Academic Journal of Computing & Information Science
ISSN 2616-5775 Vol. 7, Issue 11: 67-71, DOI: 10.25236/AJCIS.2024.071109

Electric Power Prediction Based On CNN-LSTM Network Model

Jiayi Wang*

Yunnan University of Finance and Economics, Dali, 671000, China
**Corresponding author: 420663668@qq.com*

Abstract: *In recent years, the combination of modern power grid system and renewable energy has put forward higher requirements for the accurate prediction of electric power. Under this background, the CNN-LSTM model combines the spatial feature recognition of CNN and the time series analysis of LSTM, providing a novel and effective method for power prediction. In the empirical analysis, the wind power data set collected in this paper mainly includes wind power, wind speed, wind direction, air pressure, air density, temperature, etc. The wind power data set contains massive multidimensional data for verification, and the results show that the proposed CNN-LSTM model has high accuracy and reliability in power power prediction. Test set results RMSE=9100.1494, SMAPE=0.72639%. Compared with the traditional method, the model can capture the nonlinear relationship in the data better, improve the prediction accuracy, and provide more scientific decision basis for the power system management department. The results of this study are expected to promote the intelligent development of power system and provide theoretical support for the promotion and application of clean energy.*

Keywords: *CNN; LSTM; Deep learning; Electric power prediction*

1. Introduction

Power forecasting is of great significance in the power industry, and accurate forecasting of power demand can help power companies optimize energy scheduling, improve grid efficiency, and reduce the risk of imbalance between supply and demand [1]. However, the traditional electric power prediction methods are often limited by the mining of data nonlinear features and the modeling of time series relationships. The importance of this research lies in the introduction of deep learning technology to improve the accuracy and reliability of power demand forecasting, which is helpful to optimize the operating efficiency of the power system, reduce energy consumption, and promote the development of clean energy. In addition, this study will provide more scientific decision-making basis for the power system management department and improve the overall operation level of the power system. Therefore, methods based on deep learning have become a focus of research. The power prediction based on CNN-LSTM network model can more accurately predict power demand through the combination of convolutional neural network and long short-term memory network [2]. This research shows the application prospect of deep learning in the electric power prediction based on CNN-LSTM network model, which will make important contributions to optimizing energy scheduling, reducing the risk of supply-demand imbalance and promoting the development of the power industry. In recent years, the rapid development of deep learning technology provides new ideas and methods for power demand forecasting. Cnn-lstm network, as a deep learning model combining convolutional neural network (CNN) and long short-term memory network (LSTM), has shown great ability in time series data analysis.

When studying machine learning algorithms, this study finds that a series of research methods have been proposed by experts and scholars. Li et al. [3] proposed that wind power forecasting is crucial to the stable operation and economic dispatch of power systems. In order to fully mine the effective information in historical data and improve the short-term prediction accuracy of wind power, a new method based on convolution neural network (CNN) and long short-term memory is proposed Liao et al. [4], To enhance the forecasting accuracy of wind energy generation at wind farms and to decipher the spatial and temporal dynamics as well as the underlying relationships among proximate wind farm locations, this study introduces an innovative approach that leverages the Convolutional Neural Network (CNN). This method also incorporates Mutual Information (MI) to identify and quantify the interdependencies between data points. The proposed Short-Term Wind Farm Prediction Model, denoted as MI-CNN-ALSTM-PSO, integrates the LSTM for short-term memory retention, an Attention mechanism (AT) to focus on relevant data patterns, and Particle Swarm Optimization (PSO) to refine the prediction process. Yang et al. disclosed a wind power prediction model based on CNN-LSTM. By using the weather forecast data (NWP) of wind field and historical observation data, the characteristics of wind speed, wind direction, atmospheric pressure, temperature and air humidity were extracted, and the data were normalized. The deep learning method is used to predict wind power by combining CNN and LSTM networks [5]. Based on CNN-LSTM network model, combined with historical load data and meteorological data of power system, this paper aims to achieve accurate prediction of power demand and provide more reliable support for power system operation and scheduling.

2. Materials and methods

2.1. Data collection and preprocessing

The dataset utilized in this research was sourced from Kaggle's official platform. It encompasses a range of key metrics such as wind energy output, velocity of the wind, the direction from which the wind blows, atmospheric pressure, the density of air, and temperature. This wind energy dataset is characterized by an extensive array of multi-dimensional data, with highly fluctuating characteristics that pose a challenge in developing an accurate forecasting model. To address this challenge effectively, a Convolutional Neural Network (CNN) is employed to identify and extract significant features from the input data, which are then subsequently relayed to a Long Short-Term Memory (LSTM) model for further analysis, culminating in the formulation of an integrated CNN-LSTM model for wind power forecasting.

We preprocess the data using data Normalization, also known as deviation normalization, which is a linear transformation of the original data such that the resulting values are mapped between [0-1] [6]. The conversion function is as follows

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

Where is the maximum value of sample data and the minimum value of sample data.

2.2. Model introduction

2.2.1. CNN model

The Convolutional Neural Network (CNN) is a sophisticated deep learning framework extensively applied in the realm of image analysis. It operates by identifying and isolating local patterns via its convolutional layers and synthesizing these patterns in its pooling layers, thereby adeptly securing the spatial characteristics inherent in the imagery. In power forecasting, this paper can treat power load data as a form similar to images and use CNN to extract spatial features in the data [7]. The output of one-dimensional convolution for feature extraction of time series is:

$$\mathrm{Y} = \sigma(\mathrm{W} * \mathrm{X} + \mathrm{B}) \tag{2}$$

Where, Y is the extracted feature, is the sigmoid activation function, and W is the weight matrix; X is the time series; B is the bias vector

2.2.2. LSTM model

The Long Short-term Memory (LSTM) architecture is a specialized form of recurrent neural network, tailored for the handling of sequential information, including time-based series. Characterized by their temporal dynamics, power demand datasets possess inherent patterns over time that LSTM networks are adept at uncovering, particularly the persistent relationships that extend across extended periods. With the structure of forgetting gate, input gate and output gate, LSTM can effectively remember and update information, so as to accurately predict future electrical power [8]. Its specific calculation formula is:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{3}$$

ISSN 2616-5775 Vol. 7, Issue 11: 67-71, DOI: 10.25236/AJCIS.2024.071109

$$i_t = \sigma(W_i[h_{t-1}, x_t] + \mathbf{b}_i) \tag{4}$$

$$\tilde{\mathbf{C}}_t = \tanh(\mathbf{W}_c[\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c) \tag{5}$$

$$\mathbf{C}_t = \mathbf{f}_t \otimes \mathbf{C}_{t-1} + \mathbf{i}_t \otimes \tilde{\mathbf{C}}_t \tag{6}$$

$$o_t = \sigma(W_0[h_{t-1}, x_t] + b_0) \tag{7}$$

$$\mathbf{h}_t = \mathbf{o}_t \otimes \tanh(\mathbf{C}_t) \tag{8}$$

Where: $W_f, W_i, \mathbf{W}_c, W_0$ and is the weight matrix; ; $b_f, \mathbf{b}_i, \mathbf{b}_c, b_0$ and are the corresponding bias vectors.tanh is the hyperbolic tangent function $\otimes$ is the dot product; h_{t-1} is the output of the previous time; $\mathbf{f}_t$ is the value of retention degree; $\mathbf{C}_{t-1}$ is the memory state of the previous moment; $\mathbf{i}_t$ is the addition degree value of the current moment state; $\tilde{\mathbf{C}}_t$ is the intermediate state; $\mathbf{C}_t$ is the current status; $\mathbf{o}_t$ is the output degree value; $\mathbf{h}_t$ is the output at the current time; x_t is the input at the curren

2.2.3. CNN-LSTM model

The integrated CNN-LSTM framework, as proposed in this study, leverages the strengths of both convolutional and recurrent neural network components. This hybrid model initiates the process by harnessing the CNN component to discern spatial attributes within the electricity consumption data. Subsequently, these spatial attributes are channeled into the LSTM layer, which is responsible for identifying temporal dynamics. This sequential feature integration facilitates the model's capability to forecast power demand effectively. By stacking multiple convolutional layers and LSTM layers, the CNN-LSTM network model can learn the complex relationships and timing rules in the power system [9]. CNN-LSTM network model is widely used in power forecasting. Through the input of historical power load data and other relevant information, the model can learn the underlying patterns and laws in the power system, so as to achieve accurate power prediction. In addition, the model can also be used in anomaly detection, energy scheduling and capacity planning in power systems.

3. Model results

3.1. Evaluation indicators

For the purpose of power demand forecasting through the CNN-LSTM network model, this research selects performance metrics such as the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE). The computation of these metrics serves to assess the precision, divergence, and predictive correlation of the model. This assessment is instrumental in informing strategic decisions and enhancing the operational efficiency within the power sector. The mathematical formulations for these measures are presented as follows:

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N} \frac{|\hat{y}_i - y_i|}{y_i} \tag{8}$$

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \tag{9}$$

3.2. Experimental result

This paper have a total of 1340 data points from 2018.01.01 to 2021.08.31, of which 1206 data points from 2018.01.01 to 2021.04.19 are used for training set training, 134 data points from 2021.04.20 to 2021.08.31 are used for test set testing. Secondly, this paper normalized the data, and then created a CNN-LSTM model to predict the data. The comparison between the real value and the predicted value of the training set and the test set is shown in FIG. 1 and FIG. 2. The comparison of the

ISSN 2616-5775 Vol. 7, Issue 11: 67-71, DOI: 10.25236/AJCIS.2024.071109

test result of the training set is RMSE=11878.3135 and SMAPE=1.036%. Test machine training results compared RMSE=9100.1494, SMAPE=0.72639%

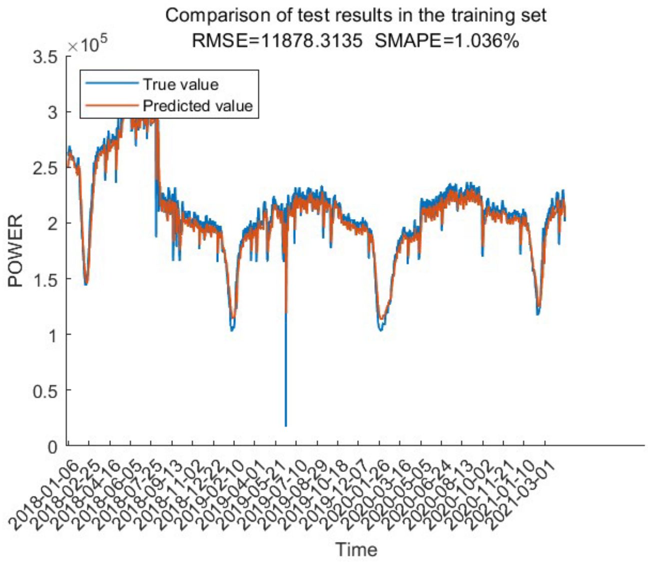

Figure 1: Test set test results comparison

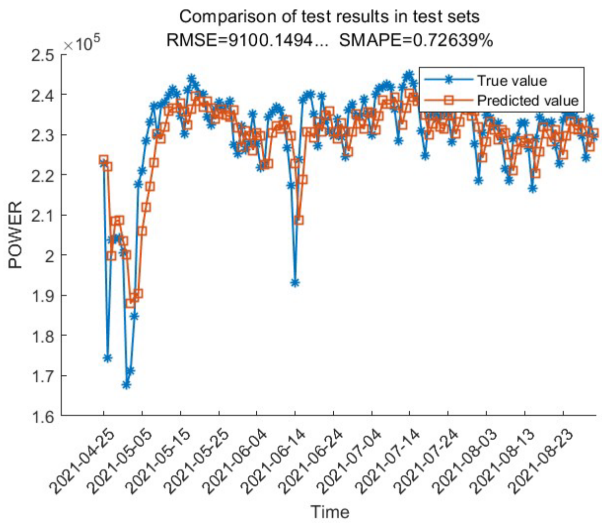

Figure 2: Comparison of training set test results

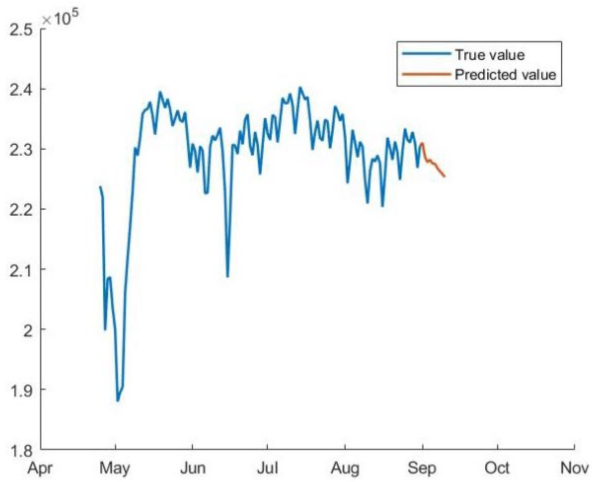

Figure 3: Prediction results of CNN-LSTM model

ISSN 2616-5775 Vol. 7, Issue 11: 67-71, DOI: 10.25236/AJCIS.2024.071109

The test set RMSE=9100.1494, SMAPE=0.72639%, the training set RMSE=11878.3135, SMAPE=1.036%. Therefore, the training set and test set of this model have a very good fitting effect, and then we use this model type to make predictions, and the prediction results are shown in Figure 3.

4. Conclusion

In our research, we harness the CNN-LSTM network model to forecast electrical power. By integrating the capabilities of Convolutional Neural Networks (CNN) with Long Short-Term Memory Networks (LSTM), the model adeptly captures the spatial and temporal nuances present within the sequential data, thereby enhancing the precision of our forecasts. The effectiveness of the model is gauged using metrics such as the Root Mean Square Error (RMSE), the Mean Absolute Percentage Error (MAPE), and additional evaluative criteria. These measures provide insights into the discrepancy between the model's forecasts and the actual outcomes, facilitating an assessment of the model's reliability and consistency. These indicators can help us understand the degree of difference between the predicted results of the model and the actual values, so as to judge the accuracy and stability of the model. After experimental comparison, we find that CNN-LSTM model performs better in electrical power prediction tasks than using CNN or LSTM model alone. The CNN-LSTM model can better capture the spatiotemporal information in the time series data, thus improving the accuracy and stability of the prediction. In future studies, we will further optimize the model structure and parameters to improve the effectiveness and reliability of electric power prediction. In future studies, this paper can conduct more diversified processing of power data, including outlier detection and processing, missing value interpolation, etc., in order to increase the robustness of the model to the data, and combine professional knowledge in the power field, including meteorological data, consumption habits, etc., to guide the model to better consider external influence factors in power prediction. At the same time, how to improve the model will be studied to make it suitable for the case of strong real-time, maintain accuracy and stability to meet the needs of real scenes.

References

[1] Tang J, He B, Zhou B, et al. Process Quality Prediction Method Based on CNN_LSTM Hybrid Neural Network Model[J]. Ocean engineering, 2023.

[2] Sun B, Liu X, Wang J, et al. Short-term performance degradation prediction of a commercial vehicle fuel cell system based on CNN and LSTM hybrid neural network[J]. International Journal of Hydrogen Energy, 2023, 48(23):8613-8628.

[3] Han Z, Lv H, Liang Z, et al. Transmission line icing thickness prediction model based on ISSA-CNN-LSTM[J]. Journal of Physics: Conference Series, 2023, 2588(1).

[4] Wang K, Wu C, Shi J. Prediction of battery temperature in electric bus charging stage based on CNN-LSTM [J]. Applied Energy, 2023, 367.

[5] Dong Z, Yao L, Bao Y, et al. Prediction of Soil Organic Carbon Content in Complex Vegetation Areas Based on CNN-LSTM Model[J]. Soil Science & Plant Nutrition, 2024, 53(3).

[6] Zhang D, Wang S. A protein succinylation sites prediction method based on the hybrid architecture of LSTM network and CNN[J]. Journal of Bioinformatics and Computational Biology, 2022(2):20. DOI:10.1142/S0219720022500032.

[7] Zhang J, Zhao Z, Yan J C P. Ultra-Short-Term Wind Power Forecasting Based on CGAN-CNN-LSTM Model Supported by Lidar[J]. Sensors, 2023, 23(9).

[8] Wang C, Zhang M. Research on dynamic rolling force prediction model based on CNN-BN-LSTM[J]. Journal of Advanced Mechanical Design, Systems, and Manufacturing, 2022. DOI:10.1299/jamdsm.2022jamdsm0029.

[9] Heng F, Gao J, Xu R, et al. Multiaxial fatigue life prediction for various metallic materials based on the hybrid CNN-LSTM neural network[J]. Fatigue & Fracture of Engineering Materials & Structures, 2023. DOI:10.1111/ffe.13977.