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Determining the Amount and Location of Leakage in Water Supply Networks Using a Neural Network Improved by the Bat Optimization Algorithm

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ABSTRACT: At present, water waste has become a global concern. On the other hand, the amount of sweet water on the earth is fixed and limited but the demand for water is increasing. This, more than ever before, makes it necessary to modify the consumption pattern. One of the most important consumption management activities is to decrease the uncounted water. Water leakage not only results in loss of good-quality water resources, but also pollutes the drinking water and in its worst form brings about serious damages to people and building around the point of leakage. In this paper, a model is presented for determining the amount and location of leakage in water supply networks. In this model which uses a neural network improved by the bat optimization algorithm, the amount and location of leakage in the network is determined by the minimum number of pressure-measuring. The proposed model is applied on the Poulakis network when several simultaneous leakages have occurred, and the accuracy of the model is verified by the results.

Keywords: Leakage Detection, Barometers Placement, Neural Network, Bat Algorithm.

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INTRODUCTION

During the last several decades, international organizations and advanced countries have paid a great attention to the problem of limited water resources and have made a great effort to find solutions for water shortage and particularly to prevent water loss. In the last three decades, the problem of uncounted water and leakage in water supply systems and urban water distribution networks is one of the subjects that have attracted the attention of many countries, and many valuable experiences have been obtained in the domain of its theoretical discussions and practical solutions for decreasing it. Decreasing water loss in water supply networks requires being aware of the amount and components of loss, the reasons of its occurrence, and methods and priorities in fighting each component. In the next stage, determining the locations of risky points from leakage point of view, maintenance, and reconstruction and renovation of the network are of interest.

Several factors are involved in the occurrence of water leakage. These factors include the age, diameter and material of the pipes, water hammering, and pressure in the network (Jing et al., 2012; Li et al., 2011; Chen et al., 2013; Marunga et al., 2006; Nicolini et al., 2011; and Berardi et al., 2007). In this paper, the factor of pressure is used for determining the location and amount of the leakage in the network.

Many researchers have worked on leakage detection. For example, in (Prodon et al., 2010), leakage detection in Lausanne is carried out by using sonic detection systems. Needing many detection devices and being costly are the disadvantages of this method. Also, this method is only capable of determining the location of leakage and it cannot determine the amount of leakage. In (Perez et al., 2011), leakage detection is carried out by sensitivity analysis of pressure. If the barometers are not optimally distributed or the demand in the network is not estimated accurately, the error of this approach is high. Also, in (Marunga et al., 2006), an effort is made to decrease the amount of leakage by controlling the pressure. However, in these approaches, when a leakage occurs, the location and amount of leakage could not be determined.

In this paper, a model is proposed for determining the location and amount of leakage. In this model, an algorithm is presented for placement of barometers. The results show that although the amount of leakage is not accurately determined by placing the first barometer in the network, but the locations of leaky nodes could be determined in a fairly proper way, and increasing the number of pressure-measuring, is aimed at increasing the accuracy of the solutions. Therefore, for different permutations of the leakage in the network nodes, the amount and location of the leakage could be determined with minimum number of pressure-measuring.

Neural networks are used in this method of leakage detection. Neural networks are capable of extracting the nonlinear relationships between the input variables by learning from training data (Aghaebrahimi et al. 2013). Selecting appropriate data is one of the factors that can improve the learning of neural networks. In this paper, based on the mutual pressure, the different states of the location and amount of leakage are taught to the neural network.

The back propagation (BP) algorithm is one of the common techniques that are used to train the neural networks which are based on gradient descent or continuous gradient descent (Rumelhart et al., 1986). However, this algorithm is slow and sensitive to the initial guess and might get stuck in local minimums. Therefore, in this paper, the intelligent bat algorithm is used as an optimization tool for improving the training process of the network. The proposed model is applied on Poulakis network for different states of the location and amount of leakage. Then, the results are compared with those of the conventional neural network (which their training is based on gradient methods). This comparison reveals the high accuracy of the model.

The remainder of this paper is organized as follows: determining the total amount of the leakage in the network is discussed in section 2. The proposed model is presented in section 3. Also, in section 4, the numerical results of simulations are presented. Finally, section 5 concludes and terminates the paper.

Determining the Total Leakage In The Network

The total leakage could be calculated by using the pressure of the network. For example, Fig. 1 shows the network of Poulakis et al. (2003). The pressure decreases nonlinearly with the increase of the leakage in the network. But within a small range -which in this paper stretches from zero up to three times the amount of nodal consumption investigated- linear changes are observed in the pressure. This is shown in Figure 2. If the variations of the leakage is investigated in a wider range, the relationship between the leakage and pressure will be a nonlinear one.

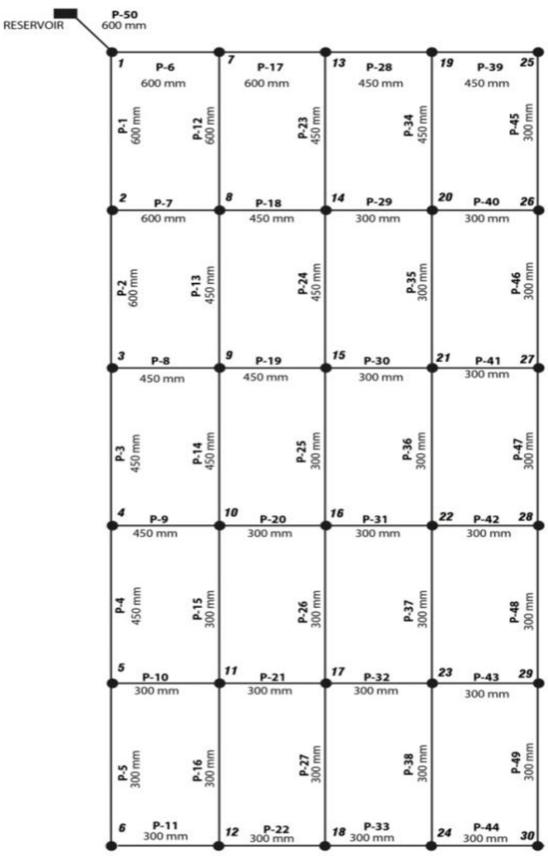

Figure 1. Poulakis network

Generally, for a fixed amount of leakage, the values of nodal pressures change with the change in the location of the leakage, except for the node connected to the reservoir, where the pressure only depends on the amount of leakage and does not depend on the location of leakage or the number of leaky nodes.

It should be noted that this could be true only if the reservoir is directly connected to the network through a single node. Therefore, only measuring the pressure in the node that is connected to the reservoir (node 1) is enough for determining the accurate amount of the total leakage in the network under study. The total leakage in the network can be determined by measuring the pressure in node (1). In order to do this, for different leakages, the values of pressure in the node that is connected to the reservoir (i.e. node 1) is calculated by using the *EPANET2.0* software.

Now if the pressure in node (1) is measured on a system that is calibrated in real world, the total loss could simply be determined.

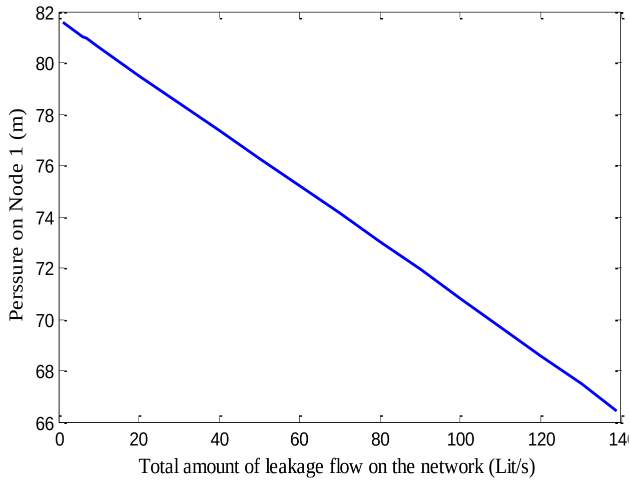

Figure 2. Pressure on node 1

MATERIAL AND METHODS

Proposed model

The model proposed in this paper uses the improved bat algorithm-based neural network. This model is applied on the network of Poulakis and his colleagues. The proposed model which is shown in Fig. 3 is composed of the following parts:

1- Generating the proper training data: The total leakage in the network could be created by one, or two or several simultaneous leakages in different nodes which create the different permutations for generating the training data of the network. The data of location and amount of the leakage in different nodes are used for training the neural network. The number of vectors which could be considered as the input of the neural network is calculated by the following formula:

$$\text{The total number of permutations}=\binom{N}{M} \qquad (1)$$

where,

N is the number of nodes and M is the number of simultaneous leakages occurred in the network.

In this paper, the different combination of the location and amount of the leakage are taught to the neural network, based on mutual pressure.

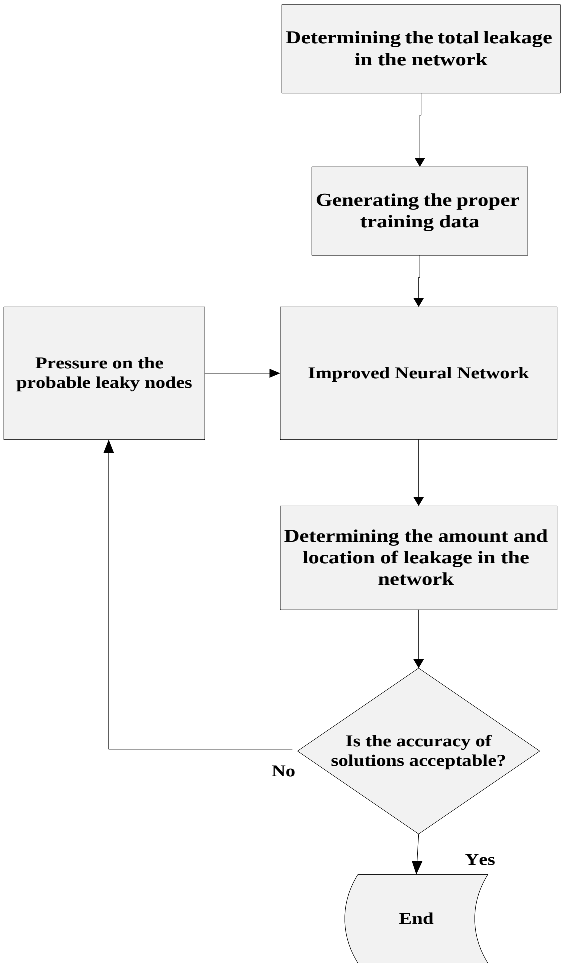

Figure 3. The proposed model

2- Neural Network: Multilayer feed-forward neural network is one of the most commonly used networks in various applications. In this paper, a multi-layer feed-forward network is applied for determining the amount and location of leakage in water supply networks. The calculation of weight adjustment for a given neuron is denoted as:

$$\Delta W(t+1) = \mu \times \Delta W(t) + (1-\mu) \times \delta \times u(t) \qquad (2)$$

Where

μ is the momentum, $\Delta W(t)$ is the previous weight change, δ is an associated error term, and $u(t)$ is the input to the neuron (Vahidinasab et al., 2008).

A neural network uses a learning function to modify the variable connection weights at the inputs of each processing element according to some neural based algorithm. Multiple layers of neurons with nonlinear activation functions allow the network to learn linear and nonlinear relationships between the input and the output of the network. The training process in our network requires a set of examples to make proper network behavior. Hence, the network can be trained for function approximation. Through the training process, the weights and biases are taken to be a dimension in space and updated iteratively to minimize the error function to find the lowest point in this multi-dimensional surface.

The perceptron training algorithm is a form of supervised learning algorithm where the weights and biases are updated to reduce errors whenever the network output does not match the desired values. Based on the principle mentioned above, real number coding is used in this paper. Each weight is represented by a real number. All the weights in a network are represented by a group of real numbers. The weights connected with the same hidden node are put together. On the other hand, the BAT Algorithm (BA) is one of the recently introduced metaheuristic algorithms. This algorithm is highly efficient in solving nonlinear optimization problems and is equipped with the self-adaptive learning approach in order to create diversity in increasing the population and modification of the convergence criteria. Therefore, this algorithm is used for optimizing the learning parameters of the neural network which is described as follows:

- **BAT algorithm**

Bat Algorithm (BA), developed in 2010 by Xing-She Yang, is one of the latest optimization algorithms which imitates microbat's echolocation behavior.

Bats are interesting animals. They are the only mammals which fly and also have advanced capability of echolocation. Most bats use short, frequency-modulated signals to discover their environment. Microbat is a famous example through all the species which uses echolocation extensively. These bats emit a very loud sound pulse and listen to the resulting echo that bounces back from the surrounding objects. For the sake of simplicity, the following idealized rules are used to develop this algorithm:

All microbats use echolocation to determine distance, and they also can recognize the difference between echoes of prey/food and other objects.

Microbats fly randomly with a constant frequency f_{min} with velocity v_i at position p_i, varying wavelength λ and loudness R to search for food/prey. They can automatically adjust the frequency of their emitted pulses and the rate of pulse emission $r \in [0, 1]$, depending on the proximity of their target.

According to the aforementioned rules, a given virtual bat i in a d-dimensional search space, has a position as p_i, and velocity as v_i which should be update in each algorithm iteration as follows:

$$f_i = f_{\min} + (f_{\max} - f_{\min})\beta \qquad (3)$$

$$v_i^{\tau+1} = v_i^{\tau} + \left(p_i^{\tau} - p_*\right) f_i \qquad (4)$$

$$p_i^{\tau+1} = p_i^{\tau} + v_i^{\tau} \qquad (5)$$

where $\beta \in [0\ 1]$ is a random vector used for a uniform distribution, and τ is the iteration counter. In (4) p_* is the current global best location which is located after comparing all the locations among all the n virtual bats at each iteration. Moreover, for the local search, a new solution for each bat is generated locally using random walk around the current best solutions:

$$p_{new} = p_{old} + \varepsilon R^{\tau} \qquad (6)$$

where ε is a random number in $[-1, 1]$ to restrict the local search and $p^{\tau} = \langle p_i^{\tau} \rangle$ is defined as the average loudness of all bats in iteration τ.

Furthermore, in each iteration, loudness R_i and pulse rate r will be update as follows:

$$R_i^{\tau+1} = \alpha R_i^{\tau} \qquad \forall\ 0 \le \alpha \le 1 \qquad (7)$$

$$r_i = \left[1 - \exp(-\gamma\tau)\right] \qquad \forall\ \gamma \ge 0 \qquad (8)$$

According to (8) it is obvious that $r \in [0, 1]$. Fig. 4 shows general steps of the standard BA.

Regardless of what type of algorithm to be used, firstly the related cost function of weights optimization should be extracted. So, to find the solution, a row vector of real numbers (called in this article as: A variable) is defined. Actually, this variable is one of the population matrix rows which contain neural network weights. Hence, a function is formed according to its number of layers and neurons in each layer which its main task is to create the network. After the network creation, the assessment phase based on different values of variables is started. Finally, assuming a weight function, by adding input values, the output is simulated; subsequently, the *MSE* is obtained by subtracting the network output and the actual output and is stored as a cost function *MSE* is defined as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Act.Lak(i) - For.Lak(i))^2 \qquad (9)$$

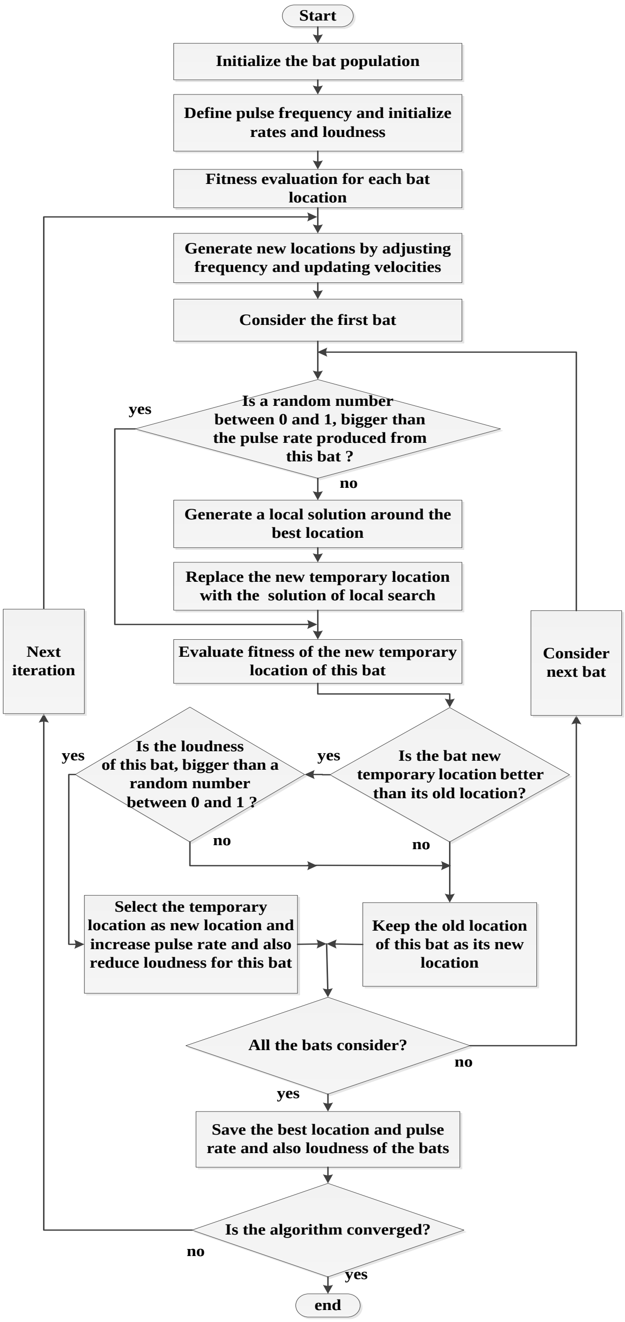

Figure 4. Bat algorithm flow chart

3- Optimum barometer placement

Once the neural network is trained, the pressure of one or several nodes of the network is fed to the system as an input so that the location and amount of the leakage is obtained. Determining the locations of pressure measurements in the network is of great importance. Therefore, if a wrong node is selected for pressure measurement, proper solutions will not be achieved while, if the nodes are properly selected for measurement, it could be expected that the best solutions will be obtained with minimum number of barometers. In other words, after training, the factor which causes the model to obtain desirable solutions is the proper selection of nodes for pressure measurement.

3-1- How to select the location of the first barometer?

Assuming that the amount of leakage in the network is fixed, the pressure in the node that is connected or close to the reservoir will nearly be fixed for different permutations of the leakages. For example, if the total leakage in Poulakis network is assumed to be 50 liters/second, the curve of pressure variations in nodes (1) and (2) for different permutations and for two leakages of 25 liters/second will be as shown in Fig. 5. While, for different permutations of the leakages, the pressure of nodes that are located far from the reservoir has more fluctuations in comparison to pressure of the nodes that are close to the reservoir. Fig.5 shows the fluctuations of the pressure of node (6) which is located far from the reservoir. Therefore, the first pressure measurements must be carried out in the nodes that are far from the reservoir because they have different pressures for each different combination of the leakages. Thus, the pressure of the node that is far from the reservoir is applied to the trained neural network as the first input in order to obtain the amount of leakage in other nodes. The nodes with highest leakage are selected as the probable leaky nodes.

3-2- How to select proper places for other barometers

In this stage, placement of barometers is carried out step by step in probable leaky nodes. In each step, the barometers must be placed in probable leaky nodes and as an input, their location must be applied to the trained neural network. The different steps of selecting minimum number of barometers are summarized as follows:

- **The first step**: Determining the amount and location of leakage in the network by applying the pressure of a node far from the reservoir to the trained neural network.
- **The second step**: Selecting the next barometer among *P%* of the nodes with maximum leakage.
- **The third step**: Applying the pressures obtained from the first and the second step to the trained neural network and determining the new amount and location of the leakage in the network .
- **The forth step**: The nodes whose leakage is zero or close to zero are removed from the set of probable leaky nodes.
- **The fifth step**: The nodes that have an increasing rate of leakage are added to the set of probable leaky nodes.

- **The sixth step**: Repeating the seconds step until the amount and location of the leakage in the network is determined.
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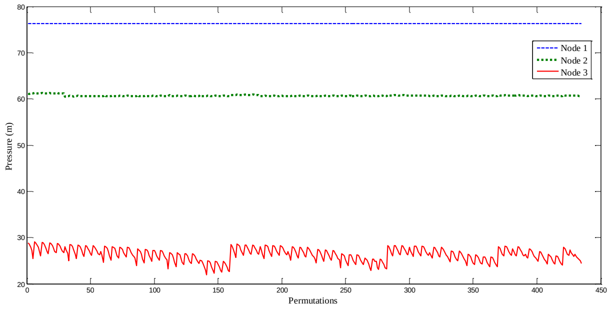

Figure 5. Pressure variation in Nodes 1, 2 and 3

RESULTS

In this paper, the proposed model is used for determining the amount and location of the leakage in Poulakis network with minimum number of pressure measurements for different permutations of leakages. 975 vectors that contain the amount and location of different leakages are applied to the improved neural network, based on mutual pressure. In this model the bat evolutionary algorithm is used to train the neural network. It should be mentioned that the cost function in this case is the *MSE* index. Fig. 6 shows the convergence of this function during the training of the neural network when there are two 25-liter leakages in nodes (1) and (2), and the total leakage in the network is equal to 50 liters (Test I).

In this paper, the bat algorithm has 50 bats, also the baud rate of transmitted pulse (*r*) is selected as 0.1 for the first population, and it progressively increases for the next iterations. The loudness of the voice (*R*) is selected as 0.9 and finally f_{min} and f_{max} are selected as 0 and 2, respectively.

In this paper, 30 % of the nodes that had the highest leakage in the output on the neural network were considered as the probable leaky nodes. This simulation is carried out on a Dual Core 2.3 GHz processor, and the time spent for calculations is less than 5 minutes.

In order to investigate the effectiveness of the proposed model, when the pressure in a node is equal to that of 76.28 meters of water column, the network is tested for different permutations of the leakage. Table 1 compares the results obtained by using the proposed model with those of the conventional neural networks (the trainings of which are based on gradient decent approaches).

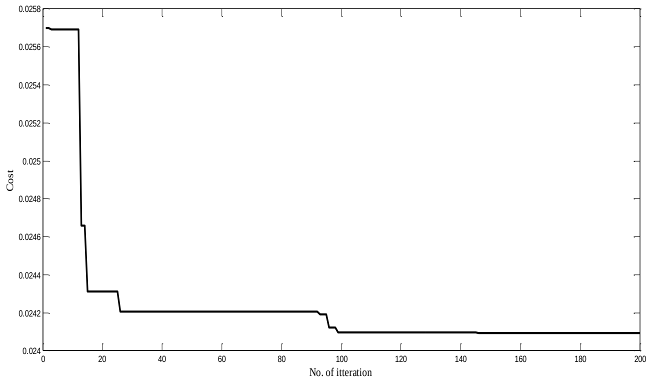

Figure 6. Trajectories of the best solution for BA

Table 1. Comparison of the results obtained by using the proposed model with conventional neural networks (the total leakage in the network is equal to 50 liters)

			Conventional Neural Network			Proposed Model		
	Position of Leakage	Amount of Leakage	Position of minimum number of pressure measurements	Amount of forecasted leakage	Mean Percentage Error in each Test	Position of minimum number of pressure measurements	Amount of forecasted leakage	Mean Percentage Error in each Test
Test I	1	25	6-7-8-9-10	20.3	17.2 %	6-7-8-9	23.6	5.2 %
	2	25		21.1			26.2	
Test II	12	4	6-11-22-24	5.8	27.5 %	6-14-25	4.7	9.9 %
	25	46		41.4			44.9	
Test III	3	12.5	6-5-12-22-26	14.4	17 %	6-11-19-20	10.9	10.2 %
	4	12.5		9.9			11.2	
	5	12.5		10.7			11.4	
	6	12.5		14.7			13.6	

As it is observed, with minimum number of pressure measurements, the proposed model has been able to obtain the amount and location of the leakage more accurately than conventional neural networks, and this is done with an acceptable level of accuracy only with 3 or 4 pressure measurements. The proposed model is capable of determining the location and amount of the leakage for different permutations of the leakages. While, increasing the training data is an effective way for improving the output of the model.

CONCLUSION

Controlling the leakage in water distribution networks, in addition to preventing the waste of water, prevents the pollution of drinking water and decreases

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severe damages to people and building around the leakage. In most of the researches on leakage detection in water supply networks, the approximate location has been determined while the accurate amount of the leakage has not been determined.

This paper proposes a model for determining the location and amount of the leakage in Poulakis water supply network. The main idea is to present an algorithm for barometer placement which requires minimum number of pressure measurements in the network. This model includes a trained neural network that is capable of identifying the location and amount of the leakages that simultaneously occur in different nodes of the network. The training of conventional neural networks is based on gradient decent or continuous gradient decent approaches which are slow and sensitive to the initial guess and might get stuck in local minimums. Therefore, in this paper, the new and intelligent bat algorithm has been used to better train the neural network. Simulation results of the proposed model show that its convergence speed in obtaining the location and amount of the leakage is so high, and this is done with an acceptable level of accuracy, only with a small number of pressure measurements.

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