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ARTICLE

Deep Learning Network for Energy Storage Scheduling in Power Market Environment Short-Term Load Forecasting Model

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ABSTRACT

In the electricity market, fluctuations in real-time prices are unstable, and changes in short-term load are determined by many factors. By studying the timing of charging and discharging, as well as the economic benefits of energy storage in the process of participating in the power market, this paper takes energy storage scheduling as merely one factor affecting short-term power load, which affects short-term load time series along with time-of-use price, holidays, and temperature. A deep learning network is used to predict the short-term load, a convolutional neural network (CNN) is used to extract the features, and a long short-term memory (LSTM) network is used to learn the temporal characteristics of the load value, which can effectively improve prediction accuracy. Taking the load data of a certain region as an example, the CNN-LSTM prediction model is compared with the single LSTM prediction model. The experimental results show that the CNN-LSTM deep learning network with the participation of energy storage in dispatching can have high prediction accuracy for short-term power load forecasting.

KEYWORDS

Energy storage scheduling; short-term load forecasting; deep learning network; convolutional neural network; CNN; long and short term memory network; LTSM

1 Introduction

With increases in the proportion of renewable energy consumption, as well as the massive openness of power systems, energy storage has become more actively involved in all aspects of power grid systems and dispatching in order to achieve economically positive and efficient system operations. At present, hybrid energy storage systems composed of energy and power storage are widely used in power systems [1]. Scholars have gradually added energy storage as a schedulable resource to the optimal scheduling model. Flexible regulation of energy storage helps to improve system reliability and its economy, or to maximize the interests of energy storage holders according to spot market signals [2].

From the point of view of practical demand, the application of energy storage helps the consumer to achieve "peak shaving and valley filling", reducing the electricity consumption of users, avoiding the huge losses caused by the frequent startup and shutdown of some generating units, ensuring the stability of power systems, and reducing production costs [3,4]. With the development of energy storage technology and decreased battery prices, it is presently possible for enterprises to use energy storage technology to achieve the purpose of peak shaving and valley filling. In addition, microgrids, incremental distribution networks, and the active participation of users in ancillary services will bring new opportunities and challenges to energy storage [5,6].

Connecting energy storage to the power grid will affect the power load, change the power consumption curve, and increase the difficulty of prediction. Some traditional power consumption models are applied to energy storage, which can reduce the prediction accuracy [7]. Domestic and foreign scholars have previously carried out extensive, in-depth research on energy storage participation in load forecasting, power consumption forecasting, power system peak shaving, frequency modulation auxiliary services, and other related issues [8,9]. For research on energy storage control strategies, an adaptive optimization control strategy is proposed for energy storage systems to participate in the primary frequency regulation of the power grid, which effectively meets the demand on the basis of considering the state of the energy storage system itself [10]. In the load and SOC states of energy, storage is divided [11], the charging and discharging modes of energy storage are optimized, and the charging and discharging control strategies of energy storage participating in peak load regulation of the power grid are formulated. A secondary frequency regulation capacity allocation method for energy storage, in terms of capacity planning and configuration, was proposed in [12]. Based on life cycle theory, this method provides an effective energy storage configuration planning scheme with the goal of maximizing net benefits.

An energy storage system capacity allocation method for relaxing the peak shaving bottleneck was proposed in [13], to solve the problem of consumption and grid-connected difficulty caused by intermittent and volatile wind power output, providing a reference for energy storage capacity allocation against the background of new high-permeability grid-connected energy. A peak and frequency power modulation allocation strategy for energy storage of power stations based on load forecasting was proposed in [14]. By introducing a genetic algorithm, the weights and thresholds of the BP neural network were optimized to construct a more accurate power load forecasting model. According to the aggregation principle of the load aggregator mechanism in a smart network, an energy storage scheduling method was proposed in [15] based on price contracts, and a real-time scheduling model of energy storage in power systems was constructed.

Based on several environmental factors, an improved whale optimization algorithm Elman neural network model, considering energy storage scheduling factors under time-of-use electricity prices, was constructed [16]. A new optimal scheduling model of combined peak shaving for wind and solar storage was proposed in [17]. The multi-objective particle swarm optimization algorithm was used to solve the two scheduling models of combined peak shaving for wind and solar storage and stable economic output of hydropower units. Simultaneous placement of control and protection devices in an emergency demand response program to improve the duration-based and frequency-based reliability indices were proposed in [18]. A price-based demand bidding mechanism was proposed in [19], which plays an important role in balancing electricity production and consumption. A new generalized demand-side resource coordination scheduling model that can be realized through electricity price contracts was proposed in [20]. This model takes the maximum economic benefits of a load aggregator regarding all kinds of demand-side resources as the scheduling optimization objective and can provide scheduling results to system dispatchers in the form of demand response signals for use.

Based on the above background, this paper first considers the charging and discharging sequence of energy storage under real-time electricity prices, as well as the economic benefits of the operation. This is done so as to determine the energy storage scheduling factors, and to establish an energy storage scheduling model. Combined with convolutional neural networks (CNN) and long short term dependencies (LSTM) models, the Convolutional Neural Networks-Long Short Term Dependencies network hybrid model is proposed, which takes the time series characteristic diagram as the input of the network. It combines the respective characteristics of CNN and LSTM network, mines the internal relationships between input data through CNN and extracts data feature information, and, furthermore, uses the long-term memory ability of LSTM to save data feature information so as to further improve the performance of the model. Based on the prior knowledge of load forecasting, a continuous feature map is constructed according to the time sliding window of a large number of real-time prices, temperature data, holiday information, and energy storage scheduling data, and the electricity consumption in the actual area is simulated and tested.

2 Energy Storage Scheduling Model in Electricity Market Environment

2.1 Impact of Energy Storage on Electricity Market

Nowadays, grid-side energy storage technology is more widely used in power systems than previously [21]. The integration of new energy sources, such as water power, solar energy, and nuclear energy, seriously threatens the security and stability of power grid systems, and it is therefore necessary to improve the flexibility and stability of power grid self-regulation in general. To increase the flexibility of peak and frequency modulation, improve the system reserve capacity, the quality of power supply and the peak load supply capacity, energy storage power stations have been built all over the country to deal with the instability caused by new energy power generation [22]. In addition, the user side gives full play to the advantages of energy space-time transfer. Under the time-of-use electricity price mechanism, peak load shifting (peak discharge during valley charging periods) improves the power consumption structure of the consumer side and reduces the cost of electricity. As shown in Fig. 1, the energy storage system is connected to both the user, as well as to the city power grids. Based on the real-time electricity price, the energy storage is reasonably dispatched to adjust its own electricity consumption, and the difference between high and low electricity prices in the peak and valley periods of the power grid is used to reduce the electricity purchase cost. At the same time, user-side energy storage also has the economic value of reducing the specific variable capacity of users, optimizing the peak shaving and valley filling load curve and power consumption, improving the reliability of the user power supply, and functioning as a reserve capacity of wind, solar, and other new sources of energy power generation.

To reduce peak load, increase valley load, and guide users to participate in demand response, many provinces in China have built commercial user-side energy storage system projects, charging–swapping–storage integrated power station projects, etc., to adjust energy storage charging and discharging behavior according to actual needs, and to improve the stability of user-side energy consumption.

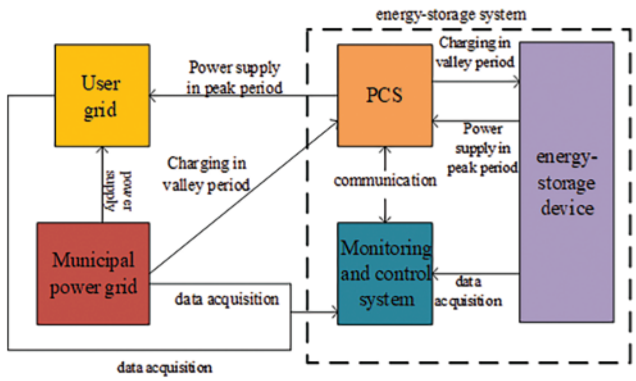

Figure 1: User-side energy storage system

2.2 Energy Storage Scheduling Model Considering Real-Time Electricity Price

As a flexible, efficient, and schedulable resource, energy storage can participate in demand response. Since energy storage is a relatively decentralized resource, unified scheduling can be carried out through load clustering, and energy storage users who participate in the scheduling can be gathered together to carry out the demand-side management.

Based on the implementation of the time-of-use electricity price policy in the power market, energy storage users can charge and discharge according to the electricity price in different periods. In general, the electricity price in a peak load period is higher than in other periods, while the price in a valley load period is lower than in other periods. Therefore, energy storage users can discharge in peak load periods and charge in valley load periods. This not only can meet the requirements of the contract, but also can obtain the maximum economic benefits in the process. According to the energy storage scheduling model under real-time electricity prices, the charging and discharging of energy storage are reasonably arranged under the optimal profit.

The maximum revenue of energy storage users during the discharge period is:

$$W_{\max} = \sum_{t \in T_e} (\rho_t P_t - W_t) \tag{1}$$

where ρ_t represents the real-time electricity price on the electricity trading market, P_t represents the energy release of the energy storage user at time t, W_t represents the total expenditure for load clustering at time t, and T_e represents the discharge period, $T_e = 1, 2, 3, \ldots, 24$.

The expression of transaction cost W is:

$$W_t = \sum_{t \in N} c_t P_t \tag{2}$$

where c_t denotes the agreed price of energy storage discharge at time t.

Here, the size of P_t is restricted by the energy storage device, namely:

$$0 \le P_t \le \eta_{\max} P_t \tag{3}$$

where $\eta_{\max}$ represents the maximum discharge efficiency of the energy storage device, and:

$$0 \le \sum P_t t \le E_{\max} \tag{4}$$

where $E_{\max}$ represents the maximum storage power of the energy storage device.

The optimal economic benefit of energy storage users during the charging period is:

$$W_{\min} = \sum_{t \in T_f} (c_t - \rho_t)\, Q_n \tag{5}$$

where Q_n represents the charging amount for energy storage users at the time t and T_f represents the charging period.

$$0 \le \sum_{t \in T_e} P_t \le \sum_{t \in T_f} Q_n \tag{6}$$

3 CNN-LSTM Model Construction

3.1 CNN

A convolutional neural network (CNN) is a typical algorithm for deep learning. It is a kind of feedforward neural network with convolution calculation and depth structure [23,24]. By using local connections and sharing weights, convolution and pooling layers are alternately used to obtain effective representation directly from the original data, the local characteristics of the data are automatically extracted, and a dense and complete feature vector is established. In this paper, 1D-CNN is used to extract data features to improve prediction accuracy. The working principle of 1D-CNN is shown in Fig. 2.

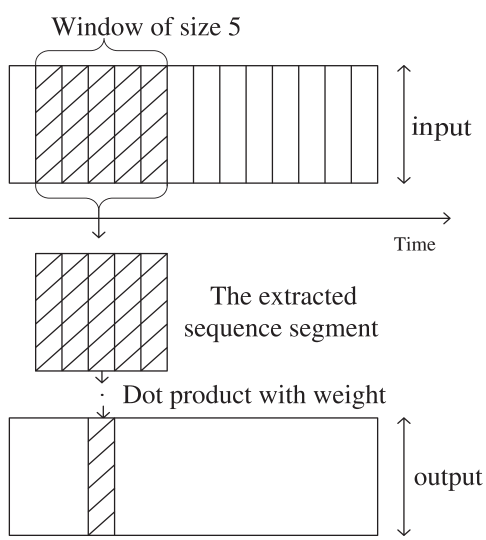

Figure 2: One-dimensional convolutional neural network

CNN is especially used to deal with data with similar network structures. At present, it has dealt with tasks in the field of computer vision more precisely. When dealing with time-series data, it is regarded as a one-dimensional grid arranged by sampling at a certain time interval in the time dimension. Then one-dimensional convolution is used to gradually translate, and the convolution sum of the original discrete sequence is calculated. The low-level time-series feature is mapped to a higher level of abstract representation. The key is to perform the convolution operation in sequence. In addition, a pooling operation is generally needed to screen features and adjust the length of the sequence. Two convolution layers and two maximum pooling layers are used to construct the network structure [25].

CNN uses simple patterns identified in the data to generate more complex patterns in higher layers. 1D-CNN is very effective when the location correlation of interested features obtained from shorter (fixed length) segments of the overall dataset is not high. Therefore, when CNN is used to process time-series data, a one-dimensional convolution construction model is commonly used. When dealing with a single time series, a single channel convolution operation is used, and for multivariate time series, a multi-channel convolution operation is used. In addition, a convolutional neural network is also considered for the preprocessing of time series data to automatically extract local features in sequence data. When the original sequence data needs the input of long time steps, the convolution operation can be converted to a short high-level feature sequence to reduce redundant information.

Through the above description, it is found that in a specific convolution operation process, the weight will not change with the sliding of the window. The features after sliding demonstrates that all of the windows share the weight, which is one of the most important characteristics of the convolutional neural network. This also enables the network to extract features from multiple perspectives.

The input data in this paper includes four one-dimensional time series: marginal price, temperature, holiday information, and energy storage scheduling factors. It was necessary to form two-dimensional 2×2 matrices with these four values at the same time as the input of the convolution layer.

3.2 LSTM Network

The long short-term memory (LSTM) network, used in language modeling, machine translation, speech recognition, and other fields, is an effective nonlinear recurrent neural network (RNN). Because it can consider the timing and nonlinear relationship of data, it is used in the field of load forecasting [26]. It was also improved by the addition of a forgetting door. The improved LSTM network solves the problem of "gradient disappearance" in model training, and can learn the long-term and short-term dependence information of time series. It is the most successful RNN architecture at present and has been applied in many scenarios. Fig. 3 shows the basic unit of LSTM, and the detailed calculation rules are as follows [27].

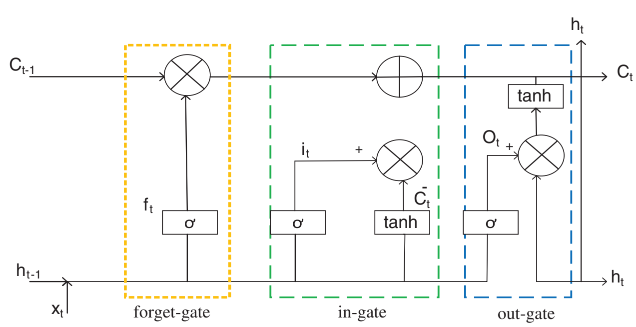

Figure 3: LSTM basic unit

As shown in Fig. 3, the forgetting gate determines the forgetting of useless information in the information of the current input and the output of the previous moment. The output result f_t of the forgetting gate is expressed as:

$$f_t = \sigma\left(W_f x_t + W_f h_{t-1} + b_f\right) \tag{7}$$

In the formula, σ is a sigmoid function; a value of 0 indicates that the information is completely forgotten, and a value of 1 indicates that the information is completely retained. When the value is (0, 1), it indicates that some information is retained, and the closer the value is to 1, the more information is retained. W_f is the training weight of the forgetting gate network, h_{t-1} is the output of the previous moment, x_t represents the sequence input at the current time, and b_f is the forgetting gate network training offset.

The input gate makes the input information pass through sigmoid and tanh functions to determine the parts that need to be retained in the unit state. The output result i_t of the input gate is expressed as:

$$i_t = \sigma\left(W_i x_t + W_i h_{t-1} + b_i\right) \tag{8}$$

Vector C_t is built to store the candidate values to be added to the new cell state, which is represented as:

$$C_t = \tanh\left(W_C x_t + W_C h_{t-1} + b_C\right) \tag{9}$$

The old unit state C_{t-1} and f_t are multiplied to determine the amount of information that needs to be updated to the new unit state. The updated state C_t is expressed as:

$$C_{t-1} = f_t \cdot C_{t-1} + i_i \cdot C_t \tag{10}$$

The hidden layer output h_t is obtained by output gate output unit state O_t multiplied by the activation function:

$$O_t = \left(W_o \cdot [h_{t-1}, x_t] + b_o\right) \tag{11}$$

$$h_t = O_t \cdot \tanh\left(C_t\right) \tag{12}$$

3.3 CNN-LSTM Network Hybrid Model

Although the LSTM network model can fully reflect the long-term historical process in input time series data, it cannot excavate the effective information and potential relationships between discontinuous data [28]. In order to improve the short-term load forecasting accuracy for energy storage scheduling, this paper conducts short-term load forecasting based on a hybrid model of CNN and LSTM networks. Compared with the LSTM network model, the CNN model is used to extract the potential features of time series data in the CNN-LSTM hybrid model, which provides a large amount of effective input data for the LSTM model, thus improving the prediction accuracy. The structure of the CNN-LSTM hybrid network prediction model is shown in Fig. 4. It can be seen that the CNN-LSTM model is mainly composed of two parts: CNN first extracts features from the original time series to obtain the feature information sequence, and then further processes the information sequence through the stacked convolution and pooling layers, which is transformed into the feature map as the input of the LSTM network [29].

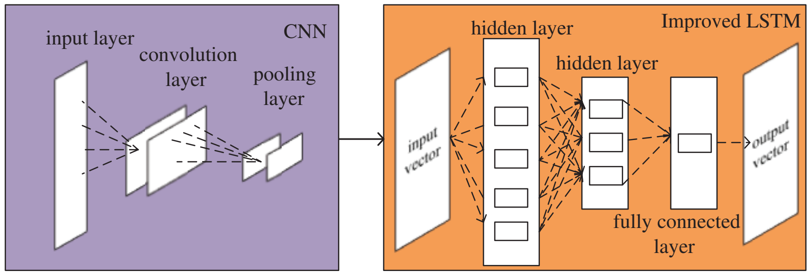

Figure 4: CNN-LSTM prediction model

3.4 CNN-LSTM Prediction Model Construction

The hybrid CNN-LSTM model proposed in this paper takes the time series feature map as the input of the network. It combines the respective characteristics of CNN and LSTM networks and uses the prior knowledge of load forecasting to construct a continuous feature map according to the sliding time window of massive real-time price, temperature data, holiday information, and energy storage scheduling data. Since these are actually independent time series, in order to couple the characteristic information that affects the load, this paper refers to the word vector representation method in natural language processing and concatenates the load value of a certain moment from its related characteristics into a vector representation, thus forming new time series data. The historical load at each moment is represented by its related characteristics. Then, the sliding window method is used to generate a feature map of the input time series data in turn. The specific steps of the algorithm are shown in Fig. 5.

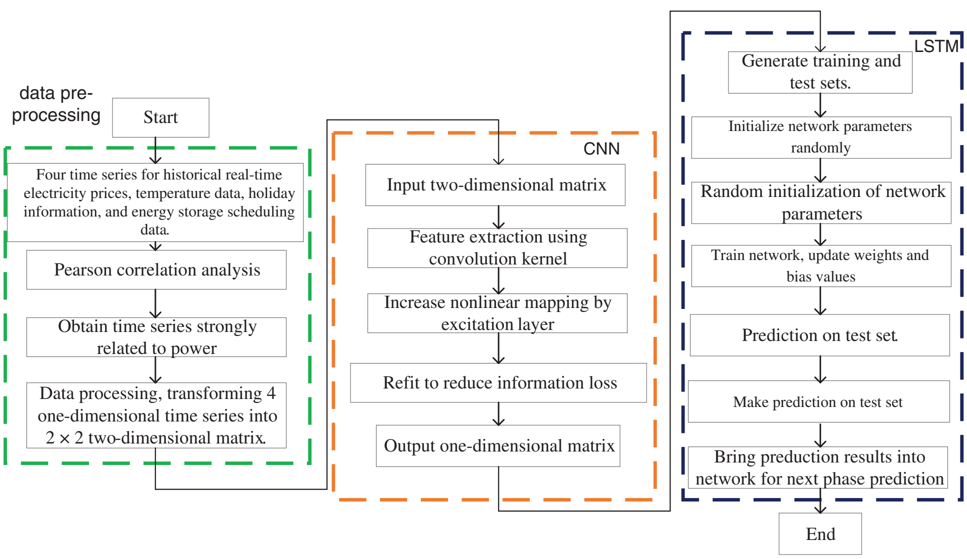

Figure 5: CNN-LSTM prediction process

4 Example Analysis

4.1 Input Parameter Pretreatment

The short-term load data of a regional power grid with energy storage over 97 days from May 01 to August 06, 2021, were used as experimental sample data. The power consumption data was collected every hour, 24 h a day. Using 1464 points from 61 days (May 01 to June 31) as training data, the accuracy of the proposed model was verified.

This paper considers the influence of energy storage scheduling factor, holiday factor, weather factor, and real-time electricity price on short-term load time series as the input of the deep learning network. In the CNN-LSTM model constructed in this paper, the CNN is responsible for the feature extraction of the original data and the LSTM predicts the short-term load.

4.2 Analysis of Demand Forecast Results

The CNN-LSTM neural network prediction model constructed in this paper is used to predict the load at each point from July 01 to August 06 as a test set. The predicted power consumption data is then compared with the actual hourly data. MAE represents the average value of the absolute error between the predicted value and the observed value. The smaller the MAE value is, the closer the predicted value is to the actual data. MSE is a convenient method to measure the average error. MSE can evaluate the degree of change in the data. The smaller the MSE value is, the better the accuracy of the prediction model to describe the experimental data is; by calculating the mean absolute error (MAE) and mean square error (MSE) of the model, the adaptability and accuracy of the proposed model are verified. The prediction results are shown in Figs. 6–9.

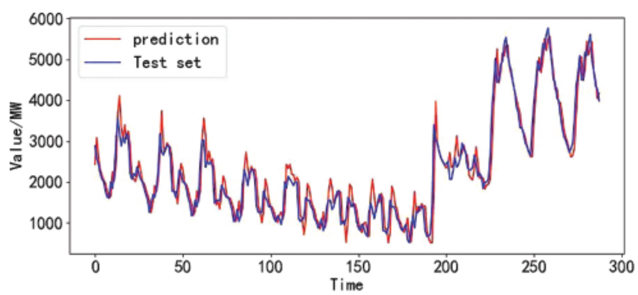

Figure 6: LSTM prediction results considering a single factor

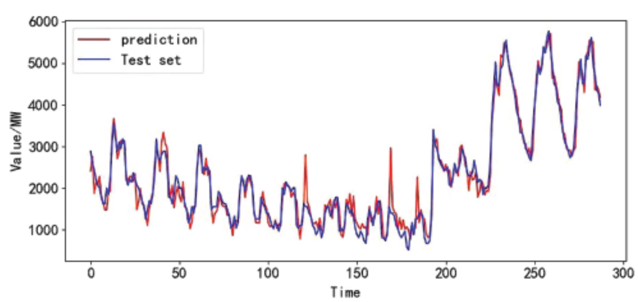

Figure 7: LSTM prediction results considering two factors

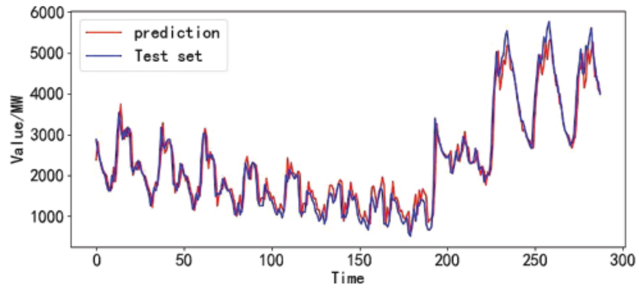

Figure 8: CNN-LSTM prediction results considering a single factor

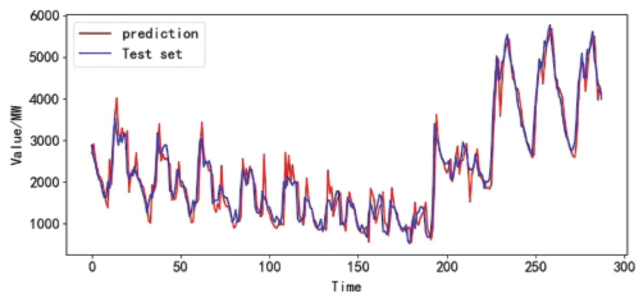

Figure 9: CNN-LSTM prediction results considering two factors

Comparing Figs. 6 and 7 (and Figs. 8 and 9), shows considerations regarding how energy storage scheduling in the short-term load forecasting model can improve the prediction accuracy. Figs. 6 and 8 (and Figs. 7 and 9) show that the CNN-LSTM model has a significantly shorter convergence time than the traditional LSTM model, so the convergence speed is significantly improved. According to Table 1, the phase errors obtained by the model in Fig. 9 are better than those in Figs. 6–8, which proves the effectiveness of the proposed method.

Table 1: Comparison of load accuracy

Predicted model error		Scheduling without energy storage	Energy storage participation scheduling
LSTM	MAE	4.04698	0.27785
	MSE	12.19144	6.564
CNN-LSTM	MAE	0.17317	0.083348
	MSE	2.1145	0.17859

MAE and MSE are used for the accuracy index of the model prediction. The mean square error reflects the difference between the predicted value of the model and the actual data. The smaller the MSE value, the higher the prediction accuracy. For the mean absolute error, the smaller the value, the higher the prediction accuracy. The MAE and MSE were obtained for the model (see Table 1).

By comparing the actual value and predicted value and the error statistical analysis, the following conclusions are drawn.

First, the MAE and MSE values of the CNN-LSTM model proposed in this paper are the smallest, indicating that the model is superior to the single LSTM model in average prediction accuracy and stability.

Second, since the proposed model takes into account the energy storage scheduling factor, the variation trend of the prediction results fits well with the actual value, and it can properly grasp the variation trend of daily electricity consumption, with the highest prediction accuracy.

5 Conclusion

In order to improve the accuracy of short-term load forecasting, we constructed a CNN-LSTM forecasting model which considered energy storage scheduling factors under real-time electricity prices, and obtained the following conclusions through practical example analysis:

(1) By constructing an energy storage scheduling model under real-time electricity prices, it can be seen that when energy storage participates in the power market, load clustering operators use energy storage scheduling to make users discharge at high prices and charge at low prices, which plays a role in reducing peak–valley differences. However, the application of energy storage leads to changes in the traditional load curve as well, which increases the difficulty of prediction. When traditional power consumption models are applied to energy storage, the prediction accuracy will decrease. Therefore, the influence of energy storage scheduling factors should be considered in short-term load forecasting.

(2) When using the traditional LSTM model to predict, there are problems such as slow convergence speed and easily falling into local optimum. By using a CNN network to optimize the LSTM prediction model, the convergence speed and global optimization ability of the network are effectively improved. Since the CNN model is used in the CNN-LSTM network hybrid model to extract the potential characteristics of time series data, a large amount of effective input data is provided for the LSTM model, thereby improving the prediction accuracy.

(3) Through a simulation analysis of the example and a comparison with other models, it can be seen that the CNN-LSTM model, considering the energy storage scheduling factor, has higher prediction accuracy. The proposed method can improve the accuracy of short-term load forecasting and can be applied to power grid load forecasting. How to further improve the prediction accuracy and convergence speed is the content of further research.

(4) In this paper, the CNN-LSTM model considering energy storage and scheduling factors can effectively improve prediction accuracy. In the future, the prediction problem in a more complex environment, considering rainfall, daily weather type, and other influencing factors can be studied, and these studies can be combined with other load forecasting methods to further improve the prediction accuracy and universality of the model.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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