Identification of Heat Supply Network Pipeline Roughness Based on AIOX-GA

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ABSTRACT The scale of heating system is expanding day by day and the structure of pipeline network is becoming more and more complex. Therefore, it is urgent for heating enterprises to establish accurate hydraulic models of pipeline network to assist their operation and management. The pipe roughness of heating pipeline is critical to hydraulic models, but unfortunately it is however uncertain. Thus, it is necessary to obtain the resistance coefficient values of pipe roughness of heating pipeline. At present, the pipeline roughness is commonly estimated with optimization calculation based on collected measurement data of heating systems. The optimization problem is however multi-dimensional and complex to solve. In this work, an auxiliary individual oriented crossover genetic algorithm (AIOX-GA) is proposed to optimize the problem of estimating the resistance coefficient values of pipe roughness. AIOX-GA adopts a crossover framework and is an auxiliary individual-oriented scheme, which is helpful to solve multi-dimensional problems. The performance of the improved algorithm is evaluated with simulation experiments. The results show that the proposed algorithm can accurately estimate the pipeline roughness and effectively improve the identification accuracy.

INDEX TERMS Auxiliary individuals, heating pipeline network, genetic algorithms, pipeline roughness.

I. INTRODUCTION

With the expansion of heating scale and the development of related technology, difficulties such as regulation of heating operation and early warning and diagnosis of faults have attracted more and more attention. The solution of these problems depends on the establishment of accurate and reasonable hydraulic simulation model of heating network. However, in the actual heating pipe network, it is difficult to avoid scaling and impurity deposition on the inner wall of the pipeline, and the roughness of the pipeline is easy to change. The resistance coefficient can be calculated by arranging pressure and flow collectors, but the actual pipe network generally does not have the observation conditions for direct calculation, which is not conducive to further research on the optimal operation and scheduling of the heating system.

Therefore, the identification of roughness is the key part of the whole heating model and related research. To solve this problem, a large number of scholars have conducted a significant amount of research on the identification of resistance coefficient of pipeline network.

At present, many new technologies are applied to this problem. The combination of heating network and Internet of things(IoT) is a new way, which can acquire, transmit and process data of heating network easily, so the identification of roughness will not be difficult. In terms of data collection and transmission, Wu et al. [22] proposes a dynamic trust relationships aware data privacy protection (DTRPP) mechanism for mobile crowd-sensing, which can protect the data privacy effectively and has better performance on the average delay, the delivery rate and the loading rate when compared to traditional mechanisms. For the collected data processing, lots of associated methods are also proposed, for instance, Wu et al. [21] proposes a new feature-based learning system...
for IoT applications to effectively classify data and detect anomaly event, which can reduce the computation overhead and energy consumption. Efficient data collection, transmission and processing are of great significance to the research of heat network, but at present, the combination of heating network and IoT is still in the experimental stage and almost all practical networks are absent of these conditions, so in this paper, we study the identification of resistance coefficient mainly from the current network observation conditions with the tradition methods.

At present, the widely used methods are mechanism model method and implicit calculation method. The mechanism method [1], [2] uses the resistance model of the pipeline network and other relevant pipeline network’s hydraulic laws to obtain the mathematical equation containing the pipeline roughness, and uses the mathematical theory to solve the pipeline roughness in the equation. Such as Liu et al. [1], [2] uses moore-penrose pseudo-inverse solution and minimum norm solution methods to identify resistance coefficient. This method is accurate and of low calculate, but it requires a high number of monitoring points and operating conditions of the pipeline network, and cannot be identified with a small amount of network data. At present, there are often fewer monitoring points in the actual pipe network, so this method cannot be widely applied to the actual network.

Implicit calculation is based on the uncalibrated mathematical model of pipeline network, the value of model’s pipeline roughness is constantly changed in a certain range, then the output flow and pressure calculated by the forward model are compared with the observed results in advance. The roughness which minimizes the error between the output value and the measured value is used as the identification result. Lindell [3], Kang and Lansey [4], Gao [5] used classical optimization methods such as generalized reduced gradient method and gradient method to identify the roughness of pipeline network. In addition to classical optimization methods, intelligent optimization algorithms have also been widely used in implicit computing. Dini and Tabesh [7] applies ant colony optimization algorithm to calibrate the pipeline roughness and node demand of networks. Sherri and Mahvi [6] uses pipeline grouping method to reduce the dimension of decision variables, and identify pipeline roughness with fast messy genetic algorithm(fmGA). Through practical case tests, the calculation efficiency and accuracy can reach the applicable scope. Zhou et al. [8] and Song et al. [9] both pointed out that the standard optimization method had some difficulties in the identification of resistance coefficient of pipe network, and both improved the identification of standard genetic algorithm to some extent, which improved the overall performance of the algorithm. Through experiments, it was proved that the improved algorithm improved the identification problem to some extent. From the above literature about implicit calculation, it can be seen that the quality of the optimization method determines the efficiency and accuracy of this method, and it is also the research focus of this method.

The above research provides a theoretical basis for the direction of resistance identification of pipeline network. Relevant studies of the above two methods provide theoretical basis for roughness identification of pipeline network. It can be seen from this that the main difficulties of actual pipe network identification are few observation points and limited data. All kinds of methods have some breakthroughs on this issue. Among them, the implicit method does not need to consider the mechanism of the model, and has low requirement on the data volume which is suitable for practical problems. However, it needs to be supported by optimization methods that meet the characteristics of this problem. At present, many optimization algorithms have been applied to pipeline network problems, such as genetic algorithm(GA), ant colony algorithm(ACO) and so on. Each optimization algorithm has its own advantages, for example, ant colony algorithm has fast convergence in the later stage, but strong randomness and slow convergence in the earlier stage; particle swarm optimization has fast convergence, but weak global search ability; the genetic algorithm has strong global search ability, but converges slowly in the later stage. Besides, according to the theory of “there is no free lunch in the world” [15], these intelligent optimization algorithms often show great performance differences for different optimization problems. From the point of view of optimization problems, the main difficulties of pipeline network problems are multi-dimension and large search space. According to the above characteristics of the problem in this paper, the global exploration ability is an important criterion for algorithm selection.

GA has strong global exploring ability and is more suitable for pipeline network problems. However, genetic algorithm is prone to be trapped in local optimum and “premature” phenomena still need to be solved urgently. These problems have a great impact on the accuracy of resistance coefficient identification. In genetic algorithm, the main function of crossover operation is to search in search space with higher precision according to certain rules. The generation of new individuals mainly depends on crossover operator, which is the most important evolutionary mechanism of genetic algorithm [16]. In addition, [16], [18] shows that crossover and mutation operations combined with individual fitness information are more conducive to searching global optimal solutions and accelerating convergence speed. Therefore, this paper proposes an auxiliary individual oriented crossover operator genetic algorithm for pipe network optimization, which is based on the use of the global optimal solution, combined with the currently excellent crossover operators [17], [14]. The proposed method has great advantages in solving multi-dimensional complex problems of pipeline network.

II. HYDRAULIC MODEL OF HEATING NETWORK AND ITS SOLUTION

The foundation of implicit computational identification method is the pipe network model and hydraulic calculation.
In the process of identification, the hydraulic model needs to be solved continuously.

### A. HYDRAULIC MODEL OF HEATING PIPELINE NETWORK

Hydraulic model of heating network is the basis of studying heating network, but because of the large heating area in the city, the topological structure of the network is extremely complex. In order to study the pipeline network more conveniently, the pipeline network can be partially abstracted, simplified or omitted. At present, the heating network modeling based on graph theory is mainly adopted. Its advantage is that the relationship between nodes, branches and segments in the pipeline network is clear, and the matrix form is more convenient to realize the calculation, storage and analysis of the pipeline network by computer [10].

Hydraulic calculation model has been mature. It expresses the network topology by basic correlation matrix, basic loop matrix and Kirchhoff current and voltage law, the energy equation of pipeline. Among them, the energy equation mainly includes parameters such as pipe flow rate, nodal head, pipeline roughness. There are two main expressions of hydraulic calculation equations of hot water pipeline network. For outdoor thermal pipeline, but because of the large heating area in the heating network, but because of the large heating area in the heating network, but because of the large heating area in the heating network, but because of the large heating area in the heating network, but because of the large heating area in the heating network, but because of the large heating area in the heating network, but because of the large heating area in the heating network, but because of the large heating area in the heating network, but because of the large heating area in the heating network, but because of the large heating area in the heating network, but because of the large heating area in the heating network, but because of the large heating area in the heating network, but because of

The general model is as follows:

\[
\begin{align*}
AG & = Q \\
BP & = \Delta P \\
\Delta P & = S |G| G + Z - H_p
\end{align*}
\]

Assuming that the number of nodes is \( m \) and the number of pipelines is \( n \), the variables in the model are as follows:

- \( A \) is an \((m - 1) \times n\) order basic correlation matrix. Each location element is obtained by the following way:

\[
\begin{cases}
1 & \text{pipeline } j \text{ flows from node } i \\
0 & \text{pipeline } j \text{ is not connected to node } i \\
-1 & \text{pipeline } j \text{ flows in node } i
\end{cases}
\]

- \( B \) is basic loop matrix.

- \( P \) is the nodal head column vector (relative reference node), expressed as \( P = (P_1, P_2, \ldots, P_m)^T \);

- \( \Delta P \) is a pressure drop vector, expressed as \( \Delta P = (\Delta P_1, \Delta P_2, \ldots, \Delta P_n)^T \);

- \( Q \) is a column vector of node traffic, expressed as \( Q = (Q_1, Q_2, \ldots, Q_m)^T \);

- \( G \) is flow column vectors for pipe sections, expressed as \( G = (G_1, G_2, \ldots, G_n)^T \).

- \( S \) is a diagonal matrix of drag coefficient, expressed as \( S = \text{diag}(S_1, S_2, \ldots, S_n) \);

- \( |G| \) is the diagonal matrix of the absolute value of pipeline flow, expressed as \( |G| = \text{diag}(|G_1|, |G_2|, \ldots, |G_n|) \);

- \( Z \) is the potential energy difference vector (position head) of two nodes in a branch of a pipeline, expressed as \( Z = (Z_1, Z_2, \ldots, Z_n)^T \);

- \( H_p \) is the lift vector of the water pump in the pipeline, expressed as \( H_p = (H_{P_1}, H_{P_2}, \ldots, H_{P_n})^T \).

### B. SOLUTION OF PIPELINE NETWORK MODEL

Hydraulic calculation of heating network is to calculate the pressure of each node and the flow of each pipeline under the condition that the network topology, node flow, node elevation, pump operation parameters and pipeline resistance coefficient are known.

Node equation method [11] is generally used to solve the hydraulic calculation equations of hot water pipeline network. The nodal equation method takes the nodal head as an unknown variable and formulates the initial value of each nodal head. Then, increments are continuously applied to the nodal head of each fixed flow node (positive value increases nodal head, negative value decreases nodal head) in order to satisfy the continuity energy equation.

For the convenience of calculation and solution by program, the position elevation of the pump and the pipeline can be omitted, and then the model (1) becomes as follows:

\[
\begin{align*}
AG & = Q \\
BP & = \Delta P \\
\Delta P & = S |G| G
\end{align*}
\]

There are two main steps to solve the above equations: linearization and iteration. After simplification and deformation of the second part in the appendix, (5) can be obtained

\[
M^k \Delta G_k^{i+1} = -\Delta h^k
\]

where, \( M^k = B2S|G|^kG^TB^T \), \( \Delta h^k = B(S|G|^kG + Z - H_p) \).

After the nonlinear equation is linearized, and the steps of iterative calculation are as follows:

1. Given the initial value \( G_0 \), let \( k = 0 \);
2. Calculate \( G_0 \) according to \( G_i = A_i^{-1}Q - A_i^{-1}A_i^*G_i \) in the appendix and then combine them into \( G_0 \);
3. Calculate \( \Delta G_{K+1} \) from (5) and calculate \( G_{K+1} \);
4. Judge \( |\Delta G_{K+1}| < \varepsilon \) (given accuracy), if it is satisfied, \( G_i = G_{K+1} \);
5. Otherwise, let \( k = k + 1 \) and repeat step 3-5.

### III. IDENTIFICATION MODEL OF PIPELINE ROUGHNESS

According to the analysis in the introduction, most heating systems do not have the conditions for smooth identification with the mechanism method. Therefore, the optimization identification method is selected in this paper. This method has low requirement for the quantities of monitoring points of network, and is suitable for almost any observation conditions of the pipeline network. For outdoor thermal pipeline, the nominal diameter is generally greater than DN40, and the hot water flow rate is greater than 0.5m/s, moving in the square resistance area, so this model ignores the cause of resistance. A complete description of the optimal identification model for pipeline roughness of heating pipeline is given below.
A. OBJECTIVE FUNCTION
Equation (6) is the basic model expression [13]. The main idea of this method is to take the pipeline roughness as a variable. The difference between the observed data of flow and pressure and the output data of the model is taken as the objective function value, and combined with the optimization algorithm to find a set of roughness that minimizes the objective function value. This set of roughness coefficients which are most in line with the actual pipeline network under the condition of existing data.

\[
\min f(s) = \sum_{e=1}^{NL} \left[ \sum_{i=1}^{NP} WH_{ie} |PC_{ie} - P0_{ie}|^{n} - \sum_{j=1}^{NG} WG_{je} |GC_{je} - GO_{je}|^{n} \right]
\]

where,
- \( F(S) \) is the objective function, representing the deviation between the measured values of pressure and flow and the calculated values of the model;
- \( S \) is the roughness vector to be identified;
- \( P0_{ie} \) is the actual pressure observation data of node \( i \) in condition \( e \);
- \( PC_{ie} \) is the pressure calculation value of node \( i \) in condition \( e \);
- \( GO_{je} \) is the actual observed flow data at \( j \) pipeline in condition \( e \);
- \( GC_{je} \) is the flow calculation value of \( j \) pipeline in condition \( e \);
- \( n \) usually is 1 or 2, corresponding to the calculation of absolute deviation and square deviation;
- \( NP \) is the number of pressure observation points;
- \( NG \) is the number of flow observation points;
- \( WH \) is the weight coefficient of pressure measurement points;
- \( WG \) is the weight coefficient of flow measurement points;

B. CONSTRAINT CONDITION
The constraints of this optimization problem can be classified into explicit and implicit constraints. Explicit constraints are only for decision variable \( S \). For the normal heat network, the actual roughness of each pipeline should be within a certain range, and the deviation from the calculated design value is little. The constraints can be expressed as follows:

\[
s_{i \text{min}} < s_i < s_{i \text{max}}
\]

\[
\sum_{j=1}^{b} a_{ij} g_j = q_i
\]

\[
\sum_{j=1}^{b} b_{ij} (s_j g_j^2 + z_j - dh_j) = 0
\]

where:
- \( s_i \) is the accurate roughness;
- \( s_{i \text{min}}, s_{i \text{max}} \) are upper and lower limits of roughness range;
- \( a_{ij}, b_{ij} \) are the basic relationship variable of pipeline network;
- \( g_j \) is pipe flow, \( q_i \) is node flow;
- \( z_j, dh_j \) is the water head and Pump lift;
- \( b \) represents the number of pipelines in the network.

The implicit constraints consist of (8), (9), which means that the basic data of the pipeline network must satisfy the basic hydraulic equation in the optimal calculation process.

IV. IMPROVED GENETIC ALGORITHM AND ITS APPLICATION IN IDENTIFICATION PROBLEM
To solve the problem of pipeline roughness identification, it is necessary to design an efficient and reasonable optimization algorithm. Considering the characteristics of optimization problem, the difficulty of this problem is multi-dimension, large search space and implicit constraints. Therefore, genetic algorithm with strong global exploration ability is adopted as the optimization method. Although the theory of genetic algorithm is mature and the research scope is wide, the phenomena of easily trapping in local optimum and premature in multidimensional problems are still urgent to be solved, otherwise, it will affect its application in pipe network problems.

Concerning the difficulties in pipe network optimization, this paper proposes an auxiliary individual oriented crossover (AIOX). AIOX is improved on the basis of the original oriented crossover (OX) [19] framework.

A. INTRODUCTION OF AIOX
1) REVIEW OF OX PRINCIPLE
In this paper, AIOX is improved on the basis of the original OX framework [19]. The OX solves the blindness problem of crossover operator producing offspring landing point, and makes the crossover offspring toward the better solution probabilistically. However, OX has some shortcomings in multidimensional problems. This paper uses the original OX alternative individual mechanism and a new alternative individual generation method to improve the optimization performance of RCGAs for multidimensional functions. In order to describe the principle of AIOX, the principle and process of OX are briefly reviewed in the appendix.

2) THE PRINCIPLE OF AIOX
The OX performs well in lower dimension problems, but the control of landing point is carried out separately in each dimension. For multi-dimensional problems, the descendant placement will become a combination problem of placement selection in each dimension. If the dimension number is \( n \), there are \( 2^n \) kinds of descendant placement. With the increase of dimension, the descendant placement selection will increase exponentially, which weakens the OX guidance function of descendants and makes it difficult to ensure that descendants fall into a better position.

Aiming at the difficulties of OX in multidimensional problems and improving the efficiency of RCGAs in exploring multidimensional problems, this paper proposes AIOX...
operator which can solve the optimization problem of descendant placement of multidimensional functions to a certain extent, guide descendants to explore space and reduce meaningless exploration. Auxiliary individuals are generated according to the fitness information of the current population. They are the better individuals in the population. The advantages of assistant individuals are considered from two perspectives.

Firstly, when the function presents two shapes of single peak and monotony, the assistant individual can be similar to the OX operator in guiding the placement effect. As shown in Fig. 1, the red dotted line in the figure represents a better interval. Because the assistant individuals are the better individuals in the population, they lie in the better spatial (between two dashed lines) under the two shapes analyzed in appendix 2) with a high probability. The population tends to move forward by crossing with auxiliary individuals. So, similar to the OX, the AIOX can also make the offspring move in the optimal direction.

For high-dimensional complex functions, although it is difficult to directly analyze the excellent solution interval of the function, the potential interval of assistant individuals is larger. The offspring generated by the crossover of the other individual \(D\) and assistant individuals are located in the interval composed of assistant individuals and \(D\). When a large number of individual crossover with assistant individuals in the population, the distribution of offspring tends to explore the interval near assistant individuals, and the potential interval is explored of highly efficiency. Therefore, the assistant individual strategy has certain guiding significance to the descendant landing point.

Secondly, assistant individuals directly use fitness information to generate and guide their offspring, so it is not difficult for them to generate and guide their offspring to explore as the dimension of the problem increases. Although the increase of dimensionality will make the exploration space of offspring larger, it is caused by the increase of difficulty of the problem itself, not by the use of assistant individuals, which is the improvement of AIOX over oriented crossover on high-dimensional problems.

In addition, because the AIOX descendants tend to aggregate to the better individuals in the current population, but the direction of the best individuals in the current population may not be the actual global optimum, so AIOX uses two strategies to balance this trend and prevent the algorithm from convergence to the local optimum too quickly.

On the one hand the parents-center strategy is introduced to improve stability of convergence process; on the other hand, when the offspring are generated, the search regions of the alternative offspring overlap in the region with a moderate distance from the best individual in the population to prevent individuals from gathering too quickly. In addition, AIOX also generate alternative offspring with a small probability of KBS, increasing the exchange of information between different loci, while preventing bias in the search. Using the above strategies and techniques, AIOX achieves the optimization of multi-dimensional and multi-modal functions.

3) BASIC STRUCTURE OF AIOX
AIOX process pseudocode is as follows, in which the auxiliary individual generation method, Gauss arithmetic crossover and KBS operator will be described in detail in the following sections.

Set parameter \(P_{kbs}\);
for \(i = 1: \) number of population do
Set \(XY\) = take the next two strings from the population;
Set \(0 < r \leq 1\) value;
if \(r > P_{kbs}\) then
generate offspring \(x_1x_2\) with KBS and \(X, Y\);
else if \(r < P_{kbs}\) then
generate offspring \(x_1x_2\) with Gaussian arithmetic crossover and \(X, Y\);
end if
Set \(A\) = generate auxiliary individual;
Set \(D\) = find individual close to \(A\) from \(x_1x_2\);
generate \(x_3x_4\) with Gaussian arithmetic crossover and \(A, D\);
evaluate individuals \((x_1, x_2, x_3, x_4)\);
Set \(x, y\) = select two better individuals \((x_1, x_2, x_3, x_4)\);
end for

4) SELECTION METHOD OF AUXILIARY INDIVIDUAL
AIOX adds assistant individual technology on the basis of basic oriented crossover, which greatly reduces the exploration space of candidate individuals and thus reduces the randomness of the generation of candidate individuals. The specific generation methods are as follows: take the minimization problem as an example, set the population size as \(N\) auxiliary individual numbers as \(K\), and the fitness function as \(f\). \(K\) individuals were randomly selected without
replacement from all \( N \) individuals in the population, and the individuals with the best fitness were used as assistant individuals.

The value of \( K \) determines the degree to which cross-search is biased towards the region near the optimal individual in the current population. When \( k \) approaches \( N \), the crossover tends to search the region near the optimal individual of the population, and the convergence speed of the algorithm is faster, but it is easy to fall into the local optimal value. When \( K \) approaches 1, the auxiliary individual \( A \) tends to approach the random selection without considering the fitness value, and the cross-search tends to be relatively random. At this time, the convergence speed of the algorithm is slow but the robustness is better. In order to give the reasonable value of \( k \), the relationship between \( k \) and assistant individual \( A \) is analyzed.

Firstly, all individuals in the population are ranked from small to large according to fitness value (taking the minimum value optimization as an example), and then assistant individuals are generated according to the above selection rules of assistant individuals, then the probability \( P(i) \) of the selected individuals ranked as \( i \) is as follows:

\[
P(i) = \frac{C^{k-1}}{C_{N-i}^k}
\]

Based on the above formulas, we can analyze the value of \( N \) in different populations, and give a reasonable \( k \) value corresponding to different populations. That is, each assistant individual has a probability of more than 90% to get the top \( N/5 \) of the population. Quantitative analysis is shown in Table 1.

**TABLE 1. Reasonable value of \( K \).**

| Population | Reasonable \( K \) Value | Select the top \( N/5 \) probability |
|------------|--------------------------|-----------------------------------|
| 100        | 10                       | 91%                               |
| 300        | 12                       | 94%                               |
| 500        | 15                       | 94%                               |
| 800        | 18                       | 98%                               |
| 1000       | 20                       | 98%                               |

5) ARITHMETIC CROSSOVER BASED ON GAUSSIAN DISTRIBUTION

The Gaussian arithmetic crossover used by the AIOX operator is based on the basic arithmetic crossover and is designed with the search strategy of parents-center. Let the parents vector be \( X = (X_1, X_2, \ldots, X_N)^T \) and \( Y = (Y_1, Y_2, \ldots, Y_N)^T \), \( N \) be the function dimension, and the calculation method of the offspring is represented by vector as follows:

\[
x_1 = \alpha X + (E - \alpha)Y \\
x_2 = \alpha Y + (E - \alpha)X
\]

where \( E = \) identity matrix, \( \alpha = \) the random number diagonal matrix. The matrix \( \alpha \) satisfies the equation \( \alpha = \text{diag}(\alpha_1, \alpha_2, \ldots, \alpha_i, \ldots, \alpha_N) \), where \( \alpha_i \sim N(1, \frac{1}{2}) \).

6) K-BIT-SWAP CROSSOVER OPERATOR

The way K-Bit-Swap crossover(KBS)[14] produces offspring is calculated as follows. For the \( N \)-dimensional optimization problem, let the parents be \( X = (X_1, X_2, \ldots, X_N)^T \) and \( Y = (Y_1, Y_2, \ldots, Y_N)^T \), and the offspring be \( x = (\alpha X_1, \alpha X_2, \ldots, \alpha X_N)^T \) and \( y = (\alpha Y_1, \alpha Y_2, \ldots, \alpha Y_N)^T \). Randomly select \( N/2 \) loci in two parents (round up when a decimal occurs), and calculate the following equation for each selected locus.

\[
x_i = X_i \alpha + Y_i (1 - \alpha) \\
y_j = Y_j \alpha + X_j (1 - \alpha)
\]

where, \( i = \) one of selected loci in parent \( X \), and \( j = \) one of selected loci in parent \( Y \). The random number \( \alpha \) satisfies \( \alpha \sim U(0, 0.4) \).

B. COMBINATION OF GENETIC ALGORITHM AND IDENTIFICATION MODEL

The combination of genetic algorithm and identification model mainly needs to consider the range of decision variables and the treatment of constraints.

1) DECISION VARIABLE RANGE DETERMINATION

Reasonable range of decision variables can make the optimization problem find the optimal solution quickly and improve the optimization efficiency greatly. In this problem, the range of decision identification refers to the range of \( S \) in (4).

\[
c_j S_j \leq S \leq d_j S_j
\]

where,

\( S \) is design roughness of pipeline \( j \);

\( c_j, d_j \) are proportional factors, according to the empirical value, they can be 0.5 and 1.5 respectively.

For the normal heat network (without serious corrosion, aging and damage), the actual resistance coefficient of each pipeline should be within a certain range including the design roughness, and the deviation from the design value is little, the range can be expressed as (13). The design roughness of the pipeline can be calculated by (14).

\[
S_j = 6.88 \times 10^{-3} K_{ij}^{0.25} l_j \frac{d_j^2}{\rho} (1 + a)
\]

From (14), the ratio between the real roughness and the design roughness can be expressed as (15). According to (15), the main reason for the deviation between the real value of roughness and the design value is the inaccurate estimation of the absolute equivalent roughness \( K \) and the ratio of local resistance to the frictional drag coefficient (resistance along the way) \( a \). According to the empirical values and relevant specifications, this paper assumes that the absolute equivalent...
roughness of the inner wall of the pipeline is 0.0004m, and the ratio of the local c to the resistance along the pipeline is 0.3.

\[
\frac{S_j'}{S_j} = \left(\frac{K_j'}{K_j}\right)^{0.25} \frac{(1 + a_j)(1 + a'_j)}{(1 + a_j)}
\]

(15)

where,

- \(K_j\) is design absolute equivalent roughness;
- \(K_j'\) is actual equivalent roughness;
- \(a_j\) is proportion of design local coefficient to resistance along the way ratio;
- \(a'_j\) is proportion of actual local coefficient to resistance along the way roughness ratio.

2) TREATMENT OF CONSTRAINTS
The constraints of the identification model are (7), (8), (9). Among them (7) has been analyzed in B-1) of this chapter, and will not be discussed here. (8), (9) are hydraulic operation constraints. If constraints are handled directly, penalty functions are needed. But the implicit constraints of this optimization problem are not for the decision variable \(S\). And the implicit method needs to call hydraulic calculation module to solve the flow and pressure in the calculation process, and the hydraulic calculation module itself will automatically meet the hydraulic relationship conservation in the operation process, therefore (8), (9) constraints are naturally satisfied and no punishment is required.

V. EXAMPLE ANALYSIS
In order to verify the performance of the proposed algorithm (AIOX-GA), two heating networks with different number of pipelines are used for identification experiments. In the experiment, we compare with several classical evolutionary algorithms, including real coded genetic algorithm (AX-GA), particle swarm optimization (PSO), differential evolution algorithm (DE). In order to verify the algorithm more fully, we add a comparison to the optimization methods which have achieved good results in the references. The comparison algorithms include ant colony algorithm (AG) [7], fast messy genetic algorithm (fmGA) [8].

In this paper, the pipeline network is simplified from two residential districts in Beijing. The simulation observation data are generated by heating pipeline network simulation software. At the same time, the pipeline roughness used in the software simulation calculation is considered the accurate value, which will be compared with the identification results in the experiment.

In order to facilitate the experiment, the following assumptions are made: 1. The water supply network and the water return network is mirror symmetrical, the heat source flow, the node flow, the length and the diameter of each pipeline are known, and the fluid in the network is incompressible fluid; 2. For outdoor thermal pipelines, the nominal diameter is usually greater than DN40, and the flow velocity of hot water is generally greater than 0.5m/s. The movement is in square resistance region. 3. Because the landform has no obvious slope fluctuation, the elevation of each node in the pipeline network is considered to be the same.

A. PIPELINE NETWORK 1 IDENTIFICATION EXPERIMENT
The network topology is shown in Fig. 2. The information on the pipe section represents the [number length (m) diameter (mm)] respectively. Node 9 in pipeline network 1 is the heat source, and the rest are the heat users. The network is regulated once in the whole heating period, so two kinds of working condition data can be obtained for identification. There are six observation points in the network, among which the pressure observation points are nodes 1, 6, 8, and the flow observation points are segments 2, 5 and 9.

1) ALGORITHM PARAMETER SETTING
The parameters of PSO are: population is 500, maximum number of iterations is 800, learning factor \(C1 = C2 = 2\), inertia factor \(W = 0.7\). The parameters of fmGA: the maximum number of external cycles is 10, the maximum number of internal cycles is 5, the probability of cut and splice is 1, the probability of mutation is 0.05, the length of building blocks \(k = 4\), and the population number is obtained by referring to the population calculation formula of fmGA [6], [20]. In this experiment, the population number is 352. Several kinds of genetic algorithms and differential evolution parameters are showed in Table 2, the fitness function calculation times of AIOX-GA is twice as other algorithms in each generation, so the iteration times of AIOX-GA is set as half of the other algorithms. Due to the long calculation time of the hydraulic model, this paper evaluates the efficiency of the algorithm by the calculation times of the fitness function. According to the parameter setting scheme in this experiment, the calculation times of AIOX-GA, AX-GA and PSO fitness functions are 400000, and the calculation times of DE and AG fitness functions are 500000. According to the formula of population setting, fmGA has the same calculation times as other GA. Therefore, it can be considered...
that the total execution time of this experimental algorithm is approximately the same.

In order to prove the stability of the algorithm, the experiment is carried out 10 times, the best of which is taken as the final identification result. At the same time, the average error of the results of 10 times will be statistically analyzed to prove the stability of the algorithm in this paper.

2) RESULTS AND ANALYSIS
The identification results of Experiment 1 are shown in table 4. The accuracy values of roughness, the identification values and deviations of each identification method are separately shown in table. The unit of roughness is \( Pa/(t/h)^2 \), and the identification results all retain two decimal numbers. The deviation calculation method is \( |S_{acc} - S_{ide}| ÷ S_{acc} × 100\% \), where \( S_{acc} \) and \( S_{ide} \) represent the accurate value and identification value of resistance coefficient respectively.

Because the calculation times of fitness function of parameter setting are approximately the same, the algorithm used in the test can be considered to be approximately equal in time. Under these conditions, the average error of AIOX-GA identification results is the smallest, and the maximum deviation is 5.6%. Considering the limitation of the layout scheme of measuring points in the heat network, the general error can be less than 10%. The identification accuracy of this identification method can fully meet the actual engineering needs.

Among other algorithms’ results, the average error of AX-GA is the smallest, it is 2.68%. The average error of PSO, DE, fmGA and AG algorithm is much higher than that of AIOX-GA algorithm. And the maximum relative error of single root canal segment, AIOX-GA is also the smallest PSO is 41%, AX-GA is 5.88%, fmGA is 20.92%, AG is 37%, which cannot meet the engineering requirements.

TABLE 2. Experiment 1 algorithm parameter setting.

| Algorithm | AX-GA | DE | AIOX-GA |
|-----------|-------|----|---------|
| Population| 500   | 500| 500     |
| Max iterations| 1000 | 1000| 500    |
| \(Pc\)  | 0.7   | 0.9| 0.7     |
| \(Pm\)  | 0.1   | 0.5| 0.1     |

TABLE 3. Stability results of experiment 1.

| Algorithm | Maximum error | Minimum error | Average Error |
|-----------|---------------|---------------|---------------|
| AIOX-GA   | 3.185%        | 0.002%        | 1.690%        |
| DE        | 14.283%       | 0.009%        | 7.757%        |
| PSO       | 32.639%       | 0.015%        | 11.670%       |
| AX-GA     | 3.406%        | 0.158%        | 2.180%        |
| fmGA      | 15%           | 2.478%        | 11.773%       |
| AG        | 14.931%       | 1.266%        | 11.460%       |

FIGURE 3. Topology of pipeline network 2.

The statistics of the average results of algorithm operation are shown in Table 3. Among the 10 identification results, the maximum average error of single pipe section, the minimum average error of single pipe section and the average error of all pipe sections of each algorithm are calculated. It can be seen from the results that in terms of the maximum error of a single pipeline, AIOX-GA and AX-GA perform well at 3%, while the other algorithms perform poorly at 30%; in terms of the minimum error of a single pipeline, AIOX-GA, DE, POS and AX-GA have little error at 1%, while the minimum error of fmGA and AG is 2.478% and 1.266%; in terms of the average error, AIOX-GA has the same advantages. Obviously, AX-GA also performs well, the average error of other algorithms is more than 7%, and the stability is poor.

B. PIPELINE NETWORK 2 IDENTIFICATION EXPERIMENT
The pipeline network topology is shown in Fig. 3, and the pipeline information representation method is the same as experiment 1. Node 16 in network 2 is the heat source, and the rest are the heat users. The network is regulated twice in the whole heating period, so there are three working conditions for identification. The numbers of observation points in the network are 11, and the pressure observation points are nodes 2, 4, 8, 13, 15, and the flow observation points are pipeline 2, 4, 10, 12, 19 and 21. The pipeline network 2 has more pipelines and more complexity than pipeline 1, so the coupling between pipelines increases accordingly. From the point of view of optimization identification, the dimension of optimization problem is higher, the exploration space is
larger, and the requirements of optimization algorithm’s performance is higher.

1) ALGORITHM PARAMETER SETTING

The parameters of PSO are: population 1000, maximum number of iterations 800, learning factor $C_1 = C_2 = 2$, inertia factor $W = 0.7$. The parameters of fmGA are as follows: the maximum number of external cycles is 10, the maximum number of internal cycles is 5, the probability of cutting and splicing is 1, the probability of variation is 0.05, the length of building blocks is $k = 4$, and the number of population is 788 by calculation. Several genetic algorithms and differential evolution parameter settings are shown in Table 5, the fitness function calculation times of AIOX-GA is twice as other algorithms in each generation, so the iteration times of AIOX-GA is set as half of the other algorithms. The above parameters can make the calculation times of fitness function close to each other in order to compare the performance of the algorithm. The calculation times of AIOX-GA, AX-GA and PSO fitness functions are 800000, and the calculation times of DE and AG fitness functions are 1000000. According to the formula of population setting, fmGA has the same calculation times as other GA. Therefore, it can be considered that the total execution time of this experimental algorithm is approximately the same. In order to prove the stability of the algorithm, the experiment will be repeated 10 times, the same as experiment 1.

2) RESULTS AND ANALYSIS

The statistical results of pipeline 2 are shown in Table 7. The numerical significance and error calculation method in the table are the same as that in Experiment 1. Because the calculation times of fitness function of parameter setting are approximately the same, it can be considered that the running time of the program is approximately the same. Under this condition, the average error of AIOX-GA identification results is the smallest and the maximum deviation is 5.13%. Considering the limitation of the layout scheme of measuring points and the large number of pipe sections, the identification method in this case can also meet the actual engineering needs.

Among other algorithms’ results, the average error of AX-GA algorithm is the smallest, which is 3.78%, slightly lower than the identification accuracy of the algorithm in this paper, and the average error of PSO, DE, fmGA and AG algorithm is much higher than that of AIOX-GA algorithm, while AX-GA performs better in the maximum relative error of single root canal segment, which is 6.8%, slightly higher than that of the algorithm in this paper; other algorithms, DE and AG, even reach 40%, PSO exceeds 30%, and fmGA exceeds 37%, which are much higher than the algorithm in this paper. And it cannot meet the needs of the engineering demand.

The statistics of the average results of algorithm operation are shown in Table 6. Among the 10 identification results, the maximum average error of single pipe section, the minimum average error of single pipe section and the average error of all pipeline of each algorithm are calculated. It can be seen from the results that in terms of the maximum error of a single pipeline, AIOX-GA performs best at 8.45%, but
TABLE 7. Results of experiment 2.

| Number | Exact value | AIOX-GA | Error | PSO | Error | DE | Error | AX-GA | Error | AG | Error | fmGA | Error |
|--------|-------------|---------|-------|-----|-------|----|-------|-------|-------|----|-------|------|-------|
| 1      | 135.66      | 133.06  | 1.92% | 136.86 | 0.89% | 162.83 | 20.00% | 138.35 | 1.98% | 199.95 | 10.54% | 133.06 | 1.90% |
| 2      | 438.78      | 438.75  | 0.01% | 433.6 | 8.02% | 459.36 | 4.70% | 422.98 | 3.60% | 648.23 | 47.74% | 367.78 | 16.20% |
| 3      | 758.2       | 797.1   | 5.13% | 899.63 | 18.65% | 1006.14 | 40.60% | 698.24 | 7.91% | 498.15 | 34.29% | 698.24 | 7.90% |
| 4      | 381.51      | 379.69  | 1.53% | 338.56 | 11.26% | 295.79 | 22.50% | 348.55 | 8.64% | 234.68 | 38.49% | 343.48 | 10.00% |
| 5      | 495.36      | 495.34  | 0.0%  | 406.61 | 17.92% | 522.04 | 5.40% | 479.79 | 3.14% | 503.43 | 1.63% | 424.48 | 14.30% |
| 6      | 733.28      | 734.38  | 0.15% | 678.7 | 7.44% | 743.21 | 1.40% | 709.63 | 3.23% | 888.01 | 21.10% | 556.41 | 24.10% |
| 7      | 385.34      | 384.82  | 0.07% | 396   | 3.49% | 476.64 | 23.60% | 360.65 | 6.46% | 666.15 | 73.30% | 372.78 | 3.30% |
| 8      | 721.3       | 698.25  | 3.20% | 709.63 | 1.62% | 965.93 | 33.90% | 687.14 | 4.74% | 939.01 | 30.18% | 540.90 | 25.00% |
| 9      | 698.24      | 709.63  | 1.63% | 771.09 | 10.43% | 911.97 | 30.60% | 687.14 | 1.55% | 472.48 | 32.33% | 645.32 | 7.60% |
| 10     | 455.51      | 447.02  | 1.86% | 447.02 | 1.86% | 460.25 | 1.00% | 447.02 | 1.86% | 567.88 | 24.67% | 400.87 | 12.00% |
| 11     | 1344.65     | 1322.3  | 1.66% | 1344.2 | 0.03% | 1475.25 | 9.70% | 1322.3 | 1.66% | 1574.95 | 17.13% | 1258.58 | 6.40% |
| 12     | 313.04      | 308.27  | 1.53% | 315   | 0.01% | 240.38 | 23.20% | 299.05 | 4.47% | 256.11 | 14.99% | 299.05 | 4.50% |
| 13     | 482.51      | 473.24  | 1.92% | 380.49 | 21.14% | 422.14 | 12.50% | 492.05 | 1.98% | 455.51 | 5.60% | 387.10 | 19.80% |
| 14     | 19380.2     | 19976.19 | 2.02% | 23878 | 32.14% | 18250.29 | 6.80% | 19380.00% | 20384.64 | 4.11% | 22363.76 | 15.60% |
| 15     | 5639.09     | 5834.02 | 3.46% | 7291.9 | 29.31% | 3260.91 | 42.20% | 5363 | 4.86% | 6485.46 | 15.01% | 7398.17 | 31.20% |
| 16     | 4932.11     | 4745.44 | 3.79% | 5477.3 | 11.06% | 6986.37 | 41.70% | 4745.4 | 3.79% | 5029.73 | 1.98% | 6780.39 | 37.50% |
| 17     | 11846.9     | 11411.86 | 3.67% | 10809 | 8.76% | 6702.18 | 26.50% | 11626 | 1.86% | 10612.33 | 10.42% | 7438.24 | 37.20% |
| 18     | 2055.05     | 2092.53 | 1.82% | 1477.4 | 29.06% | 2268.78 | 10.40% | 1915.1 | 6.81% | 2296.67 | 11.75% | 1850.49 | 10.00% |
| 19     | 533.01      | 506.28  | 5.02% | 497.28 | 6.70% | 456.34 | 14.70% | 506.26 | 5.02% | 772.26 | 44.42% | 688.55 | 8.60% |
| 20     | 2341.17     | 2253.46 | 3.75% | 1915.1 | 18.20% | 2792.10 | 19.30% | 2211.5 | 5.54% | 1623.00 | 30.68% | 2170.70 | 7.30% |
| 21     | 5643.77     | 5460.17 | 3.25% | 4666.6 | 17.31% | 6900.96 | 7.90% | 5371.8 | 4.82% | 3576.49 | 36.63% | 4810.49 | 14.80% |
| 22     | 3672.81     | 3739.17 | 1.56% | 3974 | 8.29% | 3917.60 | 6.70% | 3732.1 | 1.56% | 3672.85 | 0.00% | 4105.26 | 11.80% |
| 23     | 9436.03     | 9577.44 | 1.50% | 9436 | 0.0% | 9490.73 | 0.60% | 9077.4 | 1.56% | 7856.16 | 16.74% | 11106.91 | 17.60% |
| Average error | – | – | 2.19% | 11.46% | – | 17.65% | – | 3.78% | – | 22.77% | – | 14.98% | – |
B. REVIEW OF OX PRINCIPLE

Assuming that $x,y$ is the parent, $x',y'$ is the offspring and $a,b$ is the function boundary, the optimization problem is illustrated by finding the maximum value. Firstly, the function is divided into I, II and III intervals by boundaries $a,b$ and $x,y$ as shown in Fig. 4. All the conclusions of OX are based on this interval. In this paper, the following three conclusions are summarized for OX.

1) REAL CODE CROSSOVER DESCENDANT LANDING POINT CHARACTERISTICS:
OX guides the descendant landing point to guide the descendant landing point. Firstly, the location of the descendant landing point is analyzed. As shown in Fig. 4, the distribution of the descendant landing point is as follows:

- Interval I: $x \leq x' \leq y' \leq y$
- Interval II and III: $a \leq x' \leq xy \leq y' \leq b$

2) INTERVAL ANALYSIS OF CROSSOVER GENERATIVE BETTER SOLUTIONS
After obtaining the interval distribution characteristics of descendant landing points, we analyze the intervals where the monotonic shape and single peak shape of the two typical functions produce better solutions than the paternal ones.

① For monotone functions, as shown in Fig. 5, it is obvious that excellent solutions must be found in interval III after crossover.

② For a single peak function, let $x_{best}$ be the individual corresponding to the peak value, as shown in Fig. 6:

Case 1, when $x \leq y \leq x_{best}$ or $x_{best} \leq x \leq y$, is equivalent to ①;

Case 2, when $x \leq x_{best} \leq y$, let $f(x) > f(y)$, because the parents are on both sides of the peak. Therefore, we must find a point $x_1$, so that $f(x) = f(x_1)$, if the offspring fall into the interval $[x, x_1]$, we can find excellent solutions.

Because of the existence of the selection operator, $\Delta = f(x) - f(y)$ will gradually approach 0, and the interval $[x, x_1]$ will also tend to coincide with interval I. Therefore, after crossover, it is possible to find the excellent solution in interval I.

For multi-modal functions, after multi-generation evolution, due to the existence of selection, after multi-generation selection, the population will focus on a few peaks of the multimodal function, it will gradually be transformed into one of the case 1 or case 2. Through the above analysis, if we can optimize the control of the placement of the crossing offspring and orient the crossover to the interval I (or II) where the excellent solution can be obtained, then the crossed offspring will be more likely to be superior to the parent individuals.

3) OX FLOW
Combining the relationship between the offspring and the excellent offspring, we propose an oriented crossover framework, which is represented by pseudo-code as follows:

```
initialize parameter crossover probability $P_c$ and function boundary value $a,b$
for $i=1$: number of population do
Set $XY=take$ the next two strings from the population
Set $0 < r \leq 1$ value
if $r > P_c$ then
    Set $0 \leq a_1 \leq 1$ value
    $max = \max (X, Y)$;
    $min = \min (X, Y)$;
    $temp1 = b - max$;
    $temp2 = min - a$;
    $delt = \min (temp1, temp2)$;
    generating inner individuals:
    $x_1 = max + a_1 delt$;
    $y_1 = min - a_1 delt$;
    Set $0 \leq a_2 \leq 1$ value;
    generating outer individuals:
    $x_2 = a_2 X + (1 - a_2)Y$;
    $y_2 = a_2 Y + (1 - a_2)X$;
    evaluate individuals $(x_1, x_2, y_1, y_2)$;
    Set $x, y = select$ two better individuals $(x_1, x_2, y_1, y_2)$;
end if
end for
```
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