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Short-term Power Load Forecasting based on Machine Learning

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Abstract

In order to improve the accuracy of short-term power load prediction, a short-term power load prediction model (VMD-CS-LSTM) based on variational mode decomposition and cuckoo algorithm was proposed to optimize the long and short term memory (LSTM) neural network. In view of the problem that the parameters of LSTM model are difficult to select, CS is used to optimize the parameters of LSTM model. For the simulation of the prediction model, this paper chooses the Jupyter Notebook programming environment and uses Python language to program under the framework of TensorFlow. The model obtained can be used to predict the future power load value. The simulation results show that the method of variational mode decomposition and cuckoo algorithm to optimize LSTM can effectively improve the accuracy and stability of short-term power load prediction.

Keywords

Short-term Power Load Forecasting; Variational Mode Decomposition; Cuckoo Algorithm; Long and Short Term Memory Algorithm; Error Analysis.

1. Introduction

The development and utilization of energy maintain the daily production activities of human beings. With the gradual advancement of the industrialization process, the development of energy is deepening and the demand for energy is also increasing. Natural resources are seriously damaged, and the monitoring of climate change is becoming more difficult and the situation is becoming increasingly severe. Power industry network is an efficient and efficient energy transmission channel and optimal allocation platform. It is a key link in the sustainable development of energy and electricity. It plays an important pivotal role in the modern energy supply system and is related to national energy security. The stable and reliable output of electric energy plays a key role in China's social construction, economic stability and sustainable development. In China, the installed capacity of generators is constantly expanding, and the power grid is constantly developing and constructing. As a result, the change of power load is becoming more and more complex, so the research on the prediction of power load is becoming more and more important[2].

In essence, the power load forecast is an advance estimate of the future electricity demand by the power sector based on the reality. Power load forecasting is according to the historical load data, social and economic development situation, the effects of climate change, social activities, and many other factors, reasonable analysis and processing of all influence factors on, looking for load change and the intrinsic relationship between these factors, as well as their influence on the future load, establish a good prediction model. The higher the accuracy of the prediction, the more conducive to the power system planning, dispatching and maintaining the stability of the system; At the same time, reasonable power allocation can not only improve the quality of power, but also facilitate the electricity market transaction, reasonable pricing to improve economy.

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2. Characteristics of power load forecasting

Power load forecasting is to predict the load change in the future. By analyzing the historical data collected before and combining with some other correlation factors, the approximate value of the load in a certain period of time can be deduced. According to different time length, the load forecast can be divided into different categories. Different types of prediction also play different roles[3]. The following table shows the load forecasting types divided by time length and the different roles played by different types:

Table 1. Time series classification of power system load forecasting

Predict type	The type definition	role
Long-term load forecasting	More than one year	Determine the annual maintenance plan and operation mode
Medium term load forecasting	A month to a year	Determine monthly plan and allocate power generation operation mode
Short term load forecasting	A day to a week	Determine daily shutdown and power generation schedule
Ultra-short-term load forecasting	Minutes to a day	Real-time monitoring, real-time safety analysis, automatic control

3. Short-term power load prediction of CS+LSTM based on variational mode decomposition

3.1 Variational modal decomposition

VMD is to decompose the original time series signals into K IMF (modal components) by alternating direction multiplier method and update iteration.By iteratively searching for the variational optimal solution, it determines the mode $u_k(t)$ and the center frequency and finite bandwidth. Each mode has a central frequency and a limited bandwidth, and the superposition of all modes is the original signal.

The inherent modal component is an amplitude-frequency modulation (AM-FM) signal, and the definition of "modal" is given here, denoted by X:

$$u_k(t) = A_k(t)\, cos(\, \varphi_k(t)) \tag{1}$$

In the formula, $A_k(t)$ is the instantaneous amplitude, $\varphi_k(t)$ is the phase change, and neither the instantaneous amplitude nor the phase change is less than zero.

In this paper, the measured power load values from 0:00 on July 1, 2014 to 24:00 on September 7 in a region are taken as the research object, and the data sampling interval is 15min, that is, 96 sampling points a day[4]. According to the important parameter values obtained from the analysis in the above section, VMD algorithm is used to decompose the original power load sequence. The initial center frequency and the convergence criterion are. The decomposition results obtained and the original load sequence are shown in the figure below.

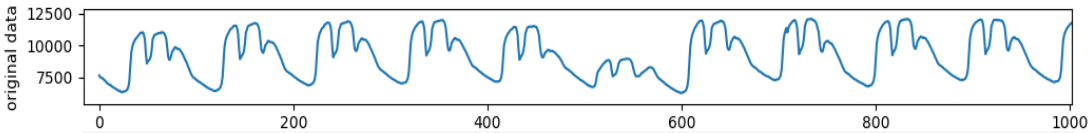

Figure 1. Original power load sequence

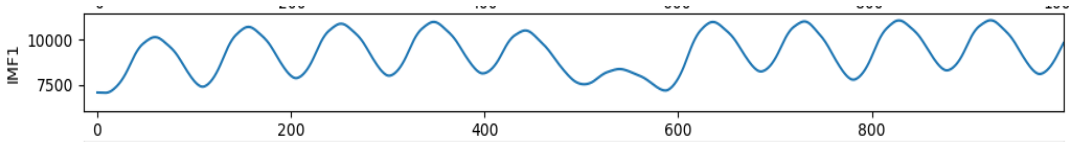

Figure 2. VMD decomposes the vector IMF1

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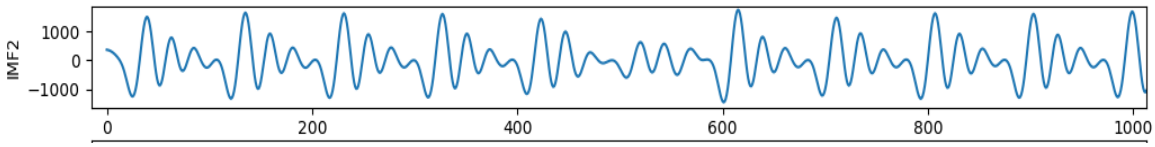

Figure 3. VMD decomposes the vector IMF2

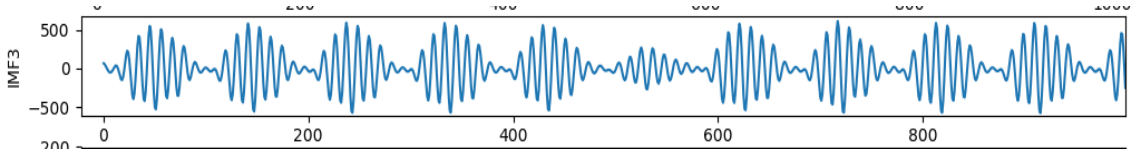

Figure4. VMD decomposes the vector IMF3

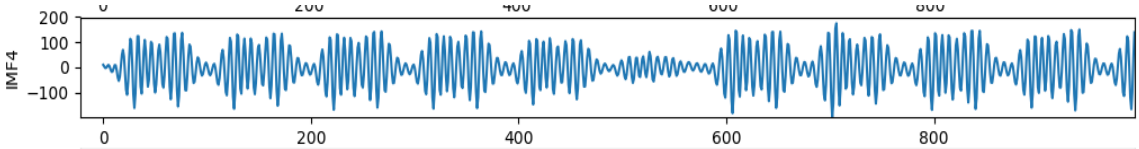

Figure 5. VMD decomposes the vector IMF4

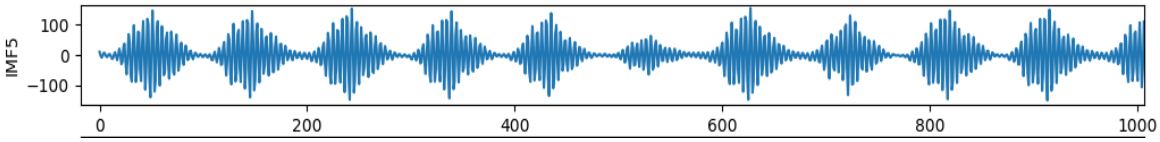

Figure 6. VMD decomposes the vector IMF5

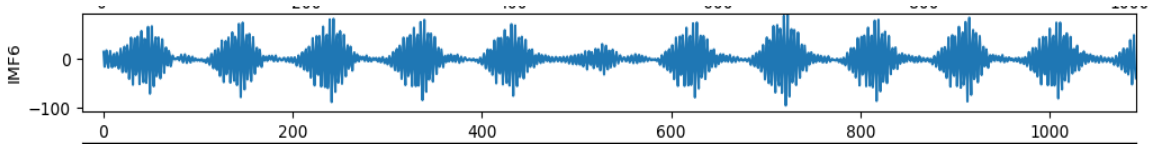

Figure 7. VMD decomposes the vector IMF6

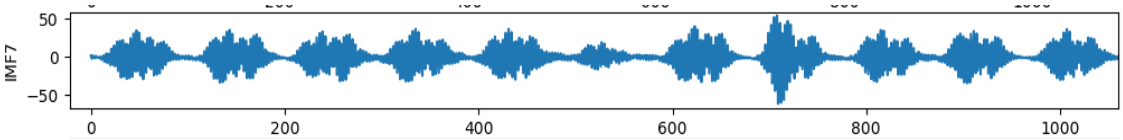

Figure 8. VMD decomposes the vector IMF7

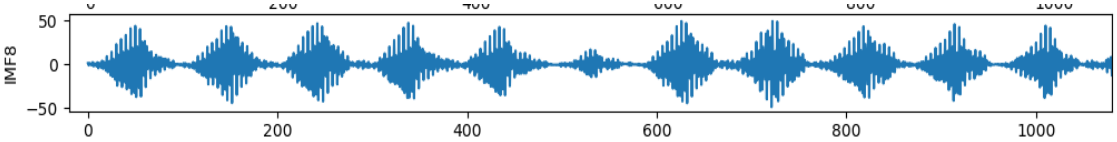

Figure 9. VMD decomposes the vector IMF8

The above figure shows the original curves of VMD decomposition and the curves of the 8 modal components obtained by decomposition. As can be seen from the figure, the average amplitude of the subsequence IMF1 is large and the variation is gentle. The subsequences IMF2 and IMF3 have good regularity and obvious periodicity. The average amplitude of modes IMF4, IMF5, IMF6, IMF7 and IMF8 decreased successively, and IMF8 fluctuated greatly with the worst regularity and stronger randomness volatility, reflecting that the load was greatly affected by random factors.

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3.2 Cuckoo algorithm

CS algorithm is a kind of intelligent optimization algorithm, the biggest characteristic of this kind of algorithm is to draw lessons from the natural law phenomenon or the principle of bionics, researchers get inspiration from it, so that a variety of algorithms with intelligent characteristics can be born. The optimization idea of CS algorithm comes from the parasitic brooding behavior of cuckoos[5]. To establish a connection between parasitic brooding behavior of cuckoos and CS algorithm, the following three idealized rules need to be assumed:

(1) The cuckoo lays only one egg at a time and randomly chooses the nest to store the eggs.

(2) The nest that produces the best eggs will be preserved for the next generation.

(3) The number of nests is a fixed value, and the eggs in the nest will be found by the host with a certain probability of $P_a \in [0,1]$.

CS algorithm is carried out through global search and local search. Global search mainly relies on Levy flight to find the optimal solution. Levy flight was originally proposed by French mathematician Paul Levy, which is a random walk mechanism. On the basis of this study, researchers found that the animal movement law was consistent with Levy's flight characteristics, and based on its theoretical assumptions, Levy's flight model was established, which was widely used in different research fields such as transportation system simulation, earthquake search and rescue simulation.

3.3 LSTM algorithm

From the perspective of network structure, the cyclic neural network and the neural network of long and short-term memory are analyzed. The hidden layer of the cyclic neural network has only one state quantity S, and this state quantity will be greatly affected by the input changes in the short term, so it does not have the ability of long-term memory. In addition to the state quantity S of the hidden layer of the cyclic neural network, a new state quantity C is added in the hidden layer of the long and short-term memory neural network, which is specially used to store the long-term state in the network.

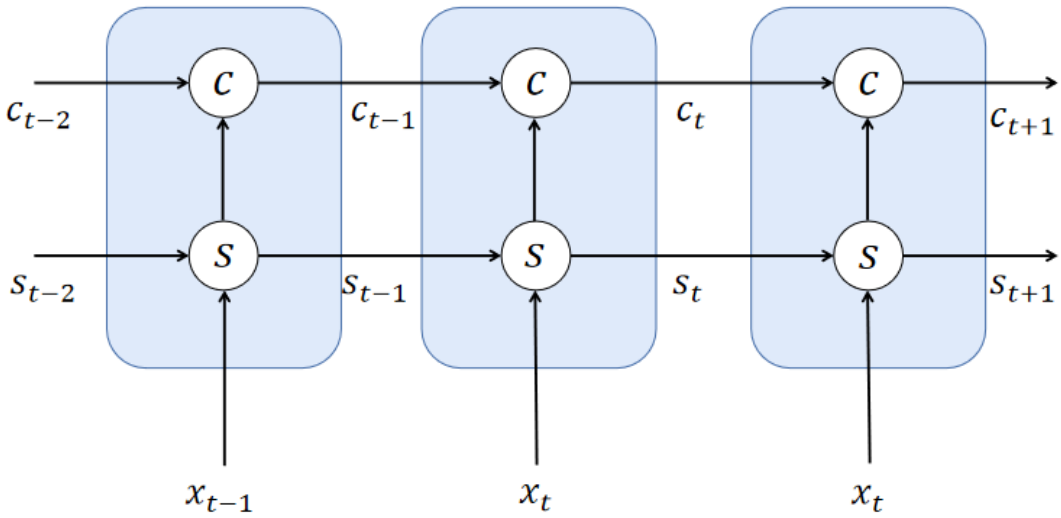

Figure 10. LSTM network time expansion diagram

It can be seen from Figure 10 that the input of the hidden layer of the long and short-term memory neural network has three components: the current input value x, the output value y at the previous moment, and the unit state t at the previous moment. The key to the long-term memory of information by LSMM neural network is the management and control of unit state C[6]. LSMM neural network introduces input gate, output gate and forgetting gate to achieve this (as shown in Fig. 11).

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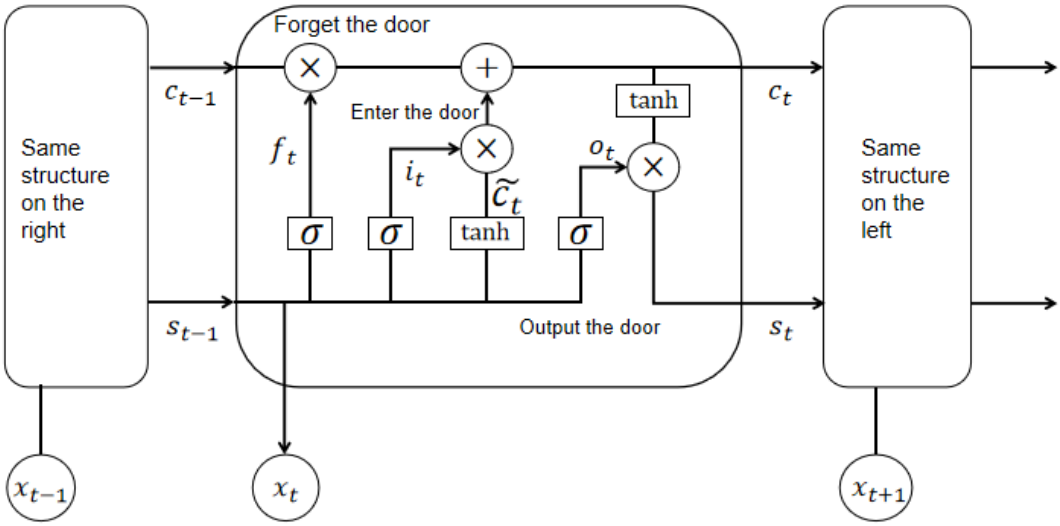

Figure 11. LSTM network structure diagram

(1) Forgetting gate is used to control the information that needs to be saved in the cell state at the last moment to be saved in the current cell state. The calculation formula is as follows:

$$f_t = \sigma\left(w_f \cdot [s_{t-1}, x_t] + b_f\right) \tag{2}$$

(2) The input gate controls how much information of the input at the current time is saved in the current cell state c_t, and the calculation formula is:

$$i_t = \sigma(w_i \cdot [s_{t-1}, x_t] + b_i) \tag{3}$$

(3) Before the current cell state, it is necessary to obtain the candidate value vector $\tilde{c}_t$ of the current cell state. The calculation formula is as follows:

$$\tilde{c}_t = tanh(w_c \cdot [s_{t-1}, x_t] + b_c) \tag{4}$$

(4) The current cell state calculation formula is as follows:

$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t \tag{5}$$

(5) Output gate controls how much information is saved to the current output s_t in the current state of the unit. The calculation formula is as follows:

$$o_t = \sigma(w_o \cdot [s_{t-1}, x_t] + b_o) \tag{6}$$

$$s_t = o_t * tanh(c_t) \tag{7}$$

3.4 CS+LSTM short-term load prediction process based on variational mode decomposition

The flow chart of the model used in this paper is shown in Figure 12, and the detailed description is as follows[7].

(1) Data preprocessing: including normalization, deletion of missing values, etc.

(2) Decomposition of original data: VMD is used to decompose the original load sequence into several specific sub-sequences.

(3) Model training: each sub-modal component is predicted respectively to build a short-term power load prediction model of CS-LSTM.

(4) Prediction result output: the prediction result of each submode is reconstructed to get the final prediction result.

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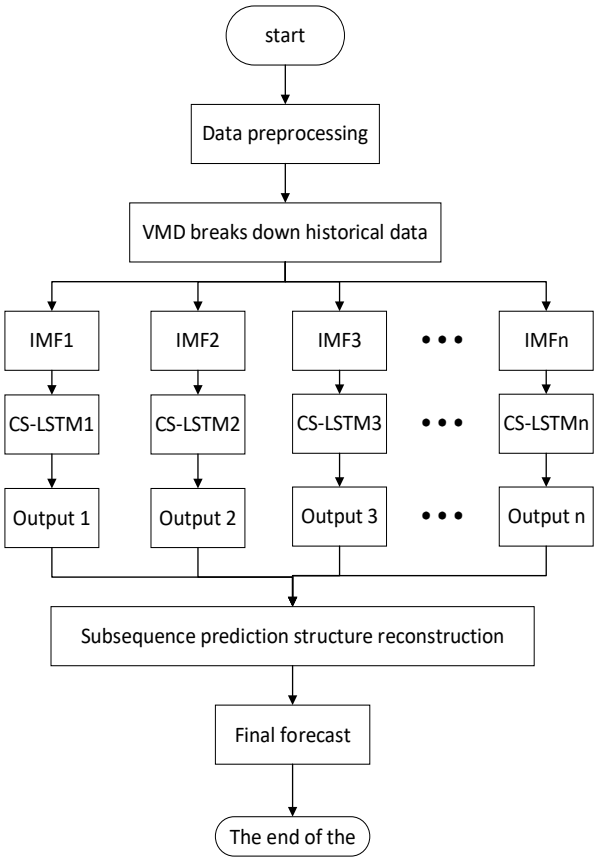

Figure 12. Structure diagram of power load forecasting model based on VMD-CS-LSTM

4. The example analysis

4.1 Power load time series analysis

The power load data used in this paper is the load value data of a region in China from July 2014 to September 2014, and 96 points are collected every day with a time interval of 15min. Firstly, the data is preprocessed, including missing value filling and data normalization[8]. Through the preliminary analysis of the data, it is found that the power load data has obvious periodicity rule. The following is the curve graph of part of the historical load data:

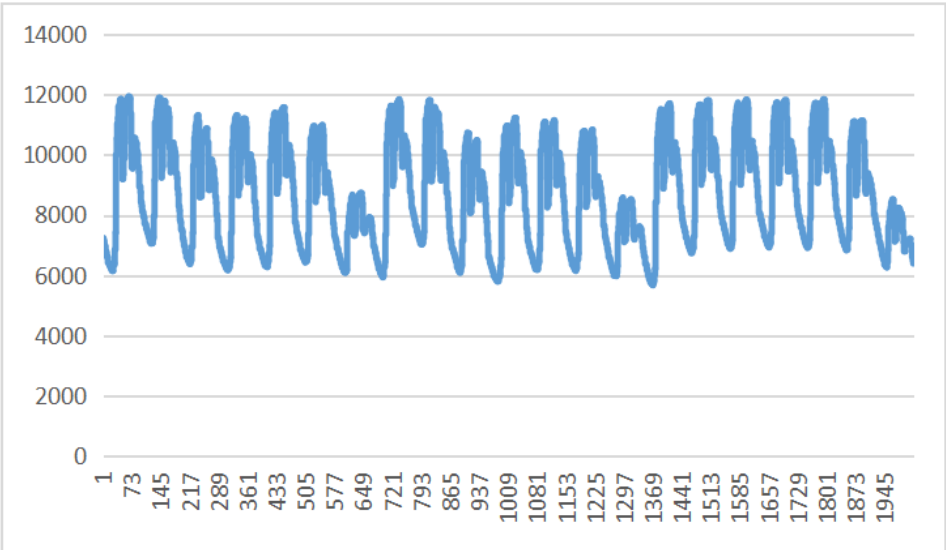

Figure 13. Historical load change curve

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4.2 Model parameter setting

In the decomposition process of VMD, K represents the number of IMF of the modal component, and the value of K directly affects the decomposition effect of the signal sequence. The value of K in this experiment is 8. Secondly, the determination of the quadratic penalty coefficient α also directly affects the bandwidth of the modal component, where $\alpha = 2000$ is taken. For the parameters of LSTM, cuckoo algorithm is used to optimize the number of iterations, learning rate and nodes of the two hidden layers of LSTM[9].

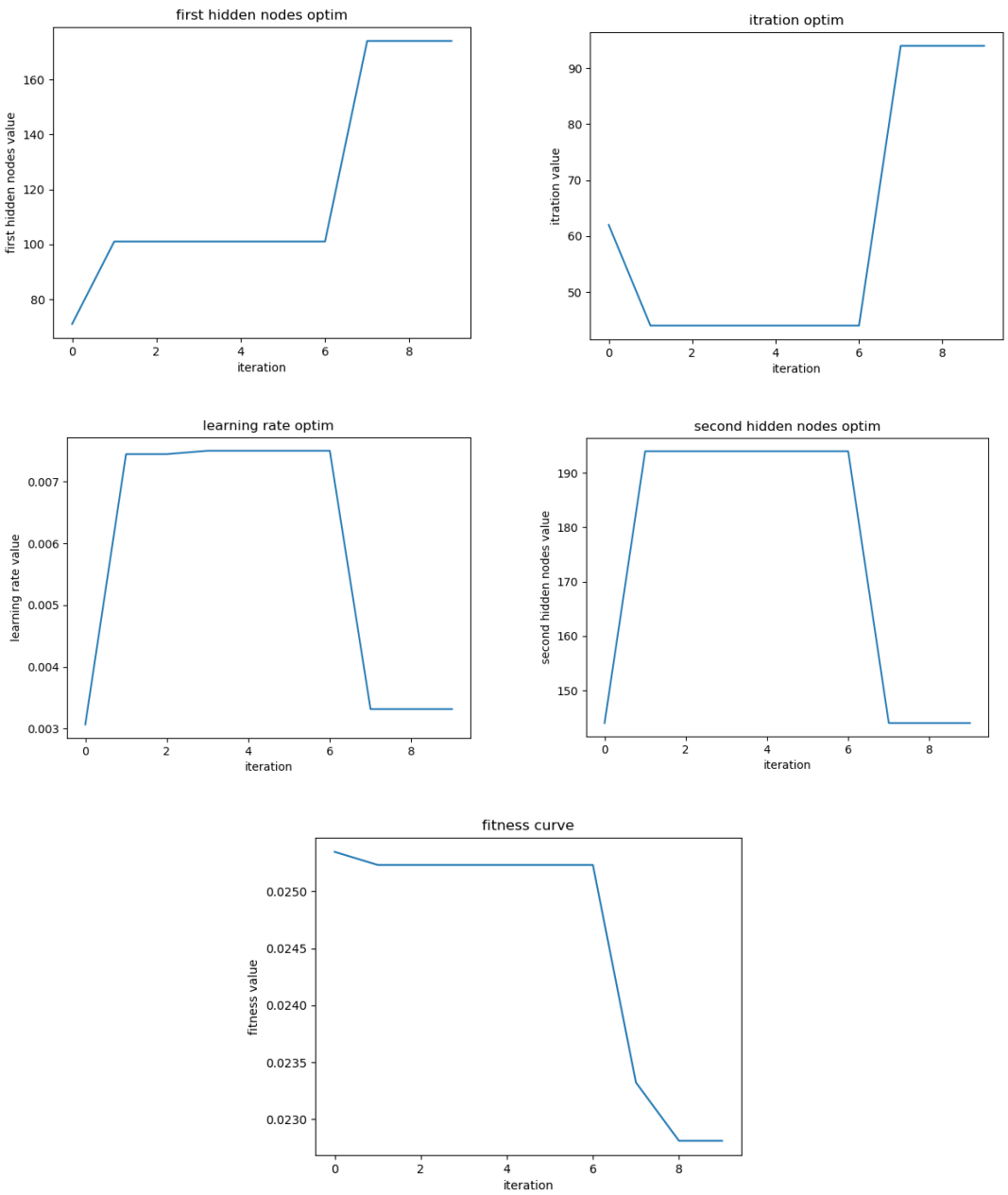

Figure 14. CS-LSTM optimization process

4.3 Analysis of prediction results

For the neural network model simulation based on VMD-CS-LSTM power load data prediction, Jupyter Notebook programming environment is selected and implemented in Python language under the framework of TensorFlow, and the obtained model can predict the future power load value. The following is the curve comparison between the predicted results of the VMD-CS-LSTM prediction method and the real value:

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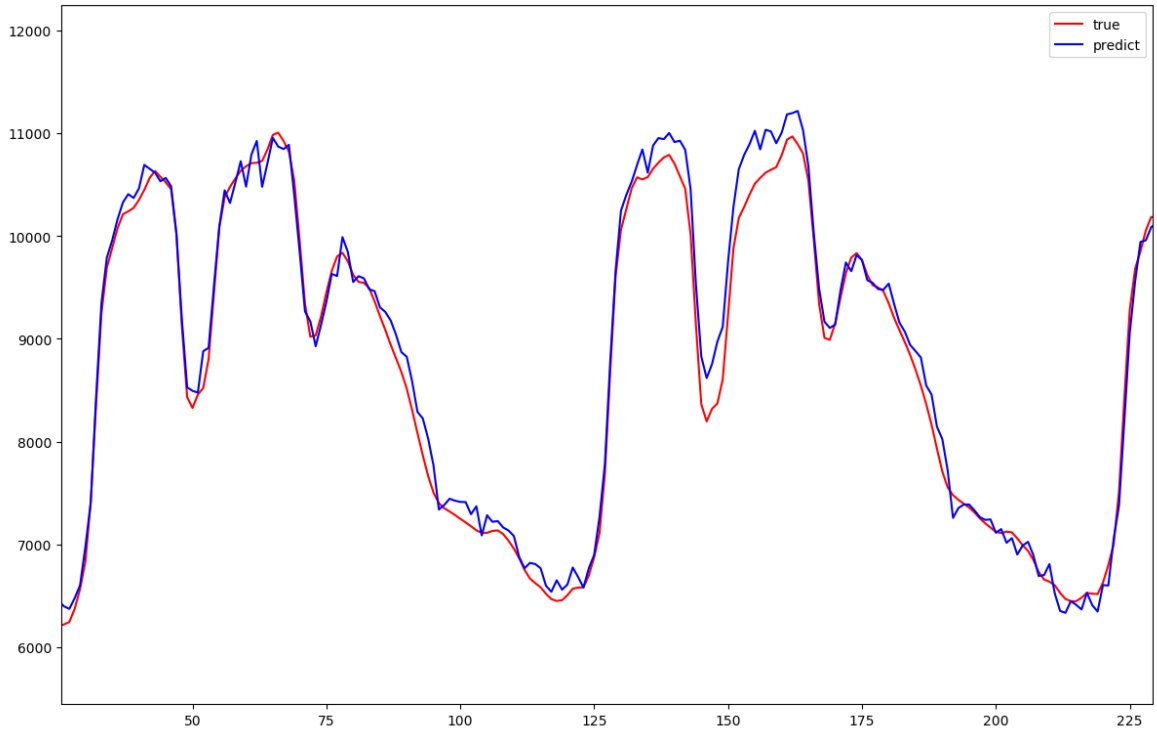

Figure 15. VMD-CS-LSTM prediction curve

The prediction model of VMD-CS-LSTM was compared with the results of VMD-BP and VMD-LSTM respectively. The prediction results of each model are shown in Fig. 16, and the prediction errors are shown in Table 2.

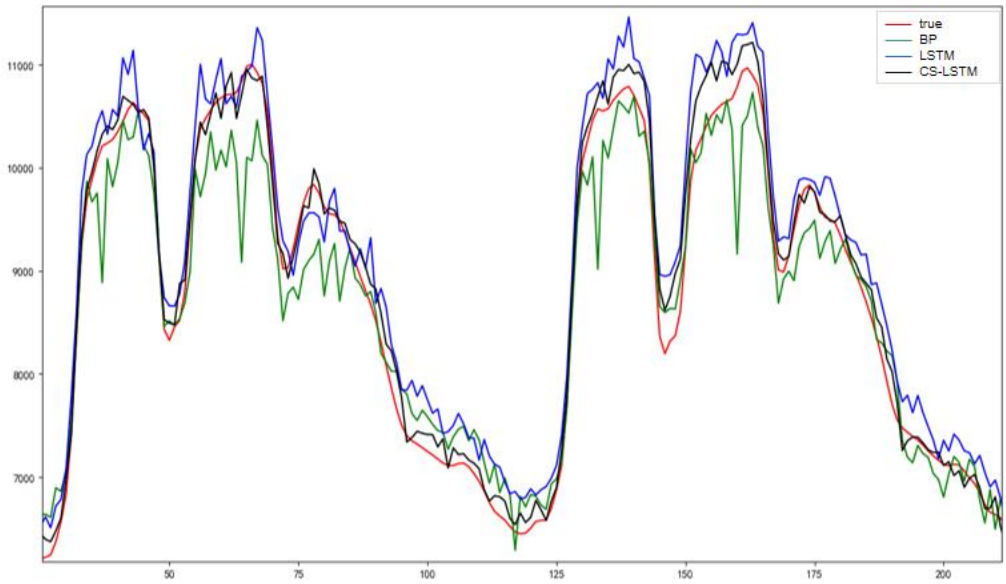

Figure 16. Comparison curves of the results of each model

Table 1. Time series classification of power system load forecasting

Error types	VMD-BP	VMD-LSTM	VMD-CS-LSTM
MAPE	0.0559871415342	0.0436029994867	0.0372740318083
RMSE	607.188687343	495.864076989	434.878119343
MAE	473.969387546	368.674741446	322.771581492
R2	0.440441832009	0.672835126136	0.753864748353

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Through the analysis of prediction results, we can see that, similar to a single model, the optimized model prediction effect is superior to single model, according to the RMSE and MAPE, prediction accuracy of VMD respectively from high to low - CS - LSTM, VMD LSTM, VMD BP, and the cuckoo volatility smaller algorithm to optimize the model prediction curve, the most close to the actual and estimated values. Compared with the prediction results of the single model, it can be seen that the prediction performance of the optimized model is significantly improved, indicating that the optimization of LSTM model parameters using the cuckoo algorithm can significantly improve the stability and accuracy of short-term load prediction.

5. Conclusion

Aiming at the complex problem of short-term power load forecasting, this paper proposes a short-term load forecasting method based on cuckoo algorithm to optimize LSTM. From the analysis process and simulation results of the optimization algorithm, it can be seen that:

(1) Variational Mode Decomposition (VMD) technique, which can change the constrained problem into a non-constrained problem; The non-recursive and variational problem solving method of VMD has better adaptability and reduces the workload of model building.

(2) LSTM neural network has a unique network structure and strong learning ability for nonlinear data. Cuckoo algorithm can avoid the adverse effects of artificial selection of LSTM model parameters.

(3) The VMD-CS-LSTM prediction model proposed in this paper has a high prediction accuracy in short-term power load prediction, and can also be applied to wind speed prediction, photovoltaic power generation prediction and other fields prediction, which can be further explored and improved.

References

[1] Tang W, Zhong S, Shu J, etal. Research on spatial load forecasting of distribution network based on GRA-LSSVM method[J]. Dianli Xitong Baohu Yu Kongzhi/power System Protection & Control, 2018, 46(24):76-82.

[2] HOU Luting, GAO Junwei. Forecasting of Short-term Load based on LMD and BBO-RBF Model[J]. International Journal of Plant Engineering and Management, 2019,24(02):101-108.

[3] Yanhua Chen, Marius Kloft, Yi Yang, Caihong Li, Lian Li. Mixed kernel based extreme learning machine for electric load forecasting[J]. Neurocomputing, 2018.

[4] Wu Jinran; Wang You-Gan; Tian Yu-Chu. Support vector regression with asymmetric loss for optimal electric load forecasting[J]. Energy Volume 223, 2021.

[5] Lv Shengwei; Liu Gang; Bai Xue. Multifeature pool importance fusion based GBDT (MPIF-GBDT) for short-term electricity load prediction [J]. IOP Conference Series: Earth and Environmental Science, 2021, 702.

[6] X. Sun, J. Kong, Z. Liu. Middle-term power load forecasting model based on kernel principal component analysis and improved neural network [J]. Nanjing Li Gong Daxue Xuebao/ Journal of Nanjing University of Science and Technology, 2018, 42(3):259-265.

[7] A Sujil, Rajesh Kumar, Ramesh C Bansal. FCM Clustering-ANFIS-based PV and wind generation forecasting agent for energy management in a smart microgrid[J]. The Journal of Engineering, 2019, 2019(18).

[8] Lei Tang, Xifan Wang, Xiuli Wang, Chengcheng Shao, Shiyu Liu, Shijun Tian. Long-term electricity consumption forecasting based on expert prediction and fuzzy Bayesian theory[J]. Energy,2019,167.

[9] Jian Wei, Hongtao Zhao. Short-term power load forecasting method of CNN-LSTM based on attention mechanism[J]. Journal of North China Electric Power University, 2021,48(1).