Intelligent Leakage Location of Urban Small Water Supply Network

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Abstract. In this paper, the leakage location model of pipe network is established based on EPANET software. Two intelligent swarm optimization algorithms, ant lion optimization algorithm and particle swarm optimization algorithm, are used to solve the model. Taking the industrial water supply network of a coastal city in North China as an example, the operation of the two algorithms is analyzed and compared. The results show that the ant lion optimization algorithm has stronger global optimization ability and higher search efficiency in the problem of leakage location; it also has high application value in practical engineering.

1. Introduction

As an important link in the normal operation of the city, the municipal water supply network is the "main road" to ensure the life of residents. In recent years, due to a series of problems such as aging of urban pipe network and improper control of water pressure, the frequent occurrence of pipe network leakage and pipe explosion accidents has a great impact on the normal life of residents. Therefore, how to locate the accident point quickly and accurately and repair the fault when a leakage or pipe explosion accident occurs is a key issue to minimize the loss.

Regarding the problem of pipe network leakage location, scholars at home and abroad have conducted a lot of research and made some progress. Jowitt [1] introduced the pressure related leakage factor into the water supply network model to explain the correlation between leakage and water supply pressure. Liu Tianshun [2] located the leakage point through numerical simulation of transient flow analysis. Li Shanshan [3] established the leakage location model of pipe network based on pressure monitoring, analyzed the weight of the factors causing leakage and solved the model by particle swarm optimization (PSO). Liu Shuming [4] used Cuckoo Search (CS) algorithm to locate leakage points and verified the feasibility of the new intelligent optimization algorithm in the leakage location of pipe network.

The traditional optimization algorithm has been widely used in the leakage location of pipe network, but there are also some problems such as slow convergence speed, low convergence accuracy, too many algorithm parameters and difficult to implement. The author used ant lion optimizer (ALO) to solve the leakage location model, compared its performance with that of particle swarm optimization (PSO) and discussed the superiority of the new algorithm in the leakage location problem.

2. Construction of leakage location model

When a leakage accident occurred in a water supply pipe network system, the hydraulic pressure of the nodes in the pipe network will be affected and the degree of influence is closely related to the location
and severity of leakage. Therefore, we simplified the leakage accident on the pipe section to the node connecting the pipe section, simulated the leakage accident by constantly changing the location of the node with leakage and the degree of leakage, used the hydraulic simulation software EPANET to calculate the pipe network adjustment and compared the calculated value of the pressure monitoring point with the measured value. An appropriate objective function was constructed to determine the location and severity of leakage.

2.1. Determination of decision variables

The leakage state of pipe network can be simulated by setting the ejector coefficient of the node on EPANET software, which was essentially to set a pressure-related water demand. The relationship between the injection flow rate and the coefficient can be expressed by the following formula:

\[ Q_i(t) = K_i [P_i(t)]^{n} \]  \hspace{1cm} (1)

Where \( Q_i(t) \) is the aggregation leakage of node \( i \) at time \( t \); \( P_i(t) \) is the pressure of node \( i \) at time \( t \); \( K_i \) is the ejector coefficient of node \( i \); \( n \) is the leakage index, which is 0.5 ~ 2.5 and most metal pipes are 0.5.

According to the above formula, at a certain moment in the operation of the pipe network, the value of the leakage coefficient of the node was proportional to the injection flow and each node had its corresponding value of the ejector coefficient. When the coefficient was zero, it meant that there was no leakage at the node. When the coefficient was positive, it meant there was leakage at the node. The larger the coefficient value was, the more serious the leakage was. Therefore, we optimized the ejector coefficient corresponding to each node and used the optimized ejector coefficient value as a sign of the existence of leakage.

In summary, considering the node index value to represent the location where the leakage occurred, the ejector coefficient corresponding to the leakage node represented the severity of the leakage, the decision variable \( X \) of leakage location can be expressed as the combination of the node index of leakage and the leakage coefficient corresponding to the node.

2.2. Determination of objective function

In this paper, the objective function was defined as the minimum sum of squares of the difference between the simulated value and the measured value at the pressure monitoring point. The smaller the objective function value was, the closer the simulated operation of pipe network was to the actual operation of pipe network. The objective function is shown in the following formula:

\[ \min f(X) = \frac{1}{n} \sum_{i=1}^{n} \sqrt{(P_i - P_i')^2} \]  \hspace{1cm} (2)

Where \( f(X) \) is the objective function to be optimized; \( X \) is the decision variable; \( N \) is the number of pressure monitoring points; \( P_i \) is the pressure simulation value of node \( i \); \( P_i' \) is the measured pressure value of node \( i \).

2.3. Determination of constraints

The constraints of the leakage location model are as follows:

\[ 0 \leq K_i \leq K_{max}, 1 \leq i \leq N \]  \hspace{1cm} (3)
\[ P_i > 0, 1 \leq i \leq N \]  \hspace{1cm} (4)
\[ \sum_{j=1}^{N} q_{ij} + Q_i = 0 \]  \hspace{1cm} (5)
\[ \sum_{j=1}^{N} h_{ij} - \Delta H_k = 0 \]  \hspace{1cm} (6)

Where \( K_i \) is the ejector coefficient corresponding to node \( i \); \( K_{max} \) is the maximum ejector coefficient corresponding to node \( i \); \( N \) is the total number of nodes in the pipe network; \( P_i \) is the node pressure corresponding to node \( i \); \( q_{ij} \) is the flow rate of each pipe section connected to node \( i \); \( Q_i \) is
the node traffic corresponding to node i; $h_{ij}$ is the head loss of the pipe section of base ring $K$; $\Delta H_k$ is the closure difference of the base ring $K$; $i$ and $j$ are node numbers.

2.4. Solution of leakage location model

Ant lion optimization algorithm was a new meta-heuristic swarm intelligence algorithm proposed by Mirjalili [5] in 2015, which imitated the intelligent behavior of ant lions in nature when hunting ants. There are the same number of ants and ant lions in the solution space. Each ant has its own position $X_{A_i}$ (the solution vector corresponding to the optimization problem) and its fitness, carries out different random movement in the search space. Each ant lion also has a corresponding position $X_{A_L_i}$ and its fitness, the ant lion sets a trap to catch ants that move randomly. The ant lion with higher adaptability builds larger traps and the ant lion with the highest adaptability is the elite ant lion. During each iteration, each ant will move randomly between the selected ant lion and the elite ant lion, once the ant enters the trap, the range of random movement will be reduced by updating the movement vectors $C_i$ and $d_i$. Each iteration will compare the fitness values of the ant and the ant lion. If the ant has high fitness, it will be captured and the ant lion will reposition according to the captured prey, Choose a location where it is easier to catch prey. The flow chart of ant lion optimization algorithm is shown in figure 1.

Figure 1. Flow chart of ALO.

3. Case study

In order to verify the rationality of leakage location model, this paper selected an industrial network in a coastal city in North China as the research object to conduct leakage location analysis. EPANET hydraulic modeling was carried out on the example network, the ant lion algorithm and particle swarm optimization algorithm were programmed by Matlab. After simplification, the pipe network consists of 46 nodes, 47 pipe segments and one water source. The example pipe network is shown in figure 2.

3.1. Realization of leakage location

For the example pipe network, if all nodes are used as the solution space for leakage location, as the number of nodes increases, the dimension of variables will increase exponentially, resulting in "dimension disaster" [6], which greatly increases the amount of calculation and even makes it impossible to obtain the optimal solution of the objective function. In order to avoid this problem, the number of leaking nodes was used to determine the optimization dimension of variables. Since the
decision variable was the combination of the node index and the ejector coefficient corresponding to the node, the encoding method of the optimization algorithm adopted the real number encoding.

To sum up, parameters of the optimization algorithm were set as follows: ant lion algorithm population size was 30, maximum iteration number was 200, variable dimension was 1, boundary value was (0,100). The population size of PSO was 100, the evolution algebra was 200, the learning factor was 1.494 15 and the maximum speed was 0.5. In order to comprehensively compare the operation of the two algorithms and exclude the influence of accidental factors, nodes 43, 21, 36 and 3 were selected as the nodes with leakage, the two algorithms were used to locate the leakage for 5 times under each working condition at the same time. Assuming that there was only one leakage point in each calculation, the ejector coefficient of each leakage node was set to 0.3. The distribution of leakage nodes is shown in the circle in figure 2, the position of the pressure measuring point is shown in the triangle in figure 2. Result of leakage locating is shown in table 1.

![Example pipe network topology (Black numbers represent node indexes and blue numbers represent segment indexes).](image)

**Table 1. Leakage location results of ALO and PSO.**

| Leakage node ID | Number of runs | Optimization results of node index | Optimization results of ejector coefficient | Optimization results of node index | Optimization results of ejector coefficient |
|-----------------|----------------|-----------------------------------|---------------------------------------------|-----------------------------------|---------------------------------------------|
|                 |                | Ant lion optimization (ALO)        | Particle swarm optimization (PSO)           |                                   |                                             |
| 43              | 1              | 43                                | 0.27                                        | 43                                | 0.29                                        |
|                 | 2              | 43                                | 0.25                                        | 43                                | 0.32                                        |
|                 | 3              | 43                                | 0.32                                        | 42                                | 0.74                                        |
|                 | 4              | 43                                | 0.30                                        | 43                                | 0.38                                        |
|                 | 5              | 43                                | 0.27                                        | 43                                | 0.27                                        |
|                 | 1              | 21                                | 0.26                                        | 20                                | 0.13                                        |
|                 | 2              | 20                                | 0.09                                        | 21                                | 0.34                                        |
| 21              | 3              | 21                                | 0.32                                        | 21                                | 0.27                                        |
|                 | 4              | 21                                | 0.27                                        | 21                                | 0.30                                        |
|                 | 5              | 21                                | 0.31                                        | 21                                | 0.24                                        |
|                 | 1              | 36                                | 0.37                                        | 36                                | 0.40                                        |
|                 | 2              | 39                                | 1.00                                        | 37                                | 0.63                                        |
| 36              | 3              | 36                                | 0.41                                        | 36                                | 0.36                                        |
|                 | 4              | 36                                | 0.35                                        | 40                                | 0.89                                        |
|                 | 5              | 36                                | 0.37                                        | 36                                | 0.38                                        |
|                 | 1              | 6                                 | 0.92                                        | 3                                 | 0.40                                        |
|                 | 2              | 3                                 | 0.37                                        | 7                                 | 0.05                                        |
| 3               | 3              | 3                                 | 0.36                                        | 3                                 | 0.38                                        |
|                 | 4              | 6                                 | 0.87                                        | 6                                 | 0.91                                        |
|                 | 5              | 3                                 | 0.36                                        | 3                                 | 0.36                                        |
3.2. Comparison and analysis of optimization results
Comparing the two intelligent optimization algorithms, in the 20 leaking point search and positioning,
the ant lion algorithm located the target node 16 times with an accuracy rate of 80%, while the particle
swarm algorithm located the target node 14 times with an accuracy rate of 70 %, according to the
optimization results of the leakage coefficient in table 1, it can be known that compared with particle
swarm optimization, The average leakage coefficient calculated by ant Lion algorithm was closer to
the set value 0.3. The optimization iterative process diagrams of two intelligent optimization
algorithms were generated by MATLAB, as shown in figure 3 and figure 4. It can be seen that the
generation time of ant lion algorithm was shorter, and the fitness value was close to the optimal fitness
within 10 generations, with fast convergence speed and higher search efficiency than particle swarm
optimization algorithm.

![Figure 3. Iterative optimization process of ALO. Figure 4. Iterative optimization process of PSO.](image)

4. Conclusion
In this paper, a small urban water supply network is taken as an example and two intelligent
optimization algorithms are used to locate the leakage. The results show that the positioning accuracy
of ant lion algorithm has reached 80% and the simulated value of leakage coefficient obtained by
calculation is closer to the actual value of leakage coefficient. Compared with the traditional particle
swarm optimization algorithm, ant lion optimization algorithm shows higher accuracy, better stability
and faster solution speed in the solution of leakage positioning problem. It provides a reliable method
for the realization of leakage location.

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