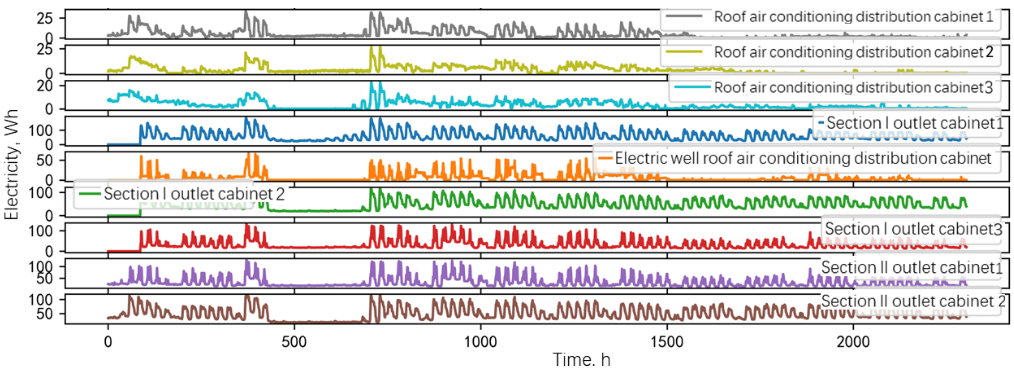

Fig. 1 Overview of the historical electricity load data

3. RESULT AND DISCUSSION

Based on the TensorFlow 2.0 framework, code was written in Python language to complete the construction and training of the CNN–LSTM combination model. Among the monitored historical load data, 70% are training sets and 30% are test sets. Set a sampling point every fifteen minutes for historical load data, with 96 sampling points in a day, to predict electricity load. Fig. 3 shows the loss function curves of the training set and the test set, while Fig. 4 shows the comparison results between historical data and predicted values.

In order to improve prediction accuracy, this study further processed the raw data and randomly divided the majority class samples into n subsets, with each subset having a quantity equal to the number of minority class samples. Next, each subset is combined with minority class samples to train a model separately, and finally n models are integrated to form a dataset after down-sampling processing. And compare the loss function curve and load prediction results of the processed dataset, as shown in Fig. 5 and Fig. 6.

Further incorporating time features into the down-sampled dataset, marking workdays and non-workdays, in order to better fit the load curve characteristics of the research object and further perform load forecasting, as shown in Fig. 7 and 8.

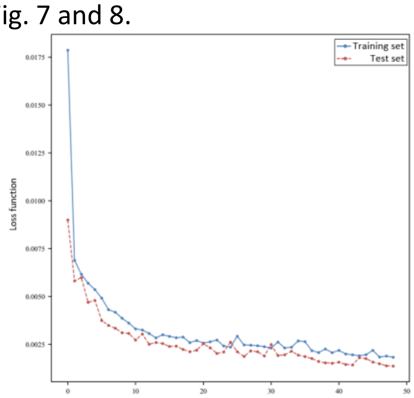

Fig. 3 Loss function curves of the basic data

Table 1 shows the comparison of prediction results error after three different processing methods: raw data, down-sampling, down-sampling and introducing time features. It can be seen that the prediction accuracy is continuously improving with further processing of historical data. The prediction accuracy obtained by introducing time features after down-sampling the data is significantly better than the other two processing methods.

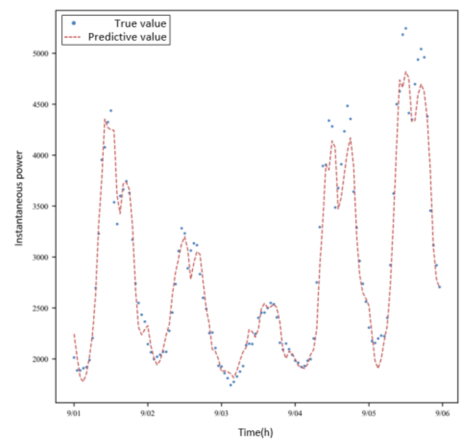

Fig. 4 Comparison results between historical data and predicted values of the basic data

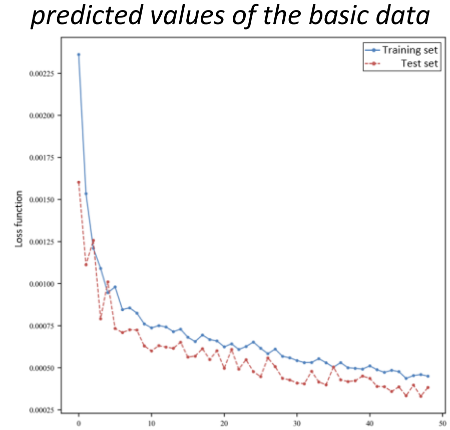

Fig. 5 Loss function curve after down-sampling processing

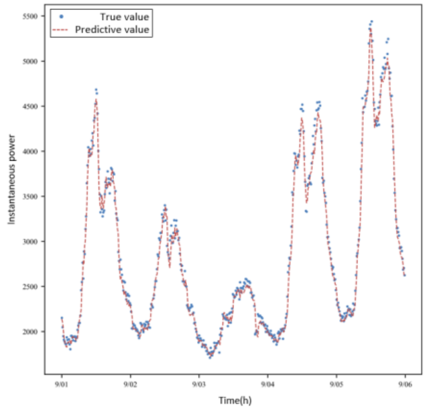

Fig. 6 Comparison results between historical data and predicted values after down-sampling processing

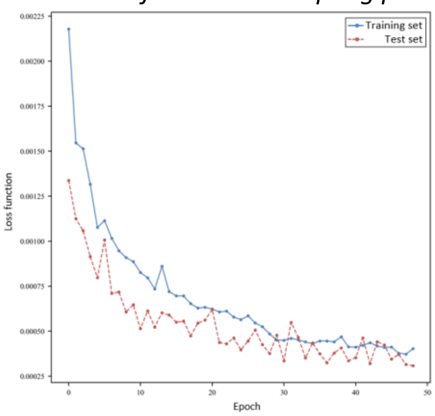

Fig. 7 Loss function curve of introducing time features after down-sampling processing

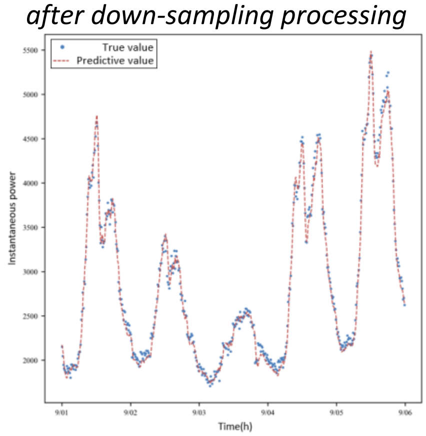

Fig. 8 Comparison results of introducing time features after down-sampling processing

Table 1 Comparison of prediction results error

	MAPE%	RMSE(kW)
Basic data	0.54	0.1913
Down-sampling	0.32	0.1010
Down-sampling and time features	0.29	0.0938

4. CONCLUSIONS

According to the current research status of short-term power load forecasting at home and abroad, CNN and LSTM models have shortcomings such as low prediction accuracy and single model structure. In order to improve the accuracy of energy system load forecasting, assist decision-makers in more reasonable system resource allocation and scheduling, and improve the resource utilization efficiency of the energy supply and consumption sides, this study proposes a method for short-term power load forecasting based on the CNN-LSTM combination model. This method explores the advantages of each module, and CNN is responsible for extracting the feature factors of the input data, LSTM is used to receive CNN output data for prediction. At the same time, three different methods were compared in the data preprocessing section. Through the comparison of prediction results, it was found that down-sampling processing and time characteristics can improve the accuracy of load forecasting. The CNN-LSTM model has good prediction ability for complex nonlinear problems and is suitable for use in the field of short-term load forecasting of electricity. It can predict short-term load demand and provide theoretical support for the power sector to formulate power generation plans and dispatch.

ACKNOWLEDGEMENT

The present study was supported by Procurement Project for 2023 Building Energy Efficiency Standard Technology Research Special Project，Item 16: Research on Multi source Collaborative Operation of Distributed Energy Storage Systems Based on Demand Side Response (No. ZJZX-20230610).

REFERENCE

[1]Sha B, Yna C, Mn A, et al. A Comparative Study of Predictive Approaches for Load Forecasting in Smart Buildings[J]. Procedia Computer Science, 2019, 160: 173-180.

[2]Chen Z, Sun L X. Short-term Electrical Load Forecasting Based on Deep Learning LSTM Networks[J]. Electronic Technology, 2018, 47(1): 39-41.

[3]Moon J, Jung S, Rew J, et al. Combination of Short-term Load Forecasting Models Based on a Stacking Ensemble Approach[J]. Energy and Buildings, 2020, 216(6): 109921.1-109921.20.

[4] Memarzadeh G , Keynia F . Short-term Electricity Load and Price Forecasting by a New Optimal LSTM-NN Based Prediction Algorithm[J]. Electric Power Systems Research, 2021, 192: 106995.

[5] Agga A, Abbou A , Labbadi M , et al. Short-term Self Consumption PV Plant Power Production Forecasts Based on Hybrid CNN-LSTM, ConvLSTM Models[J]. Renewable Energy, 2021, 177: 101-112.

[6] Demirhan H, Renwick Z. Missing Value Imputation for Short to Mid-termhorizontal Solar Irradiance Data[J]. Applied Energy, 2018, 225(9): 998-1012.