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FRACTAL-BASED MONITORING OF GAS PIPELINE OPERATION USING FLOW RATE VARIATIONS

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A B S T R A C T

Reliable monitoring of gas pipeline operation is a critical task for ensuring the safe and efficient transportation of natural gas. Traditional inspection techniques, such as in-line inspection tools, provide detailed information; however, they are applied periodically and lack the capacity for continuous assessment of pipeline operating conditions. In contrast, SCADA systems generate large volumes of real-time operational data, including gas flow rate measurements, which can be effectively utilized for online monitoring purposes. This paper proposes a fractal-based approach for monitoring gas pipeline operation using SCADA flow rate data. The proposed methodology is based on the analysis of flow rate time series to identify fractal characteristics associated with different operating regimes of the pipeline. Fractal indicators, including the fractal dimension and long-range dependence measures, are employed to quantify the complexity and variability of gas flow dynamics. Changes in these fractal parameters are analyzed to distinguish between normal steady-state operation and disturbed operating conditions caused by transient regimes, demand fluctuations, or potential anomalies. The approach allows the extraction of informative features from flow rate data without the need for direct physical inspection of the pipeline. The results demonstrate that fractal indicators derived from SCADA flow rate signals are sensitive to operational changes and can serve as reliable diagnostic parameters for pipeline monitoring. The proposed fractal-based monitoring framework can be integrated into existing SCADA systems to enhance continuous operational control and support timely decision-making. This method is particularly suitable for complementing conventional inspection techniques by providing an additional layer of real-time monitoring between scheduled inspection intervals.

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1. Introduction

The safe and efficient transportation of natural gas through pipeline systems plays a crucial role in modern energy infrastructure. Gas pipelines operate under varying demand conditions, which lead to continuous changes in flow rate and pressure along the pipeline. Monitoring these operational parameters is essential for maintaining system reliability, minimizing energy losses, and preventing abnormal operating conditions. Traditional pipeline inspection methods, such as in-line inspection tools, provide detailed information on pipeline integrity; however, they are typically applied at discrete time intervals and cannot ensure continuous monitoring of pipeline operation.

With the widespread implementation of the Supervisory Control and Data Acquisition (SCADA) systems, large volumes of real-time operational data have become available for pipeline monitoring. Flow rate measurements obtained from SCADA systems reflect the dynamic behavior of gas transportation processes and contain valuable information about the operating state of the pipeline. Nevertheless, conventional data analysis techniques often focus on average values or short-term fluctuations and may fail to capture the complex structure of flow rate variations under different operating regimes [1-3].

In recent years, fractal analysis has been increasingly applied to the study of complex dynamic systems due to its ability to describe irregular, nonlinear, and self-similar processes. Gas flow in pipelines exhibits characteristics of complex dynamics, especially under transient operating conditions caused by demand changes, valve operations, or compressor adjustments. Fractal-based methods provide a quantitative framework for analyzing the complexity and long-range correlations present in flow rate time series, enabling the identification of subtle changes in pipeline operation [4-6].

Despite the growing interest in data-driven monitoring approaches, the application of fractal analysis to SCADA flow rate data for gas pipeline monitoring remains limited. Most existing studies focus on pressure-based diagnostics or numerical modeling, while the diagnostic potential of flow rate variations has not been sufficiently explored. Therefore, the aim of this paper is to develop a fractal-based approach for monitoring gas pipeline operation using SCADA flow

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rate data and to evaluate its capability to distinguish between normal and disturbed operating conditions [7].

2. Literature review

Pipeline monitoring and diagnostics have been widely studied due to their importance for ensuring the safety and reliability of gas transportation systems. Traditional integrity assessment methods mainly rely on periodic inspections using in-line inspection tools, hydraulic testing, and visual examination. These approaches provide detailed information on pipeline defects and structural conditions; however, they are applied intermittently and do not allow for continuous monitoring of pipeline operation. As a result, operational disturbances occurring between inspection intervals may remain undetected for extended periods [8-10].

With the development of automation technologies, SCADA systems have become a key component of modern gas pipeline operations. Numerous studies have demonstrated the effectiveness of SCADA data for monitoring pressure, flow rate, and temperature in real time. Flow rate measurements, in particular, reflect the response of the pipeline system to demand variations, control actions, and transient events. Conventional SCADA-based monitoring techniques typically employ threshold analysis, statistical indicators, or mass balance methods. While these approaches are useful for detecting large deviations, they often exhibit limited sensitivity to subtle changes in operating conditions [11-14].

In parallel, data-driven and signal processing techniques have gained increasing attention in pipeline monitoring research. Time-series analysis methods, including spectral analysis and correlation-based approaches, have been applied to identify abnormal operating regimes. However, gas flow dynamics in pipelines are inherently nonlinear and influenced by multiple interacting factors, which complicates their interpretation using traditional linear methods.

Fractal analysis has been successfully applied to various complex systems characterized by irregular and scale-dependent behavior. In energy and fluid flow applications, fractal-based methods have been used to analyze turbulence, pressure fluctuations, and flow instability. Indicators such as the fractal dimension and measures of long-range dependence have been shown to capture changes in system dynamics that are not evident in conventional statistical metrics. Despite these advantages, the application of fractal analysis to gas pipeline monitoring remains relatively limited [15-17].

Existing studies that employ fractal methods in pipeline-related research primarily focus on pressure signals or simulated data. The potential of SCADA flow rate time series as a source of fractal-based diagnostic information has not been sufficiently investigated. This gap highlights the need for developing monitoring approaches that combine real operational data with fractal analysis to improve the continuous assessment of gas pipeline operating conditions [18].

Methodology

3.1. SCADA flow rate data description and preprocessing

The proposed monitoring approach is based on the analysis of gas flow rate data obtained from the Supervisory Control and Data Acquisition (SCADA) system of a gas pipeline. SCADA systems continuously collect operational parameters at predefined sampling intervals, providing time series that reflect the dynamic behavior of gas transportation processes. In this study, the gas flow rate signal is considered the primary source of diagnostic information, as it directly responds to changes in demand, control actions, and transient operating regimes. Figure 1 illustrates the general framework of the proposed monitoring methodology, highlighting the key stages from SCADA data collection to fractal feature extraction and analysis.

The flow rate data are represented as a discrete time series $Q(t)$, where t denotes the sampling time index. Prior to fractal analysis, the raw SCADA data undergos a preprocessing stage to ensure data quality and reliability of the extracted indicators. This stage includes the removal of missing or erroneous measurements caused by communication failures or sensor malfunctions. In addition, outliers associated with obvious measurement errors are identified and excluded using statistical consistency checks [19-22].

To eliminate the influence of long-term trends and operational scheduling effects, the flow rate time series is normalized and detrended. This step allows the analysis to focus on the intrinsic fluctuations of the signal that are associated with the internal dynamics of the pipeline system. When necessary, the data are segmented into time windows corresponding to different operating conditions, such as steady-state operation or transient regimes caused by demand changes or control actions.

The selection of an appropriate time window length is an important factor in fractal analysis. Short windows may fail to capture the underlying long-range correlations, while excessively long windows may mask local operational disturbances. Therefore, an optimal window length is chosen based on the sampling frequency and the typical duration of transient events observed in pipeline operation.

The preprocessed flow rate time series forms the basis for subsequent fractal analysis, which aims to extract quantitative indicators describing the complexity and scaling behavior of gas flow dynamics. These indicators are then used to assess the operational state of the pipeline and to identify deviations from normal operating conditions [23-25].

Figure 2 illustrates the general workflow of the proposed SCADA-based fractal monitoring approach, including data

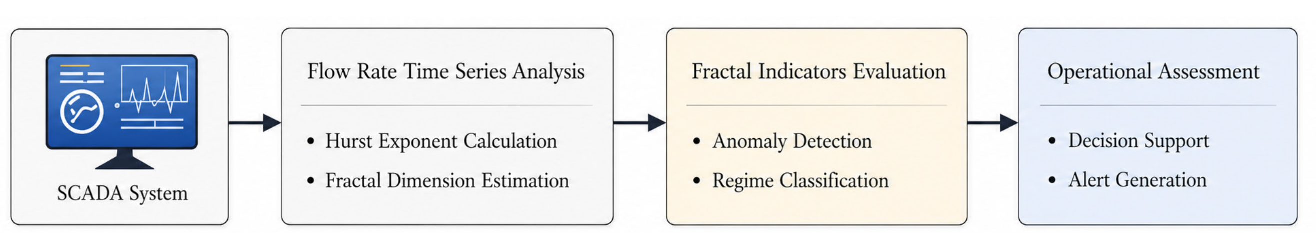

Fig. 1. Workflow of SCADA-based fractal monitoring approach

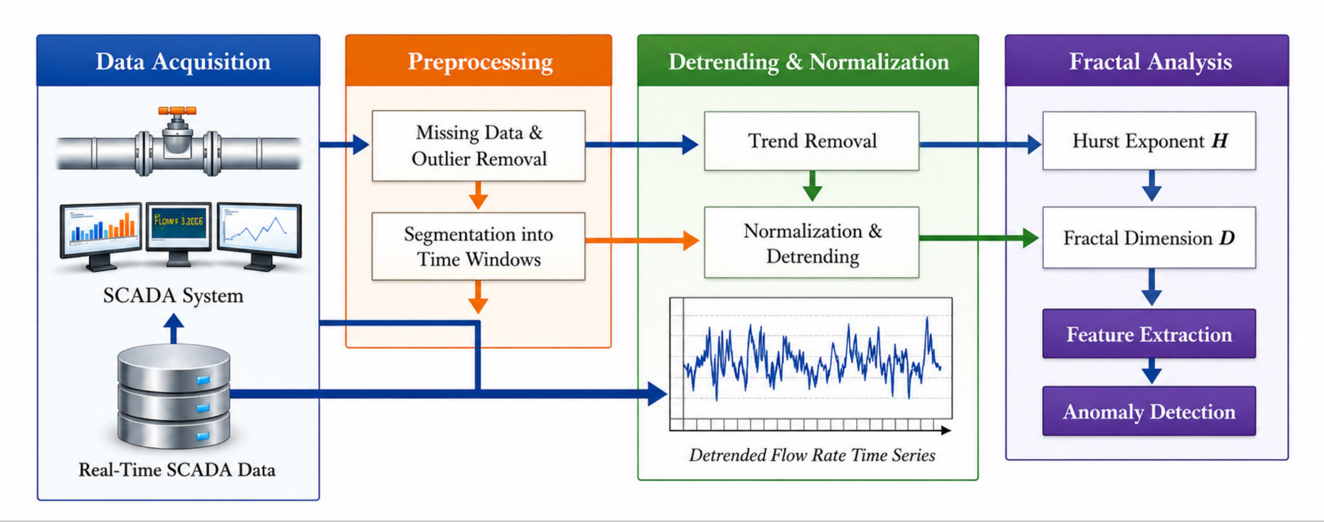

Fig. 2. General workflow of SCADA flow rate data preprocessing for fractal-based gas pipeline monitoring

acquisition, preprocessing, and preparation for fractal analysis.

3.2. Fractal analysis of flow rate time series

Fractal analysis provides a quantitative framework for characterizing the complexity and self-similarity of time series. In this study, the preprocessed SCADA flow rate time series *Q(t)* is analyzed using two commonly employed fractal indicators: the Hurst exponent *H* and the fractal dimension *D*. These measures capture the long-range dependence and scaling behavior of the flow rate signal, which are indicative of both normal and disturbed operating conditions [26, 27].

3.3. Hurst exponent

The Hurst exponent *H* quantifies the degree of long-range correlation in a time series and is calculated using rescaled range (*R*/*S*) analysis. For a discrete time series *Q*(*t*) of length *N*, the rescaled range is defined as:

$$\frac{R}{S}=\frac{\max_{1\le t\le N}\left(\sum_{i=1}^{t}(Q_i-Q^{-})\right)-\min_{1\le t\le N}\left(\sum_{i=1}^{t}(Q_i-Q^{-})\right)}{S}$$

where *Q-bar* is the mean of the series and *S* is the standard deviation. The Hurst exponent is estimated from the following scaling relationship:

$$R/S\sim N^{H}$$

Values of $H>0.5$ indicate persistent behavior, $H=0.5$ corresponds to random behavior, and $H<0.5$ indicates anti-persistent behavior in the flow rate dynamics. Figure 3 illustrates the differences in flow rate dynamics across various operating regimes, highlighting changes in variability and irregularity of the signal [29-32].

3.4. Fractal dimension

The fractal dimension *D* is another measure of signal complexity, representing the degree to which the time series fills the space. It is related to the Hurst exponent by:

$$D=2-H$$

Figure 4 illustrates the temporal variation of the Hurst exponent, highlighting changes in long-range dependence under different pipeline operating conditions [28, 29].

A higher fractal dimension corresponds to increased irregularity in the flow rate signal, which may reflect transient operating regimes or potential anomalies in the pipeline system [14, 15].

3.5. Feature extraction and analysis

After computing *H* and *D* for each time window, the resulting indicators are organized into a structured table for subsequent analysis. The table summarizes the average and standard deviation of fractal measures corresponding to different operational regimes, enabling the easy identification of deviations from normal behavior. Table 1 summarizes the values of the Hurst exponent (*H*) and fractal dimension (*D*) obtained from SCADA flow rate data under steady-state, transient, and disturbed operating conditions.

The extracted fractal indicators serve as inputs for

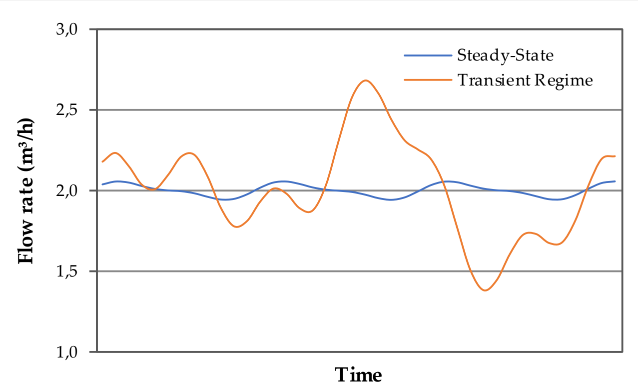

Fig. 3. Examples of SCADA flow rate time series under different operating conditions

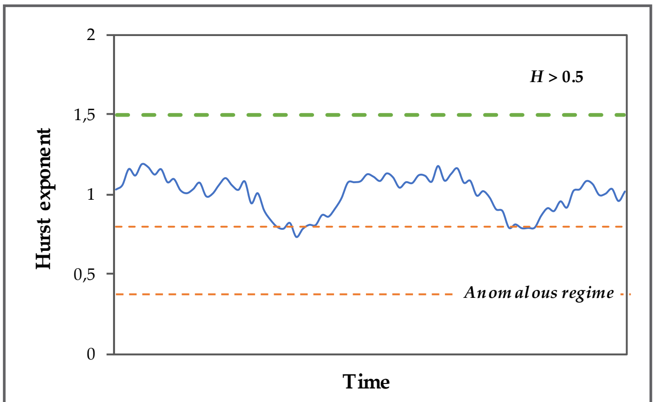

Fig. 4. Variation of Hurst exponent over time

monitoring algorithms that assess the operational state of the gas pipeline. Significant deviations in *H* and *D* values from baseline ranges are interpreted as early warning signs of abnormal operating conditions. Figure 5 illustrates the relationship between the Hurst exponent and fractal dimension, showing how variations in long-range dependence correspond to changes in signal complexity [30].

4. Results and discussion

The proposed fractal-based monitoring methodology was applied to SCADA flow rate data from a gas pipeline system. The analysis focused on three representative operating conditions: steady-state, transient, and disturbed/anomalous regimes. For each condition, the Hurst exponent *H* and fractal dimension *D* were computed for consecutive time windows, as described in this section. The resulting indicators provide quantitative insight into the complexity and variability of gas flow dynamics.

4.1. Fractal indicators across operating conditions

Table 1 (see Methodology) summarizes the average values of *H* and *D* for different operating regimes. During steady-state operation, the Hurst exponent was observed to be approximately 0.72, indicating persistent behavior and relatively stable flow patterns. Correspondingly, the fractal dimension of 1.28 reflects moderate complexity in the signal. In transient regimes, associated with valve operations and demand fluctuations, *H* decreased to 0.63 while *D* increased to 1.37, reflecting increased irregularity in the flow rate signal. The disturbed or anomalous regime exhibited further reduction in *H* (0.55) and higher *D* (1.45), indicating strong deviations from normal operating conditions and potential operational issues. Based on the obtained results, threshold ranges of fractal indicators were established for practical classification of pipeline operating conditions, as presented in table 2 [31].

These results demonstrate that fractal indicators are sensitive to operational changes and can distinguish between normal and disturbed flow conditions. The Hurst exponent captures long-range correlations, while the fractal dimension quantifies the degree of irregularity. Together, these indicators provide complementary information that is not evident from conventional statistical metrics such as mean flow rate or standard deviation.

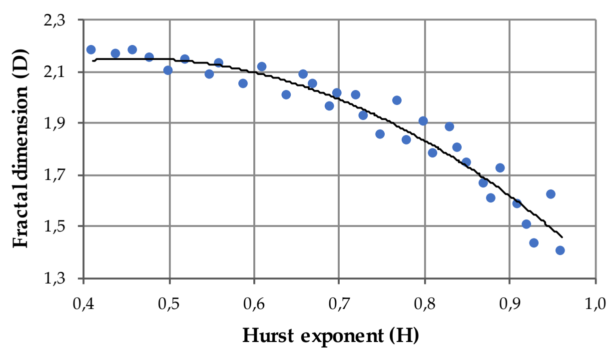

Fig. 4. Reletionship between Hurst exponent and fractal dimension

4.2. Temporal variations and early warning potential

The temporal evolution of the fractal indicators was analyzed over a 48-hour period. During intervals of operational disturbances, significant shifts in both *H* and *D* were observed, serving as early warning signals for operators. The method is particularly effective for detecting subtle deviations in flow behavior that may precede major anomalies, thereby enabling timely intervention and maintenance planning.

4.3 Comparison with conventional monitoring approaches

Compared to threshold-based SCADA monitoring or periodic PIG inspections, the fractal-based approach offers several advantages. First, it provides continuous assessment of pipeline operation without interrupting service. Second, it captures the intrinsic complexity of flow dynamics that is often overlooked by linear or average-based methods. Finally, it can be integrated with existing SCADA systems, allowing operators to complement traditional monitoring techniques with an additional, real-time diagnostic layer.

In summary, the results confirm that fractal analysis of SCADA flow rate data is a valuable tool for monitoring gas pipeline operation. By quantifying the complexity and correlation structure of flow rate signals, the method enhances situational awareness, supports early detection of anomalies, and contributes to safer and more efficient

Table 1

Fractal indicators derived from SCADA flow rate data under different operating conditions

Operating condition	Hurst exponent (*H*)	Fractal dimension (*D*)	Remarks
Steady-state	0.72	1.28	Normal
Transient	0.63	1.37	Slight deviation
Disturbed/Anomalous	0.55	1.45	Potential issue

Table 2

Fractal indicator thresholds for pipeline condition classification

Parameter	Normal operation	Transient condition	Disturbed/Anomalous condition
Hurst exponent (*H*)	$H > 0.70$	$0.60 \le H \le 0.70$	$H < 0.60$
Fractal dimension (*D*)	$D < 1.30$	$1.30 \le D \le 1.40$	$D > 1.40$
Signal behavior	Stable, persistent	Moderately irregular	Highly irregular
Operational interpretation	Normal operation	Minor deviations	Potential anomaly

pipeline operation [32].

5. Practical application of the fractal approach in Azerbaijani gas pipeline systems

The proposed fractal-based monitoring approach has significant potential for application in Azerbaijan's gas transportation infrastructure, particularly in systems operated by SOCAR.

Gas pipelines in Azerbaijan operate under varying demand conditions due to seasonal consumption patterns and export operations. These fluctuations lead to dynamic changes in flow rate, making continuous monitoring essential for maintaining system stability.

Integration of fractal analysis into existing SCADA systems can provide several practical benefits:

– Early detection of abnormal operating conditions;
– Improved operational decision-making;
– Reduction of unplanned downtime;
– Enhanced safety of gas transportation systems.

Furthermore, the method can be applied to major pipeline networks, including export pipelines and domestic distribution systems. The use of flow rate data makes the approach cost-effective, as it does not require additional hardware installation.

Overall, the implementation of fractal-based monitoring can contribute to the digital transformation of Azerbaijan's oil and gas sector and support more efficient pipeline management strategies.

Conclusion

1. A fractal-based approach for monitoring gas pipeline operation using SCADA flow rate data has been proposed and systematically developed. The method provides a continuous assessment of pipeline operating conditions without interrupting service.

2. The Hurst exponent and fractal dimension were employed as quantitative indicators to capture the complexity and long-range correlations in flow rate time series. These indicators effectively distinguish between steady-state, transient, and disturbed operational regimes.

3. The results demonstrate that fractal measures are sensitive to subtle changes in flow dynamics, allowing for the early detection of potential anomalies that may not be visible through conventional statistical analysis or periodic inspections.

4. Compared to traditional monitoring approaches, the proposed method complements existing SCADA systems and periodic inspection tools, offering an additional diagnostic layer that enhances operational control and safety.

5. The methodology is adaptable to different pipeline systems and operating conditions, providing a framework for integrating real-time data-driven monitoring with advanced signal analysis techniques.

6. Future work may include combining fractal indicators with other sensor measurements, such as pressure and temperature, and implementing automated alarm systems for proactive pipeline management.

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