Available online www.jsaer.com

***Journal of Scientific and Engineering Research*, 2024, 11(5):199-207**

Research Article

ISSN: 2394-2630
CODEN(USA): JSERBR

Research on Intelligent Fault Diagnosis Method of Gas Drainage Pipe Network in Coal Mine

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Abstract Coal seam gas drainage is one of the important means to solve mine gas disasters. In order to address the problems such as increased negative pressure loss and decreased gas extraction efficiency caused by pipeline blockage and leakage during the gas extraction process, a mathematical model of the gas extraction pipe network working condition was established, and the variation laws of the negative pressure, flow, and other parameters of the pipe network under blockage and leakage conditions in the gas extraction system were analyzed. Based on the BP neural network, fault diagnosis models for network leakage and blockage were established respectively. The model was trained using the network working condition data when different levels of leakage and blockage occurred at different locations of the network. It was verified that the model can accurately identify network faults.

Keywords Gas drainage, Neural network, Fault diagnosis, Blockage, and Leakage

1. Introduction

Currently, mine gas accidents are still one of the main disasters seriously endangering the safety production of mines, and coal seam gas drainage is an important means to effectively solve gas accidents. By arranging a large number of extraction drilling holes in the coal seam and relying on the negative pressure provided by the extraction pump, the adsorbed gas in the coal seam is desorbed, thereby reducing the gas content in the coal body. However, in the actual extraction process, impurities such as coal mud and water in the pipeline can accumulate in large amounts, causing pipeline blockage, which increases the local resistance and reduces the extraction efficiency. Network leakage can cause increased negative pressure loss, reduced gas extraction concentration, and bring the risk of gas explosion. Therefore, how to determine whether the gas extraction pipe network has faults such as blockage and leakage, and how to determine the location and severity of the faults are of great significance for improving the efficiency of gas extraction.

Domestic and foreign scholars have conducted less research on the fault diagnosis of gas extraction pipe networks, focusing mainly on network leakage diagnosis. Liu, Y. B. [1] used ultrasonic leak detection instruments to detect network leakage and achieved the purpose of locating the leakage points. Xiong, W. [2] used a multivariate Gaussian beam model to process the sound of network gas leakage points and determined whether the network had leakage by comparing with pre-stored samples. She, X. G. [3] established a gas leakage judgment model based on the principle of mass conservation, using the method of monitoring network flow to detect the leakage status of the pipeline. Lei, B. W. [4] used the pressure square gradient method to analyze the leakage and blockage conditions of a single pipeline and established a diagnostic method for the operating state of a single pipeline.

In the fields of urban water supply, oil, and natural gas, scholars have conducted many studies on pipeline fault diagnosis technology based on artificial neural networks, which has greatly promoted the development of artificial intelligence pipeline systems. Duan, L. L. [5] used BP neural networks to study the pressure changes under different leakage conditions in water supply and gas supply pipelines, providing an intelligent diagnostic method for water supply and gas supply pipelines. Ma, G. X. [6] used deep convolutional neural networks to predict the leakage status of heating pipelines, obtaining a leakage degree and leakage point diagnostic model with high accuracy. Liu, W. L. [7] proposed a city sewage pipeline blockage fault diagnosis method based on radial basis neural networks, and verified its accuracy using a ring-shaped network. Wang, J. L [8], for the blockage of the gas pipe network, adopted a wide-approximation gradient method and genetic algorithm to solve the established fault model and established evaluation criteria for network blockage and severity.

In summary, scholars have conducted less research on the fault diagnosis technology of gas extraction pipe networks, especially blockage diagnosis, and have not applied artificial neural networks to the diagnosis of network faults. Therefore, this paper establishes a mathematical model of the working condition of the gas extraction pipe network, solves the node flow and negative pressure data after different blockages and leakages occur in each pipe segment; establishes a BP neural network fault diagnosis model for the extraction pipe network, and trains the model using the node flow and negative pressure change data under network fault conditions, enabling the model to identify the blocked pipe segments and pipeline leakage locations, providing guidance for the safe and efficient operation and intelligent construction of the gas extraction pipe network.

2. Mathematical Model of Gas Extraction Pipe Network Working Condition

2.1 Establishment of the Mathematical Model for Pipe Network Working Condition

During the gas extraction process, the negative pressure of the gas within the pipeline gradually decreases in the direction opposite to the gas flow. Due to the long pipeline length and significant pressure difference, the gas within the pipeline is analyzed as a one-dimensional compressible viscous fluid.

- Gas State Equation

The gas in the extraction pipeline is a mixed gas composed of air, gas, and water vapor. The mixed gas constant R can be calculated using Equation (1):

$$R = \sum R_i(\frac{m_i}{m} \times 100\%) \tag{1}$$

Where R is the gas constant of the mixed gas, kj/ (kg· K); R_i is the gas constant of the single component gas; $\frac{m_i}{m}$×100% is the universal gas constant.

The density of the mixed gas can be calculated using Equation (2):

$$\rho = \frac{P}{ZRT} \tag{2}$$

Where ρ is the density of the mixed gas, kg/m^3; P is the absolute pressure of the mixed gas, Pa; Z is the compressibility factor, and T is the temperature of the mixed gas, K.

The viscosity of the mixed gas in the extraction pipeline can be calculated using Equation (3):

$$\mu = \frac{M'}{\sum \frac{m_i M_i'}{m \mu_i}} \tag{3}$$

Where M' is the relative molecular mass of the mixed gas, M_i' is the relative molecular mass of the single component gas, and μ_i is the gas viscosity of the single component gas under standard conditions, kg/ (m· s).

- Pipeline Pressure Drop Equation

For the extraction network, there is no mechanical work done during the gas flow inside the pipeline, and the pressure change in the pipeline satisfies the following Equation (4) and (5):

$$P_j = P_i - 2kL \tag{4}$$

$$k = \frac{8\lambda M^2 ZRT}{\pi D^5} \tag{5}$$

Where P_i and P_j are the pressures at the pipeline inlet and outlet, Pa； λ is the along-channel resistance coefficient; M is the mass flow rate of the gas, kg/s; L is the pipeline length, m; D is the pipeline diameter, m.

- Gas Extraction Pump Characteristic Equation

$$P_0 - P_1 = AM^2 + BM + C \tag{6}$$

Where P_0 is the atmospheric pressure, taken as 101325 Pa; P_1 is the absolute pressure at the gas extraction pump inlet, Pa; M is the mass flow rate of the gas at the gas extraction pump inlet, kg/s; A, B and C are the characteristic coefficients of the gas extraction pump.

- Source Node Flow Characteristic Equation

During the gas extraction process, the negative pressure at the hole mouth significantly affects the flow rate of the drilling hole. The functional relationship between the extraction negative pressure and the extraction flow rate is defined as follows:

$$P_2 = aM_i^2 + bM_i + c \tag{7}$$

Where P_2 is the negative pressure at the hole mouth, Pa; M_i is the mass flow rate of the gas extracted from the i-th drilling hole, kg/s; a, b, and c are the gas source characteristic coefficients.

- Mass Flow Conservation Equation.

According to the law of mass conservation, the mass flow rate of gas entering and leaving the node should satisfy the following relationship:

$$\rho_{in} Q_{in} = \rho_{out} Q_{mout} \tag{8}$$

Where ρ_{in} and ρ_{out} are the densities of the mixed gas entering and leaving the node, kg/m³.

2.2 Gas Extraction System Network Diagram

The mine gas extraction pipe network mainly consists of branch pipes connecting extraction drilling holes or drilling fields, trunk pipes arranged on the working face or mining area, and main pipes extending to the ground gas extraction pump station. Based on graph theory knowledge, its network diagram has a simple tree structure. The nodes and pipes of the entire extraction pipe network are numbered along the direction of gas flow. If the extraction pipe network has N nodes, there are N-1 pipe segments.

In the actual production process, common extraction pipe network faults mainly include blockage and leakage. When a blockage fault occurs in the pipe network, it can be regarded as adding a section of pipe with a smaller diameter to the pipe segment. At this time, the network structure of the pipe network will change, with the number of nodes in the pipe network being N+2 and the number of pipe segments being N+1. The location of the added pipe segment is the blockage location, and the diameter of the added pipe segment represents the degree of blockage of the original pipe segment; pipe network leakage can be regarded as adding a new gas source node, with the location of the leakage point being the location of this new node. The number of nodes and pipe segments in the pipe network are N+1 and N, respectively.

2.3 Solution of the Gas Extraction Pipe Network Model

In the gas extraction system, changes in extraction negative pressure will cause changes in extraction flow rate, flow rate changes will lead to changes in pipe segment resistance, and then cause changes in negative pressure again. Throughout the process, the network flow and negative pressure continuously adjust until a new balance is reached. Based on this characteristic, this paper establishes the corresponding mathematical model of the gas extraction pipe network through Equations (1)-(8) and the extraction system network diagram, and obtains the precise values of the extraction pipe network flow and negative pressure using the iterative approximation method. The solution process is shown in Figure 1.

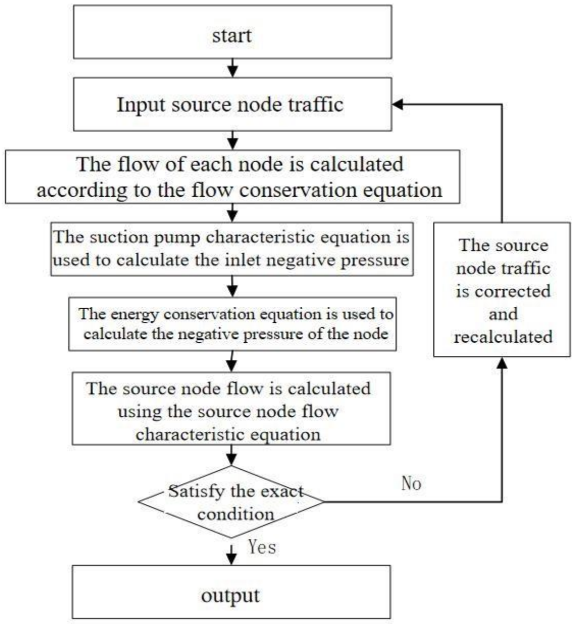

Figure 1: Flow chart of pipe network working condition model solution.

3. Gas Extraction Pipe Network Fault Diagnosis Model

3.1 Establishment of the Gas Extraction Pipe Network Blockage Diagnosis Model

BP neural network is a multi-layer neural network with forward input of information and reverse propagation of errors. Its structure is mainly composed of output layer, hidden layer and output layer, as shown in Figure 2.

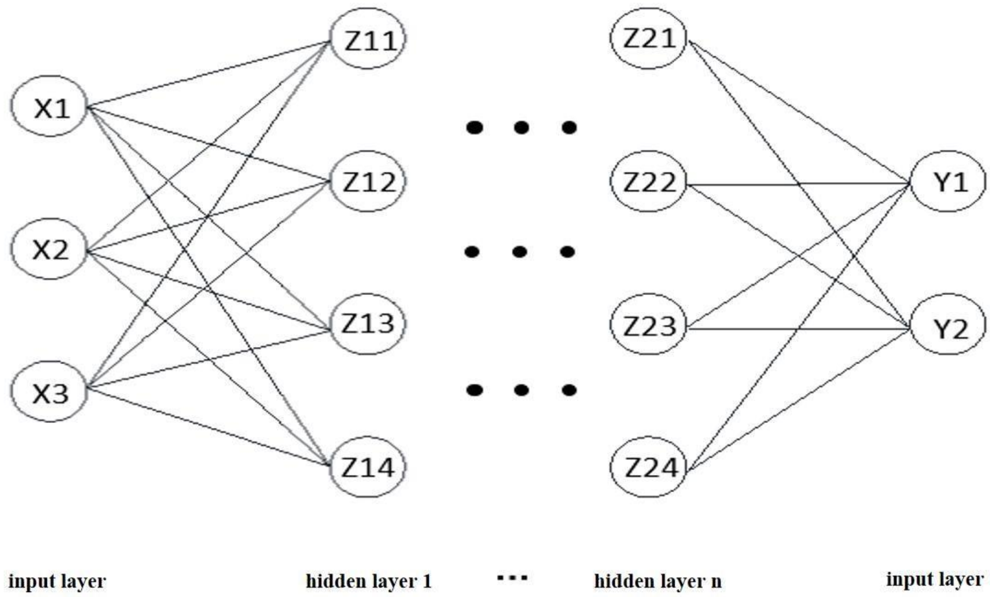

Figure 2: BP neural network structure diagram.

The implementation of the algorithm mainly includes the following two processes: (1) The input layer information is calculated layer by layer and applied to the output layer, and then the error between the output layer information and the expected value can be obtained; (2) The error passes through the output layer and passes through the hidden layer to the input layer in reverse, during which the error is apportioned to each hidden layer by modifying the weight function between the layers continuously, so as to minimize the error.

Repeat these two steps until the error is within the allowable range.

The BP neural network input layer is the negative pressure change value of the network node, and the output layer is the plugging probability value of each pipe segment. In order to make the model more readable, the hidden layer is selected as 1 layer, and the number of neurons in the hidden layer can be determined through repeated training. In order to speed up the convergence, Logistic function is used to normalize the input layer data.

3.2 Case Analysis of Gas Extraction Pipe Network Blockage

The gas extraction pipe network system is shown in Figure 3. The system network diagram includes 14 nodes (including 7 gas source nodes, 6 extraction branch convergence nodes, and 1 extraction pump convergence node), and 13 pipe segments. The characteristic parameters of each pipe segment in the extraction pipe network are shown in Table 1.

Table 1: Characteristic Parameters of Extraction Pipe Network Segments

Segment No	Length L/m	Diameter D/mm	Absolute Roughness e/m
v_1	100	400	0.0001
v2	100	300	0.0001
v3 - v6	100	200	0.0001
v_7	100	400	0.0001
v8 - v11	300	400	0.0001
v12	500	400	0.0001
v13	500	600	0.0001

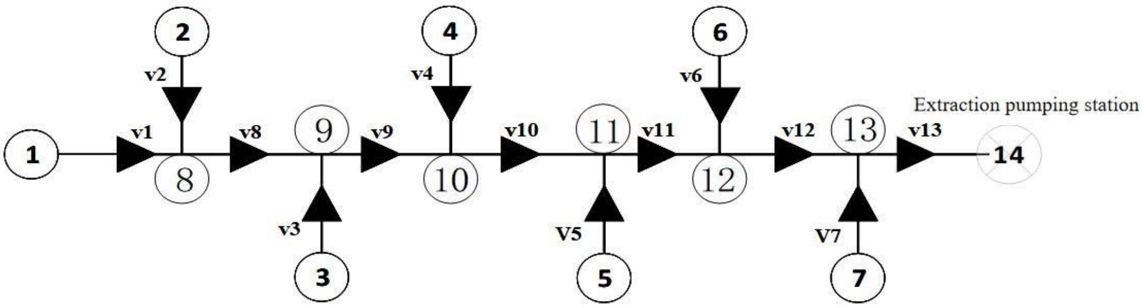

Figure 3: Extraction system network diagram.

To obtain the blockage condition sample data for model training, first, the mathematical model of the gas extraction pipe network working condition was used to calculate the node flow and node pressure under normal operating conditions of the extraction system; then, the following treatments were applied to the extraction system network diagram and solved:

- A blockage point was sequentially added at the midpoint of each extraction pipe segment, and the pressure change values of the nodes were calculated at this time;
- The location of the blockage point was changed, and the pressure change values of the network nodes were calculated at this time (the distances from the blockage point to the gas inlet end of the pipe segment were 0%, 25%, 50%, and 75% of the pipe segment length, respectively); □□The degree of blockage was divided into the following four categories:
- no blockage or slight blockage;
- moderate blockage;
- severe blockage;
- complete blockage.

The ratios of the pipe diameters to the original pipe diameters under different degrees of blockage were 0.8, 0.5, 0.2, and 0.05, respectively, and the pressure change values of the network nodes under different degrees of blockage were calculated.

Through the above treatment, 208 sets of extraction pipe network working condition samples under different blockage conditions can be obtained. However, through comparative analysis of the data, it was found that when the main pipe close to the extraction pump is blocked, it has a significant impact on the node negative pressure of the network, while when the branch pipe far from the extraction pump is blocked, its impact on the network negative pressure is minimal, and it is even not easily perceived by sensors in the actual production process. Therefore, some samples with small network negative pressure changes were removed, and finally, 142 sets of sample data were obtained. 85% of the sample data was randomly extracted as the training set to train the model, and the remaining sample data were used to predict the blockage pipe segments. To better reflect the prediction effect, the pipe segment with the highest blockage probability value in the prediction results was compared with the actual blocked pipe segment, as shown in Figure 4.

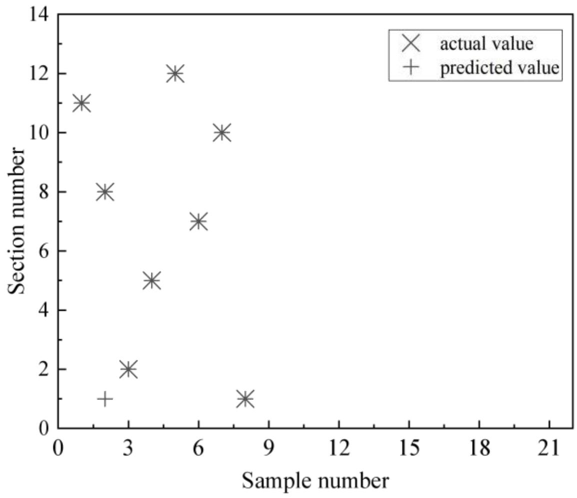

Figure 4: Blockage Pipe Segment Prediction Effect Diagram.

From Figure 4, it can be seen that the extraction pipe network blockage diagnosis model can make a relatively accurate judgment on the blocked pipe segments. In the prediction results of Sample 2, two blocked pipe segments appeared. It can be known from the extraction system network diagram that when the pipe segment No. 8 is blocked, the negative pressure influences on pipe segments v1 and v2 are the greatest. From the pressure change data, the pressure changes at nodes 1 and 8 are very close, and the data are very small after normalization, which leads to the above error in the output results. However, when pipe segment v1 is blocked, it does not lead to v8 appearing in the prediction results. The reason is that when v1 is blocked, the negative pressure at node 1 decreases, and the negative pressure at node 8 increases. It can be seen that when two values appear in the prediction results, the blockage mainly occurs on the main and branch pipes. Overall, the model's prediction results are relatively accurate, and the BP neural network model can be used to preliminarily identify the blocked pipe segments in the network.

3.3 Gas Extraction Pipe Network Leakage Diagnosis Model

The construction of the gas extraction pipe network leakage diagnosis model mainly includes two parts:

- Leakage Identification Model: It is known from field experience that when a leakage occurs in the network, the flow parameters after the leakage point in the extraction pipe network change the most significantly. Therefore, by monitoring the gas mass flow of each node in real-time through sensors, it is possible to determine whether a pipe segment has leaked. When a pipe segment leaks, the node flow after the leakage point will be greater than the node flow before the leakage point. According to Equation (9), it can be known that:

$$\rho_{in}Q_{in} + \rho_{leak}Q_{leak} = \rho_{out}Q_{out} \tag{9}$$

where ρ_{leak} is the density of the leaked gas, kg/m³; Q_{leak} is the leakage gas flow rate, m³/s. Setting $\rho_{leak}Q_{leak} = \eta$, we have:

$$\frac{\rho_{out}Q_{out}}{\rho_{in}Q_{in}} = 1 + \eta \tag{10}$$

where η is the ratio of the leakage gas mass flow to the total gas mass flow in the network, reflecting the degree of network leakage. In the actual extraction process, network leakage is inevitable, so η>0. By dividing the η value, the degree of network leakage can be graded. After a leakage occurs in the extraction network, the leakage pipe segment number and leakage degree can be accurately determined using this leakage identification model.

- Leakage Location Model: Based on the BP neural network, a leakage location model is established for each pipe segment of the extraction pipe network. The input layer of the BP neural network is the pressure change values of all nodes in the network, and the output layer is the leakage location information. Among them, the leakage location information is the ratio of the length of the leakage point from the gas inlet end of the pipe segment to the total length of the pipe segment.

After a leakage occurs in the network, the leakage pipe segment is first identified by the leakage identification model, and then the leakage location is predicted through the leakage location model established for that pipe segment.

3.4 Case Analysis of Gas Extraction Pipe Network Leakage

The leakage diagnosis model of the gas extraction pipe network includes a leakage identification model and a leakage location model. The leakage identification model of the extraction pipe network relies solely on the calculation of the difference in the measured flow data to achieve the purpose of identifying the leakage pipe segment, with a small error and effective on-site verification, so this part only analyzes the leakage location model. Taking the network system shown in Figure 3 as an example, to obtain the training samples required for the leakage location model, the mathematical model of the gas extraction pipe network working condition established was used to calculate the node flow and node pressure after different pipe segment positions and different degrees of leakage. The ratios of the length of the leakage point from the gas inlet end of the pipe segment to the total length of the pipe segment are 0.01, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9, and the leakage degrees are 5%, 10%, 15%, 20%, 25%, 30%, 35%, and 40%.

Assuming that the leakage identification model determines that the extraction pipe segment v11 has a leakage, and the leakage degree corresponds to a flow range of 15% to 30% of the pipe segment flow, then the training sample data is 40 sets. Table 2 shows the prediction result of the leakage location model when the test set is 20% of the training set.

Table 2: Prediction Result of Leakage Location Model

Predicted position	0.2254	0.2819	0.7361	0.9468	0.4783	0.6515
True position	0.20	0.30	0.70	0.90	0.50	0.60
relative error/%	12.71	6.09	5.16	5.20	4.34	8.58

From Table 2, it can be seen that the prediction results of the random sample leakage positions are relatively accurate, with a relative error between 12.71% and 1.90%. Overall, the model's prediction effect for leakage locations is good.

3.5 Multi-level Fault Diagnosis Model of Gas Extraction Pipe Network

The above study shows that the BP neural network can identify blocked pipe segments based on the changes in node negative pressure. However, when a leakage fault occurs in the extraction pipe network, it not only changes the flow of the network but also affects the entire extraction pipe network's negative pressure. Therefore, to avoid the impact of network leakage on the diagnosis of network blockage, it is necessary to first diagnose the leakage fault of the network, and then diagnose the blockage fault of the network. In view of this, the above network blockage diagnosis model and leakage diagnosis model are combined to obtain a multi-level fault diagnosis model for the gas extraction pipe network, as shown in Figure 5.

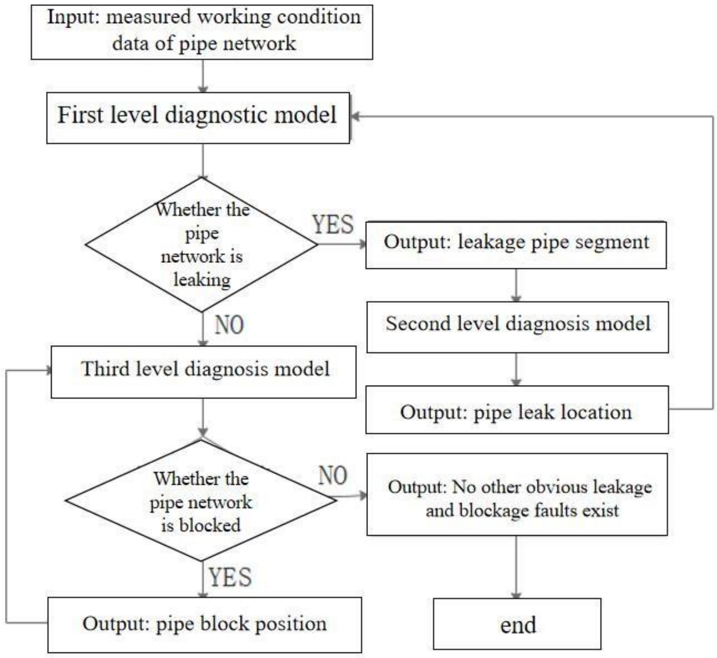

Figure 5: Multi-level Fault Diagnosis Model of Extraction Pipe Network.

4. Conclusion

- Based on the mutual influence law of flow and negative pressure during the extraction process, a mathematical model of the gas extraction pipe network operating condition was established. This model can be used to solve for the extraction flow, negative pressure, and other data of the extraction pipe network under normal and blockage and leakage fault conditions.
- A BP neural network blockage diagnosis model for the extraction pipe network was established, with node negative pressure change as the input and pipe segment blockage probability value as the output. After training with blockage sample data, it can accurately predict the blocked pipe segments in the extraction pipe network.
- Leakage pipe segment identification and leakage location fault diagnosis models were established. Among them, the leakage location model based on the BP neural network can predict the leakage location according to the node negative pressure change after the leakage pipe segment is known, with good results.

References

[1]. Liu, Y. B. (2016). Leak Detection Technology and Field Application of Negative Pressure Gas Extraction Pipeline Network in Coal Mines. China Mining, 25(05), 156-159.

[2]. Xiong, W. (2020). Research on the Self-renewal Leak Detection Technology of the Coal Mine Gas Extraction Pipeline Network System. Automation in Mines, 46(09), 33-37(43).

[3]. She, X. G., Zhou, H. Q., & Yang, L. P. (2013). Leakage Detection Technology of Gas Extraction Pipeline Network in Coal Mines. Coal Safety, 44(10), 75-77.

[4]. Lei, B. W., Wu, B., & Li, X. (2017). Research on the Diagnostic Method of Operating State of Gas Extraction Pipeline Based on Pressure Measurement. Mining Safety and Environmental Protection, 44(01), 32-35(52).
[5]. Duan, L. L. (2014). Fault Diagnosis Model of Heating Network Based on Genetically Optimized BP Neural Network. Journal of North University of China (Natural Science Edition), 35(03), 303308.
[6]. Ma, G.X. (2022). Research on a CNN-based Leakage Identification Method for Heating Pipes. Electronic Measurement Technology, 1-9.
[7]. Liu, W. L. (2019). Sewer Network Blockage Diagnosis Method Based on Radial Basis Neural Network. Journal of Tianjin University of Science and Technology, 34(04), 76-80.
[8]. Wang, J. L. (2010). Research on Fault Diagnosis Technology of Gas Pipeline Networks. Shandong University of Architecture, 2010.