Research on a LSTM Based Method of Forecasting Primary Frequency Modulation of Grid

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Abstract

The increasing scale of power grid and the integration of a large number of new energy sources, the prediction accuracy of FM frequency is limited. In order to quickly and accurately predict the frequency change curve of power system after disturbance. In this paper, a prediction method of primary frequency modulation based on long short-term memory network (LSTM) is proposed. Firstly, this method uses correlation analysis method to analyze various factors affecting frequency fluctuation, and selects strong correlation quantity; then constructs the power grid frequency prediction model based on LSTM recurrent neural network; finally, uses the historical data of a power grid company from 2016 to 2019 as a simulation example to verify the validity of the model. This method can realize the real-time analysis of power grid frequency and provide decision support for power grid to make frequency control strategy after disturbance.

Keywords: Grid, Frequency, LSTM, Data processing

1 Introduction

Frequency is the critical index to reflect operating states of the system and it also is the important parameter that control stable operation of the system in the power system [1]. It is not only related to the economic, safe and stable operation of the power system, but also an important indicator for evaluating the quality of power. Frequency stability refers to the power system's ability to maintain or recover the frequency to the allowable range without frequency collapse after suffering from serious disturbance, resulting in serious generation load imbalance [2-3]. The stability of power system frequency is closely related to the balance of active power in the system. When the system frequency is stable, the active power generated by the unit and the active power consumed by the load are in equilibrium. When the disturbance occurs, the active power balance in the system will be broken, causing the frequency to shift. Once the frequency offset exceeds a certain range and the power control center can't make timely prediction and interference to the disturbance, it is likely to lead to chain failure and system frequency collapse. If the offset is outside the normal range, it may result in the units was cut off and even cause the system frequency to collapse.

Nowadays, with the rapid development of the power grid, Once the line fault occurs, the stability of the power grid frequency will be seriously affected. Moreover, the randomness, intermittence and fluctuation of new energy reduce the power regulation ability of power grid, which makes the power grid system more complex and unstable, and the frequency after disturbance is more likely to collapse. Therefore, it is necessary to predict the frequency change curve of power system after disturbance quickly and accurately, so as to formulate control strategy in time, which plays an important role in improving the safe and stable operation of power grid [4].

At present, there are two kinds of methods for dynamic analysis and prediction of power system frequency at home and abroad: one is the traditional method based on numerical simulation deduction, the other is the new artificial intelligence method based on artificial neural network. The former mainly includes full-state time domain simulation method [5-6] and prediction method based on wide-area measurement data [7]. These methods are mainly based on the pure mathematical theory, according to a large number of numerical calculations to get the frequency curve and frequency index to judge the frequency safety of the system after the disturbance, and whether it will trigger low-frequency load shedding, high-frequency machine cutting and other device actions. However, with the increasing scale of power grid system and the

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increasing demand of users, the traditional methods show the disadvantages of long prediction time and low prediction accuracy. In the new artificial intelligence method, the most typical one is neural network method. In [8], the most common BP neural network is used, but the traditional BP neural network is prone to local optimization during training, which leads to its further research blocked. With the development of research, the single neural network method gradually shows its limitations. Some scholars have proposed an online frequency security evaluation method based on multi-layer limit learning machine (ml-elm) [9], which establishes the nonlinear mapping relationship between input and output through the deep structure, In the bottom-up layer by layer unsupervised training process, the automatic encoder algorithm and regularization coefficient are introduced. The weight matrix between input layer and hidden layer is optimized layer by layer so that ml-elm can effectively represent complex functions and improve prediction accuracy and generalization ability. In recent years, the idea of combining neural network with other algorithms has been adopted by more and more researchers. In [10], combining the deep belief network and the deep neural network, an implementation scheme of frequency response mode prediction and analysis based on the deep belief neural network (DBN-DNN) after large disturbance is proposed, and the frequency prediction process and model based on DBN-DNN are constructed. However, the input characteristic dimension of the extracted prediction model is approximately proportional to the system scale, when facing the super large power system, the input feature dimension is very large, which will result in poor efficiency and accuracy.

Aiming at the computational complexity and prediction accuracy in the frequency prediction process, this paper proposes an LSTM cyclic neural network method to predict the short-term frequency of the entire network after primary frequency modulation. From the perspective of the whole network, the main factors affecting the frequency fluctuation are analyzed, with the disturbance quantity, the disturbance time, the disturbance area, the whole network active, the whole network frequency and the DC delivery as the input feature vector of the model, and three years of historical second level data are used as training set for model training, using the characteristics of the LSTM cyclic neural network, takes the result of the previous unit as the input of the next unit, and uses 20 units as the step size to predict the frequency change trend of the frequency modulation for 60 seconds after the occurrence of the disturbance event.

The rest of this paper is organized as follows. In section 2: introduces the basic structure and principle of LSTM neural network. In section 3: the principle of using LSTM neural network to do frequency prediction is introduced in detail, and then the processing method of power grid data is also introduced, and Pearson coefficient is used to do correlation analysis to select the feature vector needed for model training. In section 4: this section mainly analyzes the experimental results, including the model super parameter adjustment and the comparative evaluation of the prediction results. In section 5: the summary of this paper, as well as the prospect of future work.

2 Long Short-Term Memory

Recurrent Neural Networks (RNN) is a neural network with feedback structure. Its input is not only related to the current network input, the weight of the network, but also related to the network output before the input time. Sepp Hochreiter and Jürgen Schmidhuber proposed a long short-time memory neural network in 1997 [9]. LSTM is a variant of RNN [10] that uses memory cells to overcome the gradient dispersion and gradient explosion problems of RNN, when the number of network layers increases, the subsequent nodes’ perception of the previous nodes becomes weaker, and the phenomenon that the previous information is forgotten over time appears. LSTM mainly solves the problem of data classification. It is applied to natural language translation, image subtitles, speech recognition and so on. It can also be used to simulate multiple input variables perfectly, and to deal with short -term and long-term correlations in time series. Also widely used in time series prediction.

LSTM adds a memory unit dedicated to storing historical information. This is also the main difference from RNN. LSTM neurons can maintain memory in their pipelines to solve sequential and time series problems. The gradient that does not affect its performance disappears. Memory cell structure [11] is shown in Figure 1:

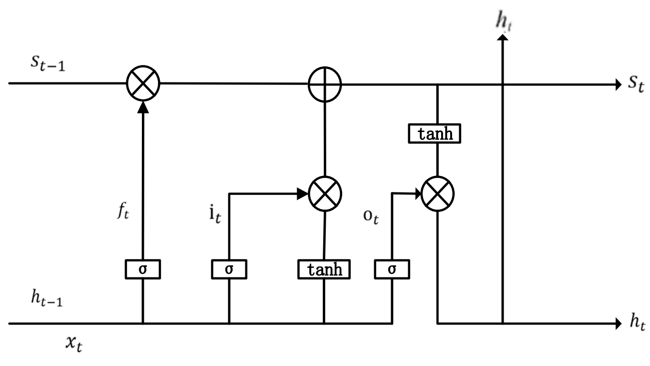

Figure 1. LSTM Memory Unit Structure

The input is the known data, and the output is the predicted data. The output information of the neuron at the previous moment is transmitted to the neuron at the next moment through three gates: input gate, forgetting gate and output gate Input of the gate control information The state information of the last unit of forgetting gate control is reserved, and the output of the information is controlled by the output gate. σ is the activation function, generally relu or sigmoid function, so that the output of forgetting gate is between [0, 1], when the output value of the forgetting gate is 0, indicating that all status information of the previous unit is discarded. When the output value of the forgetting gate is 1, it indicates that the state information of the previous unit is all retained. The detailed process can be expressed by formula (1)-(6) [12].

$$f_t = \sigma(W_{fx}x_i + W_{fh}h_{i-1} + b_f) \quad (1)$$

$$i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i) \quad (2)$$

$$g_t = \sigma(W_{gx}x_t + W_{gh}h_{t-1} + b_g) \quad (3)$$

$$o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o) \quad (4)$$

$$s_t = g_t \cdot x_t + s_{t-1} \cdot f_t \quad (5)$$

$$h_t = \phi(s_t) \cdot o_t \quad (6)$$

Where x_t is the input vector, h_t is the output, i_t is the output of the input gate, f_t is output of the forgetting gate, s_t is the state of the unit, and h_t is the outputof the unit, where W and b represent the paramenter matrix.

3 The Frequency Prediction Model

3.1 Grid Frequency Prediction Principle

The LSTM unit can mine the characteristics and laws of data from historical information. Using LSTM neurons to construct neural networks can help solve nonlinear time series prediction problems [13]. As a complex time series affected by many factors, power grid frequency can be predict-ed by using LSTM model Enter the feature vector Xt of the current disturbance occurrence time and the feature vector Xt-20 ··· Xt-1 of the first 20 seconds of the current time, and use the forgetting gate of the LSTM unit to select the state information in the sliding window. The state preservation information of the previous 20 sets of data plus the feature vector Xt of the current time is the prediction model input, and the next second feature vector Xt+1 at the time T is predicted, and then the sliding window forward sliding continues to predict Xt+2 ···, and so on until the characteristics of the next 60 seconds are predicted. The specific prediction process is show in Figure 2.

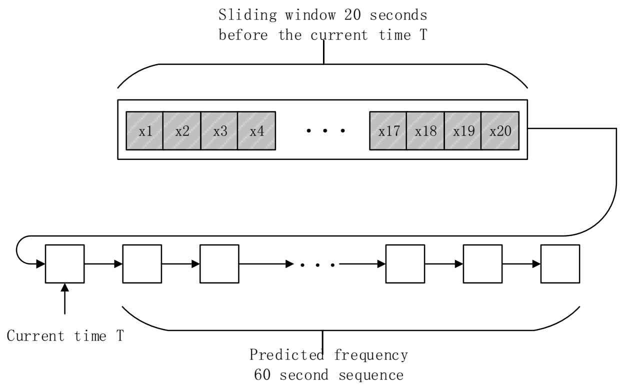

Figure 2. Frequency prediction principle

3.2 Data Processing

The data in this paper comes from a grid system. The data includes the real-time operational data of the unit from 2016 to 2019 and the real-time dynamic data of the whole network. The data acquisition frequency is collected and stored every second, and there will be data loss during the collection and transmission process. The unit shutdown or off-grid will also result in the collection of useless data, so the collected data needs to be preprocessed. Then the preprocessed data is classified according to the capture strategy of the disturbance event, and finally the data set needed to construct the LSTM model is obtained.

3.2.1 Data Preprocessing

Since the data collection and transmission are interfered by various factors, it is necessary to preprocess the collected data to ensure the validity of the data and improve the prediction accuracy of the model. For the missing data, this paper adopts the method of automatic completion, that is, according to the statistical principle, a null value is automatically filled by the data distribution recorded in the data set. In the case of automatic completion of missing data, there are two cases: First, the missing frequency is steady state data, then the median method is used to fill the null value in the frequency steady state range, and the second is the non-steady state data. Then we need to consider the data size before and after the missing data time series to fill in. In this case, the K-means clustering algorithm is used to fill the missing data. The useless data caused by unit shutdown or unit fault are directly deleted, and the training set will affect the accuracy of the model prediction. In this paper, the unit's load value is used to judge whether the unit is running normally, and the relevant data of the unstarted or faulty unit is removed.

3.2.2 Classify Data Based on Disturbance Event Definitions

There are not only effective disturbances in the collected data, but also frequency fluctuations caused by many disturbances. Therefore, it is necessary to filter out the data of effective disturbance events ac-cording to the disturbance time definition. The effective frequency disturbance of the power grid is defined as: within a specified time (called the length of the transition time, generally 10~15s), the grid frequency occurs greater than the set threshold (called the effective disturbance frequency change), and the frequency value after mutation exceeds or is lower than the dead band of primary frequency regulation that specified by the grid, and the duration after the sudden change of frequency exceeds the set value (called the effective duration, generally 20s) [14]. According to formula (7), the grid system disturbance event is selected, and then the disturbance event is screened according to the transition time and the disturbance effective duration in the definition to obtain the large disturbance event data set. Table 1 is the data of the next disturbance event.

Table 1. Disturbance event data

Time	Frequence	Power	DC_Outgoing	Power_Gap	Hydropower	Thermalpower	Event_Type
0	49.9655	85535.83	14150.82	-330	19017.24	44968.2	-1
1	49.9634	85535.83	14150.82	-330	19017.24	44968.2	-1
2	49.9627	85535.83	14150.82	-330	19017.24	44968.2	-1
3	49.9619	85535.83	14150.82	-330	19017.24	44968.2	-1
4	49.961	85535.83	14150.82	-330	19017.24	44968.2	-1
5	49.961	85535.83	14150.82	-330	19017.24	44968.2	-1
6	49.9628	85535.83	14150.82	-330	19017.24	44968.2	-1
7	49.9638	85535.83	14150.82	-330	19017.24	44968.2	-1
8	49.9607	85535.83	14150.82	-330	19017.24	44968.2	-1
9	49.9375	85535.83	14150.82	-330	19017.24	44968.2	-1
10	49.9234	85535.83	14150.82	-330	19017.24	44968.2	-1
…	…	…	…	…	…	…	…
53	49.9564	85535.83	14150.82	-330	19017.24	44968.2	-1
54	49.9567	85535.83	14150.82	-330	19017.24	44968.2	-1
55	49.9556	85535.83	14150.82	-330	19017.24	44968.2	-1
56	49.9553	85535.83	14150.82	-330	19017.24	44968.2	-1
57	49.9562	85535.83	14150.82	-330	19017.24	44968.2	-1
58	49.958	85535.83	14150.82	-330	19017.24	44968.2	-1
59	49.9583	85535.83	14150.82	-330	19017.24	44968.2	-1

$$\begin{cases} |f_{i-1}-f_{ref}| \leq \Delta f \\ |f_i - f_{ref}| \geq \Delta f \\ \vdots \\ |f_{i+N}-f_{ref}| \geq \Delta f \end{cases} \tag{7}$$

Where f_i is the grid frequency exceeding the dead zone of primary frequency regulation, f_{ref} is the standard frequency of China's power grid 50Hz, Δf is the effective disturbance frequency change value 0.07Hz.

3.2.3 Feature Vector Selection

When the power grid is disturbed, the magnitude of disturbance, the location of disturbance and the operation state of the power grid will lead to different changes in the frequency of the power grid system. Pearson correlation coefficient is a method to measure vector similarity. The output range is (-1,1), 0 means no correlation, negative value is negative correlation, positive value is positive correlation. Therefore, Pearson phase is used the influence factors of frequency fluctuation after primary frequency modulation are analyzed [15].

The frequency is the reference eigenvector, and the vectors to be compared are: time, stations, disturbance, instantaneous power of the whole network, DC transmission, thermal power, hydropower, new energy, upregulation capacity of the whole network, down regulation capacity of the whole network, disturbance type and other 11 factors. First, standardize the frequency and other 11 factors, and then analyze the correlation according to formula (8). See the correlation results Table 2.

Table 2. Correlation analysis of factors influencing frequency fluctuation

Target eigenvector	Compare eigenvectors	Relevance
Frequency	Time	-0.7476
	Stations	0.6356
	Disturbance	0.7835
	Power	-0.7693
	DC_outgoing	-0.6691
	Thermalpower	-0.5631
	Hydropower	-0.5094
	New energy	0.4578
	Capacity_up	0.4563
	Capacity_down	0.4789
	Even_type	0.9008

$$\rho(X,Y)=\frac{E[(X-\mu_X)(Y-\mu_X)]}{\sigma_X\sigma_Y}=\frac{E(X-\mu_X)(Y-\mu_X)}{\sqrt{\sum_{i=1}^{n}(X_i-\mu_X)^2\sum_{i=1}^{n}(Y_i-\mu_Y)^2}} \quad (8)$$

Where ρ is used to express Pearson correlation coefficient, E to express mathematical and σ to mathematical expectation, and σ to express standard deviation. The closer the absolute value of ρ is to 1, the greater the correlation between two eigenvectors.

It can be seen that among the 11 factors involved in the correlation analysis, there are eight eigenvectors with absolute correlation value greater than 0.5: time, station, disturbance, instantaneous power of the whole network, DC transmission, thermal power hydropower, disturbance type, etc. The above eight eigenvectors and instantaneous frequency of the whole network when disturbance occurs are selected as the eigenvectors of model input.

3.2.4 Data Standardization and Normalization

Normalization of data is to scale the data to fit into a small specific interval. It is often used in the processing of some comparison and evaluation indicators. The main principle is to remove the unit limit of the data and convert it into a dimensionless pure value, which is convenient for different units or magnitude indicators to be compared and weighted. The most typical one is the normalization of data, the data is uniformly mapped to the interval [0, 1]. After normalization, the convergence speed and accuracy of the model can be improved. Since the steady state frequency of the grid is around 50 Hz but the disturbance wave is only at 0.07Hz Direct training will result in the model's perception of frequency fluctuations being insignificant, so the frequency signature sequence should be normalized and normalized [16].

2.3 LSTM Network Model Construction

In this paper, the TensorFlow deep learning framework is used to establish the LSTM neural network prediction model. The specific process is shown in the figure below. The historical data processing is divided into three data sets, the training set is used for model training, the verification set is used for model hyperparameter adjustment, and the test set is used for predictive performance test after model generation. The model is converged by multiple iterations, and the performance of the model after convergence is evaluated using the test set. If the prediction accuracy is not ideal, the model parameters are adjusted and the results of the parameter adjustment are evaluated using the verification set.

Then get an ideal prediction model through repeated experiments the specific process is shown in Figure 3.

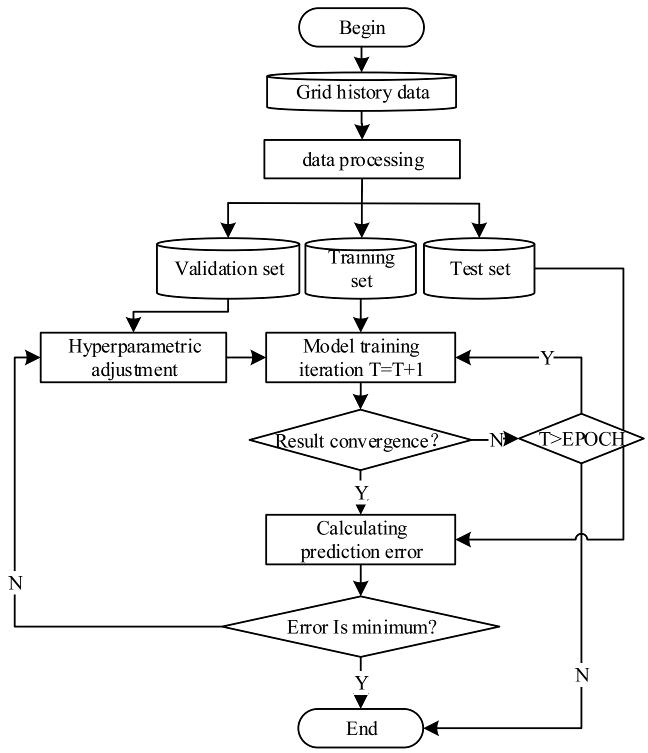

Figure 3. Flow Diagram of Experiment

3.3.1 Model Parameter Settings

The LSTM-based prediction model consists of an input layer, a hidden layer, and an output layer. The most core design is a hidden layer. The model set in this paper contains a layer of LSTM hidden unit. By operating forward, the information of the previous moment is continuously transmitted backwards in the form of memory stream, which affects the processing of each new input data and the output of each stage. The input data contains nine characteristics (time, power, disturbance, frequency, DC de-livery, station, thermal power ratio, hydropower ratio, new energy ratio), so 9 neurons are set. The out-put layer is one for Neurons that predict grid frequency.

3.3.2 Model Hyperparameter Setting

The choice of hidden layer neurons: After the training set is determined, the number of input layer nodes and the number of output layer nodes are determined accordingly. The first problem encountered is how to optimize the number of hidden layer nodes and the number of hidden layers. If the number of hidden layer nodes is too small, the network cannot have the necessary learning ability and information processing ability; on the contrary, if the number of nodes is too large, it will not only greatly increase the complexity of the network structure, the network is more likely to fall into local minimum points in the learning process, and will make the learning speed of the network becomes very slow. This paper first sets the hidden layer with the number of nodes to 10, and reaches the upper limit of 100 with the increment of 10 iteration models. The model prediction performance is compared by the verification set, and the relatively good model network structure is obtained [17-18].

Learning rate selection: Learning rate is a key factor in training in the deep learning model. The learning rate is too low and the convergence speed will be very slow. If the learning rate is too high, the loss value will be unstable when iterating to a certain number of times. So that cannot approach the lowest value. Therefore, the choice of appropriate learning rate needs to be tested continuously. This paper tests through the basic range of learning rate of 0.1, 0.01, 0.001, 0.0001, through continuous adjustment until the appropriate learning rate is found.

4 Experimental Results

This paper uses the historical data of the grid from 2016 to 2019, unit data and grid operation data. There are more than 18,000 pieces of raw data, and more than 16,000 pieces of data can be used after pre-processing of data, of which 1000 pieces of data are used as test sets and the rest of the data in the validation set is used as the training set. Figure 4 shows the trend of Loss worthy of the model training process.

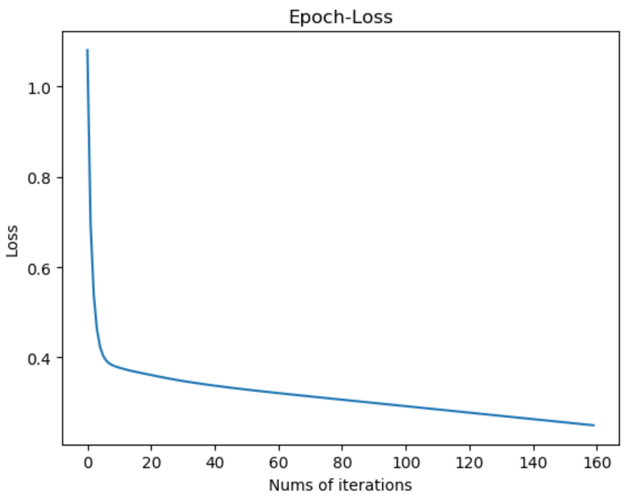

Figure 4. Change trend of loss value in model training

After repeated experiments, the parameters of the model were adjusted. When the parameters of the LSTM network model were adjusted, the prediction error (Acc) was minimized as the goal. Through the above multiple experiments, the model parameters are adjusted to obtain a relatively better.

After repeated experiment many times to adjust the parameters of the model, the parameters of the model of the LSTM network adjustment, the minimum prediction error (acc) as the goal, the experiment is mainly to adjust the number of neurons in hidden layer, training step length (Epoch) vector and, first of all determine whether Loss value repeated horizontal jump if appear this kind of circumstance suggests parameter setting is not appropriate to directly does not consider, in the case of normal Loss value take the acc parameter values. The optimal conditions of Table 3 is a vector in the same case on the number of iterations (Epoch) adjust the Loss value of the change process.

Table 3. Loss values corresponding to different number of neurons prediction model, and the verification set is used for prediction verification

Neurons	Learning Rate	Loss
10	0.0006	0.014594851
20	0.0006	0.0061945776
30	0.0006	0.0026128585
40	0.0006	0.006190795
50	0.0006	0.0029830195
60	0.0006	0.0023794489
70	0.0006	0.0026325902
80	0.0006	0.0025328767
90	0.0006	0.0026676578
100	0.0006	0.0025687685

Figure 5 is a perturbation event of 2019-03-13 23:08:06 using the LSTM prediction model. Comparing the predicted value with the actual value, the total network active power at the time of the event is 94562.578 MW, the whole net-work frequency is 50.115HZ, and the whole network deficiencies are 900MW. The comparison shows that the model has better prediction effect and can better react to a frequency change trend after a disturbance, it can provide reliable support for the grid response to a disturbance decision.

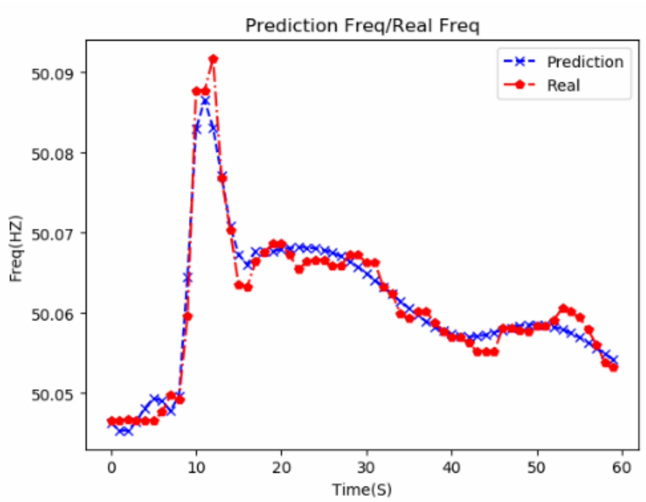

Figure 5. Comparison of predicted results with actual frequency

5 Conclusion

In this paper, a method of power network frequency prediction based on LSTM recurrent neural network is proposed for the prediction of power network frequency after the disturbance of primary frequency modulation. The prediction ability of LSTM recurrent neural network for this kind of time-series nonlinear problem is used, which is also a significant ad-vantage compared with the traditional model. This model not only uses historical data but also uses real-time data in the prediction. The comparison be-tween the measured data and the real data shows that this method has a high prediction accuracy and stability. In the aspect of power grid frequency pre-diction, the model is practical and effective, which provides decision-making basis for automatic response to power grid disturbance. However, this paper only considers some factors that affect the frequency fluctuation of the whole network. In the future work, we should add more factors to do correlation analysis. In the aspect of model super parameter optimization, manual parameter adjustment is carried out in this paper, so it may not be the optimal parameter set. Next, we can use machine learning and LSTM to adjust parameters adaptively to improve the prediction accuracy of the model.

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References

[1] X. Gao, Z. Yan, R. C. Li, C. Q. Shen, *Modern Power Grid Frequency Control Application Technology*, China Electric Power Press, 2010. ISBN: 9787508399294.

[2] P. Kundur, J. Paserba, V. Ajjarapu, G. Andersson, A. Bose, C. Canizares, N. Hatziargyriou, D. Hill, A. Stankovic, C. Taylor, T. V. Cutsem, V. Vittal, Definition and Classification of Power System Stability, *IEEE Transactions on Power Systems*, Vol. 19, No. 3, pp. 1387-1401, August, 2004.

[3] H. D. Sun, Y. Tang, S. Y. Ma, A Commentary on Definition and Classification of Power System Stability, *Power System Technology*, Vol. 30, No. 17, pp.31-35, September 2006.

[4] G. P. Chen, M. J. Li, T. Xu, M. S. Liu, Study on Technical Bottleneck of New Energy Development, *Proceedings of the CSEE*, Vol. 37, No. 1, pp. 20-26, January, 2017.

[5] C. G. Li, Studies on Assessment and Control of Power System Transient Frequency Stability, Master's Thesis, Shandong University, Shandong, China, 2012.

[6] K. T. Liu, *Analysis on Power System Frequency Dynamics and Study on Auto Load-Shedding Control*, Ph.D. Thesis, Southwest Jiaotong University, Chendu, China, 2014.

[7] K. T. Liu, X. R. Wang, Q. B. Bo, Minimum Frequency Prediction of Power System after Disturbance Based on the WAMS Data, *Proceedings of the CSEE*, Vol. 34, No. 13, pp. 2188-2195, May, 2014.

[8] X. B. Li, M. Luo, K. Feng, Comparison of Neural Network Methods for Short-term Load Forecasting, *RELAY*, Vol. 35, No. 6, pp. 49-53, March, 2007.

[9] Y. F. Wen, R. Z. Zhao, Y. Q. Xiao, Z. B. Liu, Frequency Safety Assessment of Power System Based on Multi-layer Extreme Learning Machine, *Automation of Electric Power Systems*, Vol. 43, No.1, pp. 133-140, January, 2019.

[10] Y. Zhang, *Power System Frequency Prediction after Disturbances Based on Deep Learning*, Master's Thesis, Shandong University, Shandong, China, 2018.

[11] S. Hochreiter, J. Schmidhuber, Long Short-Term Memory, *Neural Computation*, Vol. 9, No. 8, pp. 1735-1780, November, 1997.

[12] S. N. Bai, X. L. Shen, PM2.5 Prediction Based on LSTM Recurrent Neural Network, *Computer Applications and Software*, Vol. 36, No. 1, pp. 67-70+104, January, 2019.

[13] S. Srrelekshmy, R. Vinayakumar, E. A. Gopalakrishnanl, K. M. Vijay, K. P. Soman, Stock Price Prediction Using LSTM, RNN and CNN-sliding Window Model, *International Conference on Advances in Computing, Communications and Informatics*, Karnataka, India, 2017, pp.1643-1647.

[14] X. Wang, J. Wu, C. Liu, H. Yang, Y. Du, W. Niu, Exploring LSTM Based Recurrent Neural Network for Failure Time Series Prediction, *Journal of Beijing University of Aeronautics and Astronautics*, Vol. 44, No. 4, pp. 772-784, April, 2018.

[15] Y. Liu, S. Dong, M. Lu, J. Wang, LSTM Based Reserve Prediction for Bank Outlets, *Tsinghua Science and Technology*, Vol. 24, No. 1, pp. 77-85, February, 2019.

[16] W. H. Chen, Z. J. Yan, X. S. Li, M1 FM Function Test and Evaluation of Generation Power Unit, *Jiangsu Electrical Engineering*, Vol. 27, No. 3, pp. 54-56, May, 2008.

[17] W. Wei, X. L. Yang, P. Y. Shen, B. Zhou, Holes Detection in Anisotropic Sensor Nets: Topological Methods, *International Journal of Distributed Sensor Networks*, Vol. 8, No. 10, pp.1-9, October, 2012.

[18] W. Wei, Q. Xu, L. Wang, X. H. Hei, P. Shen, W. Shi, L. Shan, GI/Geom/1 Queue Based on Communication Model for Mesh Networks, *International Journal of Communication Systems*, Vol. 27, No. 11, pp. 3013-3029, November, 2014.

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