Research on Auxiliary RAIM Model Based on Wavelet Neural Network

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Abstract: In the background of wavelet neural wave network, the relevant staff should further use the neural network algorithm to monitor the big data load to ensure that the data load is monitored as closely and correctly as possible, and the monitoring data should be compared to the threshold. If the actual load value is higher than the threshold, it can be regarded as the abnormal load that the platform should clear to ensure the reliability of the large online load data platform connection and improve the detection efficiency.

1. Wavelet Neural Network Overview

From the previous load monitoring state, it can be seen that the online level of the load can not be detected through the communication state between the server and the load. this method is mainly to use the point-to-point network to further evaluate each other in the line. Due to the need of a large number of network resources to support, can not make full use of the existing bandwidth, in order to make up for this deficiency, this paper will focus on the analysis and use of wavelet neural network, combined with wave theory and neural network algorithm to further monitor the actual online load information status of large data platform.

The main function of wavelet neural network (WNN) is to transform the waveform, further segment the signal, and study it in detail from two aspects of scale and translation. Neural network has the characteristics of fault tolerance, self-learning and so on. It combines the position of waveform transformation and the autonomous characteristics of neural network, and synthesizes the advantages of waveform transformation and neural network; at present, this method is very popular, mainly used for data processing and image signaling. compared with the wavelet neural network, this method is of great significance to the optimization and adjustment of complex nonlinear functions.

2. Wavelet Neural Network Principle and Prediction Model

2.1. Principle of Wavelet Neural Network

The main principle of the neural network is to detect the Z error between the experimental simulation exercise output y and the theoretical output X in the output layer, then multiply the Z error to get the deviation of each node and continue to adjust the model parameter. when the deviation of each node meets the default error requirement, the network process is completed [1].

the horizontal neural network prediction model proposed in this paper replaces the activation of neurons with a full-scale analytical wavelength function. the wavelength function is set as a morlet wavelength function, and its expression is shown in formula (1).

Figure 1 Network traffic

2.2. Establishment of Network Traffic Forecasting Model

The basic process of the prediction model is as follows.

First, the proper neural network topology is selected to determine the number of nodes in the hidden layer and the scale and translation parameters of the wave function.

Secondly, generate the simulation data, divide the data generated by the /off model into the training plan and the test set, because of the self-similar flow, we need many simulations when we generate the data, and finally choose the more stable data [2].

Third, training the model, inject traffic data for the training set in the model, and adjust the model parameters according to the received error until the error is reduced to the predetermined target,. Complete the model training.

fourth, input their own similar data packets in the trained model, get the self-adjusting traffic volume of the prediction, repeat the simulation, get the prediction simulation result with the least error, and compare with the similar traffic volume itself, analyze the prediction results of the model [3]. because the absolute error mean (mae) can better reflect the average absolute error of the predicted data packet number and the actual packet number, we select the mae to evaluate the performance of the prediction model of the fluctuation neural network, and its function expression is shown in formula (2).

3. RAIM Model of Load Anomaly Monitoring Technology Based on Wavelet Neural Network

3.1. Introduction

As the horizontal neural network is gradually identified, the relevant models will only increase and decrease. This paper takes the monitoring of large online data portal as the basic research condition, and constructs the RAM model of the nonlinear time series anomaly monitoring technology of horizontal neural network from the point of view of function approximation [4].

Since one calculation may make the data inaccurate, workers can add multiple calculated values to get the average to ensure that the forecast results are correct.

The actual norm for shipment of goods is further defined by ε as well as the difference between m. To ensure that the results are correct, they can be reviewed to clarify their online status and load categories.

3.2. Neural Network Algorithm Validation

In order to further establish the online state of the load and avoid wasting a lot of resources in the pseudo-online loading state, the workers can use the neural network algorithm to evaluate the load condition online, and take the load generated by the model as the input of the neural network on the basis of the prediction model, and use the traffic quantity as the output of the neural network, given the value of the above formula, the prediction value is the main research goal of the neural network algorithm. n) Further assess and identify the connection and communication status of the load in that state based on the baseline position, and, in order to avoid errors as much as possible, use a forward-looking and reversible approach to further assess and differentiate the actual load in that state based on the output of the algorithm [5].

Figure 2 Neural network algorithm validation

4. Example Analysis

to further elucidate the main value of the algorithm in load monitoring, the relevant staff can further detect the main performance of the simulation algorithm using the cloudsim simulation platform and select suitable data samples, including a total of 10000 negatives [6]. The specific steps are as follows: build 10000 sample sets, connect to the data platform, optimize the load state within 1 hour, disconnect the load by the special person, and judge the mainness of the algorithm. Within 1 hour, adjust the actual off-line load. off-line load upper limit is 100, test the mainness of the algorithm. the specific simulation data are shown in figure 1.

as shown in figure 1, the algorithm in this paper can get the actual abnormal load on the platform. in the first 20 minutes, the two lines can overlap, and the installation is very. But within 20-30 minutes, this is a decline situation, so the actual load situation can not be determined. the algorithm can detect the actual drop value of the goods in 30 minutes. in order to further illustrate the benefit of using the algorithm to calculate the data flow, the author compares it with the situation of offline detection, and the main content of sending a signal through the time label in the process of off-line detection is: in the agreed time, the server sends a specific signal to the different load, and the specific worker records the transmission and response of the signal [7]. further define the main connection state of online goods. the practice shows that even if the method can obtain more accurate data, the network information resources are very wasteful, and the large data platform can not use the method. the specific test simulation results are shown in figure 2.

By analyzing figure 2, we are able to understand that when the monitored load increases, the monitoring flow will be increased. if the load quantity reaches 5000, then the actual flow monitored using the time tag calculation is 370 mb, and the actual flow monitored using the algorithm is 180 mb, it can be seen that the former consumes twice the latter [8].

5. Classification of Small and Medium Wave Neural Networks for on-line load anomaly monitoring of big data

There are several types of wavelet neural networks:

(1) Loose combination

The sample data is optimized by wavelet, and the optimized data is regarded as the input signal of the neural network.

(2) Embedded integration

The wavelet transform and the artificial neural network are intersected. the type mainly utilizes wavelet functions to replace the activation function.

6. Application of Wavelet Neural Network in Load Pattern Recognition

A load recognition system based on wavelet neural network is set up to further identify the load species in the power link. Specific methods include.

6.1. Data Acquisition and Feature Extraction

When sampling the A/D, the 12-bit ADL674 is mainly used to obtain the voltage and current signals of the electrical load, and after the acquisition is completed, the specialized workers do the transform Fourier processing to obtain the amplitude of the current 50Hz ,100Hz ,150Hz and voltage 50Hz, which is based on the calculation of the actual total power of these signals load [9].

6.2. Construction of a Wavelet Neural Network Structure

Based on the input eigenvector dimension and the actual state of the circuit, the input and output layer nodes of the network are clearly defined. If the output signal of the circuit is further decomposed by wavelet of layer IV, then the actual input node number of the neural network is IV+1.

6.3. Trained Wavelet Neural Network

Set a specific voltage as well as current signal in advance as an input to the training sample.

6.4. Output of Results for Load Identification

The collected voltage and current signals are taken as the actual sample input, and the load classification is further clarified based on the output results.

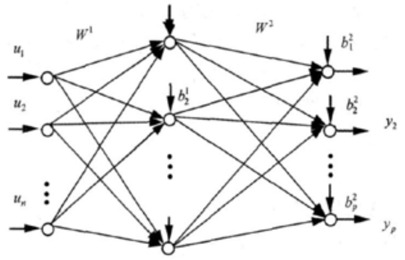

Figure 3 Result output of load identification

7. Summary and Outlook

In the use of large data platforms, staff should be clear: receiving network online goods are vulnerable to bandwidth, computer power and many other factors dry. The staff are required to carry out data exchange between the network platform and the platform to ensure that the platform is in close contact with the platform [10]. In order to avoid the problem of data channel being occupied and excessive waste of resources, the staff should further effectively monitor the network load and make full use of the network load; resources.

With the rapid development of the Internet, network congestion is becoming more and more serious. The main analysis data of the network is generated by the load itself resources, on the basis of this, according to the concrete change of the goods quantity in the foreseeable time period, the cargo forecast model corresponding to the present situation is established, in the period of the load change, the staff should clean up the load condition through the neural network algorithm, and carry on the forward and reverse operation of the load flow, although this kind of data is the important resource of decision-making and analysis, and the bigger the load, the more practical the data is, but your large number of goods connected to the network is undoubtedly a challenge to the stability of the network system [11].

8. Conclusion

In conclusion, waveform conversion is a practical signal analysis tool, which is essential for many working links. It is characterized by strong signalling, popular and plays an important role in many industries. Its main advantage is that it can show the local characteristics of the signal and analyze the non-stationary signal. This method can effectively detect the actual load capacity of big data.

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3) 2015 College level scientific research project "Research on clock deviation prediction model assisted RAIM algorithm based on wavelet neural network theory" ky201504.

References

[1] HILBERTM. Bigdata for development: a review of promises and challenges. Development policy review, vol. 34, no. 1, pp. 13? 174, 2016.

[2] BORGMANC. Bigdata, littledata, nodata: scholarship in the networked world. Journal of the association for information science & Technology, vol. 67, no. 3, pp. 751-753, 2016.

[3] WANGD, SUNZ. Big data analysis and parallel load foreca? ting of electric power user side. Proceedings of the CSEE, vol. 35, no. 3, pp. 52? 537, 2015.

[4] ZHANG P, WUX, WANG X. Shor? termloadforeca? ting based on big data technologies. Journal of Power & Energy Systems, no. 3, pp. 118? 1192, 2015.

[5] GANINY, USTINOVAE, AJAKANH, et al. Domai? adversarial training of neural networks. The Journal of Machine lea? ning research, vol. 17, no. 1, pp. 209? 2100, 2017.

[6] Wang Ya. neural network based image sequence feature point matching. Chinese Journal of Graphics, vol. 7, no. 4, pp. 31? 318, 2002.

[7] WANG Yaming. Feature point matching of image sequences based on neural network. Journal of Image and Graphics, vol. 7, no. 4, pp. 310-318, 2002.

[8] PANDASK, MOHANTYSN, JAGADEVAK. Long term electrical load forecasting: an empirical study across techniques and domains. Indian journal of science and technology, vol. 10, no. 26, pp. 16, 2017.

[9] CHENLG, CHIANGHD, DONGN, et al. Group? based chaos genetic algorithm and no? linear ensemble of neural networks for shor? term loading for forecasting. IET generation transmission & distribution, vol. 10, no. 6, pp. 144-1447, 2016.

[10] Li Rongrong, Niu Lidong, Sun Ji. CloudSim based classification load balancing scheduling model. Computer Measurement and Control, vol. 26, no. 3, pp. 190-199, 2018.

[11] LI Rongrong, NIU Lidong, SUN Jimin. Classificationloadb? lancing scheduling model based on CloudSim. Journal of computer measurement and control, vol. 26, no. 3, pp. 195-199, 2018.