

Research on Intelligent Location Method of Water Supply Pipe Network Burst Based on BP Neural Network Deep Learning

Luohua Wang¹, Mou Lv^{1,a}, Xiaobo Miao¹, Li Li¹, and Fengchao Liang¹

¹School of Environment and Municipal Engineering, Qingdao University of Technology, 266033 Qingdao, China

Abstract. Based on the in-depth analysis of the causes of the large-scale water supply pipe network explosion at home and abroad, the paper discusses the neural network modeling technology for quickly and accurately locating the water pipe network. Furthermore, the remedial measures of the pipe network squib in the field were adopted, and the BP neural network deep learning method was proposed to carry out the intelligent positioning of the water pipe network bursting. Based on the construction of a miniature hydraulic model based on BP neural network analysis, through the correlation analysis of the flow change of 5 positions and the pressure monitoring point change of 17 positions when the pipe network bursts, the artificial neural network deep learning is further used to diagnose the position of the pipe network where the pipe burst is located. In this paper, the small-scale water supply pipe network built by the laboratory is taken as an example to verify the research method of the pipe burst positioning.

1 Current status and detection method of urban water supply pipe bursting

Water is an indispensable part of life, the foundation on which human beings depend and the blood that sustains urban development. Although there is a large amount of water on the earth, only about 2.5% is fresh water, and since most of the water is stored in glaciers or deep groundwater, only a small amount of water is easily available. Urban water supply pipe network often produces pipe bursting accidents due to erosion and aging, surrounding soil deformation, temperature changes and other phenomena. Once a tube burst accident occurs, it may cause the foundation to sink, which in turn affects the safety of the building; At the same time, it will also pollute the water quality of the water supply and endanger the health of the people. Therefore, research on the location of the pipe bursting in the water supply network is imminent. By establishing an online monitoring network of the water supply pipe network, the node flow and water pressure of the water supply pipe network are automatically detected, through the transmission, the real-time flow and water pressure signals of the pipe network can be transmitted to the information management center, so that the operation state of the water supply pipe network can be understood and controlled, and real-time diagnosis of the large-scale water supply pipe network failure can be realized. Li Yanlan[1] proposed two methods for leaking the network of pipelines: the first one uses BP neural network to predict the pressure changes of other nodes based on the monitoring point data, and then determines the missing area through the pressure change contour map; Method 2, In view of the defect that the first

method is easy to fall into the local minimum, the genetic algorithm is used to optimize the neural network to reduce the fixed error. Liu Chang[2] carried out the squib simulation test, and established the squib detection and positioning model by using the differential pressure and flow data. The neural network was used to establish the mapping relationship between the fault point and the "simulation condition", which realized the switching between online detection and manual detection. At the same time, the MSSQL database is integrated into Delphi's visualization platform. On the basis of establishing the SCADA system in the urban pipe network, Huang Tinglin[3] estimates the normal conditions of the pipe network and the squib. The blast characteristic value matrix is established according to the pressure changes before and after, and the fuzzy similarity ratio method is used to find the location of the squib. Zhu Donghai et al.[4] proposed a neural network method for dynamic positioning of explosion points based on water pressure monitoring. However, it is difficult to monitor the pressure of all nodes in the water supply network because it is impossible to monitor the pressure of all nodes. Jiang Chaoyuan et al.[5] used the time difference of the negative pressure wave to propagate to the upstream and downstream and the propagation velocity of the pressure wave inside the pipe, and combined with the flow detection method to locate the leak point.

Although the above research is based on the analysis and research of flow and pressure in the pipe network, the accuracy and speed of diagnosis in the event of tube burst and leakage are significantly increased, but real-time online diagnosis of large pipe network bursts cannot be achieved. Through online monitoring of flow and

^a Corresponding author: Lvmou1@163.com

pressure of water supply pipe network, BP neural network deep learning is used to predict the position of the pipe burst, which can achieve more accurate tube burst positioning.

2 Constructing a simulation model of water pipe bursting

2.1 Experimental theoretical analysis

The urban water supply pipe network bursting accident has a strong randomness. However, whenever a pipe burst occurs, it will cause sudden large flow loss at a certain point in the pipe network, which will result in changes in pressure, flow fluctuations and system conditions of the entire pipe network. The pressure value and flow value of the pipe network are directly related to the pipe burst accident, and become the main input parameters of the pipe burst positioning program. When a pipe burst accident occurs, it will cause loss of pipe network pressure and flow, and there will be sudden changes in the online pressure monitoring point. The multi-layer BP feedforward neural network deep learning method, that is, the error back propagation training method can satisfy a mapping relationship between "pipe network working condition" and "whether or not bursting occurs". In turn, it provides the possibility to predict the pipe burst and the location of the pipe burst in real time. The experimental design of this paper is based on this principle. The laboratory is used to build a successful water supply pipe network simulation experimental platform to conduct experiments, and to study the feasibility of using BP neural network deep learning to predict the pipe burst.



Figure 1. Leakage simulation experiment platform

2.2 Model Construction

As shown in Figure 1, the pipe network simulation experimental platform is a three-layer pipe network model with a height of about 2.7 m. There are two water supply tanks in the platform as simulated water source points, 2 pressurized pipeline centrifugal pumps (flow rate 12.5m³/h, head 12.5m), 4 inlet points, 5 online flow sensors, 17 online pressure sensors and several control valves (which can change the pipe network topology), can adjust the valve and variable frequency water pump

to meet the needs of various experimental conditions. Among them, the 7-segment pipe network is equipped with a faucet to simulate the pipe network blasting point, and each faucet is followed by a water meter, which can realize the simulation analysis of the squib location and the squib leakage amount under various working conditions. Before the simulation experiment, in order to better simulate the pipe burst state, it is necessary to determine the pipe sections, nodes, simulated water source points of the access pipe network, and the working conditions of the lift pump.

3 Burst positioning by deep learning of BP neural network

3.1 Introduction to BP Neural Network

BP artificial neural network is a nonlinear and adaptive information processing system which is developed on the basis of simulating the processing and memory information of brain neural network. It is characterized by the ability to fully approximate arbitrarily complex nonlinear relationships. The input layer, the hidden layer and the output layer are composed, and the hidden layer can be divided into multiple layers, wherein each layer can comprise a plurality of neurons.

3.2 Construction of BP neural network model structure under the condition of tube bursting in water supply network

Experimental scheme: First, the seven simulated squib points of the pipe network model are sorted according to their distance from the water source (1-7), in order to simulate the seven squib states under the same working conditions, the experiment is unchanged in the two pump conditions. The entire pipe network valve opening degree is unchanged. In order to simulate the state of the squib, open the faucet at a 90 degree angle. The experiment is based on the calculation of the forward displacement when the faucet valve is opened, and the pressure and flow change value that is closer and the largest decrease is regarded as the abnormal change value, that is, the squib occurs at this time. The data of the online detection point when each squib point leaks will change due to the change of the fluid operating state in the pipe network. However, the abnormal value of the monitoring point near the squib is larger than other points. According to this feature, a large number of self-learning and analysis through neural networks, that is, a typical pattern classification problem in deep learning of neural networks (the pattern recognition flowchart is shown in Figure 3). Among them, 7 kinds of leakage states are used as the 7 modes of the output layer, and the output is set to 0 without leakage. Accurate positioning of the squib position. The experiment was divided into 8 groups, including 7 groups with bursts at different locations and 1 with no leakage status.

For the online flowmeter and pressure monitoring point number, 17 pressure monitoring points and 5

flowmeters are recorded after the power is turned on, and the data is measured 100 times for each group. Exploring 17 pressure monitoring points and 5 flow meters as the BP network input in which combination is the best effect to simulate the squib.

For the selection of input points, firstly select two points of pressure monitoring points and five flow meters in the first, second and third layers as BP neural network input and input to MATLAB simulation. The result is that the ideal fit is not presented, see Figure 3 and Figure 4. After doing a large number of combined simulations, it is concluded that when the input point is 17 pressure monitoring plus 5 flowmeters, that is, 22 input points, the effect of the tube fitting is most ideal.



Figure 2. Pattern Recognition Flow Chart

3.3 Burst positioning

Using BP neural network deep learning can effectively identify and locate which of the 7 points is the squib point. We extracted 100 sets of 22-dimensional characteristic signals generated in the case of each burst, plus no leakage state, and the signal output of the burst is determined to be 0-8. This neural network is more complicated, so it needs to be set up into a network with two layers of hidden layers. According to the empirical formula, BP network structure is 22-16-7-1 best, that is, the input layer is 22 nodes. The implicit layer is 16 nodes, the hidden layer is 7 nodes, and the output layer is one node. After the construction is successful, we need to train the existing data. There are 800 sets of characteristic signals, from which 700 sets are randomly selected as training data, and 100 sets are used as test data test results. The results are shown in Figures 5 and 6.

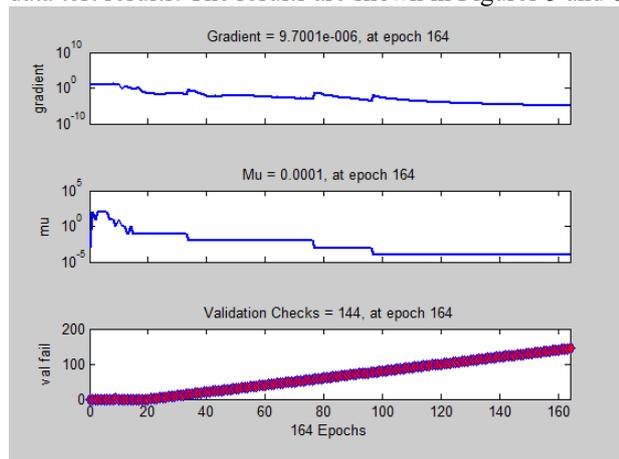


Figure 3. BP neural network training result map

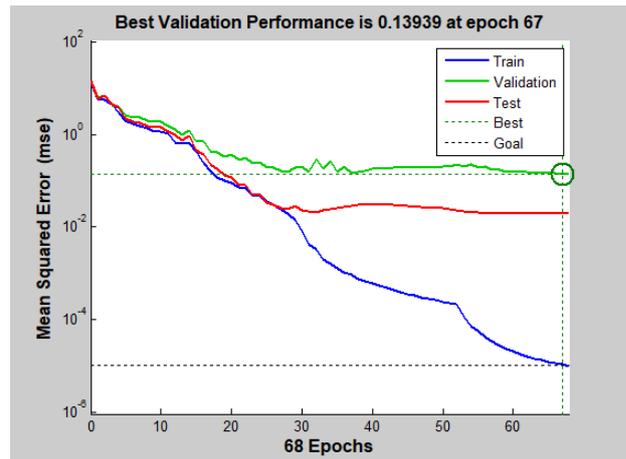


Figure 4. BP neural network training result map

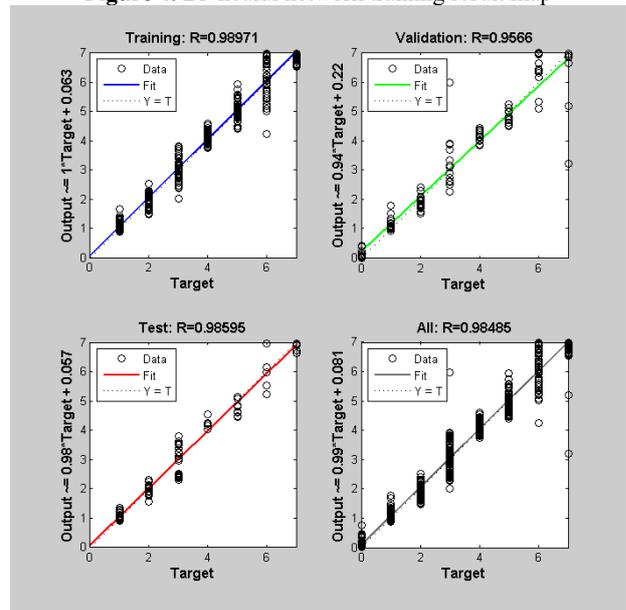


Figure 5. BP neural network training result map

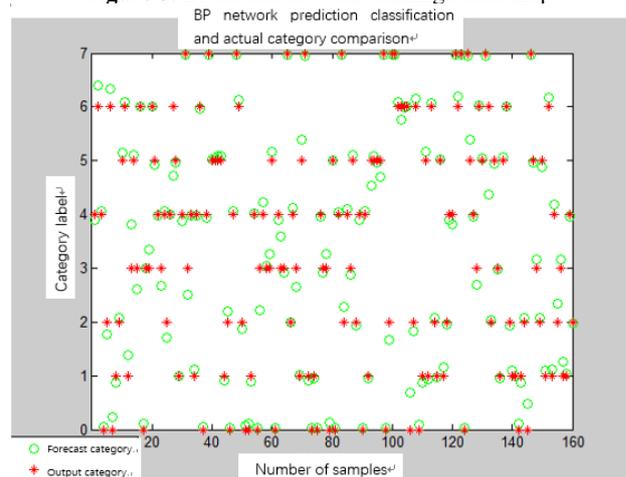


Figure 6. Comparison of BP network prediction and actual results

4 Analysis of experimental results

As can be seen from Figure 6, the BP network training, simulation, and the predicted green value after fitting are basically consistent with the actual results of red. It shows that when the water supply pipe network is

partially destroyed, the fluid state of the whole pipe network will change, and the flow and pressure of each position will change. The state of water flow after bursting at different locations is different. 17 online pressure detections and 5 online flow detections will be different from those at other points, which will result in 8 different water flow states. Under this premise, we can locate the point at which the tube bursts according to the typical pattern classification of BP.

In order to better reflect the accuracy of the experiment, the error analysis bar graph of the prediction and actual results based on the data (see Figure 7) and the positioning error of each missing point (see Table 1), As can be seen from Figure 7, the error is basically maintained at around zero, and the error will be large at individual points, indicating that there is an error in the location of the squib of a certain data during the experiment, which proves that although the prediction ability of the BP network is strong, However, there may be positioning errors, but a large amount of data analysis can still locate the location where the loss occurred; As can be seen from Table 1, the errors at 3 and 6 are large. We find that there are multiple data with excessive deviations between the 3 and 6 points from the predicted data fitting results. It shows that the fitting effect when the two points are missing is not as good as other points, which has a certain relationship with the position and height of the two points. Therefore, in the future research on the loss of two points, the two missing points with large errors should be avoided as much as possible.

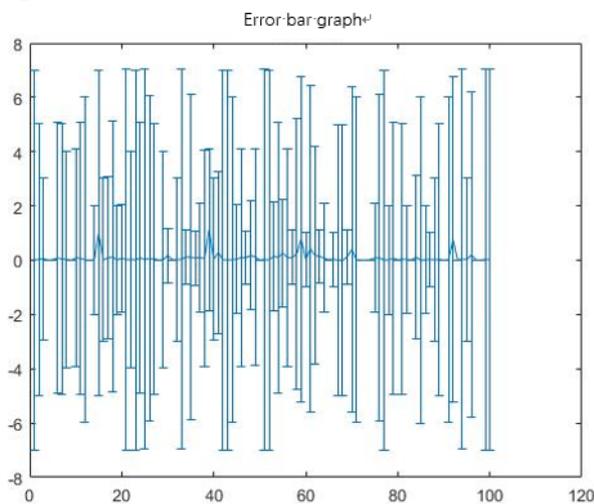


Figure 7. Burst positioning error bar graph

5 Conclusion

This paper proposes to monitor the location of the burst tube by BP artificial neural network deep learning by monitoring the data of 17 pressure monitoring points and 5 flow monitoring points in the water supply network. It is a fast and effective method for real-time diagnosis. Through the analysis and simulation of the actual monitoring data of the water supply pipe network under the blasting state, the hydraulic characteristics of the pipe network before and after the pipe burst occurs, and the preliminary positioning of the squib is achieved, and

the search area of the squib is reduced. Through the theoretical analysis, the blast tube positioning model is established, so that the initial stage of the blast tube is detected and repaired in time.

The single-point bursting tube has a small positioning error, which can provide a theoretical basis for the subsequent two-point and multi-point burst point positioning research. But the application in real life needs to pay attention to is: the hydraulic analysis of the squib state we set is based on the assumption that the user's water consumption does not change. Therefore, in the actual large-scale water supply network, we need to take into account the user's water consumption peak and water consumption, and then find the water use law, and then carry out a large amount of data collection for network training, which will benefit the learning of artificial networks and the diagnosis of squib. This study has a very far-reaching impact on the location of the missing points in the actual pipe network, laying the foundation for the subsequent occurrence of multiple losses.

Table 1. Locating point error

Burst position	Burst error
0	0.025
1	0.0388
2	0.0458
3	0.4278
4	0.0794
5	0.0942
6	0.2859
7	0.0531

Acknowledgment

The National Natural Science Foundation of China (51478230)

References

1. Li Yanlan. Research on Loss and Location of Urban Water Supply Pipeline Network[D]. Guangzhou: South China University of Technology, 2011.
2. Liu Chang, Liu Guoliang. Research on fault location of water supply network[J]. Water Supply Technology, 2010, 4(1): 38-41.
3. Huang Tinglin, CAO Meihua, ZHANG Hui. Research on Real-time Detection of Burst Position Based on Water Supply Network of SCADA System[J]. Water & Wastewater, 2007, 33(5): 104-108.
4. Zhu Donghai, Zhang Tuqiao, Mao Genhai, Research on Neural Network Model of Dynamic Location of Fire Tubes in Urban Water Supply Network, Journal of Hydraulic Engineering, 2000, (5): 1~5
5. Jiang Chaoyuan, Cao Xiaoli, Gan Siyuan, GSM/GPRS-based metropolitanized network

leakage monitoring and location system, Journal of
Chongqing University, 2005, 28(4): 56~59