Detection of two simultaneous leakages in water distribution network using hybrid feedforward artificial neural networks

Hamideh Fallahi [1], Mohammad Reza Jalili Ghazizadeh [2*], Babak Aminnejad [3], Jafar Yazdi [4]

[1] Ph.D. Student, Department of Civil Engineering, Roudehen Branch, Islamic Azad University, Roudehen, Iran

[2] Associate Professor, Faculty of Civil, Water and Environmental Engineering, Shahid Beheshti University, Tehran, Iran

[3] Assistant Professor, Department of Civil Engineering, Roudehen Branch, Islamic Azad University, Roudehen, Iran

[4] Assistant Professor, Faculty of Civil, Water and Environmental Engineering, Shahid Beheshti University, Tehran, Iran

ABSTRACT

Leakage is one of the main challenges in the operation of water distribution networks. In the present study, leakage is detected using Feedforward Artificial Neural Networks (ANNs). For this purpose, two scenarios are considered for training the ANNs. In the first scenario, two simultaneous leakages with equal values, and in the second scenario, two simultaneous unequal leakages are applied to each pair-node of a network. The training data are analyzed by EPANET2.0 hydraulic simulation software linked with the MATLAB programming language. In both scenarios, first, ANNs are trained using flow rates of total pipes number. Then, sensitivity analysis is performed by Hybrid ANNs for the flow rates of different percent of pipes numbers. The results of the proposed Hybrid ANNs indicate that in the first scenario, by having the flow rates of 10% of the total pipes, the locations of two simultaneous leakages are successfully determined. However, for the second scenario, while the difference between the two leakages is less than 80% of the maximum leakage (up to ratio value of 10 and 90 % leakages), by having 10% of the total pipes flow rates, the locations of the two leakages are still successfully determined. However, for larger differences, only the location of the bigger leak could be detected. Despite the complexities of the second scenario, the proposed ANNs could successfully detect the location of the bigger leakage.

KEYWORDS

Leakage detection, Feedforward artificial neural network, Discharge, EPANET2.0, Water distribution networks

* Corresponding Author: Email: m_jalili@sbu.ac.ir

1. Introduction

Reducing the amount of leakage in water distribution networks (WDNs) can be considered as one of the main goals of drinking water supply utilities. Some practical methods for detecting the leakage are acoustic sensors, Inverse Transient Analysis methods, numerical methods, and methods based on computational intelligence [1]. The leakage detection is investigated by: Wachala et al. [2] using the group of neuro-fuzzy classifiers, Attari et al. [3] using the combination of pressure and flow metering by ANNs[1], Kang et al. [4] based on convolutional neural network and a support vector machine, and Fallahi et al. [5] using feedforward artificial neural network in 24-hours a day. This study proposes a new methodology to locate up to two simultaneous leakages in WDNs using feedforward ANNs.

2. Methodology

2.1. ANN Training

Using feedforward neural networks and the WDN proposed by Poulakis et al. [6], the ANNs were trained. The training parameters were determined by EPANET2.0 hydraulic simulation software using MATLAB programming language. First, two simultaneous leakages were applied to two nodes as the output values of the ANN training dataset. Then, the pipes' flow was obtained by the EPANET2.0 as the inputs of the ANN training dataset. The multi-layer perceptron (MLP) was used for the function fitting of ANN in this study. Trainlm was utilized as the training function that updates weight and bias values according to Levenberg-Marquardt optimization.

2.2. First scenario: two simultaneous leakages with equal values

The average daily water demand at each node was considered 20 l/s, and the total water demand was 600 l/s. Also, the maximum leakage value was assumed 1% of total water demand (6 l/s). In this scenario, 50% of the maximum leakage is assigned to two selected nodes (each node 3l/s). Finally, the "Leakage matrix (30×435)" was produced as the output of ANN training. By entering this matrix into EPANET2.0 software, "Pipes Flow Matrix (50×435)" was produced as the input of ANN training. After that, the ANN was trained. The steps of ANN training are demonstrated in Figure 1.

[1] Artificial neural networks

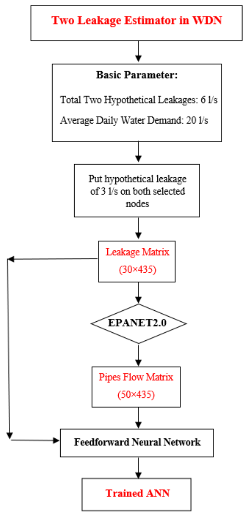

Figure 1. Proposed flow chart for leakage detection

2.3. Second scenario: two simultaneous leakages with unequal values

The main goal in this scenario was the non-uniform distribution of leakage between the two selected nodes, as shown in Table 1. In this scenario, 4 "Leakage Matrix (30×870)" and 4 "Pipes Flow Matrix (50×870)" were produced.

Table 1: Leakage distribution relative to maximum leakage in both selected nodes

Leak Group	First		Second		Third		Forth	
State	1	2	3	4	5	6	7	8
First Node	60%	40%	70%	30%	80%	20%	90%	10%
Second Node	40%	60%	30%	70%	20%	80%	10%	90%
Leakage Matrix (30×870)	40-60		30-70		20-80		10-90	

3. Discussion and Results

In the present study, to investigate the ANN's behavior, the Relative Leakage Error (RLE) is defined as:

$$RLE_i(\%) = \frac{CLD_{ANN_i} - HLD_i}{HLD_i} \times 100 \qquad (1)$$

RLE: Relative Leakage Error, CLD_{ANN}: Calculated Leakage and Demand by ANN, HLD: a total of leakage and demand, *i*: number of junctions, $i=1,2,\ldots,30$. Using Eq. (1), the *RLE* is calculated for the total nodes as the RLE Matrix in both scenarios. The results show that the first maximum (*RLEmax1*) and the second maximum (*RLEmax2*) value of each column of the RLE matrices indicate the position of the two leakages (in both scenarios). The optimal number of neurons in the hidden layer can find based on the maximum of the RLE (MaxRLE). The results illustrate the 40 as the optimal neuron number for both scenarios. Figure 2 shows the result of scenario 1.

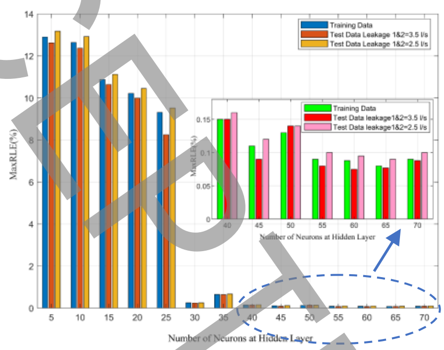

Figure 2. The number of neurons at the hidden layer

Considering 40 as the optimal neurons, the *RLEmax1* and *RLEmax2* for one of the leakage groups of the second scenario are shown in Figure 3.

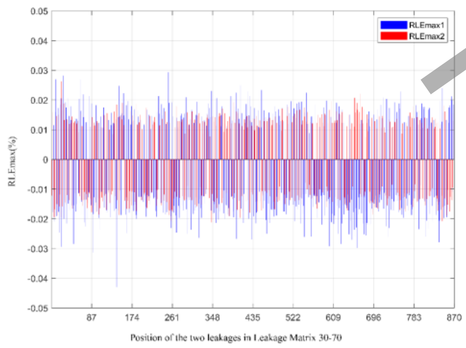

Figure 3. *RLEmax* versus two simultaneous leakages

In the previous section, the ANN was trained by considering flow rates of 100% of pipes number (50 pipes). For detecting the leakage location with a minimum number of pipes, the sensitivity analysis is performed by Hybrid ANNs for the flow rates of 2%, 4%, 6%, 8%, 10%, 20%, …,90% of the number of the total pipe. Figure 4 illustrates the flowchart of constructing the Hybrid ANNs. The results show that the proposed Hybrid ANNs has successfully detected the leakage location for the first scenario and also the leakage group 40-60, 30-70, and 20-80 of the second scenario. These results are obtained by the measured flow rates of 10% of the total pipes (five pipes). While the difference between the two leakages is larger than 80% of the maximum leakage, only the location of the bigger leakage could be detected.

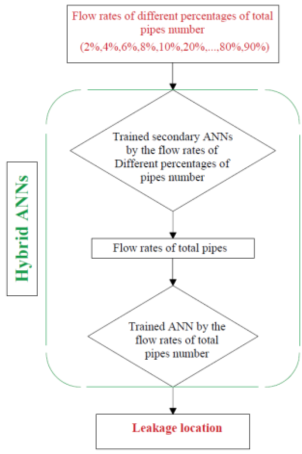

Figure 4. Flowchart of constructing the Hybrid ANNs

4. Conclusions

The accuracy of trained neural networks with total pipe flow was less than 0.2% for the first scenario and less than 0.05% for the second scenario. The sensitivity analysis was performed by Hybrid ANNs for the fewer pipe numbers with known flow rates. The obtained results indicate the promising applicability of the proposed methodology for finding leakage location in water distribution networks.

5. References

[1] Attari, M., & F.Maghrebi, M., 2018. “A new method of leak detection using artificial neural networks.” Journal of water and wastewater, 29(1), pp 14-26 (In Persian).

[2] Fallahi, H., Jalili Ghazizadeh, M.R., Aminnejad, B., & Yazdi, Y., 2021. “Leakage detection in water distribution networks using hybrid feedforward artificial neural networks.” Journal of Water Supply: Research and Technology-Aqua, 70(5) 637-653.

[3] Kang J., Park Y. J., Lee J., Wang S. H. & Eom D.S., 2018. “Novel leakage detection by ensemble CNN-SVM and graph-based localization in water distribution systems.” IEEE Trans. Ind. Electron, 65(5),4279-4289.

[4] Poulakis Z., Valougeorgis D. & Papadimitriou C., 2003. “Leakage detection in water pipe networks using a Bayesian probabilistic framework.” Probabilistic Engineering Mechanics, 18, 315-327.

[5] Wachla D., Przystalka P., & Moczulski, W. 2015.” A method of leakage location in water distribution networks using artificial neuro-fuzzy system”. IFAC-PapersOnLine, 48(21), pp 1216-1223.

[6] Yan, Y., Wang, L., Wang, T., Wang, X., Hu, Y., & Duan, Q., 2018. “Application of soft computing techniques to multiphase flow measurement: A review”. Flow Measurement and Instrumentation, 60, pp 30-43.