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Research on Load Forecasting of Power System Based on Deep Learning

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ABSTRACT

In recent years, with the continuous development of deep learning technology, its application in the fields of image recognition, speech recognition and other fields has achieved remarkable results. Therefore, the introduction of deep learning technology into power system load forecasting can improve the accuracy and stability of forecasting and provide more effective decision support for the operation and scheduling of the power system. Electricity load forecasting is an important support for demand-side resource cooperative control, and its technical principle is to forecast the baseline load and adjustable potential of users through suitable forecasting methods based on the user's gateway or sub-historical load data, historical and future meteorological data, and the combination of the user's production, living behaviour habits and external economic situation and other influencing factors. In order to achieve a more accurate prediction of short-term power loads, the study analyses the results of load prediction using recurrent neural networks and their variants, and the experimental results show that the LSTM prediction model can be well applied to the short-term prediction of power loads in a single week's prediction, and has a more stable accuracy and precision rate.

KEYWORDS

Deep learning; Load forecasting; Recurrent neural networks; Long and short term memory neural networks

1. INTRODUCTION

Electricity load forecasting is an important support for demand-side resource cooperative control, and its technical principle is to forecast the baseline load and adjustable potential of users through suitable forecasting methods based on the user's gateway or sub-historical load data, historical and future meteorological data, and the combination of internal and external influences such as the user's production and living behavior habits and the external economic situation. Regional level load characterization and forecasting of regional grids is the focus of load research work. To study the load profiles of sub-regions and time periods, and to comprehensively analyze the impact of external factors, such as weather conditions, socio-economic development trends and holidays, on loads at the regional level. Through cubic spline interpolation [1], weighting calculations [2] and other computational methods to transform non-quantitative factors into mathematical quantities that can be identified by forecasting models, to explore the non-linear relationship and complex synergies between the intrinsic law of change of the load and the external influencing factors, to analyse the characteristics of the load at the regional level in a detailed manner and to summarize the development and change of its dynamics [3]. Based on the analysis of load characteristics, the regional load forecasting model needs to integrate the high-dimensional load data through the algorithm analysis and training and model interaction, to fully explore the potential correlation between the data, and then get the relatively high accuracy of the prediction results. In the last century, computer technology is not developed, people mainly use traditional mathematical and statistical methods for prediction [4], when the scope of computer application is narrower, most scholars use mathematical and statistical methods for prediction, the main prediction methods are regression analysis, time series method, exponential smoothing method, etc.With the extensive access to electric power data and the gradual improvement of historical data management, a large amount of data makes the traditional statistical methods difficult to cope with [5], and the modern prediction methods based on data mining have gradually become the mainstream under the impetus of the significant improvement of computer performance. Power system load forecasting is one of the important tasks in power system operation and scheduling, and its accuracy has an important impact on the economic and safe operation of the power system. Traditional load forecasting methods mainly include time series analysis method [6], regression analysis method [7], etc. However, these methods have problems such as insufficient feature extraction capability and high model complexity, which are difficult to adapt to the complex and changing operating environment of the power system. In recent years, with the continuous development of deep learning technology, its application in the fields of image recognition, speech recognition, etc. has achieved remarkable results. Therefore, the introduction of deep learning technology into power system load forecasting can improve the accuracy and stability of forecasting, and provide more effective decision support for the operation and scheduling of the power system.

2. SELECTION OF PREDICTIVE MODELS

Deep learning methods can effectively improve the prediction effect by learning the hidden abstract features layer by layer from a large amount of data through multilayer nonlinear mapping. A combined short-term load forecasting method of electric, thermal and gas systems based on deep learning is presented [8]. Firstly, the deep learning architecture, which consists of a deep belief network(DBN) at the bottom and a back-propagation(BP) network at the top, is introduced. As an unsupervised learning method, the deep belief network extracts abstract high-level features, and the multitask regression layer is used for supervised prediction. Then, a two-stage load forecasting system with offline training and online prediction is established, and the indexes to verify the prediction accuracy of the model are presented. Finally, the effectiveness of the multi-load forecasting method is verified by the actual data of an integrated energy system. The results show that the proposed deep learning algorithm has excellent performances in both computational efficiency and prediction accuracy. A probability density forecasting method based on deep learning, quantile regression and kernel density estimation is proposed [9]. To verify the efficiency of the proposed methods, three case studies based on daily electricity consumption data for three Chinese cities for 2014 are conducted. The proposed probability density forecasting method is capable of forecasting high-quality prediction intervals via probability density forecasting. A new approach is proposed in this paper for short-term load forecasting [10]. The developed method is based on the integration of convolutional neural network (CNN) and long short-term memory (LSTM) network. Also, the effectiveness of the proposed technique is validated by comparing the forecasting errors with that of some existing approaches such as long short-term memory network, radial basis function network and extreme gradient boosting algorithm. It is found that the proposed strategy results in higher precision and accuracy in short-term load forecasting.

Comprehensive research on short-term power load forecasting models can be found above, there are more forecasting models can achieve better forecasting goals. However, with the rapid development of science and technology, newer technologies can be used to achieve more accurate prediction results. In order to improve the accuracy of the previous prediction models, the study selects the most mainstream deep neural network model, i.e., the recurrent neural network model and its variants to predict the load data, observes the prediction effect under the same model parameters, and selects the optimal scheme for the load prediction, so as to provide the basis and reference for the subsequent research.

3. MODEL CONSTRUCTION

3.1. Preprocessing of Power Load Data

Electricity load data is a set of multivariate time series with characteristics such as periodicity, randomness and volatility, and due to the interference of randomness and noise data are prone to anomalies and serious deviations from the range of normal values [11]. The dataset used in this study was sourced from the National Energy Market, a subsidiary of the Australian Energy Market Operator (AEMO), where electricity loads, meteorological conditions and tariffs are sampled every half hour, generating 48 value points per day with a total of 87,648 data entries.

Cyclicity is based on quarterly, monthly, and even hourly and minute, with regular changes, and there may be small cycles within the large cycle. Volatility refers to the phenomenon of oscillating changes in power load values, and randomness refers to the fact that the fluctuations in power load values show a certain degree of irregularity, and the magnitude of the fluctuations varies because of the influence of various factors. The experimental data set in the SPSS software for correlation analysis, take every day 10:00, 14:00, 18:00, 22:00 load value and the influence of the factors for correlation analysis, the results are shown in the correlation is significant. As seen in Figure 1 the X-axis is the measurement point, Y-axis bit load value and load changes periodically with time.

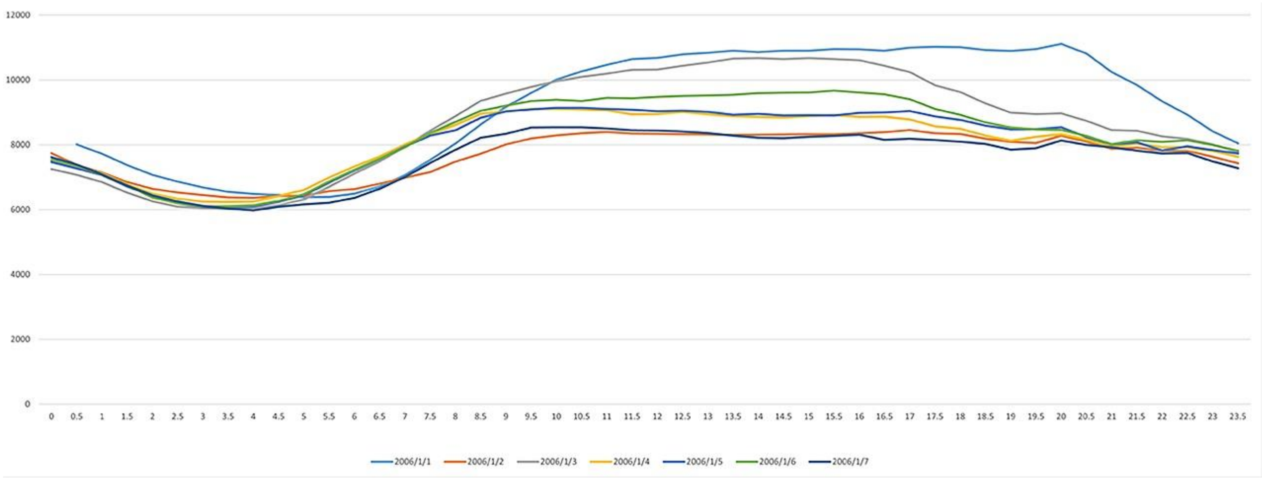


Figure 1. Plot of load data over time for a site in Australia

Historical data in its raw form can be redundant and increase the risk of overfitting in model training, so three forecasting correlates were chosen to construct the load forecasting dataset as inputs.

(1) Date and hourly information of the past k load samples is selected as *Dt*;

(2) Select temperature and humidity as the environment vector *Ht* for the past k samples;

(3) Select electricity price as *Pt*;

(4) Electricity load sequence *Yt* for the past k samples.

The data are processed for missing values and outliers, and the processed load sequences, environmental variables such as temperature and humidity, and date-time information are used as input features. Considering the sensitivity of deep learning to data, the input features were Min-Max normalised, the data were scaled to between 0 and 1, and linear transformation was performed based on the maximum and minimum values of the data. After normalisation, the data can be fed into the prediction model for training, and after the prediction model outputs the predicted value, then the inverse normalisation process is performed to obtain the real load prediction value.

3.2. Modelling

3.2.1. BP neural network.

BP neural network for load forecasting, historical load and its influencing factors for numerical quantification as input data, in the implicit layer after the fitting of the excitation function, multiple cycles, iterative error reverse transmission process, as a way to reduce the network training results and the known actual real value of the error between the network and ultimately get the prediction results from the output layer. The three-layer network structure of BP neural network is fully connected and the nodes between the layers are not connected to each other, so it is difficult to reflect the correlation of the successive output data [12].

3.2.2. Recurrent neural network.

Recurrent Neural Network (RNN) is based on BP neural network, which provides preorder connections and postorder connections to each node of the hidden layer for recording the preorder information and applying it to the postorder output calculation. Recurrent neural networks perform better in handling time series data, and the load data is a multivariate time series data is highly correlated, so the recurrent neural network and its variants are chosen as the base model. The output of the hidden layer neurons of the recurrent neural network is not only related to the current input, but also to the neuron's previous moment output, so that the previous information can be combined with the current input to make predictions and better capture the characteristics of the input data.The RNN network topology is shown in Figure 2.

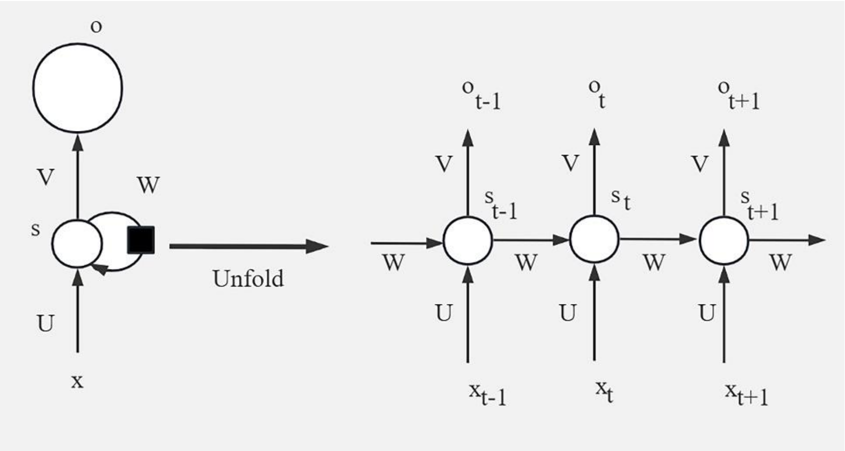


Figure 2. Network topology of RNN

3.2.3. Long short-term memory neural network.

Although the recurrent neural network has the ability to remember information, but the memory capacity is limited, when the amount of input information is increasing, it will appear the phenomenon of gradient disappearance or gradient explosion, power load forecasting and the need to analyse and study the long period of power load, it is clear that the recurrent neural network has some defects. The hidden layer of the long short-term memory neural network (LSTM) adds a new state quantity, which is specially used to store the long-term state in the network, and the forgetting gate alleviates the problem of disappearing or exploding gradient to a certain extent, which improves the performance of the recurrent neural network. Its network topology is shown in Figure 3.

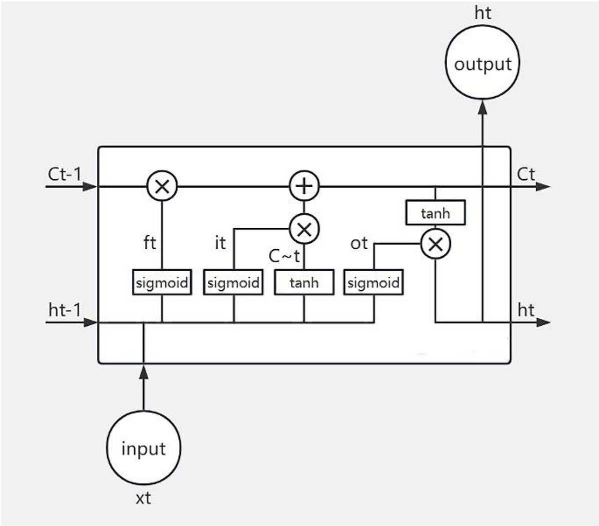


Figure 3. Network topology of LSTM

LSTM retains the implicit layer transfer relationship between adjacent time nodes in the basic structure of RNN, and updates the addition of forgetting gate, input gate and output gate inside the loop body to memorise, extract and filter the information of the preceeding sequence, which further enhances the degree of correlation between the subsequent feature signals and the preceeding feature signals, and effectively solves the problem of gradient disappearance and gradient explosion that occurs in the long time sequence training of the traditional RNN. Load forecasting using LSTM model by Weicong Kong et al. [13] The proposed framework is tested on a publicly available set of real residential smart meter data, of which the performance is comprehensively compared to various benchmarks including the state-of-the-arts in the field of load forecasting. As a result, the proposed LSTM approach outperforms the other listed rival algorithms in the task of short-term load forecasting for individual residential households. Musaed Alhussein et al. propose a deep learning framework based on a combination of a convolutional neural network (CNN) and long short-term memory (LSTM) [14]. The proposed hybrid CNN-LSTM model uses CNN layers for feature extraction from the input data with LSTM layers for sequence learning.

3.2.4. Gated recurrent unit.

The gated recurrent unit (GRU) is an improved and optimised neural network based on the LSTM, where the forgetting gate and the input gate are combined into a single update gate, resulting in a model that is simpler than the standard LSTM model, and is a variant of the very popular recurrent neural network.The construction of the GRU is even simpler, with one fewer gate than the LSTM, which results in a few less a few matrix multiplications. It has faster convergence and has similar accuracy to LSTM [15]. GRU network is suitable for processing time series data and GRU saves a lot of time in case of large training data. Muhammad Sajjad et al. achieve the mentioned tasks by developing a hybrid sequential learning-based energy forecasting model that employs Convolution Neural Network (CNN) and Gated Recurrent Units (GRU) into a unified framework for accurate energy consumption prediction [16]. In the training phase, CNN features are extracted from input dataset and fed in to GRU, that is selected as optimal and observed to have enhanced sequence learning abilities after extensive experiments. The proposed model is an effective alternative to the previous hybrid models in terms of computational complexity as well prediction accuracy, due to the representative features' extraction potentials of CNNs and effectual gated structure of multi-layered GRU.Network topology of GRU is shown in Figure 4.

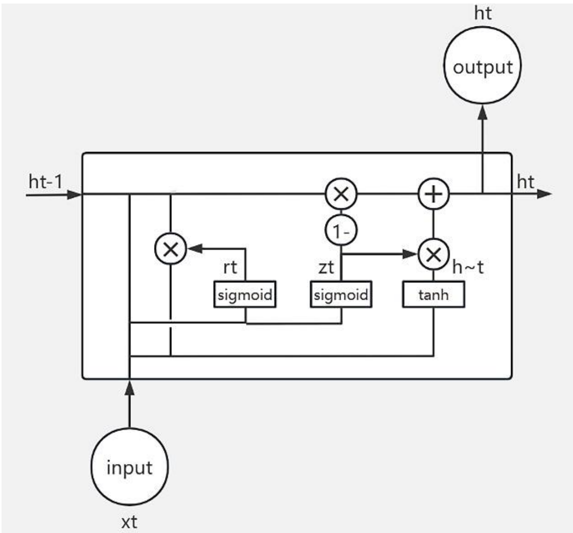


Figure 4. Network topology of GRU

3.2.5. Bidirectional long short-term memory.

The BiLSTM is composed of two independent LSTMs that are responsible for processing the input sequence from two directions (forward and reverse). This allows the model to acquire information both before and after the current time step. Only after all the time steps have been computed, the two result vectors are spliced together to obtain the final BiLSTM output.The BiLSTM is capable of handling long sequences and long-term dependencies, and is suitable for time series forecasting tasks. Through the bidirectional information flow, the contextual information in the sequence can be better captured and the model performance can be improved. The disadvantages are more model parameters, high training complexity, and the need for a large amount of data and computational resources. For shorter sequences and simple patterns, overfitting may occur. Its network topology is shown in Figure 5. Jie Du et al. proposed an Attention-BiLSTM (Attention based Bidirectional Long Short-Term Memory, Attention-BiLSTM) network to do the accurate short-term power load forecasting[17]. This model is based on BiLSTM recurrent neural network which has high robustness on time series data modeling, and the Attention mechanism which can highlight the key features playing key roles in load forecasting in input data.

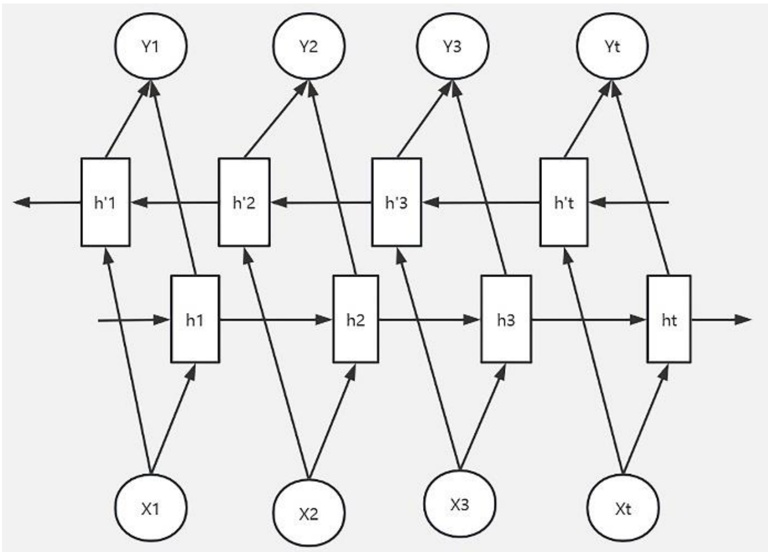


Figure 5. Network topology of BiLSTM

4. MODEL PERFORMANCE ANALYSIS

4.1. Load Dataset

This paper demonstrates the effectiveness and generalisation capability of the proposed load forecasting model using five years' worth of electricity loads and influencing factors such as date, weather and electricity price for a region in Australia for model training. The dataset is sourced from the National Energy Market, a subsidiary of the Australian Energy Market Operator, where electricity loads, meteorological conditions and electricity prices are sampled every half hour, generating 48 value points per day, totalling 87,648 pieces of data. As inputs to the forecasting model, the dataset contains uncertainty about variable weather and variable electricity prices consistent with the frequency of load sampling. Uncertainty may reduce forecast accuracy. Therefore, the dataset can also be used to test the ability of the proposed model to attenuate uncertainty.

4.2. Parameters

4.2.1. Test system settings.

Table 1. Model Parameters

Parameter	Numerical value 1	Numerical value 2
Number of hidden layer nodes	50	50
Learning rate	0.001	0.001
Number of neurons in fully connected layer	1	1
Number of iterations	10	100
Time step	20	20
Dropout	0.2	0.2
Batchsize	32	32

4.2.2. Evaluation indicators.

In this paper, four indicators are used to evaluate the prediction effect, which are rootmean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). The smaller the values of RMSE, MAPE and MAE, the higher the prediction accuracy, the formulas for each of the three indicators are as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y_i} - y_i)^2} \tag{1}$$

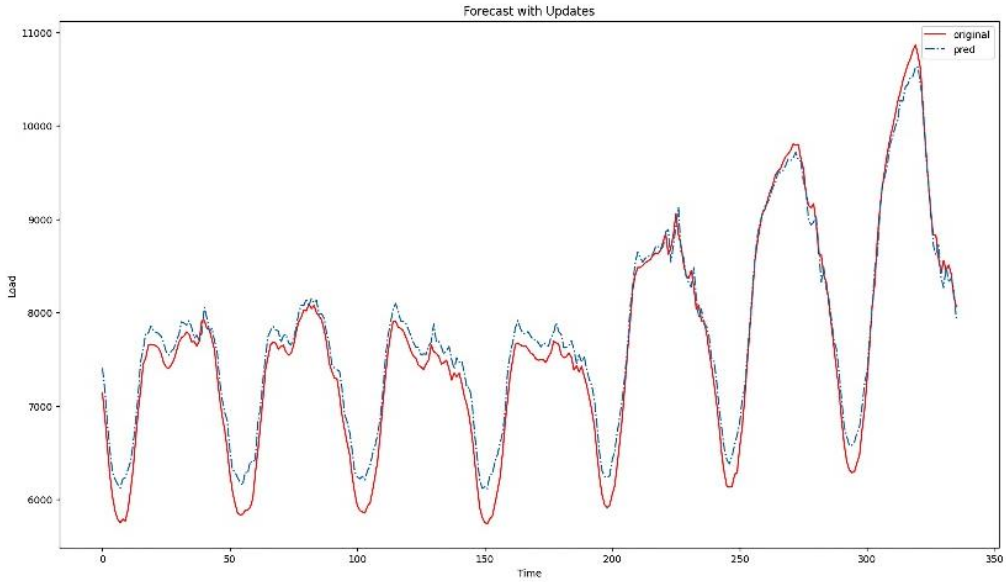
$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y_i} - y_i| \tag{2}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{\hat{y_i} - y_i}{y_i}\right| \tag{3}$$

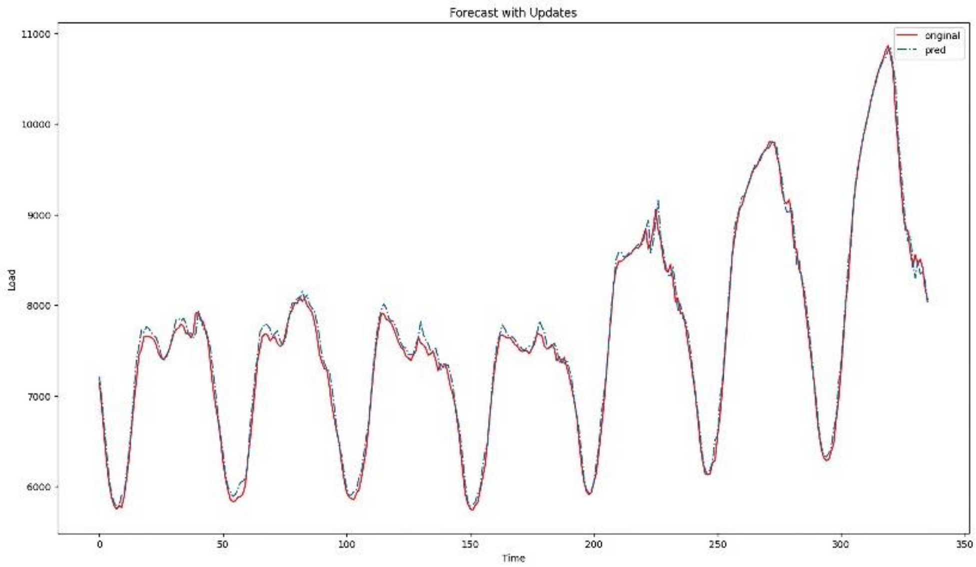
Where n is the number of samples, $\hat{y}$ is the predicted value and y is the true value.

4.3. Deep Learning Model Comparison

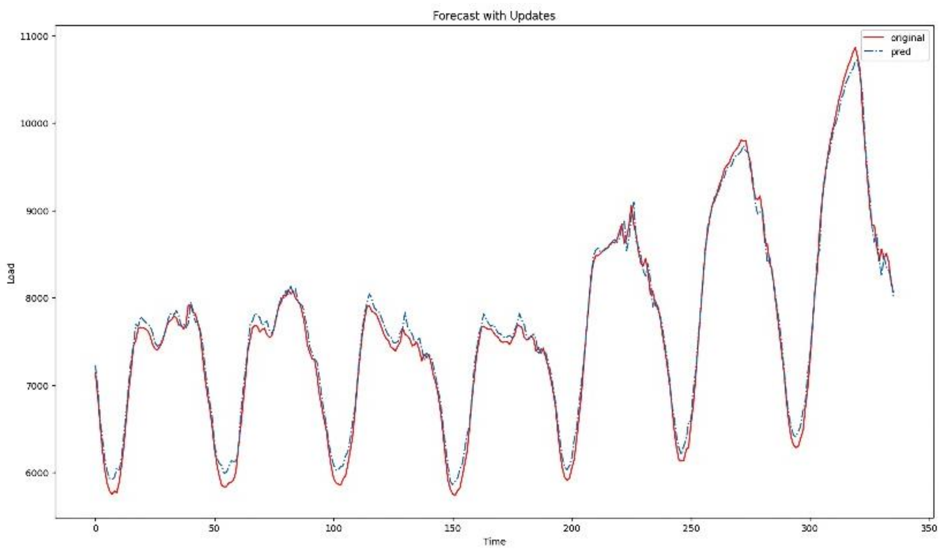
In order to compare the superiority of the recurrent neural network model and its variants for load forecasting, the four models are compared under the same parameters, and the comparison experiments strictly control the parameters of the network structure in line with Table 1, and the comparison of the prediction results are shown in Figures 6 and 7, and the comparison of prediction errors are shown in Tables 2 and 3.



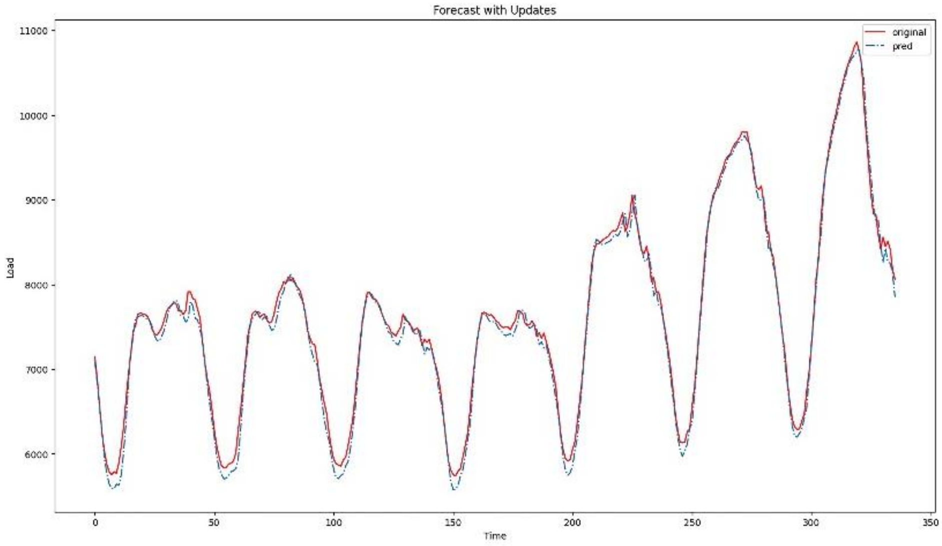
(a) Comparison of 7-day prediction results for RNN (parameter 1)



(b) Comparison of 7-day prediction results for LSTM (parameter 1)

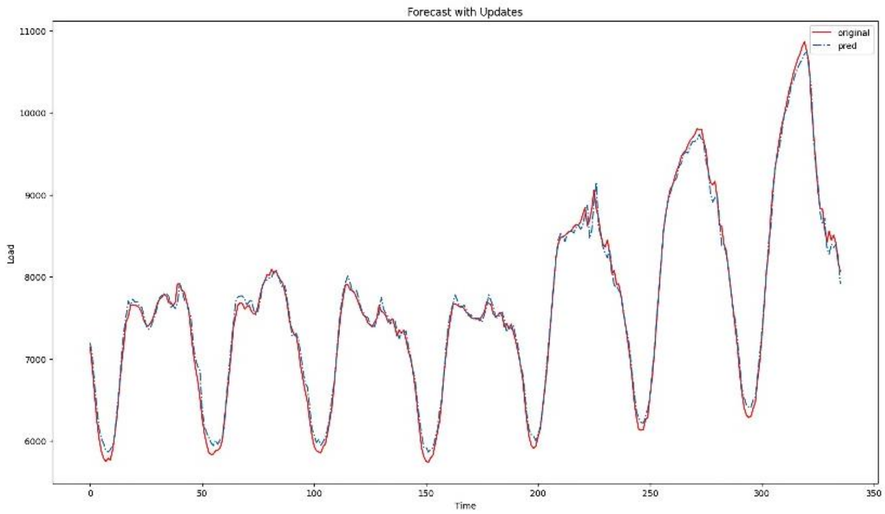


(c) Comparison of 7-day prediction results for GRU (parameter 1)

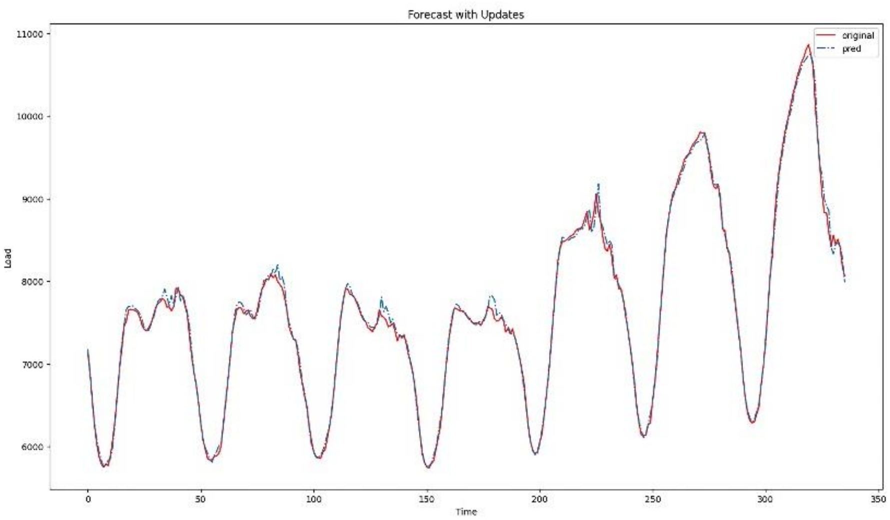


(d) Comparison of 7-day prediction results for BiLSTM (parameter 1)

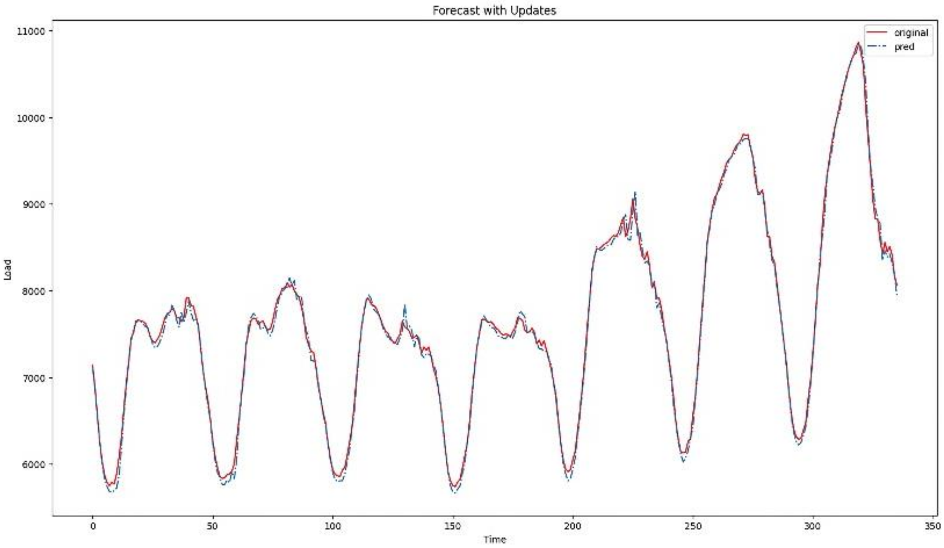
Figure 6. Comparison of 7-day prediction results of different models (parameter 1)



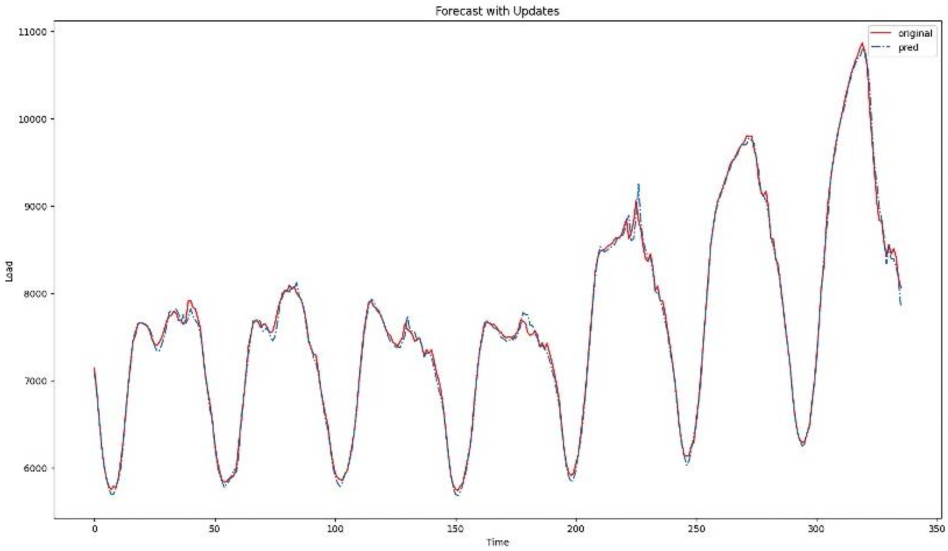
(a) Comparison of 7-day prediction results for RNN (parameter 2)



(b) Comparison of 7-day prediction results for LSTM (parameter 2)



(c) Comparison of 7-day prediction results for GRU (parameter 2)



(d) Comparison of 7-day prediction results for BiLSTM (parameter 2)

Figure 7. Comparison of 7-day prediction results of different models (parameter 2)

Table 2. Comparison of prediction accuracy and computing speed of different models (parameter 1)

Model	RMSE	MAE	MAPE	Time[ms]
RNN	179.525003	148.163712	0.0202%	208069.2109
LSTM	100.284563	78.762457	0.0100%	460000.0651
GRU	105.320462	85.852746	0.0113%	938960.8168
BiLSTM	104.019376	81.756692	0.0107%	1203704.1632

Table 3. Comparison of prediction accuracy and computing speed of different models (parameter 2)

Model	RMSE	MAE	MAPE	Time[ms]
RNN	93.553996	74.156749	0.0095%	2863272.8615
LSTM	66.521866	48.113466	0.0060%	4577607.2573
GRU	75.698398	56.666950	0.0073%	4343366.0492
BiLSTM	70.070645	51.664444	0.0066%	11335738.4133

From Table 2 and Table 3, it can be seen that in the single-week power load forecast, the RMSE of the LSTM forecast model is 66.5, which is 27 lower than that of the RNN forecast, 9.2 lower than that of the GRU model, and 3.5 lower than that of the BiLSTM model. the MAE is 48.1, which is 26 lower than that of the RNN forecast, 8.5 lower than that of the GRU model, and 3.55 lower than that of the BiLSTM model, and the MAPE is 0.0060%, 0.0035% lower than the RNN prediction, 0.0013% lower than the GRU model, and 0.0006% lower than the BiLSTM model; In summary, the LSTM prediction model can be well applied in practical prediction, and it has a very high accuracy and practicality.

5. SUMMARY

With the deepening of the "dual-carbon" process, China's high-quality development of energy and power is facing new forms and new tasks. As an important part of the energy system and the main participant and promoter of the "dual-carbon" goal, the power system is facing profound changes in its key links such as "source, network, load and storage". New energy access to the power system scheduling plan puts forward new challenges, in the face of the new power system background of the power generation side of the flexibility constraints, in order to ensure the stable operation of the system, the user side must be deeply involved in the regulation of the system operation, multi-timescale, high-precision electric power load modelling, forecasting and optimization of the new power system operation, maintenance and planning is essential. Deep learning algorithms have higher sample fault tolerance, stronger nonlinear processing ability, better generalisation ability, and are widely used in the field of power system load forecasting[18]. With the deepening of the research on deep learning algorithms, the neural network algorithms are further improved and optimised, and more and more training algorithms with better performance and more complex network structures with more complex frameworks have made the accuracy of power system load forecasting further improved. Short-term load forecasting not only ensures the safe and economic operation of the power system, but also serves as the basis for scheduling, power supply and trading in the new market environment. Power supply companies can obtain the daily cyclic pattern of power load from the results of short-term load forecast, arrange the daily starting and stopping plan of power units, power generation plan, and revise the rolling power generation plan, etc. Meanwhile, the changes of short-term load suggest the peak and trough periods of power consumption, and the off-season and peak-season of the industry, which is an important basis for the adjustment of pricing scheme of power supply companies; power consumption enterprises can also refer to the results of the daily load prediction to adjust the production plan and realize the efficient use of energy. efficient use of energy. In order to achieve more accurate prediction of short-term electricity load, the study analyses the load prediction results using recurrent neural networks and their variants, and the experimental results show that the LSTM prediction model has the highest prediction accuracy in a single week's prediction, and the average absolute error is 26 lower than that of the RNN prediction, 8.5 lower than that of the GRU model, and 3.55 lower than that of the BiLSTM model.In summary, the LSTM forecasting model can be better applied in the short-term forecasting of electricity load, and has more stable accuracy and precision. However, there are still shortcomings in the study, such as not enough input data series, and the model parameters are not adjusted to the optimal, etc. In the future, we can increase the historical load data and add the parameter optimisation module to further improve the accuracy in the further study.

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