Research on Valve Network Model for Complex Industrial Pipeline Networks

Xiao Luo*, Shuang Zhou, Yufang Zheng, Xiaoyan Han, Yichao Cao and Wenjie Ding*
School of Mechanical Engineering, Ningxia University, Yinchuan City, Ningxia Hui Autonomous Region 750021

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Abstract: In the study of valve failure behavior, traditional methods often treat valves as isolated individuals or fixed resistance components, leading to misjudgments about valve performance and the accuracy of pipeline network models, and further affecting the efficiency of fault detection and handling. Therefore, this research analyzes the current status of industrial pipeline networks and summarizes the existing problems in current studies. It proposes a new approach to judge the failure behavior of valve networks in complex industrial pipeline networks, considering the relationship between valve opening and resistance, and establishes a model correlating valve failures with pipeline flow rates. Additionally, a computer-based valve network information model is established, taking into account the mutual influence relationship between valve clusters in the pipeline network and modeling the entire pipeline network. This model provides convenience for the input and computation of large-scale pipeline network operational data sets into computers.

1 INTRODUCTION

Valves are an essential component of complex industrial pipe networks, forming the structure of the network along with straight pipes, elbows, and pipeline accessories. Since valves are movable components with variable flow and resistance, they have a relatively high failure frequency and thus become the main object of study for pipeline network operation and maintenance.

In existing research, one approach is to study the characteristics and fault manifestations of valves as independent entities, examining the changes in various parameters under single-valve failure conditions. Another approach treats valves as fixed resistance elements and studies pipeline network failures based on network models. However, in real-world industrial pipe networks, valve parameters dynamically change, and valves are used jointly to form a valve network with interconnected information. Existing pipeline network models cannot be directly used for discriminating valve failure behaviors. Therefore, in-depth research on the valve network model of complex industrial pipe networks is crucial for effectively managing intelligent valves and improving industrial production safety.

Particularly noteworthy is the fact that complex industrial pipe network systems typically consist of hundreds or even thousands of valves and pipelines, resulting in a massive operational dataset. With the continuous innovation of industrial technology, valves are gradually moving towards intelligence and the Internet of Things (IoT). High-end valves, which possess self-information collection, storage, transmission, and self-diagnostic capabilities, have become a trend in valve development. Currently, pipeline network valves are gradually developing towards the IoT, with massive numbers of valves being managed through cloud-edge collaboration techniques. Effectively categorizing and processing this vast amount of operational data has become the key to enhancing the efficiency of pipeline valve management.

2 ANALYSIS OF CURRENT RESEARCH STATUS

2.1 Characterization of Valve Faults

In studies that treat valves as independent entities,

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scholars often analyze current signals and vibration signals to delve into the fault characteristics of valves. Fabio and his team (Fabio et al, 2023), for instance, utilized current signals, acoustic emission signals, and vibration signals to represent valve faults during hydraulic valve fault diagnosis. In their specific experiments, they achieved nearly 99% accuracy in fault characterization using current and vibration signals. Liu and his colleagues (Liu et al, 2024) conducted vibration analysis and fault diagnosis research on water hydraulic relief valves, employing changes in external vibration response to diagnose internal faults. They collected and processed displacement signals and voltage signals from valve vibrations for fault diagnosis. Yang and his team (Yang et al, 2021) analyzed vibration faults in control valves and proposed optimization solutions. Zeng and his team (Zeng et al, 2021), in their study of electric valve fault characteristics, analyzed and processed acquired current signals, vibration signals, and acoustic emission signals. They proposed a method for electric valve signal processing and feature extraction, extracting fault features such as effective current value, peak impact current, stroke time, effective value of acoustic emission signals, acceleration level, impact frequency, and acceleration frequency domain signals to represent the fault state of the valve. Xiao and his colleagues (Xiao et al, 2020) utilized vibration signals, pressure signals, and key phase signals for fault diagnosis of reciprocating compressor air valves using a deep convolutional neural network. Their experiments demonstrated that vibration signals and pressure signals had the highest diagnostic accuracy when used in a two-dimensional CNN. From these studies, it is evident that valve vibration is closely related to faults. Therefore, in the study of valve networks in industrial pipe networks, vibration signals can be selected to represent valve faults.

It is noteworthy that scholars such as Venkata (Venkata, 2018) have placed valves within pipe networks and studied the dynamic correlation between flow pattern changes and valve vibrations caused by individual control valves through the training of neural network models. Based on this, they conducted fault diagnosis on the valves. However, in practical applications, valves always operate as a part of the pipe network system and cannot function independently from the network. Therefore, following the approach of Venkata and other scholars, we will delve deeper into the correlation between valve vibrations and pipe network flow rates, aiming to establish a model that links valve vibrations with changes in pipe network flow. This approach will provide a more comprehensive understanding of valve behavior within complex pipe networks and facilitate more accurate fault diagnosis and management.

2.2 Aspects of Establishing Pipeline Network Models

In the field of pipeline network modeling, scholars primarily adopt various modeling techniques such as neural network training, algorithm-based model training, graph theory, and Kirchhoff's laws. To simplify the expression of the pipeline network model, valves are generally treated as fixed resistance elements. However, in actual pipeline network operations, valves are dynamic components with variable flow rates and variable resistances, resulting in a higher frequency of failures. Therefore, when establishing pipeline network models, it is crucial to incorporate additional valve characterization parameters to investigate the failure behavior of valves within the network. By doing so, the models can more accurately reflect the dynamic characteristics of the pipeline network, including the impact of valve failures, and provide valuable insights for fault diagnosis, flow optimization, and energy management.

When utilizing neural network model training and algorithmic model training to establish pipeline network models, it is often the case that feature data is directly trained and acquired, making it difficult to directly incorporate valve characterization parameters into the model. Scholars such as Wang (Wang, 2010) have established a hybrid correlation matrix that includes valve information based on a planar pipeline network. Through matrix scanning methods, a valve network model is established to enable the search for closed valves and valve shutdown areas during fault isolation. Other scholars, such as Kim (Kim et al, 2022 and Kaliatka et al, 2012), have developed neural network models for water supply pipeline networks. By training the models using pressure data sets from both normal operating conditions (without leaks) and different leakage rates in laboratory pipeline networks, reliable fault diagnosis models have been obtained. Zhou (Zhou et al, 2008 and Lin, 2017) and other scholars have employed algorithmic training to obtain pipeline network models, and the correctness of these models has been verified through experiments.

When establishing a pipe network model based on graph theory and Kirchhoff's laws, it is possible to incorporate additional representation parameters for valves into the expressed physical model. Shuang (Shuang, 2017) explored the modeling method for urban water supply pipe networks based on graph theory, effectively describing the topological structure of the pipe network using adjacency matrices and incidence matrices. He established a topological structure representation for the water supply pipe network and developed a hydraulic calculation model for the pipe network by combining the laws of mass conservation and energy conservation with the Hazen-Williams formula. Scholars such as Lei (Lei, 2011) and Pecci (Pecci et al, 2020 and Wang et al, 2005) also adopted a hydraulic calculation model for pipe network leakage conditions based on graph theory and Kirchhoff's laws. In the case of pipeline leakage, a node is added to the leaky pipeline, dividing it into two segments, and then the model is used to calculate the changes in pressure at each node and flow rates in the pipe segments. Scholars like Manservigi (Manservigi et al, 2022) utilized physics-based equations to calculate all measurable variables in district heating networks (DHN), including flow rate, temperature, and pressure. They established a pipe network model to detect and identify the most common faults affecting DHN pipelines, namely water leakage, heat loss, and pressure loss. Zhou (Zhou et al, 2017) and other scholars proposed an "object-oriented" approach to calculate the hydraulic conditions of irregular networks. Li (Li et al, 2004) and colleagues simplified the hydraulic mathematical model based on the symmetrical characteristics of the supply and return pipe networks in branched systems, considering pressure verification for flow-limiting users and analysis of pipe network fault conditions when establishing the calculation model.

Therefore, we can draw insights from scholars' approaches in using graph theory and Kirchhoff's laws to establish pipe network models. By incorporating representation parameters for valves into the pipe network, we can delve deeper into the study of valves and valve network failures within the pipe network. This will provide theoretical support for the optimization and fault diagnosis of the pipe network system.

3 APPROACH TO ESTABLISHING A PHYSICAL MODEL LINKING VIBRATION PARAMETERS OF VALVE STEMS WITH FLOW FLUCTUATIONS IN A PIPE NETWORK SYSTEM

After reviewing relevant literature, it has been found that scholars have established neural network models linking vibration information of individual valves with flow pattern changes in pipe networks. However, these models do not fully capture the essence of the coupling between valve mechanical failures and fluid motion. Therefore, there is a need to establish a physical model that connects valve vibration information with flow variations in the pipe network system. Such a model would reveal the fundamental coupling between valve mechanical failures and fluid motion, providing scholars with a clearer and deeper understanding of the interactions involved.

The Bernoulli equation for ideal fluids is as follows (1):

$$p + \frac{1}{2}\rho v^2 + \rho g h = constant \tag{1}$$

Namely (2):

$$p_a + \frac{1}{2}\rho v_a^2 + \rho g h_a = p_b + \frac{1}{2}\rho v_b^2 + \rho g h_b \tag{2}$$

The resistance to the flow of actual fluids in pipe networks can be categorized into two types: friction resistance (also known as frictional loss or along-the-way resistance) and local resistance. These resistances result in two types of energy losses: along-the-way loss h_f and local loss h_m, respectively (Ma et al, 2011).

Local pressure loss (3):

$$P_m = \xi \frac{\rho v^2}{2} \tag{3}$$

Frictional pressure loss or along-the-way pressure loss (4):

$$P_f = \lambda \frac{l}{d} \frac{\rho v^2}{2} \tag{4}$$

In the formula (3)(4): λ: Frictional Resistance Coefficient; l: Length of Pipe Section (m); d: Pipe Diameter (m); ρ: Fluid Density (kg/m^3); v: Average Cross-sectional Velocity (m/s); ξ: Local

Resistance Coefficient. Therefore, the Bernoulli equation for actual fluids is as follows (5):

$$p_a + \frac{1}{2}\rho v_a^2 + \rho g h_a = p_b + \frac{1}{2}\rho v_b^2 + \rho g h_b + P_m + P_f \quad (5)$$

$$p_a + \frac{1}{2}\rho v_a^2 + \rho g h_a = p_b + \frac{1}{2}\rho v_b^2 + \rho g h_b + \xi \frac{\rho v^2}{2} + \lambda \frac{l}{d}\frac{\rho v^2}{2} \quad (6)$$

$$p_{a'} + \frac{1}{2}\rho v_{a'}^2 + \rho g h_a = p_{b'} + \frac{1}{2}\rho v_{b'}^2 + \rho g h_b + (\xi + \Delta\xi)\frac{\rho v'^2}{2} + \lambda \frac{l}{d}\frac{\rho v'^2}{2} \quad (7)$$

By subtracting equation (7) from equation (6), we can obtain (8):

$$\Delta v = f_1(\Delta\xi) \quad (8)$$

Wherein, according to the continuity equation, we have (9)(10)(11):

$$Q = A_a v_a = A_b v_b = Av \quad (9)$$

$$v_a = \frac{Av}{A_a} \quad (10)$$

$$v_b = \frac{Av}{A_b} \quad (11)$$

It is known that there is a relationship between the acceleration of the valve body, a_{valve}, and the vibration displacement of the valve stem, X, as follows (12)(13):

$$a_{valve} = \frac{d^2X}{dt^2} = \omega^2 A sin(\omega + \varphi + \pi) \quad (12)$$

$$X = f_2(a_{valve}) \quad (13)$$

Therefore, the objective is to explore the relationship between the local resistance coefficient of the valve and the vibration displacement of the valve stem. To address this issue, we need to conduct further analysis and calculations (14):

$$\Delta\xi = f_3(X) \quad (14)$$

By doing so, we can establish a physical model that characterizes the relationship between the vibration parameters of a single valve stem and the flow velocity fluctuations in the pipeline system (15).

$$\Delta v = F(X) \quad (15)$$

By doing so, we can derive a physical model that describes the relationship between the vibration parameters of a single valve stem and the flow rate fluctuations in the pipeline system (16).

$$\Delta Q = F(X) \quad (16)$$

The overall modeling approach is as shown in Figure 1:

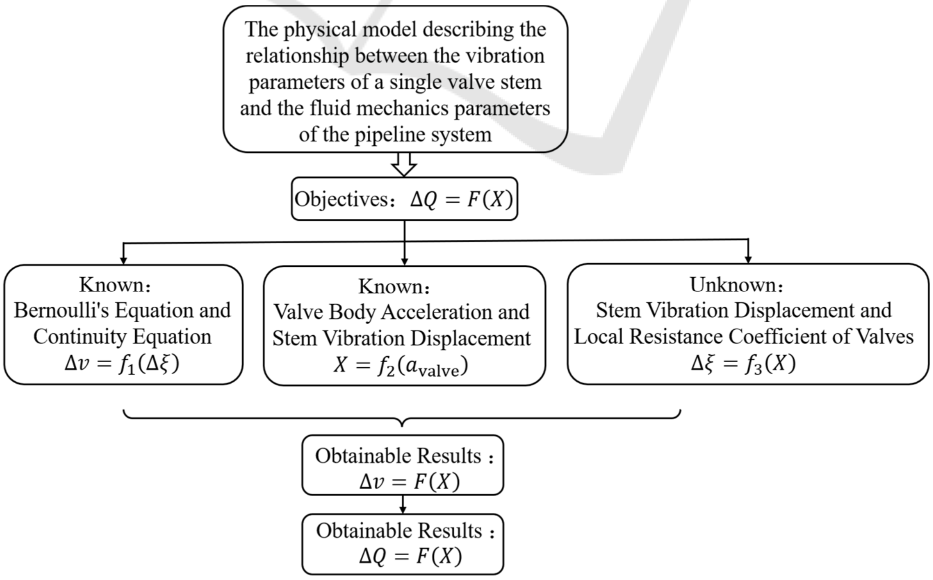

Figure 1: Establishment of a physical model for the relationship between valve stem vibration parameters and pipeline network system flow parameters.

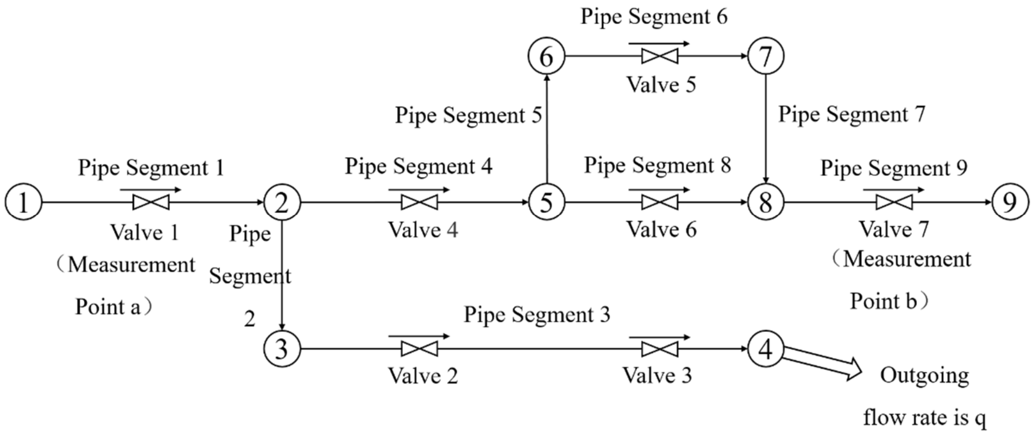

Figure 2: Schematic diagram of sub-network 1.

4 ESTABLISHMENT OF A COMPUTER-BASED VALVE NETWORK INFORMATION MODEL

A computer-based valve network information model is established to categorize and process a vast amount of pipeline network operational data, facilitating the input and computation of large datasets on computers. This model also takes into account the mutual influence relationships among valve clusters in the pipeline network, enabling the modeling of the entire pipeline network and facilitating the analysis of the valve network within the pipeline network. Complex industrial pipeline networks can be divided into several sub-networks, and the characteristics of the complex industrial pipeline network can be derived by studying the characteristics of the sub-networks. As shown in Figure 2, it is a schematic diagram of a sub-network.

The computer-based valve network information model is established based on the fundamental fluid mechanics equation-Bernoulli's equation. Taking Sub-network 1 as an example to establish a data processing model for the pipeline network, a method for establishing a dataset processing model for the valve network in complex industrial pipeline networks can be derived, thereby establishing the corresponding valve network information model.

4.1 Bernoulli's Equation

The Bernoulli equation for actual fluids is (17):

$$p_{a1} + \frac{1}{2}\rho v_{a1}^2 + \rho g h_{a1} = p_{b1} + \frac{1}{2}\rho v_{b1}^2 + \rho g h_{b1} + P_m + P_f \tag{17}$$

Let (18)(19):

$$\Delta P = P_m + P_f \tag{18}$$

$$\Delta P = \xi \frac{\rho v^2}{2} + \lambda \frac{l}{d}\frac{\rho v^2}{2} = (\xi + \lambda \frac{l}{d})\frac{\rho v^2}{2} \tag{19}$$

Then we have (20):

$$p_{a1} + \frac{1}{2}\rho v_{a1}^2 + \rho g h_{a1} = p_{b1} + \frac{1}{2}\rho v_{b1}^2 + \rho g h_{b1} + \Delta P \tag{20}$$

We can derive the pressure drop equation as follows (21):

$$p_{b1} = p_{a1} + \frac{1}{2}\rho(v_{a1}^2 - v_{b1}^2) + \rho g(h_{a1} - h_{b1}) - \Delta P \tag{21}$$

4.2 Impedance Calculation (Ma et al, 2011)[0]

For any pipe network system, it consists of numerous pipe segments connected in series and parallel. According to fluid mechanics, in a series of pipe segments, the total impedance S_c of the series is equal to the sum of the impedances S_i of each individual pipe segment. That is (22):

$$S_c = \sum_{i=1}^{m} S_i \tag{22}$$

In the formula (22), m represents the number of pipe segments connected in series.

When the gravitational effects are equal in each loop, the relationship between the total impedance S_b of the parallel pipe segments and the impedance S_j of each individual parallel pipe segment is as follows (23):

$$\frac{1}{\sqrt{S_b}} = \sum_{j=1}^{n} \frac{1}{\sqrt{S_j}} \tag{23}$$

In the formula (23), n represents the number of pipe segments connected in parallel.

Sometimes the resistance characteristics of parallel pipelines are analyzed by using the general derivative (24).

$$a_b = \sum_{j=1}^{n} a_j \tag{24}$$

In the formula (24), n represents the number of pipe segments connected in parallel. a_b represents the total conductance of the parallel pipeline (25). a_i represents the conductance of each individual pipe segment (26).

$$a_b = \frac{1}{\sqrt{S_b}} \tag{25}$$

$$a_j = \frac{1}{\sqrt{S_j}} \tag{26}$$

Using the aforementioned calculation methods for impedance in parallel and series pipe segments, the total impedance value of the entire pipe network can be gradually determined. To solve this problem, necessary calculations will be performed using Python S_z code.

4.3 The Dataset Processing Model for Pipeline Networks

When calculating the impedance of a pipeline network system, it is common to divide the network into series and parallel sections, calculate their impedances separately, and then determine the overall impedance of the network. This same approach is applicable when establishing the dataset processing model for pipeline networks.

The establishment approach for the dataset processing model of pipeline networks involves the following steps:

Pressure Drop Equation (21):

$$p_{b1} = p_{a1} + \frac{1}{2}\rho(v_{a1}^2 - v_{b1}^2) + \rho g(h_{a1} - h_{b1}) - \Delta P \tag{21}$$

Impedance Relationship:

Series Connection (22):

$$S_c = \sum_{i=1}^{m} S_i \tag{22}$$

Parallel Connection (23):

$$\frac{1}{\sqrt{S_b}} = \sum_{j=1}^{n} \frac{1}{\sqrt{S_j}} \tag{23}$$

Pressure Drop in a Single Pipe Segment (27):

$$\Delta P_i = (\xi_i + \lambda_i \frac{l_i}{d_i}) \frac{\rho v_i^2}{2} \tag{27}$$

Pressure Drop in the Pipeline Network (28):

$$\Delta P = \sum (\xi_i + \lambda_i \frac{l_i}{d_i}) \frac{\rho v_i^2}{2} = \sum \Delta P_c + \sum \Delta P_b \tag{28}$$

Divide the valve network of a complex industrial pipeline into several sub-networks, and select points a and b in each sub-network as measurement points:

(1) Measure the flow velocity v_{a1}, pressure p_{a1}, and height h_{a1} at point a in the pipeline network.

(2) Calculate the flow rate v_{b1} and height h_{b1} at point b in the pipeline network based on the structural information of the network (as the calculation of flow rate can be simply and directly derived from the pipeline structure, unaffected by factors such as gravity and valves, whereas pressure is influenced by gravity, valves, and other components).

(3) Based on the series and parallel relationships of the pipe segments, a table is established to import the data of each pipe segment in the pipeline network.

(4) Each column of the table can be expressed in matrix form, and the pressure drop in each pipe segment of the pipeline network can be obtained through matrix operations.

(5) The pressure at point b in the pipeline network is calculated as p_{b1} using the pressure equation derived from the Bernoulli equation for real fluids.

(6) The pressure at point b in the calculated pipeline network, denoted as p_{b1}, is subtracted from the actually measured pressure at point b in the pipeline network. Based on the calculation results, it is determined whether there is a fault in the pipeline network.

(7) If there is a fault in the pipeline network, the flow fluctuations $\Delta v_1, \Delta v_2, \ldots, \Delta v_n$ in each pipe segment are calculated. A relationship between the

pipeline flow fluctuations and valve vibrations is established as $\Delta Q = F(X)$. Based on the magnitude of the flow fluctuations, the specific location of the failed valve in the pipeline network is determined.

(8) By repeating steps (1) to (7) with another sub-network, it can be determined whether there is valve failure in the complex industrial pipeline network.

Taking subnetwork 1 as an example, the following dataset processing model for the pipeline network is established. For subnetwork 1, analyzing its structure reveals that the main trunk of the pipeline network consists of pipe segments 1-4-8-9. Among them, pipe segments 2 and 3 are connected in series and are also serially connected at branch point 2 of the main trunk. Pipe segments 5, 6, and 7 are connected in series and are in parallel with pipe segment 8 in the main trunk. The expression methods for various parameters of pipe segment i in the pipeline network are as follows: Pipe length is l_i; Pipe diameter is d_i; Friction resistance coefficient is λ_i; The flow velocity of each pipe segment is v_i; The flow rate of the pipe segment is represented by Q_i, which is calculated based on v_i and d_i(29).

$$Q_i = v_i \pi (\frac{d_i}{2})^2 \tag{29}$$

The local resistance coefficient of valve i in the pipe segment is ξ_i.

For each pipe segment in subnetwork 1, Tables 1 and 2 can be established as follows.

Calculate the impedance ΔP_b of the parallel section in Subnetwork 1:

Resistance relationship: Parallel connection (23):

$$\frac{1}{\sqrt{S_b}} = \sum_{j=1}^{n} \frac{1}{\sqrt{S_j}} \tag{23}$$

Generally, (24) is used to represent it.

$$a_b = \sum_{j=1}^{n} a_j \tag{24}$$

Where (25)(26):

$$a_b = \frac{1}{\sqrt{S_b}} \tag{25}$$

$$a_j = \frac{1}{\sqrt{S_j}} \tag{26}$$

The resistance of each pipe segment (30):

$$S_i = \xi_i + \lambda_i \frac{l_i}{d_i} \tag{30}$$

The pressure drop of each pipe segment (31):

$$\Delta P_i = (\xi_i + \lambda_i \frac{l_i}{d_i}) \frac{\rho v_i^2}{2} \tag{31}$$

Then it follows that (32)(33)(34)(35):

Table 1: Parameters of parallel pipe segments in subnetwork 1.

Matrix Code	A (Diagonal matrix)	J (Diagonal matrix)	B (Diagonal matrix)	C (Diagonal matrix)		D (Diagonal matrix)
Number	Local resistance coefficient ξ_i	Change in local resistance coefficient $\Delta\xi_i$	Friction resistance coefficient λ_i	Pipe length l_i	Pipe diameter d_i	Calculation $b_i = \frac{1}{d_i}$
1	ξ_6	$\Delta\xi_8$	λ_8	l_8	d_8	b_8
2	0	$\Delta\xi_5$	λ_5	l_5	d_5	b_5
3	ξ_5	$\Delta\xi_6$	λ_6	l_6	d_6	b_6
4	0	$\Delta\xi_7$	λ_7	l_7	d_7	b_7

Table 2: Parameters of serial pipe segments in subnetwork 1.

Matrix Code		E (Diagonal matrix)	F (Diagonal matrix)	K (Diagonal matrix)	G (Diagonal matrix)	H (Diagonal matrix)		I (Diagonal matrix)
Number	Pipe segment flow rate Q_i	Calculate pipe segment flow velocity v_i	Local resistance coefficient ξ_i	Change in local resistance coefficient $\Delta\xi_i$	Friction resistance coefficient λ_i	Pipe length l_i	Pipe diameter d_i	Calculation $b_i = \frac{1}{d_i}$
1	Q_1	v_1	ξ_1	$\Delta\xi_1$	λ_1	l_{a-2}	d_1	b_1
2	Q_2	v_2	0	$\Delta\xi_2$	λ_2	l_2	d_2	b_2
3	Q_3	v_3	$\xi_2 + \xi_3$	$\Delta\xi_3$	λ_3	l_3	d_3	b_3
4	Q_4	v_4	ξ_4	$\Delta\xi_4$	λ_4	l_4	d_4	b_4
5	Q_9	v_9	ξ_7	$\Delta\xi_9$	λ_9	l_{8-b}	d_9	b_9

$$S_1 = [A] + [J] + [B][C][D] = \begin{bmatrix} S_8 & & & \\ & S_5 & & \\ & & S_6 & \\ & & & S_7 \end{bmatrix} \quad (32)$$

$$S_{5-7} = S_5 + S_6 + S_7 \quad (33)$$

$$a_b = a_8 + a_{5-7} \quad (34)$$

$$\Delta P_b = \frac{\rho v_4^2}{2} S_b \quad (35)$$

Calculate the impedance ΔP_c of the serial section in Subnetwork 1:

Resistance relationship: Serial connection:

Series Connection (22):

$$S_c = \sum_{i=1}^{m} S_i \quad (22)$$

The resistance of each pipe segment (30):

$$S_i = \xi_i + \lambda_i \frac{l_i}{d_i} \quad (30)$$

The pressure drop of each pipe segment (31):

$$\Delta P_i = (\xi_i + \lambda_i \frac{l_i}{d_i}) \frac{\rho v_i^2}{2} \quad (31)$$

Then it follows that (36)(37):

$$\Delta P_C' = [E]^2 \{[F] + [K] + [G][H][I]\} \left[\frac{\rho}{2}\right] = \begin{bmatrix} P_1 & & & & \\ & P_2 & & & \\ & & P_3 & & \\ & & & P_4 & \\ & & & & P_9 \end{bmatrix} \quad (36)$$

$$\Delta P_C = P_1 + P_2 + P_3 + P_4 + P_9 \quad (37)$$

Then, for Subnetwork 1, it follows that (38)(39):

$$\Delta P = \Delta P_c + \Delta P_b \quad (38)$$

$$p_b = p_a + \frac{1}{2}\rho(v_a^2 - v_b^2) + \rho g(h_a - h_b) - \frac{\rho v2}{2}\left(\xi + (\frac{\lambda}{d} l)\right) = = p_a + \frac{1}{2}\rho(v_1^2 - v_9^2) + \rho g(h_a - h_b) - (\Delta P_c + \Delta P_b) \quad (39)$$

For the valve network in a complex industrial pipeline network, only by importing the flow rate, pressure, and other relevant parameters of each valve into the corresponding table using the aforementioned approach, and obtaining the corresponding matrix, can the desired pressure drop be calculated. By comparing this calculated result with the actual measured pressure in the pipeline network, it is possible to determine whether there is a leak in the network. This table (matrix) can store vast datasets of industrial pipeline networks, and the computation of these datasets can be carried out through computers, avoiding the uncertainty and immense workload associated with manual calculations. It provides convenience for computer input and computation of large datasets, enhancing the efficiency of pipeline valve management.

5 CONCLUSION

In the research on the valve network model of complex industrial pipeline networks, focus has been placed on the identification and establishment of industrial pipeline network models, the storage and computation of vast pipeline datasets, and the fault diagnosis of valves in the pipeline network. A new approach to judge the failure behavior of valve networks in complex industrial pipeline networks is proposed, considering the relationship between valve opening and resistance, and establishing a model correlating valve failures with pipeline flow rates. By analyzing the operational data of the pipeline network, it is possible to determine whether the valves are failing, enabling efficient and intelligent management of valves in the pipeline network. A computer-based valve network information model is established, with the measured vast pipeline dataset input into the computer through tables. The elements in the tables can be expressed as matrices, and through matrix operations, the required data can be quickly and accurately obtained, providing convenience for the input and computation of vast datasets on computers. At the same time, considering the mutual influence relationship among valve clusters in the pipeline network, the entire pipeline network is modeled, facilitating the analysis of the valve network within the pipeline network. This in-depth research on the valve network model of complex industrial pipeline networks focuses on issues such as model establishment, storage, and computation, providing a theoretical foundation for managing massive valves through cloud-edge collaboration and effectively categorizing and processing vast operational data. This enhances the management efficiency of pipeline valves.

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REFERENCES

Fabio, C., Federica, M., Antonio, B., et al, J, 2023. Electrical and mechanical data fusion for hydraulic valve leakage diagnosis. Measurement Science and Technology,vol.34,no.4.DOI:10.1088/1361-6501/ACB376

Liu, X., Nie, S., Zhang, Z., et al, J 2014. Research on vibration analysis and fault diagnosis of water hydraulic relief valve. Chinese Hydraulics & Pneumatics, no.05, pp.126-130. https://kns.cnki.net/kcms2/article/abstract?v=DFdco8SIy0JTfM29N93FM3SNrIUvhnu1jqVWGNt4gEVWa5Q4WUenzd1zpFmHlzWBvGQDde9MQQGW_YFWtVoZS9vp2GkaWlVILlUb8Rbxy6LNQ0JFSaE5zSU1gImC1u5g&uniplatform=NZKPT&language=CHS

Yang, S., Liu, S., Wu, N., et al, J, 2021. Analysis and treatment of vibration fault of pressure control valve in degassing condenser of nuclear power plant. Chinese Hydraulics & Pneumatics, vol.41, no.11, pp.92-95. https://kns.cnki.net/kcms2/article/abstract?v=DFdco8SIy0KZ48T1f9TvUsC5QrhqevkLpOViBLq5IRAWY71ophHNDyYTx9VvwaID5aVjCr5CMbThL5WLJ_aD7awWB2GpOHjnAmppK4gqYyjPEtGA_upusafQ_Ckgrg_dGfFwbQ6hXzU=&uniplatform=NZKPT&language=CHS

Zeng, J., Liu, C., Zhang, S., et al, J, 2021. Research on Fault Characteristic Analysis and Detection Methods of Electric Valves. Electronic Measurement Technology, vol.44, no.13, pp.171-176. https://kns.cnki.net/kcms2/article/abstract?v=DFdco8SIy0Lh29ku1xq8uQ92kv95PiDVHdKvlaOM1bJ6-MRrkgDZWiu93KRmzaEM3Spq0Qj9fLLQwShaLKitss0B6SzTjJeugtJtG6r2de83C9jeLMh26OhDiT5AMQY2PY5OTnPQLjM=&uniplatform=NZKPT&language=CHS

Xiao, S., Nie, A., Zhang, Z., et al, 2020. Fault Diagnosis of a Reciprocating Compressor Air Valve Based on Deep Learning. APPLIED SCIENCES-BASEL, vol. 10, no. 18, DOI: 10.3390/APP10186596

Venkata, S., Rao, S., J, 2019. Fault Detection of a Flow Control Valve Using Vibration Analysis and Support Vector Machine. Electronics, vol.8, no.10. DOI:10.3390/electronics8101062

Venkata, S., Rao, S., J, 2018. Estimation of Flow Rate Through Analysis of Pipe Vibration. Acta Mechanica et Automatica, vol.12, no.4, pp.294-300. DOI: 10.2478/ama-2018-0045

Wang, P., D, 2010. Research on Reliability of Heating System Based on Graph Theory. Harbin Institute of Technology. https://kns.cnki.net/kcms2/article/abstract?v=DFdco8SIy0LUfHaTm7GX37_FIsHlE2NRAsLpHUJYogU9RlfKqr720nY1uOEYuonPMmb56rK9m23bz8SenWNbYSFthFVJDaqzT6c3XD6ChvIYVuDeVdvYeOnDb7A3ErpE&uniplatform=NZKPT&language=CHS

Kim, H., Choi, D., Yoo, D., et al, J, 2022. Development of the Methodology for Pipe Burst Detection in Multi-Regional Water Supply Networks Using Sensor Network Maps and Deep Neural Networks. Sustainability, vol.14, no.22. DOI:10.3390/SU142215104

Kaliatka, A., Valinčius, M., J, 2012. Modeling of pipe break accident in a district heating system using RELAP5 computer code. Energy, vol.44, no.1, pp.813-819. DOI：10.1016/j.energy.2012.05.011

Zhou, Z., Zou, P., Tan, H., et al, J, 2008. Identification of Resistance Characteristics of Heating Network Based on Hybrid Genetic-Ant Algorithm. Journal of Harbin Institute of Technology, vol.40, no.11, pp.1761-1765. https://kns.cnki.net/kcms2/article/abstract?v=DFdco8SIy0LGBigKfHIWrK5mRSlDd4Q07CuwPRhAYquwiRgtFeMoJ34uMS2tDCfJl7Dvv9Tkl3bO488O2QzIY4K0PBzLKcg007hPISl4QFWCw8HwdNdGtegJnZxObgQ9&uniplatform=NZKPT&language=CHS

Lin, C., J, 2017. A Hybrid Heuristic Optimization Approach for Leak Detection in Pipe Networks Using Ordinal Optimization Approach and the Symbiotic Organism Search. Water, vol.9, no.10. DIO:10.3390/w9100812

Shuang, Q., 2017. Modeling and Analysis of Cascading Failures in Complex Networks and Reliability of Urban Water Supply Networks, Beijing Jiaotong University Press. Beijing, 1st edition. http://book.ucdrs.superlib.net/views/specific/2929/bookDetail.jsp?dxNumber=000016592491&d=FAC99F4506D94390F01D097C42242933&fenlei=182016020403

Lei, C., Zou, P., J, 2011. Fault Diagnosis of Heating Pipeline Network Leakage Based on Two-Level BP Neural Network. Journal of Harbin Institute of Technology, vol.43, no.02, pp.75-79. https://kns.cnki.net/kcms2/article/abstract?v=DFdco8SIy0IjVcBBGD2z-9X4a3kwhB6OYg1Xdd5_LXgqYdqE5G1cwsx1wvASHdYLz6tvI_UgDeR2iBc88ix5kaFTzkhUK-c4Ra96wYjQYJkST7ZTZR-vceFUIyz83bLo&uniplatform=NZKPT&language=CHS

Pecci, F., Parpas, P., Stoianov, I., J. 2020. Sequential Convex Optimization for Detecting and Locating Blockages in Water Distribution Networks. Journal of Water Resources Planning and Management, vol.146, no.8. DOI: 10.1061/ASCE.WR.1943-5452.0001233

Wang, X., Zou, P., Zhou, Z., J, 2005. Topological Structure and Hydraulic Process Simulation of Complex Spatial Heating Network. Journal of System

Simulation, no.03, pp.563-566+570. https://kns.cnki.net/kcms2/article/abstract?v=DFdco8SIy0INTsEe-ke0ccsd3eBT3hRCjFKIbVSpsLUQZkFbnA6NpEp05UdBe58HZEMhMWbaowCFCR880PCIYDvwGxU-78X-Nql5OxgOOzHOB3wb_pT5_HD2guW5gzE3&uniplatform=NZKPT&language=CHS

Manservigi, L., Bahlawan, H., Losi, E., et al, J, 2022. A diagnostic approach for fault detection and identification in district heating networks. Energy, vol.251. DOI:10.1016/J.ENERGY.2022.123988

Zhou, H., Wang, H., Zhu, T., J, 2017. A Hydraulic Calculation Method for Three-Dimensional Heating Pipeline Network. Chinese Journal of Computational Physics, vol.34, no.03, pp.355-364. https://kns.cnki.net/kcms2/article/abstract?v=DFdco8SIy0JuXOmOKMlh9unyejbrpjeZO1W2dDuK5rpawaNCyuJUkZd3JP39DTe8aCfLZeKHsz_Mjz1DvonY9L_pOYUD2qcnfRXQYEyJXh2l74E5rByGu391lJ29RN_nymp8K0y5KgE=&uniplatform=NZKPT&language=CHS

Li, X., Wang, X., Zhou, Z., et al, J, 2004. Simulation Analysis of Hydraulic Conditions in Tree-shaped Heating Pipeline Network. Gas & Heat, vol.10, pp.554-557. https://kns.cnki.net/kcms2/article/abstract?v=DFdco8SIy0ISjbvXsBw-y-mIftvdycZPt1upvM2riBpTkyyICPRGYQdOK-61fbS_Asc8is9WF1Ypz8-ub8C_vucgPAHarqRDGtF3NKHukSb9ly9WaDVF0xz8FBMHqJRW&uniplatform=NZKPT&language=CHS

Ma, Q., Guo, J., 2011. Fluid Mechanics and Transmission and Distribution Pipe Network, Metallurgical Industry Press. Beijing, 1st edition. http://book.ucdrs.superlib.net/views/specific/2929/bookDetail.jsp?dxNumber=000008167352&d=5002F793BA863A6BF291163C63530EA0&fenlei=18201201

APPENDIX

The derivation process of formula (32) is as follows:

$$S_1 = [A] + [J] + [B][C][D]$$

$$= \begin{bmatrix} \xi_6 & & & \\ & 0 & & \\ & & \xi_5 & \\ & & & 0 \end{bmatrix} + \begin{bmatrix} \Delta\xi_8 & & & \\ & \Delta\xi_5 & & \\ & & \Delta\xi_6 & \\ & & & \Delta\xi_7 \end{bmatrix}$$

$$+ \begin{bmatrix} \lambda_8 & & & \\ & \lambda_5 & & \\ & & \lambda_6 & \\ & & & \lambda_7 \end{bmatrix} \begin{bmatrix} l_8 & & & \\ & l_5 & & \\ & & l_6 & \\ & & & l_7 \end{bmatrix} \begin{bmatrix} b_8 & & & \\ & b_5 & & \\ & & b_6 & \\ & & & b_7 \end{bmatrix}$$

$$= \begin{bmatrix} \Delta\xi_8 & & & \\ & \Delta\xi_5 & & \\ & & \Delta\xi_6 & \\ & & & \Delta\xi_7 \end{bmatrix} + \begin{bmatrix} \xi_6 + \lambda_8 l_8 b_8 & & & \\ & \lambda_5 l_5 b_5 & & \\ & & \xi_5 + \lambda_6 l_6 b_6 & \\ & & & \lambda_7 l_7 b_7 \end{bmatrix}$$

$$= \begin{bmatrix} \Delta\xi_8 & & & \\ & \Delta\xi_5 & & \\ & & \Delta\xi_6 & \\ & & & \Delta\xi_7 \end{bmatrix} + \begin{bmatrix} R_8 & & & \\ & R_5 & & \\ & & R_6 & \\ & & & R_7 \end{bmatrix} = \begin{bmatrix} S_8 & & & \\ & S_5 & & \\ & & S_6 & \\ & & & S_7 \end{bmatrix}$$

The derivation process of formula (36) is as follows:

$$\Delta P_c' = [E]^2 \{[F] + [K] + [G][H][I]\} \left[\frac{\rho}{2}\right]$$

$$
= \begin{bmatrix} v_1 & & & & \\ & v_2 & & & \\ & & v_3 & & \\ & & & v_4 & \\ & & & & v_9 \end{bmatrix}^2 \left\{ \begin{bmatrix} \xi_1 & & & & \\ & 0 & & & \\ & & \xi_2 + \xi_3 & & \\ & & & \xi_4 & \\ & & & & \xi_7 \end{bmatrix} + \begin{bmatrix} \Delta\xi_1 & & & & \\ & \Delta\xi_2 & & & \\ & & \Delta\xi_3 & & \\ & & & \Delta\xi_4 & \\ & & & & \Delta\xi_9 \end{bmatrix} \right.
$$

$$
\left. + \begin{bmatrix} \lambda_1 & & & & \\ & \lambda_2 & & & \\ & & \lambda_3 & & \\ & & & \lambda_4 & \\ & & & & \lambda_9 \end{bmatrix} \begin{bmatrix} l_{a-2} & & & & \\ & l_2 & & & \\ & & l_3 & & \\ & & & l_4 & \\ & & & & l_{8-b} \end{bmatrix} \begin{bmatrix} b_1 & & & & \\ & b_2 & & & \\ & & b_3 & & \\ & & & b_4 & \\ & & & & b_9 \end{bmatrix} \right\} \left[\frac{\rho}{2}\right]
$$

$$
= \begin{bmatrix} v_1 & & & & \\ & v_2 & & & \\ & & v_3 & & \\ & & & v_4 & \\ & & & & v_9 \end{bmatrix}^2 \left\{ \begin{bmatrix} \Delta\xi_1 & & & & \\ & \Delta\xi_2 & & & \\ & & \Delta\xi_3 & & \\ & & & \Delta\xi_4 & \\ & & & & \Delta\xi_9 \end{bmatrix} \right.
$$

$$
\left. + \begin{bmatrix} \xi_1 + \lambda_1 l_{a-2} b_1 & & & & \\ & \lambda_2 l_2 l_2 & & & \\ & & \xi_2 + \xi_3 + \lambda_3 l_3 l_3 & & \\ & & & \xi_4 + \lambda_4 l_4 l_4 & \\ & & & & \xi_7 + \lambda_9 l_{8-b} l_9 \end{bmatrix} \right\} \left[\frac{\rho}{2}\right]
$$

$$
= \left\{ \begin{bmatrix} \Delta\xi_1 & & & & \\ & \Delta\xi_2 & & & \\ & & \Delta\xi_3 & & \\ & & & \Delta\xi_4 & \\ & & & & \Delta\xi_9 \end{bmatrix} + \begin{bmatrix} R_1 & & & & \\ & R_2 & & & \\ & & R_3 & & \\ & & & R_4 & \\ & & & & R_9 \end{bmatrix} \right\} \begin{bmatrix} v_1 & & & & \\ & v_2 & & & \\ & & v_3 & & \\ & & & v_4 & \\ & & & & v_9 \end{bmatrix}^2 \left[\frac{\rho}{2}\right]
$$

$$
= \begin{bmatrix} S_1 & & & & \\ & S_2 & & & \\ & & S_3 & & \\ & & & S_4 & \\ & & & & S_9 \end{bmatrix} \begin{bmatrix} v_1 & & & & \\ & v_2 & & & \\ & & v_3 & & \\ & & & v_4 & \\ & & & & v_9 \end{bmatrix}^2 \left[\frac{\rho}{2}\right] = \begin{bmatrix} P_1 & & & & \\ & P_2 & & & \\ & & P_3 & & \\ & & & P_4 & \\ & & & & P_9 \end{bmatrix}
$$