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Pressure-State Restoration for Early Fault Diagnosis in Gas Pipeline Networks

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ABSTRACT

Urban gas pipeline networks generate continuous monitoring time series from pressure sensors, flow meters, valve states, compressor stations, regulator stations, gas concentration sensors, and customer-demand meters. These signals are noisy because of daily demand fluctuation, regulator adjustment, compressor vibration, sensor drift, weather effects, and telemetry packet loss. Leakage, valve malfunction, regulator instability, and abnormal pressure drops may therefore be masked by normal operational noise. This study develops a diffusion-recovered pressure dynamics model for gas pipeline network anomaly detection. The proposed method reconstructs clean pressure-flow trajectories using a conditional diffusion process constrained by pipeline topology and operating states. A disentanglement module separates demand-driven variation, control-operation fluctuation, and fault-related pressure residuals. Experiments are conducted on a gas network dataset containing 1,280 pipeline zones, 5,640 pressure sensors, 930 flow meters, 460 regulator stations, and 31 monitoring variables collected every 30 seconds over 15 months. The dataset contains 864 million timestamped records and 1,960 verified abnormal episodes, including small leakage, regulator oscillation, valve blockage, compressor instability, and abnormal pressure loss. The proposed method shortens median leakage detection delay from 4.6 hours to 47 minutes compared with a Kalman-smoothed recurrent baseline. False dispatch alerts are controlled at 2.0 cases per pipeline zone per quarter. Diffusion recovery reduces normalized pressure reconstruction error from 0.158 to 0.061, and topology-guided denoising restores 23.4 million incomplete pressure windows during evaluation. Full city-level assessment is completed in 13.5 minutes with median scoring latency of 45 ms per zone window. These findings indicate that diffusion-guided signal recovery can improve robust anomaly detection in noisy gas pipeline operation time series.

1. Introduction

Urban gas pipeline networks provide essential energy for residential consumption, industrial production, commercial activities, and public services. Their safe and stable operation depends on the continuous monitoring of pressure, flow rate, valve status, compressor operation, regulator

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behavior, gas concentration, and customer demand. The resulting multivariate time-series data provide important information for identifying leakage, equipment degradation, and abnormal operating conditions. However, pressure and flow measurements are strongly influenced by daily and seasonal demand patterns, regulator adjustments, compressor vibration, weather variation, sensor drift, communication interruption, and telemetry loss (Yang, 2026; Salomone-González, 2025). These disturbances may conceal weak pressure changes caused by small leakage, partial valve blockage, regulator instability, compressor faults, and localized pressure loss. As a result, early-stage anomalies can remain indistinguishable from normal operational fluctuations, particularly in large urban networks containing numerous interconnected pipeline zones and heterogeneous monitoring devices. Existing gas pipeline anomaly detection approaches include threshold-based alarms, hydraulic simulation, acoustic monitoring, pressure-transient analysis, kalman filtering, recurrent neural networks, autoencoders, graph-based models, and transformer architectures. These methods have demonstrated considerable capability in detecting major leakage events and evident pressure faults (Zhang, 2026; Farooq et al., 2025). Nevertheless, their reliability frequently depends on clean sensor signals, stable hydraulic conditions, accurate physical parameters, or sufficiently labeled fault samples. Recent research on fine-grained multivariate time-series anomaly detection has shown that causal dependency modeling can help distinguish abnormal variable interactions from ordinary temporal correlations (Chen et al., 2025). This direction is particularly relevant to gas networks because a pressure deviation observed at one sensor may be caused by local demand variation, an upstream regulator action, a downstream valve condition, or an actual leakage event. Conventional correlation-based methods may assign similar anomaly scores to these fundamentally different causes, thereby reducing the interpretability and operational value of the detection results (Yin et al., 2026; Birihanu & Lendák, 2025).

Several practical limitations remain unresolved in city-scale gas monitoring. Leakage-induced pressure loss may closely resemble peak-demand fluctuation, regulator switching, or compressor adjustment (Ibrahim et al., 2026). Sensor drift may gradually alter the statistical distribution of pressure measurements without producing an abrupt alarm, while packet loss and communication failure may generate incomplete or temporally biased monitoring windows (Fu et al., 2020; Liang et al., 2025). Reconstruction-based models may classify uncommon but normal operating patterns as anomalies, whereas prediction-based models may produce large errors during rapid demand transitions even when the network remains safe (Zhang et al., 2025; Sayyaf et al., 2025). Many existing methods also process individual sensors or fixed-length windows independently, without adequately incorporating pipeline topology, upstream–downstream transmission relationships, regulator states, and zone-level operating conditions (Yang et al., 2025; Zhang et al., 2026). Consequently, they may detect that a pressure pattern is unusual but fail to determine whether the deviation originates from customer demand, control operations, sensor quality, or a physical pipeline fault (Niresi et al., 2026; Qi & Qiao, 2026). These weaknesses can delay leakage localization, increase false dispatch alerts, and impose unnecessary inspection costs on gas utility operators (Xiong et al., 2026; Sayghe, 2025). The presence of missing and corrupted measurements further complicates anomaly detection. Simple interpolation may smooth weak fault signatures, while direct removal of incomplete windows can substantially reduce monitoring coverage (Zhang & Wang, 2026; Raeispour et al., 2026). Generative recovery methods offer a potential solution because they can estimate plausible signal trajectories from partially observed data (Hong et al., 2026; Qi & Qiao, 2026). However, unconstrained generation may reconstruct statistically realistic pressure curves that are inconsistent with actual pipeline connectivity or operating states. Effective recovery therefore requires both temporal consistency and physical-context constraints (Su &

Zhang, n.d.; Chandramoorthy & de Clercq, 2026). A robust detection framework should recover incomplete measurements, preserve fault-sensitive residual information, model cross-sensor dependencies, and separate normal operational variation from genuine abnormal pressure propagation. It should also support rapid zone-level scoring and city-level assessment so that detected events can be converted into timely maintenance and dispatch decisions.

To address these challenges, this study develops a diffusion-recovered pressure dynamics model for anomaly detection in urban gas pipeline networks. The proposed method reconstructs clean and complete pressure–flow trajectories through a conditional diffusion process constrained by pipeline topology, sensor observations, regulator states, and network operating conditions. A disentanglement module is introduced to separate demand-driven variation, control-operation fluctuation, measurement disturbance, and fault-related pressure residuals. This design aims to prevent normal demand changes and regulator actions from dominating anomaly scores while retaining weak but operationally significant fault signatures. The model is evaluated using 15 months of monitoring data collected from 1,280 pipeline zones, including 5,640 pressure sensors, 930 flow meters, and 460 regulator stations. The evaluation considers leakage detection delay, false dispatch frequency, pressure reconstruction error, incomplete-window recovery performance, city-level assessment time, and zone-level scoring latency. Through the integration of diffusion-based recovery, topology-aware dynamic modeling, and source-disentangled anomaly scoring, this study seeks to improve the early identification of small leakage and pressure abnormalities under noisy, incomplete, and continuously changing operating conditions. The proposed framework is expected to provide more reliable evidence for leakage localization, maintenance prioritization, dispatch decision-making, and large-scale gas-network safety management.

2. Materials and Methods

2.1. Samples and Study Area Description

This study used a city-scale gas pipeline monitoring dataset from 1,280 pipeline zones. The monitored objects included pressure sensors, flow meters, valve nodes, compressor stations, regulator stations, gas concentration sensors, and customer-demand meters. A total of 31 variables were recorded every 30 s over 15 months. After screening, 864 million timestamped records were retained. The dataset contained 1,960 verified abnormal episodes, including small leakage, regulator oscillation, valve blockage, compressor instability, and abnormal pressure loss. The samples covered daily and seasonal demand changes, regulator adjustment, compressor operation, weather variation, telemetry loss, and sensor drift.

2.2. Experimental Design and Control Settings

The diffusion-recovered pressure dynamics model was used as the proposed approach. A Kalman-smoothed recurrent model, a recurrent reconstruction model, and a rule-based pressure-drop detector were used as baseline methods. All methods used the same pressure-flow records, topology information, operating-state labels, and verified abnormal episodes. The Kalman-smoothed recurrent model was selected because Kalman filtering is commonly used to reduce pressure-signal noise. The recurrent reconstruction model represented standard time-series anomaly detection, while the rule-based detector represented conventional pipeline alarm practice. An ablation model without topology constraints was also tested to examine whether pipeline structure improved pressure recovery and leakage detection.

2.3. Measurement Methods and Quality Control

Pressure, flow rate, valve state, compressor state, regulator outlet pressure, gas concentration, and customer-demand signals were collected from pipeline monitoring units and station control systems. All measurements were aligned using unified timestamps and zone identifiers. Quality control included duplicate removal, timestamp correction, incomplete-window exclusion, and detection of physically impossible pressure or flow values. Telemetry-loss and sensor-drift periods were marked before model training. Abnormal episodes were verified using dispatch logs, maintenance records, pressure-drop curves, regulator operation histories, and field inspection reports. Random checks were performed on selected normal and abnormal windows to reduce labeling errors. Continuous variables were standardized, and discrete operating states were encoded as binary indicators.

2.4. Data Processing and Model Formulation

Cleaned records were divided into zone-level monitoring windows and converted into multivariate pressure-flow vectors. Each window was defined as $x_t=[P_t,F_t,V_t,C_t,R_t,D_t,G_t]$, where P_t denotes pressure, F_t flow rate, V_t valve state, C_t compressor state, R_t regulator state, D_t customer demand, and G_t gas concentration. To preserve hydraulic consistency, the pressure difference between connected zones was defined as:

$$\Delta P_{ij}(t)=P_i(t)-P_j(t),$$

where $P_i(t)$ and $P_j(t)$ are the pressures of two connected pipeline zones. After diffusion-based recovery, the topology-adjusted residual score was calculated as:

$$S_t=\frac{1}{n}\sum_{i=1}^{n}\frac{|P_i(t)-\hat{P}_i(t)|+\lambda|\Delta P_{ij}(t)-\widehat{\Delta P}_{ij}(t)|}{\sigma_i+\epsilon},$$

where $P_i(t)$ is the observed pressure, $\hat{P}_i(t)$ is the recovered pressure under normal operation, $\Delta P_{ij}(t)\Delta$ is the observed pressure difference between connected zones, $\widehat{\Delta P}_{ij}(t)$ is the recovered pressure difference, λ is the topology constraint weight, σ_i is the normal pressure variation, and ϵ prevents numerical instability. A higher score indicates stronger fault-related pressure deviation after demand-driven and control-related fluctuations are reduced.

2.5. Statistical Analysis and Evaluation Metrics

Model performance was evaluated using median leakage detection delay, false dispatch alert rate, normalized pressure reconstruction error, incomplete-window recovery capacity, city-level assessment time, and zone-level scoring latency. Leakage detection delay was defined as the interval between the start of a verified abnormal episode and the first model alert. False dispatch alerts were reported as cases per pipeline zone per quarter. Reconstruction quality was measured by the normalized error between recovered and reference pressure-flow trajectories. Incomplete-window recovery was measured by the number of missing or corrupted pressure windows restored during evaluation. City-level assessment time was measured for one full monitoring cycle across all pipeline zones, and scoring latency was calculated for each zone window. Results were averaged across pipeline zones, abnormal types, and operating periods to assess model stability under different network conditions.

3. Results and Discussion

3.1. Leakage Detection Delay under Noisy Operation

The diffusion-recovered pressure dynamics model detected leakage earlier than the Kalman-smoothed recurrent baseline. The median detection delay decreased from 4.6 h to 47 min, showing earlier recognition of small leakage and abnormal pressure loss. This improvement was mainly due to topology-guided diffusion recovery, which restored cleaner pressure-flow trajectories before residual scoring (Du et al., 2026; Iadarola et al., 2025). In contrast, Kalman-smoothed recurrent models may confuse leakage-related pressure drops with demand changes or regulator adjustment. The spatiotemporal gas pipeline leak detection framework shown in Fig. 1 provides a useful reference for pressure-sensor-based network monitoring.

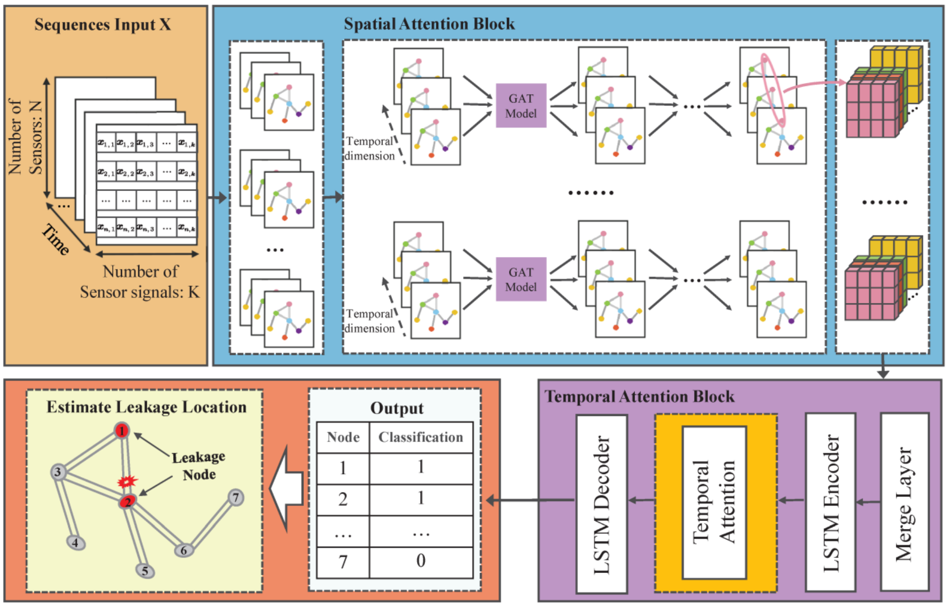


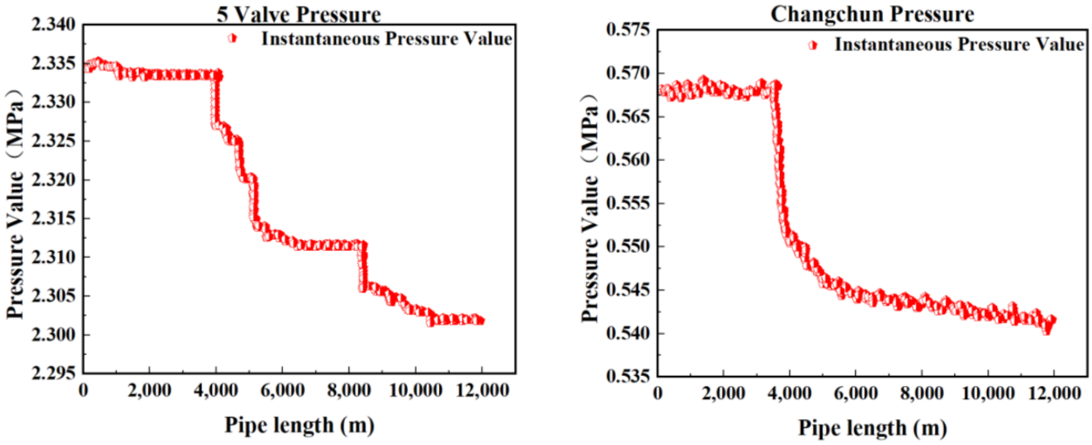
Fig. 1. Spatiotemporal framework for pressure-based gas pipeline leak detection.

3.2. False Dispatch Alerts and Operational Robustness

False dispatch alerts were controlled at 2.0 cases per pipeline zone per quarter. This result indicates that the proposed method reduced unnecessary field inspections while maintaining sensitivity to verified abnormal events. In gas network operation, false dispatch increases inspection cost and may delay response to real leakage risks. The disentanglement module separated demand-driven variation, control-operation fluctuation, and fault-related pressure residuals. This separation reduced the risk of treating normal demand peaks, regulator adjustment, or compressor vibration as leakage events (Du et al., 2026; Xiong et al., 2026). Compared with rule-based pressure-drop alarms and recurrent reconstruction models, the proposed method produced more stable anomaly scores across demand periods, weather changes, and regulator states (Mohammadi et al., 2025; Hong et al., 2026).

3.3. Pressure Recovery and Missing-Window Handling

Diffusion recovery reduced the normalized pressure reconstruction error from 0.158 to 0.061, showing better recovery of clean pressure-flow trajectories from noisy monitoring data. The topology-guided denoising process also restored 23.4 million incomplete pressure windows during evaluation. This result is important because telemetry packet loss and sensor drift are common in city-scale pipeline monitoring. The recovered pressure differences between connected zones helped preserve hydraulic consistency and improved the detection of small pressure-loss events (Li et al., 2026; Khan et al., 2025). The pressure curve pattern under leakage conditions shown in Fig. 2 supports the need to model both upstream and downstream pressure changes during leakage diagnosis.



(**a**) Pressure Curve of Valve Chamber 5 (**b**) Changchun Station Pressure Curve

Fig. 2. *Pressure variation pattern under gas pipeline leakage conditions.*

3.4. Comparison with Existing Studies

Overall, the proposed model improved leakage detection delay, false dispatch control, pressure reconstruction accuracy, incomplete-window recovery, and online scoring efficiency. Existing gas pipeline monitoring methods often use threshold rules, Kalman filtering, recurrent reconstruction, wavelet denoising, or spatiotemporal attention models. These methods can detect clear leakage events, but their performance may decline when demand fluctuation, regulator operation, compressor vibration, sensor drift, and packet loss occur at the same time. The proposed method addressed this limitation by combining diffusion-based pressure recovery with topology constraints and component separation. Full city-level assessment was completed in 13.5 min, with a median scoring latency of 45 ms per zone window, showing practical value for city-scale gas pipeline monitoring.

4. Conclusion

This study proposed a diffusion-recovered pressure dynamics model for anomaly detection in noisy urban gas pipeline networks. The method restored clean pressure-flow trajectories through topology-constrained diffusion recovery and separated demand-driven variation, control-operation fluctuation, and fault-related pressure residuals. Experiments on 1,280 pipeline zones, 5,640 pressure sensors, 930 flow meters, and 15 months of monitoring data showed that the method reduced median leakage detection delay from 4.6 h to 47 min compared with the Kalman-smoothed recurrent baseline. False dispatch alerts were limited to 2.0 cases per pipeline zone per quarter, and normalized pressure reconstruction error decreased from 0.158 to 0.061. The model also recovered 23.4 million incomplete pressure windows and completed full city-level assessment in 13.5 min. These results indicate that diffusion-based signal recovery can improve leakage detection and pressure anomaly diagnosis under noisy operating conditions. The main contribution of this work is the combined use of pressure-flow recovery, pipeline topology constraints, and residual separation for robust gas network monitoring. The method can support early leakage warning, targeted field inspection, and safer operation of urban gas infrastructure. However, this study used one city-scale dataset. Further tests are needed for different pipeline layouts, gas demand patterns, sensor densities, and climate conditions. Future work should combine recovered pressure signals with hydraulic simulation and field inspection records to improve fault localization and field use.

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