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Article

Optimized Sensor Placement of Water Supply Network Based on Multi-Objective White Whale Optimization Algorithm

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Abstract: The optimization of sensor locations in water distribution networks has been extensively studied. Previous studies of highly sensitive nodes are usually distributed in a certain area, which leads to redundant information in the sensor network. This is because these studies do not consider that the impact is different when a leak occurs in different nodes. In this study, sensitivity functions of different nodes were obtained according to the influence of the leakage of each node on the water distribution network. Combined with the water pressure correlation and water pressure sensitivity between nodes, the monitoring range of monitoring points and the water demand of covering nodes of monitoring points were taken as objective functions to build an optimal layout model. Taking a pipeline network in Qingdao as an example, the model was solved by using multi-objective White Whale Optimization and NSGA-II. By comparing the operation results of the four cases, it was found that the monitoring points found using multi-objective White Whale Optimization show better searching ability in terms of the sensitivity functions of different nodes.

Keywords: sensitivity function; water supply network; optimal sensor placement; multi-objective White Whale Optimization; multi-objective optimization

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1. Introduction

Water loss is a typical challenge faced by water companies. The problems associated with these losses are enormous in scale [1–3]. At present, most leak locations are based on hydraulic models and sensors, but the accuracy of the location depends on the number and location of sensors [4]. The current optimal configuration of sensors has been applied in various fields, such as water distribution networks [5] and air quality monitoring [6]. The optimal placement of sensors is a multi-objective optimization problem [7], with the current objective taking into account the number of sensors [8], the monitoring range of monitoring points [9], and the number of detected leakage events [10]. Most current studies have used NSGA-II [11] to optimize sensor problems, as well as the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) [12] and the ELimination Et Choix Traduisant la REalité (ELECTRE) [8] to optimize the placement of sensors [12]. In this study, the Beluga optimization algorithm is used to solve the model.

The position of the sensor is usually arranged on the nodes with relatively more sensitive pressure changes in order to improve the sensitivity of the sensor [13]. However, in current studies, highly sensitive nodes are usually distributed in a certain area, which leads to information redundancy [14]. In order to obtain the optimal sensor placement scheme, it is necessary to consider the maximization of the monitoring range and information of the monitoring point. Therefore, some studies introduced information entropy to optimize sensor position [14] but did not consider the influence of hydraulic model errors and sensor measurement errors [15].

These studies assume that each node has the same level of importance and do not consider the difference in the leakage effects of each node [14]. Therefore, it is difficult to detect all high-impact leakage events. Forconi et al. [16] first proposed an optimal sensor placement method based on the risk of leakage, making large leakages more efficient. Although this method can identify large leakage events, it only considers one goal of reducing leakages. However, leakage events will not only cause a large amount of water loss, but will also affect nodes and pipelines, thus affecting the water quality of the water distribution network [17]. Leakages at each node will have different impacts on the water distribution network [18]. Therefore, the sensitivity function of different nodes is obtained according to the influence of leakages of each node on the water distribution network.

This paper proposes a sensitivity function based on the influence of nodes on water demand. Based on the correlation and sensitivity of water pressure between nodes, the monitoring range of monitoring points and the water demand of monitoring points covering nodes were used as objective functions to construct an optimal layout model of monitoring points. Taking a main water supply pipeline network in Qingdao as an example, the model was solved by using the Beluga optimization algorithm and NSGA-II. By comparing the operation results of the two algorithms, it was found that the monitoring points found using the Beluga optimization algorithm showed better searching ability in terms of the monitoring range and water demand of the covering nodes.

The results of this study allow highly sensitive nodes to be distributed in different areas to avoid information redundancy in sensor networks. The new contribution of this study is that the obtained monitoring points can more effectively help find missing points. On the basis of Khorshidi's previous research, who has also carried out relevant work [5], this research method can not only help find leakage points but can also comprehensively monitor pipe networks.

At the same time, the method can also be applied to the sensor location of sewage, because in sewage networks, there are also problems of illegal overflow and the diffusion of pollutants, which, just like sudden loss, damage the normal operation of the system [19–21]. In addition, the method can also be applied to the setting of water quality monitoring points, because in water supply networks, water pollution will suddenly appear [22], and just like leakages, it is also possible to optimize the position of water quality sensors to monitor the water supply network to determine the source of pollution.

2. Methodology

2.1. Determine the Leak Sensitive Function for Each Node

In EPANET, losses occur at nodes. To match the actual leakage better, the increase in the emitter coefficient was set to 0.05 for all nodes. According to the normal operation of the simulated water distribution network, the influence of leakage on each node of the water distribution network was obtained. These are represented by the following equation:

$$X^t(j,i) = \begin{bmatrix} X^t(1,1) & \cdots & X^t(1,N) \\ \vdots & \ddots & \vdots \\ X^t(N,1) & \cdots & X^t(N,N) \end{bmatrix}, \tag{1}$$

where $X^t(j,i)$ represents the influence on the pressure at node j when a leakage occurs at node i at time t, i, j = 1,. . ., N; N is the total number of nodes. If the pressure drop at node j is more than 20% when a leakage occurs at node i, $X^t(j,i)$ = 1; otherwise, $X^t(j,i)$ = 0.

It is clear that a pressure drop at a node that requires more water can cause more harm because that node typically supplies water to a larger population. Therefore, the leak-sensitive function for each node is expressed by the following equation:

$$Y(i) = \frac{\sum_{j=1}^{N} \sum_{t=O}^{c} D_{jt} X(j,i)}{\sum_{j=1}^{N} \sum_{t=O}^{c} D_{jt}}, \tag{2}$$

where *Y (i)* represents the leak-sensitive function of node i that is based on the impact on the water demand, D_{jt} represents the water demand decrease in node j at time t, and $\sum_{j=1}^{N}\sum_{t=O}^{c} D_{jt}$ represents the total water demand decrease, where c is the total simulation time.

2.2. Determination of Constraints

2.2.1. Pressure Dependence of Pipe Network

The purpose of arranging pressure monitoring points in a pipe network is to monitor the water pressure of some nodes and reflect the overall operation of the pipe network. Therefore, the selected pressure measurement point should have a strong pressure correlation with other nodes in the pipe network, and the evaluation criterion of water pressure correlation between two points is the absolute water pressure difference between nodes. The formula is as follows:

$$\left| H_i - H_j \right| < h \tag{3}$$

where H_i, H_j is the pressure of nodes i and j, respectively; h is the set pressure value.

When the pressure difference between two nodes in a network is less than a predefined value h, this indicates that the pressure between the two nodes is correlated. The absolute difference in water pressure between each pair of nodes in the network is calculated using Equation (3) to obtain the pressure difference matrix $[\mathrm{P}]_{\mathrm{n}\times\mathrm{n}}$. This matrix serves as a constraint for the optimization model of pressure measurement point placement.

2.2.2. Shortest Path Matrix

Furthermore, since the water supply network can be simplified as a fully connected node network, its topological structure determines that there is a flow path between any two nodes. However, the lack of restrictions on distance or the number of nodes in the water path means that the results cannot effectively represent the pressure variations around the monitoring points. Therefore, the shortest path matrix $[\mathrm{L}]_{\mathrm{n}\times\mathrm{n}}$ is obtained by using the graph theory toolbox provided in MATLAB to calculate the shortest distance between the nodes of the network. This matrix is then used as a constraint for the optimization model, indicating the effectiveness of the water flow paths by limiting the distance d between nodes.

2.2.3. Water Pressure Sensitivity of Pipe Network

When the water demand at a particular node fluctuates, it inevitably leads to varying degrees of pressure changes at other nodes within the network. The optimal placement of pressure measurement points is determined by identifying the nodes where the pressure changes the most. Therefore, the concept of sensitivity coefficients is introduced. If there is a change in water demand ΔQ_k at any node k, then the pressure at node k changes ΔH_k and the pressure at node i changes ΔH_i, then the water pressure change rate at node i can be expressed as $\Delta H_i = \Delta H_i / \Delta Q_k$. Due to the limited comparability between pressure and flow rate, the ratio of pressure changes $\Delta H_i / \Delta H_k$ is used to characterize the water pressure sensitivity of node i. This ratio represents the sensitivity coefficient. In this study, a flow equal to 10% of the basic water demand at each node is added. The sensitivity coefficients between any two nodes are calculated using Equation (4) to form a sensitivity matrix $[\mathrm{D}]_{\mathrm{n}\times\mathrm{n}}$.

$$\mathrm{D}(\mathrm{i},\mathrm{k}) = \frac{H_i' - H_i}{H_k' - H_k}\ , \tag{4}$$

where H_i, H_k is the pressure of nodes i and k, respectively; H_i', H_k' is the water pressure of nodes i and k after the flow rate of node k increases by 10%.

The elements in the matrix $[D]_{n\times n}$ are normalized. First of all, the standard deviation of each column element of the matrix $[D]_{n\times n}$ [23] is calculated according to Formula (5). Normalization is performed to obtain the matrix $[D']_{n\times n}$.

$$D'(i,k) = \frac{D(i,k) - \overline{D}_k}{S_k}, \tag{5}$$

where S_k is the standard difference of the elements in column *k*.

Then, according to Formula (6), the extreme values of each column element of matrix $[D']_{n\times n}$ are normalized, and the matrix $[D'']_{n\times n}$ is obtained.

$$D''(i,k) = \frac{D'^{(i,k)} - D'_{k_{min}}}{D'_{k_{max}} - D'_{k_{min}}}, \tag{6}$$

The Euclidean distance method is used to analyze the matrix $[D'']_{n\times n}$, and the Euclidean distance r_{ij} between two nodes is obtained according to Formula (7).

$$r_{ij} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}[D''(i,k) - D''(j,k)]^2}, \tag{7}$$

r_{ij} represents the sensitivity of water pressure changes between node *i* and node *j*. A smaller value of r_{ij} indicates that node *i* is more sensitive to water pressure changes in node j. If $r_{ij} < \lambda$ (where λ is a predefined threshold), it indicates that the condition for hydraulic sensitivity is met between the two nodes. Therefore, the fuzzy similarity matrix of hydraulic sensitivity $[R]_{n\times n}$ can be used as a constraint in the optimization model for the layout of pressure measurement points.

2.3. Multi-Objective Optimization

Multi-objective White Whale Optimization (MOWWO) is to utilize the search strategy of the White Whale Optimization algorithm and combine it with techniques for multi-objective optimization to find multiple non-dominated solutions. The multi-objective Beluga optimization algorithm is a crowd-based algorithm inspired by the behavior of beluga whales, including swimming, predation behavior, and whale falls in the sea. The exploration, development, and whale fall stages are constructed in the mathematical model of the multi-objective Beluga optimization algorithm, and the Y-flight function is used in the development stage to improve the convergence of the multi-objective Beluga optimization algorithm. According to the above theory, the multi-objective Beluga whale optimization algorithm mainly includes three aspects: the exploration stage to simulate swimming behavior, the development stage to simulate predation behavior, and the whale fall stage inspired by beluga whale falls. The main steps of the MOWWO algorithm are as follows:

Step 1: Initialize the population: Randomly generate a set of initial solutions as the initial population.
Step 2: Evaluate fitness: Evaluate each individual in the population based on multiple objective functions to obtain their fitness values.
Step 3: Update the best solutions: Select the current pareto optimal solution set based on the fitness values.
Step 4: Update whale positions: Update the positions and velocities of the whales based on the positions of the current pareto optimal solution set.
Step 5: Update the population: Update the positions and velocities of individuals in the population based on the new whale positions.

The purpose of establishing pressure monitoring points in a municipal water supply network is to reflect the pressure distribution and changes in the network by monitoring the pressure of some nodes. Therefore, two optimization objectives were set in this study: one was to maximize the number of elements in the set of all nodes meeting the constraints, and the other was to maximize the total water demand of all nodes that meet the constraint conditions and combine the leakage sensitivity function based on the influence on water demand. This ensured that the entire network was effectively monitored and any potential problems or anomalies were detected in a timely manner. It also focused on monitoring those nodes with greater leakage impact, so that important areas could be prioritized to improve the accuracy and response speed of leakage monitoring. The objective function is as follows:

$$\begin{cases} \max F & = \mathrm{count}(A_1 \cup A_2 \cup \cdots \cup A_n), \\ \max Q & = \sum_{i=1}^{N} Q_i \cdot Y(i), \end{cases} \tag{8}$$

Subject to:

$$X = \{X_1, X_2, \cdots, X_N\}, \tag{9}$$

$$A_{Xi} = \{ j | P(X_i, j) < h, R(X_i, j) < m, L(X_i, j) < d\}, \tag{10}$$

where F represents the number of nodes that satisfy the constraints; Q is the sum of the water demand of nodes meeting the constraint conditions; X represents the selected set of pressure monitoring points. X_i represents the index of the *i-th* pressure monitoring point. A_{Xi} represents the set of nodes that satisfy the constraints for monitoring point X_i. N indicates all nodes that meet the monitoring point constraints. h, m, and d are predetermined constraint threshold values.

3. Case Study: Qingdao City

3.1. Determination of the Number of Pressure Monitoring Points

The research area was the actual pipe network in Qingdao City, located in the north of China, which covers 28 square kilometers. The nodal flow was divided into the user's water consumption and leakage, the leakage of the pipe was allocated according to the length of the pipe, and the relationship between leakage and pressure was constructed to establish the PDD model. In the PDD model, the relative error between the monitored value and the simulated pressure value at a certain time was less than 2.5%, which met the precision requirement. The relative error is shown in Table 1.

Table 1. Comparison results of monitoring values and simulated values.

Monitoring Point	Monitored	Class	Monitoring Point
CY1	27.87	27.76	0.3947
CY2	42.06	42.93	2.0685
CY3	27.59	27.41	0.6524
CY4	29.42	29.09	1.1217
CY5	29.37	29.07	1.0215
CY6	37.66	37.99	0.8763
CY7	35.06	35.05	0.0285
CY8	32.27	32.01	0.8057
CY9	22.36	22.21	0.6708
CY10	45.69	44.76	2.0355
CY11	47.67	48.00	0.6923
F1	7.91	7.78	1.6435
F2	11.56	11.61	0.4325
F3	119.98	119.54	0.3667

According to the scale and structural characteristics of the water supply network in this area, three constraint parameters of node pressure sensitivity threshold m, pressure correlation threshold h, and shortest distance threshold d were preliminarily selected and then replaced with the model for repeated verification. Finally, the values of the parameters were determined as λ = 0.5, h = 3 m, and d = 1500 m.

In the MOWWO, the following parameters can be set: a population size of 100, maximum iterations of 500, a differential evolution mutation rate of 0.5, a differential evolution crossover rate of 0.9, a cognitive acceleration factor of 1.5 for weighted particle swarm optimization, and a social acceleration factor of 1.5 for weighted particle swarm optimization. These parameter settings aimed to guide the algorithm's exploration and exploitation abilities in finding optimal solutions for multi-objective optimization problems.

According to the scale of the water supply network in this area, the number of pressure measuring points was initially determined to be within 14. In order to determine the exact number of pressure measuring points, the algorithm was used to repeatedly calculate the number of pressure measuring points in the pipeline network preliminarily, the optimal fitness obtained using the algorithm under each pressure measuring point was obtained, and the number of pressure measuring points was compared with the corresponding optimal fitness, as shown in the figure below.

According to the results shown in Figure 1, when the number of pressure measuring points ranged from 6 to 14, the fitness increased by about 5% with each new pressure measuring point, while when the number of pressure measuring points reached 11, the fitness increased slowly with each new pressure measuring point. Therefore, a total of 11 pressure monitoring points were arranged in the water supply network in this area to give full play to the maximum monitoring function of each pressure monitoring point without increasing additional costs.

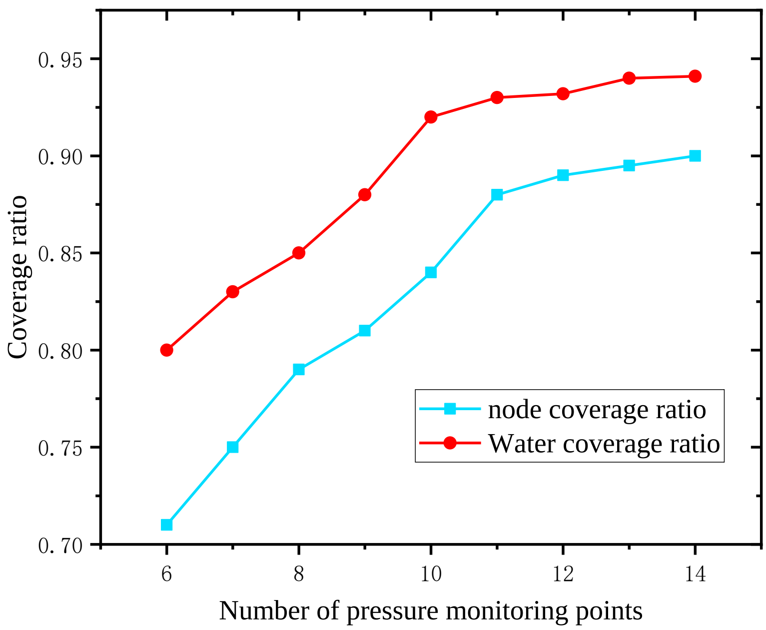

Figure 1. Comparison graph of number of pressure monitoring points and optimal fitness.

3.2. Optimal Layout Scheme

According to the value of the number of pressure monitoring points, the MOWWO (Case 1) and NSGA-II (Case 2) considering the leak sensitive function Y(i) were, respectively, run and solved, and the running results are shown in Figure 2. Meanwhile, compared with previous assumptions, each node had the same importance. That is, the leak-sensitive function for each node Y(i) was not considered, and the results of the MOWWO (Case 3) and NSGA-II (Case 4) are also shown in Figure 2.

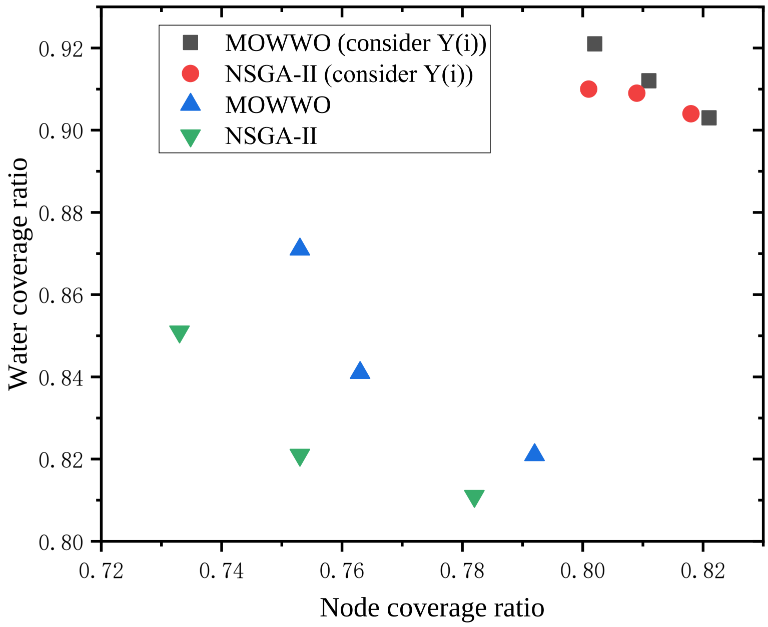

Figure 2. Pareto frontier solution set based on four conditions.

As shown in Figure 2, the areto frontier solutions of Case 3 and Case 4 are significantly worse than those of Case 1 and Case 2. This is because these studies assumed that each node had the same importance and did not consider that leakage from each node will have different effects on the water distribution network [20]. Therefore, the paper obtained the sensitivity function of different nodes to be added to the objective function to monitor the network situation better. In addition, the comparison of Case 3 and 4 shows that the three solutions of MOWWO are superior to NSGA-II; the comparison of Case 1 and 2 shows that the two solutions of MOWWO are superior to NSGA-II, and only the water coverage rate of the third scheme is slightly lower. Therefore, when optimizing the sensor layout, the change of leakage function of each node in the water distribution network is considered, and the change based on leakage sensitivity function is added to the objective function, which is helpful to obtain a more reasonable scheme. The MOWWO algorithm is also better than NSGA-II. In one research study [24], when the number of sensors was constant, the objective function could be used to achieve the optimal scheme, and the method proposed in this paper can also be extended to a situation in which the number of sensors is uncertain.

From the comparison of the above schemes, it can be concluded that by considering the leakage-sensitive function Y(i) and adopting the MOWWO algorithm, the result of scheme 1 is better. In order to further compare whether the algorithm is better, this study continued to adopt the continuous Hopfield neural network optimization algorithm to carry out optimization analysis that also considers the leakage-sensitive function Y(i). The objective function of the algorithm is usually expressed by the minimum value of the energy function. Therefore, in this study, the reciprocal of the sum of node coverage and water coverage was multiplied by 100 as the energy function (to prevent the value from being too small). The parameters were set as follows: tansig was selected as the activation function; the learning rate was set to 0.1; the update step of the input neuron was 0.0001; and the number of iterations was 10,000. Its operation process is shown in Figure 3. The optimization results can cover about 79.6% of the pipe network node and about 89.7% of the water. Compared with the results of the MOWWO algorithm, the results are inferior to the three Prado solutions in Case 1. Therefore, it is further proved that the MOWWO algorithm is more suitable for optimizing the placement of pressure measurement points.

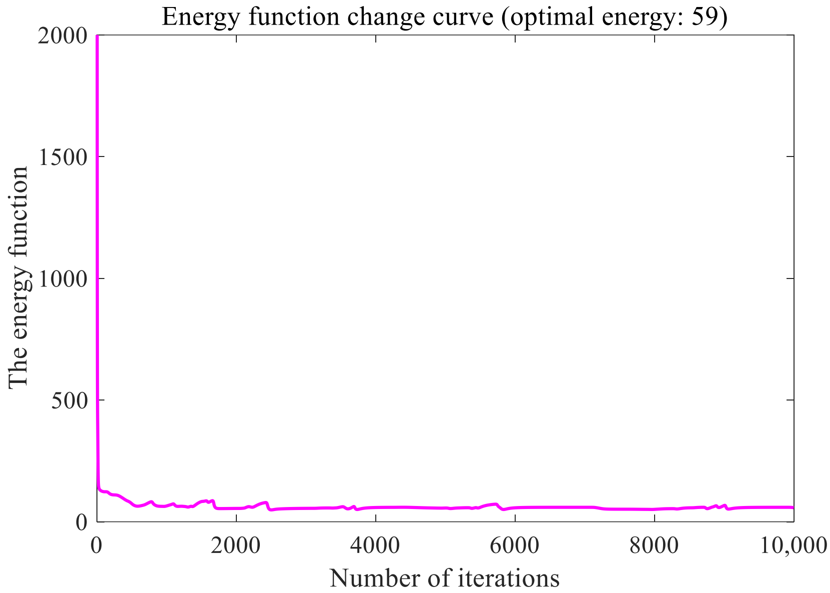

Figure 3. Energy function change curve.

Table 2 lists the fitness function values corresponding to each pareto frontier solution for Case 1. Four kinds of schemes can cover about 81% of the pipe network node and about 91% of the water. The minimum node coverage ratio of solution 1 is about 80.2%, but the maximum water coverage ratio of solution 1 is 92.1%. In solution 2, the node coverage ratio is improved to about 81.1%, but the water coverage ratio is reduced to 91.2%. Solution 3 has the largest node coverage ratio, reaching 82.1%, but its water coverage ratio is the lowest among all schemes, being about 90.3%. It can be seen that the pareto frontier output form adopted by the multi-objective optimization method can provide alternative schemes with different focus directions for decision makers, taking into account the requirements of maximizing the monitoring range or maximizing the water coverage of the layout scheme. In practical applications, if the layout scheme needs to cover more users, solution 3 with a larger node coverage ratio can be used. If a large amount of water is required to be covered by the layout scheme, solution 1 can be selected with a large proportion of water. To cover both the number of pipe network nodes and the amount of water in nodes, solution 2 can be selected according to the actual demand. The locations of monitoring points corresponding to each alternative plan are shown in Figures 4–6.

Table 2. Result of objective function for Case 1.

Solution Number	Alternative Pressure Measurement Point Number	Fitness1	Fitness2
Solution 1	9, 15, 33, 46, 68, 79, 88, 92, 104, 114, 119	0.802	0.921
Solution 2	9, 14, 35, 46, 68, 76, 88, 95, 104, 117, 115	0.811	0.912
Solution 3	9, 15, 33, 47, 66, 79, 86, 96, 102, 114, 119	0.821	0.903

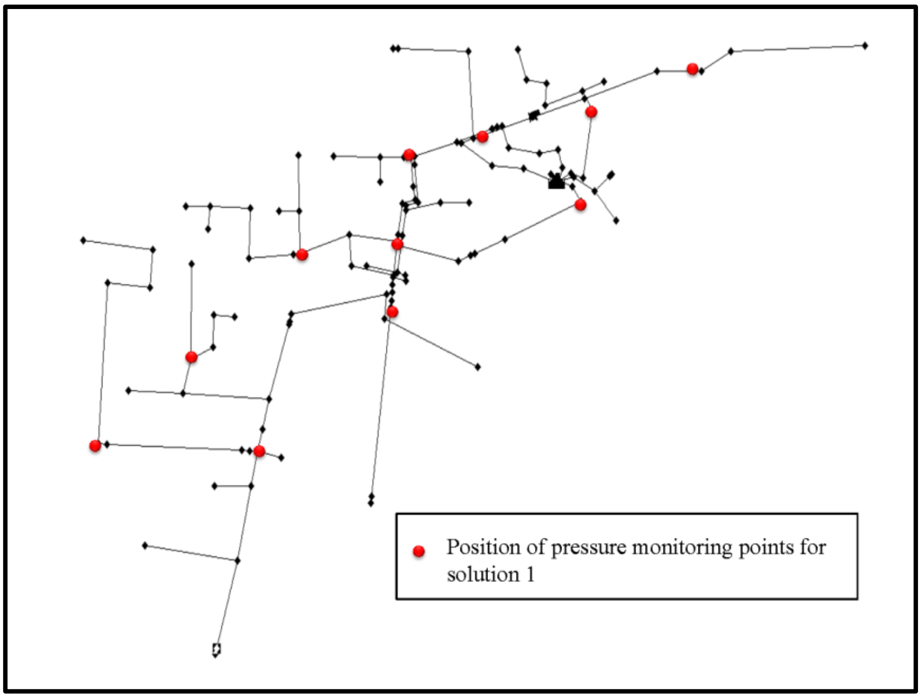

Figure 4. Specific locations of pressure monitoring points for solution 1.

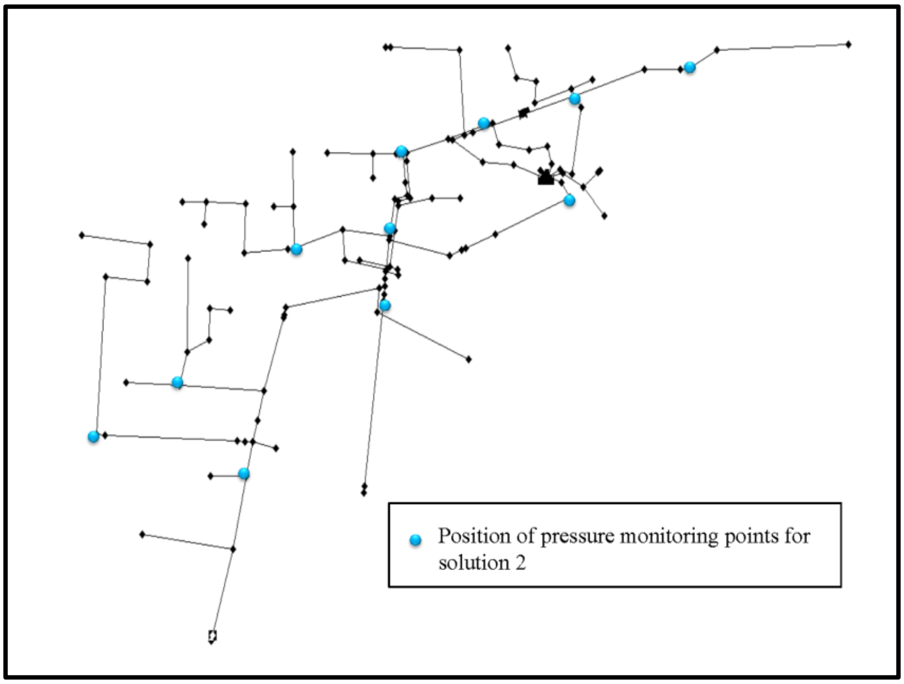

Figure 5. Specific locations of pressure monitoring points for solution 2.

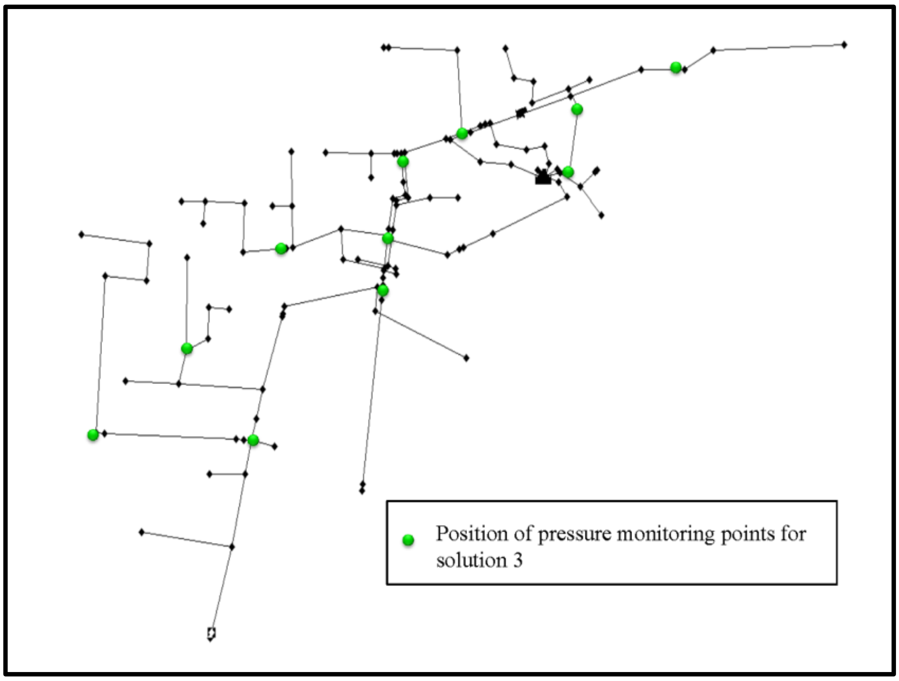

Figure 6. Specific locations of pressure monitoring points for solution 3.

By observing the locations of monitoring points in each scheme in Figures 4–6, it can be seen that even though the fitness function values of each scheme are relatively similar, the distribution of monitoring points selected using different schemes still differs greatly. For example, the node coverage ratio of solution 3 is large, and the distribution of alternative pressure measurement points is relatively scattered, so the number of nodes that can be monitored is large. Solution 1 has a large water coverage ratio, and its alternative locations are mostly located near water concentration areas and large water users. Considering that research on network leakage locations will be carried out later, the requirements for the layout plan are more inclined to give priority to maximizing the node coverage ratio. In addition, considering that large users or water concentration areas usually belong to accident-prone areas, the selected monitoring point layout plan needs to take into account a certain amount of node coverage water. Considering the characteristics of the three schemes, it is found that scheme 2 has a node coverage ratio of up to 81.1%, and at the same time, it takes into account the water coverage ratio of 91.2%, which is only 0.9% different from scheme 1. On the other hand, compared with the other two schemes, alternative monitoring points in scheme 2 are more evenly distributed, and most of them are located in the main pipe of the pipeline network, large user nodes, and water supply boundaries, which better meets the general requirements of pressure monitoring point layout principles. Therefore, scheme 2 is selected as the final layout scheme in this study. In general, the selected pressure measuring point layout scheme has strong monitoring ability, and its layout position conforms to the general layout principle, which has strong practical application value and theoretical guiding significance.

4. Discussion

Firstly, the sensitivity function Y(i) of different nodes were obtained according to the influence of the leakage of each node on the water network. Then, the selected pressure measuring point needed to have a strong pressure correlation with other nodes in the pipe network, and the absolute difference in water pressure between two nodes in the pipe network could be calculated to obtain the pressure difference matrix of the pipe network nodes $[P]_{n \times n}$. Using the graph theory toolbox provided in MATLAB, the shortest distance between nodes of the pipe network was calculated to obtain the shortest path matrix $[L]_{n \times n}$. The ratio of pressure difference was used to characterize the water pressure change rate of node i, and the fuzzy similarity matrix $[R]_{n\times n}$ of water pressure sensitivity was established after conversion. Three matrices could be used as a constraint in the optimization model for the layout of pressure measurement points.

Secondly, two optimization objectives were set in this study: one was to maximize the number of elements in the set of all nodes meeting the constraints, and the other was to maximize the sum of water requirements of all nodes meeting the constraints. The leakage sensitivity function was added to the second objective function. In order to determine the number of pressure measuring points, the number of different pressure measuring points was compared with the corresponding optimal fitness, and finally, 11 pressure measuring points were determined. The MOWWO (Case 1) and NSGA-II (Case 2) of leakage-sensitive function Y(i) were considered for the running solution, and the MOWWO (Case 3) and NSGA-II (Case 4) of the leakage sensitive function of each node Y(i) were not considered for the running solution. The results show that the pareto boundary solutions of Case 3 and Case 4 are significantly worse than those of Case 1 and Case 2. Then, the comparison of Case 3 and Case 4, Case 1 and Case 2 shows that the result of MOWWO is superior to that of NSGA-II. In order to further compare whether the algorithm is better, this study continued to use the continuous Hopfield neural network optimization algorithm for optimization analysis while considering the leakage sensitive function Y(i). The optimization results are not as good as the MOWWO algorithm. Therefore, it was further proved that the MOWWO algorithm is more suitable for the optimization of pressure measuring point arrangement.

5. Conclusions

In this research, the differential pressure matrix $[P]_{n\times n}$, the shortest path matrix $[L]_{n\times n}$, and the fuzzy similarity matrix of water pressure sensitivity $[R]_{n\times n}$ were established. Three matrices were used as constraints of the optimization model of pressure measuring point arrangement. Then, leakage sensitivity function was added to the second objective function. The monitoring range of monitoring points and the water demand of monitoring points covering nodes were used as objective functions to construct an optimal layout model of monitoring points. The multi-objective optimal location model of pressure measuring points using MOWWO algorithm is better for solving a case pipe network. Three schemes were generated in the operation result. By comparing the fitness value and distribution of each scheme in the pareto frontier solution, it could be seen that the model can meet the different needs of decision makers at the same time. By comparison, it was found that the node coverage ratio of scheme 2 is as high as 81.1% and the water coverage ratio is as high as 91.2%, which can meet the needs of maximizing the monitoring range and maximizing the water coverage.

In future work, we will add more objective functions to further improve the monitoring accuracy. In addition, we will combine more multi-objective optimization methods to optimize the monitoring point optimization model and compare the results with this work.

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