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IMPROVING THE EFFICIENCY OF PIPELINE LEAK DETECTION SYSTEMS USING NEURAL NETWORKS

Abstract: Pipeline systems for oil and gas transportation are complex distributed infrastructure facilities whose efficient and safe operation largely depends on the application of modern information and communication technologies. In the context of industrial digital transformation, intelligent monitoring systems capable of continuous acquisition, transmission, and analysis of telemetry data for the early detection of emergency conditions have become particularly relevant. One of the most critical challenges is the timely detection and accurate localization of leaks, which can result in significant economic losses, environmental damage, and threats to public safety. The objective of this study is to develop an approach for determining the coordinates of a pipeline leak based on intelligent processing of measurement data using machine learning methods. The proposed solution is intended for integration into information and communication systems for supervisory control and digital monitoring of pipeline transport. A two-layer multilayer perceptron implemented in the MATLAB environment is employed as the data analysis tool, enabling the development of a computationally efficient algorithm suitable for practical use in decision-support systems operating in near-real-time conditions. The neural network was trained on experimental datasets generated for various leak locations and flow rate values of the transported medium and was tested on independent datasets. The influence of the number of neurons in the hidden layer on leak localization accuracy was investigated. Maximum and root mean square localization errors were used as performance metrics. The results demonstrate

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that increasing model complexity by raising the number of neurons beyond 3–4 does not lead to a significant improvement in accuracy and may be accompanied by overfitting, thereby reducing the reliability of the algorithm when processing new data. It was found that the optimal neural network architecture comprises three neurons in the hidden layer, providing a root mean square error of approximately 2 km and a maximum error not exceeding 5.5 km. The obtained results confirm the effectiveness of neural network methods for intelligent analysis of telemetry information and demonstrate the feasibility of developing scalable information and communication systems for early leak detection. The practical significance of this work lies in improving the accuracy of accident localization and reducing pipeline operation risks through the implementation of intelligent data processing algorithms within digital industrial monitoring platforms.

Keywords: leak; leak detection; pipelines; artificial neural networks; multilayer perceptron; oil.

Introduction

In the context of the digitalization of industrial infrastructure and development of concepts of Industry 4.0 and the Industrial Internet of Things (IIoT), the role of information and communication technologies in ensuring the reliability and safety of distributed engineering systems is steadily increasing. Oil and gas pipeline transportation systems belong to critically important facilities whose operation requires continuous monitoring, prompt data transmission, and intelligent information processing for the early detection of emergency situations. Effective leak detection and localization are key tasks of digital pipeline monitoring systems, as they enable timely notification of dispatching services about emerging faults, minimization of economic losses, and reduction of negative environmental impacts.

To date, a number of review studies have been published addressing leak detection methods and leak localization in pipelines [1,2]. From the perspective of measurement data acquisition and processing, existing leak detection systems can generally be divided into external and internal approaches [3]. External methods are based on monitoring environmental parameters and the external condition of pipelines, including acoustic signals [4,5] and fiber-optic distributed sensing systems [6,7]. Internal methods typically rely on telemetry data obtained from pressure, flow, and temperature sensors and are implemented within supervisory control and information-communication systems such as SCADA. These methods include real-time transient flow modeling [8], the negative pressure wave method [9], pressure point analysis, and flow balance techniques.

A critical analysis of existing methods shows that, despite the diversity of technical solutions, there is no universal approach to leak localization that is simultaneously accurate, robust, and cost-effective. The main limitations remain the high implementation cost, sensitivity to operational disturbances, algorithmic complexity, and a significant number of false alarms. In this regard, the development of new intelligent data processing methods is highly relevant, particularly those focused on the use of a limited set of measurements without relying on complex mathematical pipeline models.

In recent years, within the development of information and communication technologies and computing platforms, machine learning and data analysis methods have become increasingly widespread. Owing to advances in parallel computing and graphics processing units, deep learning methods are actively applied to streaming data processing and anomaly detection in cyber-physical systems [10,11]. In pipeline monitoring applications, neural network methods are used for leak detection based on time-domain data [12–14] and frequency-domain analysis [15]. Autoencoders demonstrate effectiveness in analyzing unlabeled data and detecting deviations from nominal operating conditions [16,17], while convolutional neural networks are employed for the automatic extraction of informative features from measurement signals.

Despite the active development of these approaches, most of them rely on complex architectures and require substantial computational resources, which limits their applicability in distributed information and communication monitoring systems. This paper proposes a practice-oriented neural network approach for determining the coordinates of a leak in an oil pipeline, based on the use of a two-layer multilayer perceptron and experimental data. The scientific novelty of the study lies in the analysis of the influence of neural network architecture on leak localization accuracy and in the selection of a minimally sufficient structure that ensures stable results without overfitting. The obtained results demonstrate the feasibility of developing computationally simple and efficient algorithms for intelligent processing of telemetry data, which are promising for integration into information and communication systems for monitoring and diagnostics of pipeline transportation.

The paper is organized as follows. Section 2 formulates the leak localization problem based on measurable process parameters of pipeline transportation and describes the neural network approach to approximating the relationship between the input data and the leak coordinate. Section 3 presents the results of a computational experiment performed in the MATLAB environment, including an analysis of the effect of the number of neurons in the hidden layer on localization accuracy. Section 4 summarizes the main conclusions and outlines promising directions for future research.

Research Methods

The oil-product pipeline transportation system includes: connecting pipelines from the oil refinery to the main pumping station (MPS); the MPS with a tank farm that provides injection and the required head; the linear section of the main oil pipeline with associated line facilities; intermediate pumping stations for maintaining the head; branches to intermediate consumers; and the terminal facility intended for receiving, storing, and subsequent shipment or pumping of oil products [18-20].

When a leak occurs under steady-state transportation conditions, the only technological process parameters that may be considered unchanged are the pressure values at the beginning and at the end of the pipeline section (respectively, at the outlet of the MPS tank and at the inlet of the terminal tank).

The operating parameters of the remaining pipeline infrastructure, in one way or another, change when a leak occurs [19,20].

The head h_x at an arbitrary point of the technological section x with coordinate L_x, for a given pipeline flow rate Q_0, can be expressed as:

$$h_x(Q_0) = h_{inl} + \sum_{i=0}^{n} H_i(Q_0) - \left[\sum_{i=0}^{f} h_i^{mc}(Q_0) + \sum_{i=1}^{k} h_i^{lp}(Q_0)\right] , \tag{1}$$

where h_{inl} is the head at the inlet of the technological section (tank outlet), m; $H_i(Q_0)$ is the head generated by the pump located upstream of point L_x at the specified flow rate Q_0, m; n is the number of pumps located upstream of point L_x; $h_i^{mc}(Q_0)$ is the head loss on a local resistance located upstream of point L_x at the specified flow rate Q_0, m; f is the number of local resistances located upstream of point L_x; $h_i^{lp}(Q_0)$ is the head loss on a linear segment located upstream of point L_x at the specified flow rate Q_0, m; k is the number of linear segments located upstream of point L_x.

When a leak occurs with flow rate Q_{leak} and coordinate L_{leak}, the flow rate upstream of the leak point increases to Q_1, while downstream of the leak point it decreases to Q_2. By definition, these flow rates are related by:

$$Q_1 - Q_2 = Q_{leak} . \tag{2}$$

Next, for definiteness, we consider the case of estimating the pressure reduction at an arbitrary required point x_1 located upstream of the leak point.

(For points located downstream of the leak point, similar derivations can be performed with respect to the end of the technological section.)

The pressure reduction ΔP_{x1} up to the leak point (at the point with coordinate L_{x1}) when the pipeline flow rate increases to Q_1 is:

$$\Delta P_{x1} = P_{x1}(Q_0) - P_{x1}(Q_1) . \tag{3}$$

In the general case, the function $\Delta P(Q)$ is nonlinear with respect to Q and can be represented as follows [20,21]:

$$\Delta P_{x1} = f(Q_{leak}, l_{leak}, t_{leak}, X, Y, K, L, T^0, x_1) , \tag{4}$$

where $Q_{leak}, l_{leak}, t_{leak}$ are the leak flow rate, coordinate, and time of occurrence, respectively; X, Y are vectors of parameters of the main and booster pumps (rotation speed, switching-on and switching-off times); K is a vector of oil-product quality parameters (e.g., density, viscosity); L represents the parameters of valves on the linear section (valve position, opening/closing time, valve coordinate relative to the reference point); T^0 is the oil-product temperature; x_1 is the coordinate of the point at which the pressure drop ΔP_{x1} will be computed; and f is a function describing the dependence of the pressure drop ΔP.

Given the known dependence f, and knowing ΔP along with the values of the remaining oil-product transportation parameters, it becomes possible to determine the leak location l_{leak}. The estimation accuracy will depend on the measurement accuracy of the parameters and on the approximation accuracy of f. The function approximation problem can be addressed using artificial neural networks.

It is well known that the formation of a leak with flow rate q results in a reduction of head and, consequently, a decrease in liquid pressure within the pipeline (Figure 1).

The pressure drop ΔP at any point of the pipeline, in general form, can be described by equation (4). To compute ΔP using equation (4), it is necessary to approximate the function f. The function approximation task for f can be divided into four stages (Figure 2).

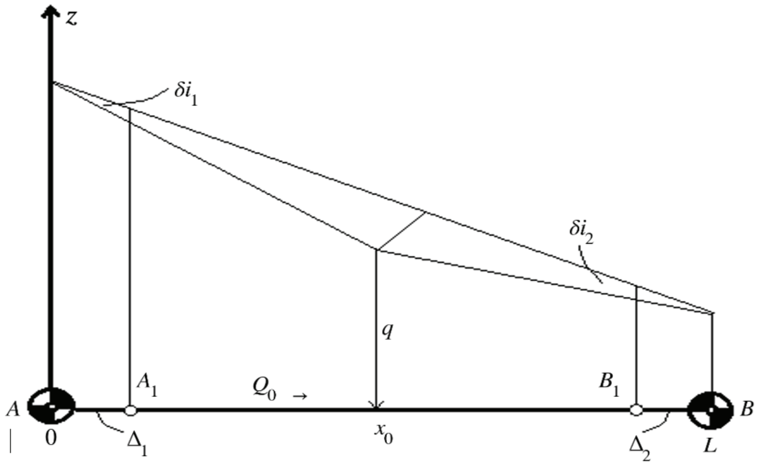

Figure 1. Pressure head reduction in the pipeline due to the formation of a leak with flow rate q.

At the first stage, the most influential parameters affecting ΔP under leak conditions are identified. The initial dataset is divided into training data (used for neural network learning) and test data (used for validation and error estimation). At the second stage, a neural network architecture that is most suitable for the approximation task is selected. Depending on the chosen architecture, various neural network hyperparameters are tuned at the third stage. By evaluating the approximation error (stage 4), it becomes possible to determine such parameter values under which the neural network, for the selected dataset, achieves the minimum error on the test dataset. Thus, given a sufficiently large dataset, an appropriate neural network can be selected for each pipeline segment to estimate the leak location with minimal error.

As the most essential parameters describing the oil-product transportation process in a pipeline, the following were selected: the pipeline gauge pressure and the oil-product flow rate. First, these parameters exhibit the most significant changes when a leak occurs. Second, they can be readily measured using sensors, and the installation and operation of pressure and flow sensors do not require substantial costs.

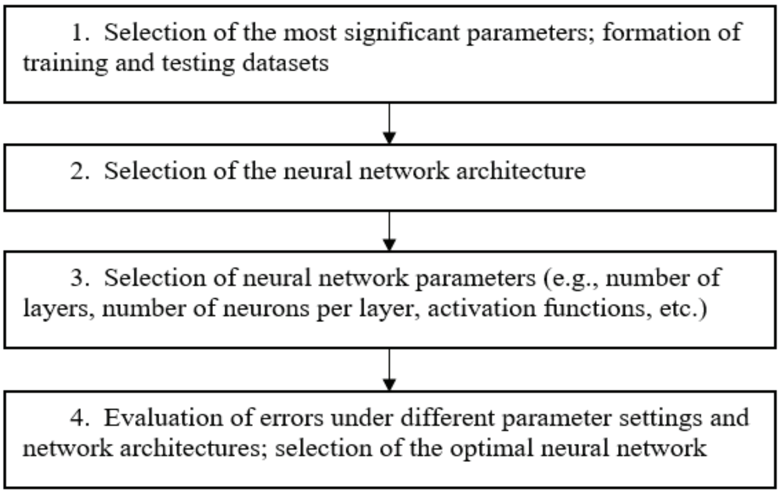

Figure 2. Stages of solving the function approximation problem using neural networks.

Let us consider the table of pressure-drop values recorded by the sensor at the moment of experimental oil-product withdrawal, under different leak locations relative to the pressure sensor and different leak flow rates (Table 1) [20-22]. The data were obtained experimentally during field testing of a pipeline leak detection system (LDS) on a main trunk pipeline. During the LDS testing, a leak was simulated by withdrawing oil product from the main pipeline into a non-pressurized tank. The magnitude of the simulated leak was controlled using a ball valve DN 25, PN 16 MPa (Figure 3).

Table 1. Pressure drop for different flow-rate magnitudes and distances between the leak location and the pressure sensor, $\mathrm{kgf/cm^2}$

Leak flow rate, L/min	Distance between leak and sensor, km				
	79	60	53	44	40
160	0,0355	0,0450	0,0500	0,0570	0,0625
120	0,0350	0,0385	0,0430	0,0495	0,0535
100	0,0290	0,0360	0,0400	0,0465	0,0500
80	0,0265	0,0278	0,0284	0,0300	0,0315
60	-	-	-	0,0240	0,0248
40	-	-	-	-	0,0195

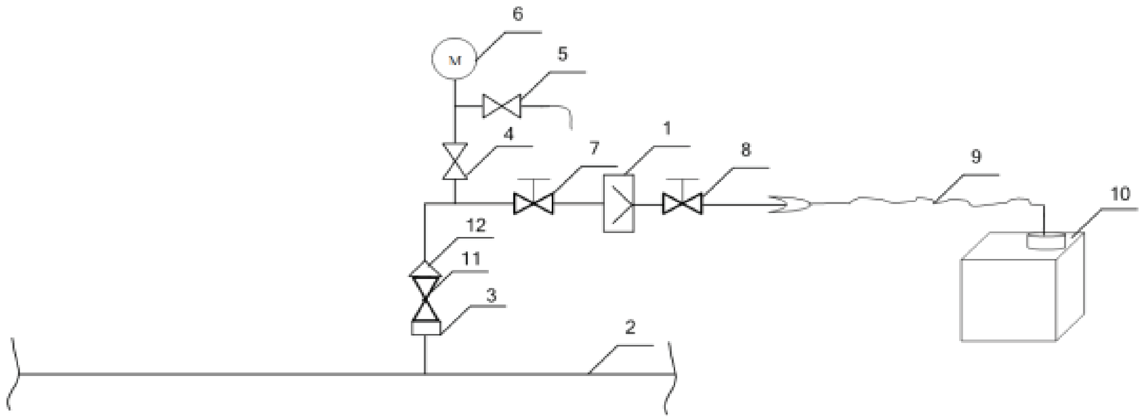

Figure 3. Schematic diagram of oil-product withdrawal from the main trunk pipeline

Figure 3 presents a schematic diagram of oil-product withdrawal from the pipeline, where: 1 – flanged connection for installing interchangeable throttle orifice plates; 2 – main trunk oil pipeline; 3 – flanged connection; 4 – shut-off valve; 5 – air release valve; 6 – MO-160 pressure gauge (0–60 $\mathrm{kgf/cm^2}$), accuracy class 0.4; 7,8 – ball valve DN 25, PN 16 MPa; 9 – high-pressure hose; 10 – non-pressurized tank; 11 – gate valve DN 100; 12 – reducer from DN 100 to DN 25.

As neural networks for approximating the function, we consider the multilayer feedforward perceptron as the most suitable option for this task (Figure 4).

A two-layer network in which the first layer employs a sigmoid activation function and the second layer uses a linear activation function can be trained to approximate any function with arbitrary accuracy [21-23].

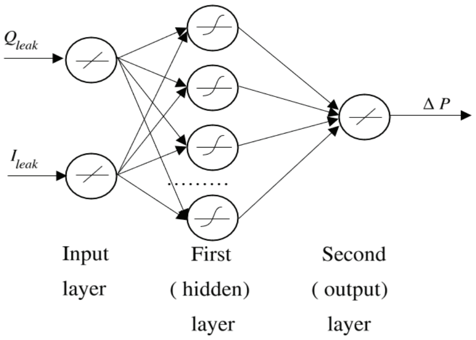

Figure 4. Two-layer neural network.

Results

During a computational experiment conducted in the MATLAB environment, the influence of the number of neurons in the hidden layer of multilayer perceptron on the accuracy of estimating the leak coordinate in a pipeline was investigated. The number of neurons in the hidden layer was varied from 1 to 40, while for each network configuration the model was trained and subsequently evaluated in terms of prediction error on the test dataset [23].

At the first stage, the neural network was trained using the test data corresponding to leaks located at 40, 53, 60, and 79 km, and it was tested using the data for a leak located at 44 km under different leak flow-rate values (Table 1). The maximum error in estimating the leak coordinate was employed as an integral performance metric (Figure 5).

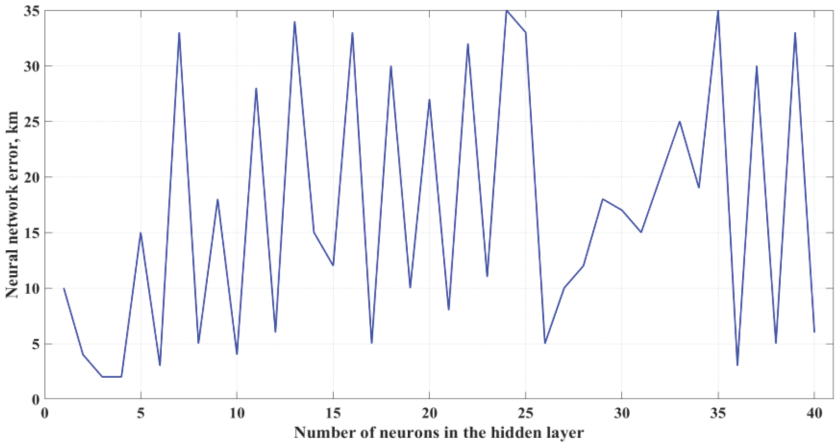

Figure 5. Dependence of error on the number of hidden-layer neurons in the multilayer perceptron when testing for a leak at 44 km.

The obtained results indicate that a small number of neurons leads to a significant error, which can be attributed to the limited approximation capability of the model. The minimum error values are achieved when using 3–4 neurons in the hidden layer. A further increase in the number of neurons does not improve accuracy and, in some cases, results in its deterioration.

Similar computational experiments were carried out for leak locations at 53 km and 60 km. In the first case, the neural network was trained using data corresponding to leaks at 40, 44, 60, and 79 km, whereas in the second case, training was performed using data for leaks at 40, 44, 53, and 79 km (Figure 6).

For the leak at 53 km, the highest accuracy is achieved when using two neurons in the hidden layer. For the leak at 60 km, the minimum error is observed when using 3–4 neurons.

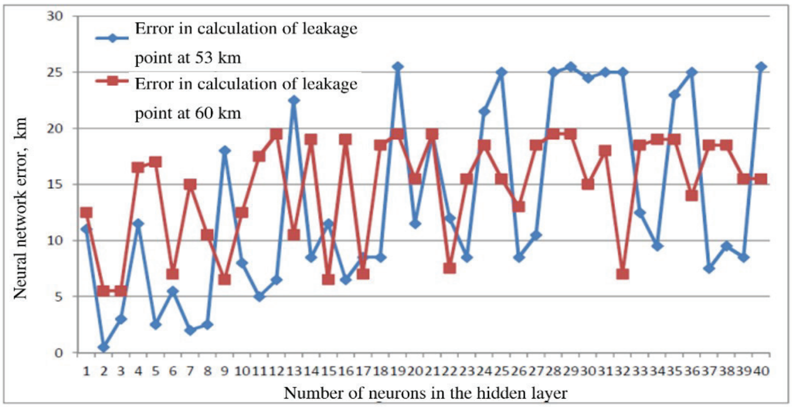

Figure 6. Dependence of error on the number of hidden-layer neurons in the multilayer perceptron when testing for leaks at 53 km and 60 km.

For a comprehensive evaluation of the neural network accuracy across all considered scenarios, the root mean square error (RMSE) of leak location estimation was calculated using the following formula:

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})} \ , \qquad (5)$$

where x_i is the actual leak location for the i-th neural network test, $\bar{x}$ is the leak location estimated by the neural network, and n is the number of neural network tests.

Based on the aggregated results, it has been established that the minimum error is achieved when using three neurons in the hidden layer. With this architecture, the root mean square error is approximately 2 km, while the maximum error does not exceed 5.5 km (Figure 7).

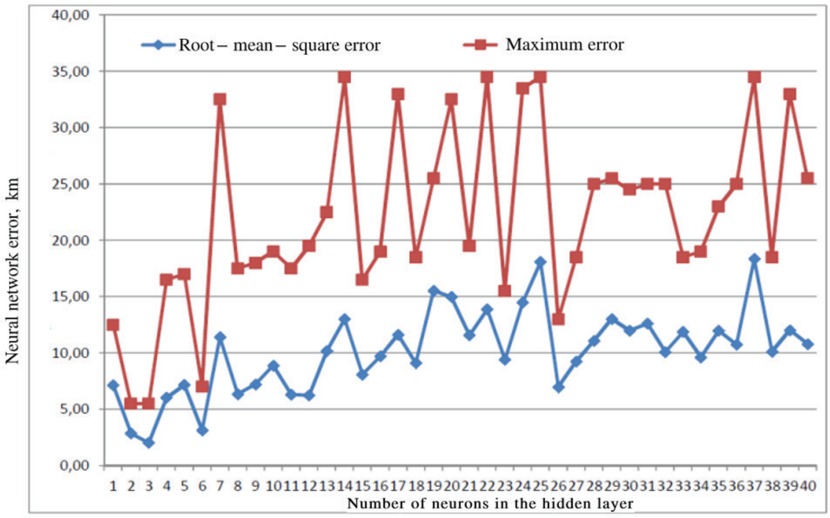

Figure 7. Dependence of root-mean-square and maximum error on the number of hidden-layer neurons.

Discussion

An analysis of the dependence of the maximum error on the number of neurons in the hidden layer shows that increasing the model complexity leads to a nonlinear change in accuracy. A small number of neurons results in a high error due to the insufficient approximation capability of the network. The reduction in error observed with 2–4 neurons indicates the existence of an optimal range of model complexity at which the best balance between generalization ability and approximation accuracy is achieved. A further increase in the number of neurons does not improve model performance and, in some cases, leads to a deterioration of the results, indicating the onset of overfitting. This effect is particularly pronounced when the training dataset is limited and the data distribution along the pipeline segments is non-uniform.

The differences in the optimal number of neurons for different sections (44, 53, and 60 km) can be explained by the heterogeneity of the training data and the specific characteristics of interpolation in different regions of the pipeline system. A combined analysis of the maximum error and the root mean square error indicates that the optimal architecture for the considered problem is a two-layer perceptron with three neurons in the hidden layer, providing a balance between accuracy, robustness, and computational complexity.

Conclusion

This study develops and implements an algorithm for the intelligent processing of telemetry data aimed at determining the coordinates of a pipeline leak, based on the application of a two-layer neural network and intended for use in information and communication monitoring systems. The model is implemented in the MATLAB environment and utilizes experimental data corresponding to various flow rate values of the transported medium, which allows the proposed approach to be considered as an element of a digital analysis and decision-support system. A computational experiment was conducted to investigate the influence of the neural network structure on leak localization accuracy, within which the effect of the number of neurons in the hidden layer on the algorithm’s performance metrics was analyzed. It was established that there exists an optimal range of model complexity at which the best trade-off between accuracy and computational efficiency is achieved. It is shown that the use of 3–4 neurons in the hidden layer ensures the minimum error in determining the leak coordinates, whereas further increasing the network dimensionality does not lead to accuracy improvement and may be accompanied by overfitting, which reduces the robustness of the algorithm when processing new data. It was determined that the optimal neural network architecture with three neurons in the hidden layer provides a root mean square error of approximately 2 km and a maximum error not exceeding 5.5 km on test datasets. The obtained results confirm the feasibility of applying small-scale neural networks for the intelligent analysis of measurement information under conditions of a limited training dataset and constrained computational resources, which is an important factor for practical implementation in distributed information and communication systems. The results of this study can be used in the development of intelligent monitoring, diagnostics, and supervisory control systems for pipeline transportation operating within digital Industrial Internet of Things platforms and SCADA systems. Future research directions are associated with extending the functional capabilities of the proposed approach through the use of alternative neural network architectures, including deep, recurrent, and convolutional models, as well as hybrid methods combining machine learning with classical signal processing and statistical analysis algorithms, which may further improve the accuracy and robustness of leak localization under real operating conditions.

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