Study of the regimes planning problem for pipeline systems tests

Oksana Grebneva

1 Melentiev Energy Systems Institute of Siberian branch of Russian Academy of Science, department of pipeline and hydraulic systems, Lermontov street 130, Irkutsk, Russia, 664033

Abstract. When determining the actual characteristics of pipeline systems based on the measurement results, the solution of two problems is required: optimal placement of measuring instruments; planning conditions in which this measure placement will be the most informative. This article presents the results of research for problem of planning test conditions of pipeline systems. The mathematical formulation of the problem under study is presented, methods for its solution are proposed, namely, genetic algorithms. The results of numerical studies that show their potential performance are presented.

1 Introduction

The effective solution of various problems for operation, adjustment and dispatching control of pipeline systems (PLS) can be obtained on the basis of the application of modern methods of mathematical and computer simulation. However, the lack of reliable initial information about actual characteristics and parameters of the PLS depreciates the entire available arsenal of these methods.

For PLS, the problem of the lack of such information is solved by actual testing [1-3]. The tasks for determining the characteristics coefficients of system elements according to the measurements results of states parameters
are related to the tasks of parametric identification. Potentially, the methods developed both in Russia [4, 5] and abroad [6–11] are useful for solving such problems.

At actual characteristics determining with required accuracy according to the measurement results, the following two difficulties can be identified:

1) not every measurement placement gives the desired result;
2) not in any state of the network operation this measurements placement will be the most informative.

As for the first problem, it was considered in [13–15]. This article is devoted to the second problem associated with the states planning.

2 Mathematical statement of states planning problem

Let all the parameters available for measurement are measurable, then the task of planning the $u$-th state is as follows:

$$\min_{\alpha} \{\det(C_u(X^{\alpha})))\} \text{ subject to } R^{(\alpha)} \leq \tilde{R}^{(\alpha)} = \begin{bmatrix} Y^{(\alpha)}(X^{(\alpha)}) \\ X^{(\alpha)} \end{bmatrix} \leq \bar{R}^{(\alpha)},$$  (1)

where $\det(\cdot)$ – a matrix determinant; $C_u$ – a covariance matrix of elements parameters; $R^{(\alpha)}$ – vector of the $u$ state variables; $\alpha$ – vector of elements parameters (model coefficients); $R^{(\alpha)}, \tilde{R}^{(\alpha)}$ – lower and upper limits of variation in the state variables, respectively; $N$ – states number; $X^{\alpha}, Y^{\alpha}$ – vectors of independent and dependent $u$ state variables, respectively. Vector $R^{(\alpha)}$ include vectors of independent and dependent variables of model (1). So, we can write $U(Z) = U(R, \alpha) = U(X, Y, \alpha) = 0$. Hence $Y = F(X, \alpha)$, where $F$ – implicit function. Thus, in the role of limitation in (1) are the flow distribution equations, written in an implicit form.

For planning the state $u$, the vector of the parameters of the elements is given by $\alpha^{(\alpha)} = \hat{a}_{u-1}$, where $\hat{a}_{u-1}$ – is the vector of estimates of the elements parameters by $u-1$ states. Hereinafter, the superscript indicates the state parameters related to the $u$-th state, and the subscript – parameters obtained as a result of processing by $u$ states. For planning the first state $\hat{a}_0$ are set either according to the previous identification, or – expertly using data on the service life of pipelines, diameter, roughness coefficient, etc.
Isothermal and non-isothermal steady-state flow distribution states [16] can be used as the initial flow distribution model for solving the state planning problem.

The determinant of the covariance matrix of the elements parameters \((\det C_p)\) is used as an optimality criterion. As shown in [4], this criterion is a function of independent state parameters \(X\), element parameters \(\alpha\), and depends on the measurements.

3 Solution methods

The problem of states planning is characterized by a fairly high dimension, non-linearity, multi-extremity, and extreme cumbersomeness analytical expressions even for the first derivatives of the objective function, respectively, by high computational complexity. For its effective solution, there are still no general global optimization methods, and therefore, this paper proposes the use of genetic algorithms that have found wide application in the modern world specifically for this kind of tasks [17–20]. The solution of the problem is reduced to a directed search with elements of "random walks" with the help of selection operators. In this case, eventually, a certain subset of points is formed, the deviation of the objective function in which is minimal. Characteristic features of genetic algorithms are the ability to solve highly linear problems, independence from the type of the objective function, and the absence of requirements for its differentiability and continuity.

3.1 The basic concepts and principle of the genetic algorithm

The flowchart of the genetic algorithm is shown in Figure 1.

The vectors of dependent and independent state parameters include, respectively:

\[ Y = (\bar{Q}^T, x^T, t_m^T, T^T)^T; \quad X = (\bar{P}^T, \alpha^T, t^T)^T; \]

\[ Z = (\bar{P}, \bar{Q}^T, x^T, t_m^T, t^T)^T; \quad \gamma \in \{s, k\}, \quad \gamma \in \{x\}, \quad \gamma \in \{x, \bar{P}\} \text{ vector of flow rates in the branches}; \]

\[ \bar{Q}, \bar{P} \text{ vectors of nodal flow rates and pressures, respectively; } \]

\[ t_{\text{begin}}, t_{\text{end}} \text{ vectors of temperatures at the beginning and end of the branches, } \]
respectively: $\mathbf{T}_s$ – vector of source temperatures; $\mathbf{\bar{T}}$ – vector of temperatures of mixed flows at nodes; $\mathbf{s}$ – vector of hydraulic characteristics (resistance coefficients); $\mathbf{k}$ – vector of thermal-physical characteristics of elements (heat transfer coefficients).

Figure 1. Genetic algorithm flowchart: $F_i$ – value of the objective function of the chromosome $i$.

Let us explain the work of the genetic algorithm using the example of the search for a non-isothermal state for the conventional scheme of PLS presented in Figure 2.

Figure 2. The conventional scheme of PLS.

It was supposed that the temperature of source and sinks at nodes 2 and 3 that played a role of varying state variables could be controlled. The ranges of variation in the variables were: $2327 \leq Q_2 \leq 675, 1625 \leq Q_3 \leq 1975, 70 \leq T_s \leq 95$.

To start the action of the genetic algorithm, it is necessary to encode the variables in the chromosomal thread (chromosome). So, if the inflow temperature, expenses in the second and third nodes are used as variable variables, then the chromosomal thread will consist of three genes, each of which is represented in binary form:
Initially, the number of chromosome threads \( N \) (population or generation) is selected. This number is kept constant throughout the duration of the genetic algorithm.

Then with probability of selection \( p^s = \frac{r}{\sum r} \) it is selected the most suitable for obtaining the optimal solution of chromosomes (parents) for crossing.

After selection, the most suitable parents cross. The probability of crossing is determined by the following formula: \( p^c = \left( \frac{F_j + F_i}{\sum F_i} \right) \).

Crossing is a random selection of a position in the chromosomal filament and the exchange of numbers either to the right or to the left of this point with another chromosome that is divided in the same way. This random position is called a crossing point. For example:

\[
\begin{align*}
H_1 &= 0000000101000101000001111011011100000000010111111 \\
H_2 &= 000000010100010100000110010110010000000001011111
\end{align*}
\]

Putting the crossing point, as shown above, and assuming that the exchange is performed on the right, we get two new chromosomes (descendant):

\[
\begin{align*}
H^c_1 &= 0000000101000101000001100101100100000000010111111 \\
H^c_2 &= 0000000101000101000001111011011100000000011111111
\end{align*}
\]

For some selected number of chromosomes, a mutation operation is performed – a chromosome transformation that randomly changes one or more of its positions. The most common type of mutation is a random change in one of the position of a gene in a chromosome. The probability of a mutation \( p_m = \%N \) is given as a percentage (how many chromosomes of their total number must be implemented) by the researcher himself.

\[
\begin{align*}
H^m_1 &= 0000000101000101000001100101101100000000010111111 \\
H^m_2 &= 0000000101000101000001111011011100000000011111111
\end{align*}
\]
As a result of the actions of the described operators, the next generation inherits the best signs of the previous one in the direction of movement towards the optimum. Ultimately, a subset of points is formed, the deviation of the objective function in which is minimal.

### 3.2 Algorithm of problem

Algorithm of problem solution for states planning:

1. An initial population of $N$ chromosomes is generated (as a rule, randomly) – we get $N$ state vectors.
2. For each of the $N$ state vectors, we calculate the values of the objective function.
3. Reproduction.
   1. **Crossbreeding.** With the probability of crossing $p_c$, we determine whether to perform a crossing operation or not. If so, then a random set of gene is exchanged. The resulting chromosomes are translated into the category of descendants.
   2. **Mutation.** With the probability of mutation $p_m$, we change certain genes in randomly selected chromosomes of descendants.

Then the old population is partially or completely destroyed. In a new generation of parents are moving, the corresponding value of the objective function is higher than that of descendants. Then the next generation is considered. The population of the next generation should contain as many chromosomes as in the previous one. Therefore, the least suitable chromosomes are screened out with a probability of selection $p_s$, so that $N_i + I = N_i = \text{const.}$

### 4 Numerical studies

Numerical studies were conducted on the example of the pipeline network depicted in Fig.2. Nodal costs were assigned as variable network parameters.

The results obtained using the genetic algorithm to solve the problem of states planning are shown in Figure 3.
Figure 3. The process and results of the genetic algorithm.

As it was shown in [0], the solution of the problem is on the borders of the studied area. As can be seen from Figure 3, in the course of the genetic algorithm the solutions gradually come closer and ultimately we get the only solution. The Figure shows that the solution is achieved in four iterations for the scheme consisting of three nodes and three branches. Also Calculations were carried out for schemes of higher dimension. So, for a scheme consisting of five nodes and six branches the solution is achieved in four iterations, and for seven node schemes – in three iterations. Thus, data analysis allows to conclude that the use of genetic algorithms makes it possible to obtain a solution of the planning states problem and the effectiveness of the genetic algorithm increases with increasing dimension of the network under study.
5 Conclusion

An original approach to solving the multi-extremal problem of planning the PLS states operation according to the information criterion, based on the use of genetic algorithms, is proposed. The adaptation of these algorithms and the software implementation of these algorithms as applied to the solution of the multi-extremal problem of mode planning were carried out and numerical studies were performed that showed their potential performance.

The research was carried out within the project III.17.4.3 of the Fundamental research program of SB RAS (AAAA-A17-117030310437-4) with finance support of RFBR and the Government of Irkutsk Region in the framework of research project № 17-48-380021

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