Development of a Predictive Maintenance Framework For Orifice Gas Metering Systems Using Machine Learning

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DOI: 10.22178/pos.131-12

LCC Subject Category: T1-995

Received 27.05.2026
Accepted 27.06.2026
Published online 30.06.2026

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Abstract. Accurate measurement of natural gas flow through orifice meters is essential for gas metering, custody transfer, and financial transparency; however, orifice meters are susceptible to faults such as erosion and particulate accumulation, which can lead to inaccurate readings. This research developed a practical, physics-informed unsupervised learning framework for early problem detection using real field data collected from January through September 2025. It combined three complementary models: Isolation Forest to detect broad outliers, Local Outlier Factor to identify local anomalies, and Exponentially Weighted Moving Average to track gradual shifts over time. These models were applied to the usual SCADA signals: differential pressure (ΔP), static pressure (P), and temperature (T). A single Composite Anomaly Index (CAI) was created to deliver a clear, easy-to-read score for the system's overall health. Of 288 data points, 14 anomalies (just under 5%) were flagged in which the CAI crossed the 0.5 threshold. The anomalies were not scattered randomly but appeared in clear temporal clusters. The strongest peaks occurred between late February and early March, then again from April into May, with CAI values reaching around 0.70–0.75. A milder set was observed in June–July, while August and September remained rock-steady with CAI scores mostly below 0.20. The sharp contrast between those calm periods and the intense spikes showed that the method effectively separated normal operation from real trouble. The integrated framework blended the three models to compensate for their individual weaknesses, capturing both sudden jumps and slow-creeping degradation patterns. Every flagged event lined up with physically expected field mechanisms rising ΔP from fouling or steady baseline drifts from sensor wear. The framework runs entirely on existing SCADA data, with no need for labelled examples, making it cheap and straightforward to roll out at other metering stations.

Keywords: Predictive Maintenance; Anomaly Detection; Gas Metering; Differential Pressure; Flow Monitoring.

INTRODUCTION

Natural gas continues to play a pivotal role in the global energy mix: as a lower-carbon alternative to coal, as feedstock for industry, and as a complement for renewables [1]. Accurate measurement of natural gas flow is essential for pipeline operation, custody transfer, and energy accounting. Among the various flow measurement technologies, such as turbine flowmeters, ultrasonic flowmeters, Coriolis flowmeters, and differential pressure (DP) meters, DP meters, particularly orifice plate meters, remain the most widely used in gas transmission systems due to their simplicity, reliability, and well-established theoretical foundation. The governing principles of orifice metering are defined in internationally recognised standards such as ISO 5167 and AGA Report No 3 [2], which establish the relationship between differential pressure and volumetric flow rate, as well as requirements for installation, calibration, and operation. The underlying principle derives from Bernoulli's equation and continuity, relating volumetric flow rate to the square root of differential pressure across a calibrated restriction:

$$Q=C_d\,A\,Y\sqrt{\frac{2\triangle P}{\rho}(1-\beta^4)} \quad (1)$$

where (Q) is the volumetric flow rate, C_d is the discharge coefficient, (A) is the orifice area, ($\triangle P$) is the differential pressure, (ρ) is the fluid density, and (β) is the diameter ratio.

In field service, however, several factors, such as plate fouling, edge erosion, impulse-line blockages, transmitter drift, and upstream flow disturbances, progressively undermine the assumptions of constant geometry and stable flow profiles. These degradations introduce bias into measured flow, compromising both accuracy and safety.

Early contributions to flow measurement research focused on improving the accuracy and reliability of differential pressure meters. These include foundational work by [3] that advanced understanding of fluid dynamics in orifice systems, including the effects of Reynolds number, upstream disturbances, and pressure recovery. These studies provided critical insights into the limitations of orifice metering and the conditions under which measurement accuracy can be compromised. Despite their widespread adoption, orifice meters are inherently sensitive to a range of operational and mechanical factors. Measurement errors may arise from pressure transmitter drift, impulse line blockage, or mechanical degradation of the orifice plate due to wear, corrosion, or fouling. Authors [4] highlighted the impact of pressure measurement inaccuracies on flow estimation, emphasising the importance of reliable instrumentation in differential pressure systems. Similarly, [5] investigated sensor drift and demonstrated that gradual degradation in measurement devices can introduce systematic errors that persist if undetected.

Furthermore, process-related disturbances also affect metering performance. Variations in upstream flow conditions, such as compressor operations or valve adjustments, can introduce transient deviations in pressure and temperature measurements. Traditional diagnostic approaches, such as periodic inspection and calibration, address this issue, but they may not be sufficient to detect early-stage faults or transient anomalies in real time.

Conventional maintenance practices have typically followed either a corrective (failure-driven) or a preventive (calendar-based) approach. Corrective strategies often result in costly unplanned outages, while preventive schedules frequently lead to unnecessary interventions on otherwise healthy assets. Predictive maintenance (PdM) addresses these shortcomings by leveraging real-time and historical sensor data to anticipate degradation before failure occurs. Advances in Supervisory Control and Data Acquisition (SCADA) systems and Industrial Internet of Things (IoT) technologies now generate high-resolution data that can support sophisticated analytics.

The increasing availability of such data has led to the adoption of data-driven approaches for anomaly detection in industrial systems. One of the earliest and most influential methods is the Local Outlier Factor (LOF) algorithm introduced by [6], which identifies anomalies based on deviations in local data density. Another widely used approach is the Isolation Forest algorithm proposed by [7], which isolates anomalous observations through recursive data partitioning. Various industrial domains have successfully applied these techniques because they can detect both global and local anomalies in complex datasets.

Recent studies have further demonstrated the effectiveness of machine learning techniques in industrial process monitoring. Authors [8] applied deep learning methods to detect abnormal operating conditions in industrial systems, showing improved sensitivity to subtle deviations in time-series data. Similarly, [9] proposed an ensemble-based anomaly detection framework that enhances robustness by combining multiple models. Authors [10] extended these approaches to gas transmission systems, highlighting the potential of machine learning for improving fault detection in large-scale energy infrastructure. Alongside machine learning methods, statistical process monitoring techniques continue to play an important role in anomaly detection. The Exponentially Weighted Moving Average (EWMA) method, as discussed by [11], is particularly effective for identifying small but persistent shifts in process variables. Unlike traditional control charts, EWMA incorporates historical data through a smoothing parameter, enabling it to detect gradual trends such as sensor drift or progressive equipment degradation.

Despite these advances, a notable gap persists in applying hybrid anomaly detection methods to differential-pressure gas metering systems. Many existing studies focus on general industrial processes or rely on large proprietary datasets that are not readily accessible. Furthermore, traditional gas metering diagnostics are often based on manual inspection and periodic calibration, limiting their ability to support continuous monitoring and predictive maintenance.

This study develops a physics-informed unsupervised machine-learning framework tailored for orifice gas metering stations. The approach transforms routinely collected differential pressure ($\triangle P$), static pressure (P), and temperature (T) signals into actionable anomaly alerts without requiring labelled fault data, an important advantage in industrial environments where maintenance records are often incomplete. At the core of the framework lies the Composite Anomaly Index (CAI), an ensemble metric that integrates Isolation Forest, Local Outlier Factor, and Exponentially Weighted Moving Average algorithms. The physics-informed feature engineering ensures that detected deviations remain interpretable in engineering terms.

METHODS

The field of predictive maintenance in gas metering systems is inherently multidisciplinary, drawing on data science, reliability engineering, fluid mechanics, and process control. The general approach used in this study is based on the idea that conclusions drawn from data must remain both operationally and physically actionable. Thus, the design has a hierarchical flow:

The collection and integration of data from metering devices (temperature, differential pressure, and pressure), preprocessing and cleaning to handle missing values, aligning temporal resolution, and eliminating noise. In addition, physics- and thermodynamics-guided feature engineering was incorporated into unsupervised machine-learning methods to detect anomalies. Then, validation and sensitivity analysis were used to assess reliability and robustness.

Finally, the deployment architecture integrates the models into an operational predictive-maintenance loop. The proposed architecture conceptually couples each layer, allowing insights to propagate from raw data to maintenance decision-making within a closed digital loop [12].

In general, oil and gas plants produce a large amount of process data but few labelled failure events. This data regime favours unsupervised anomaly-detection techniques [13]. This study selected the Local Outlier Factor (LOF), Isolation Forest (IF), and Exponentially Weighted Moving Average (EWMA) models from the available approaches because of their demonstrated industrial performance, interpretability, and scalability. By combining them, a hybrid union model is created that mitigates each detector's shortcomings while enabling high sensitivity. Instead of using subjective inference to test hypotheses about normal and abnormal flow behaviour, the research employs a quantitative, data-centric methodology that involves expert evaluation of anomalies to ensure practical relevance while maintaining engineering realism [10].

The gas metering station under this study operates within a midstream natural gas pipeline facility in Nigeria. It uses a flange-tapped concentric orifice plate for flow measurement. The orifice meter remains the industry's most widely used primary flow element due to its simplicity, robustness, and compliance with international standards such as AGA Report No. 3 and ISO 5167-2:2019. The meter system includes: orifice plate assembly ($\beta \approx 0.65$, diameter ratio), upstream and downstream impulse lines, differential pressure transmitter (Rosemount 3051 series), static pressure transmitter (Yokogawa EJA110E), RTD temperature sensor (Pt100, Class A) and flow computer (AGA3/AGA8 compliant).

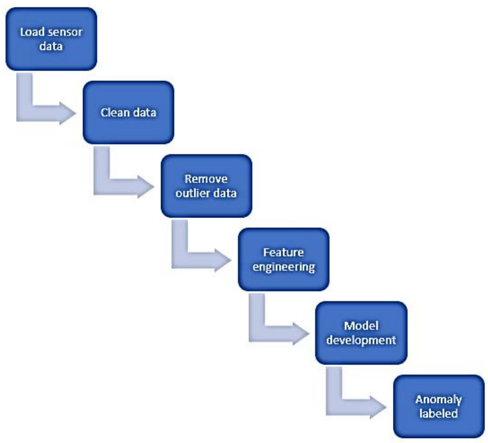

Figure 1 – Flowchart Of Methodology

Data Sources and Preprocessing. The quality, representativeness, and reliability of the input data are critical to the integrity of predictive maintenance research. The main data source for this study was a gas metering station that operated from January to September 2025 under typical production conditions. Critical flow-control variables, including Inlet Pressure (IP), Outlet Pressure (OP), Differential Pressure (ΔP), and Temperature (T), are continuously recorded by the station's supervisory control and data acquisition (SCADA) system. According to the authors [2, 14], these metrics serve as fundamental signals for both custody transfer and operational integrity monitoring.

Missing data is another prevalent issue in industrial time-series measurements, primarily caused by maintenance shutdowns, sensor recalibration, and telemetry outages. While ignoring them can skew model training, overzealous interpolation may obscure real abnormalities. Therefore, how they are handled is crucial. Using linear interpolation, short gaps (less than three days) were filled while maintaining local patterns. To mitigate the impact of temporary spikes, moderate gaps (3–7 days) were imputed using the rolling median of nearby data. To maintain transparency, extended gaps (>7 days) were set to NaN and excluded from model training.

Normalisation and Scaling. Normalisation was required to prevent any single variable from controlling the distance metrics used by LOF and Isolation Forest, due to large magnitude differences between the variables (temperature in °K vs pressure in kPa). The analysis examined two methods:

Z-score normalisation. Suitable for Gaussian-like variables (P, T).

$$x' = \frac{x-\mu}{\sigma} \tag{2}$$

Min–max scaling:

$$x' = \frac{x-x_{min}}{x_{max}-x_{min}} \tag{3}$$

ensuring that all variables fall within [0,1] to aid model convergence.

The final model adopted Z-score normalisation, as it preserves interpretability of deviations (e.g., a 3σ excursion clearly indicates rarity). Predictive maintenance depends on how well the input data represent the underlying physics of the system. Feature engineering bridges raw sensor data with machine-learning algorithms.

Core Process Variables. In an orifice flow measurement, three parameters provide the foundation for condition monitoring:

- Differential Pressure (ΔP): Represents the flow-dependent pressure drop across the orifice;

- Static Pressure (P): Used to correct for gas density and compressibility;

- Temperature (T): Used to adjust density and expansion factors, compensating for thermal effects.

Implementing Unsupervised Anomaly Detection

Feature Engineering and Derived Parameters. This study computed the following derived features to capture the physical and temporal dynamics of the system:

Normalised Differential Pressure (ΔP_norm). To account for variations in total pressure, ΔP was normalised using the mean inlet pressure over a rolling time window.

$$\Delta P_{norm} = \frac{\Delta P}{P_{in}} \tag{4}$$

where {P_{in}) represents the 7-day rolling mean of the inlet pressure. This normalisation prevents the anomaly-detection model from misinterpreting sudden fluctuations in ΔP caused by natural pressure variations as anomalies.

Pressure Ratio (PR). The ratio of outlet to inlet pressure:

$$PR = \frac{P_{out}}{P_{in}} \tag{5}$$

A significant deviation from its typical range indicates potential flow restriction or sensor drift.

Temperature-Normalised Differential Pressure (ΔP/T). Temperature affects gas density; therefore, ΔP was adjusted by temperature to obtain a temperature-compensated indicator:

$$\Delta P_t = \frac{\Delta P}{T+273.15} \tag{6}$$

Rolling Mean (7-day). Each primary variable was smoothed using a 7-day moving average to highlight medium-term trends:

$$X_t = \frac{1}{7}\sum X_{t-1} \quad (7)$$

where (X_t) represents any of the core parameters (IP, OP, ΔP, or T).

Daily Change (First Difference). The first-order difference of each variable highlights the rate of change from one day to the next:

$$\Delta X_t = X_t - X_{t-1} \quad (8)$$

Composite Flow Indicator (CFI). A synthetic variable combining normalised ΔP and PR to summarise flow stability:

$$CFI = \frac{\Delta P_{norm}}{PR} \quad (9)$$

Consistent CFI values indicate stable flow conditions; sharp deviations can signal disturbances or partial blockages. This study subsequently standardised all variables by mean-centring and scaling them by their standard deviation to ensure numerical comparability before model input.

Statistical justification for feature selection. The chosen set of engineered features was not arbitrary; it was developed based on both the mathematical properties of the data and the physics of fluid flow through an orifice. In orifice flow, the relationship between differential pressure and flow rate follows the equation:

$$Q = C.A\sqrt{\frac{2\Delta P}{\rho}} \quad (10)$$

where (Q) is the volumetric flow rate, (C) is the discharge coefficient, (A) is the orifice area, and (ρ) is the gas density.

The proposed framework creates engineered features that directly reflect these physical correlations, enabling machine learning models to detect deviations from expected process behaviour. Furthermore, the feature-engineering process improves the signal-to-noise ratio and reduces noise from a data science perspective. The preprocessing pipeline transforms raw sensor data, via smoothing and normalisation, into a stable representation that captures the underlying process rather than transient oscillations.

Table 1 – Comparative Analysis of Methods for Flow Control PdM

Algorithm	Detection Principle	Strengths	Limitations	Applicability to Gas Metering
Z-score/ Control Chart	Statistical deviation from the rolling mean	Simple, interpretable	Sensitive to noise; univariate only	Good for drift monitoring
Isolation Forest	Random partitioning (tree ensemble)	Handles multivariate data; efficient	Requires tuning contamination	Ideal for general anomalies
LOF	Local density comparison	Detects local outliers; handles multi-mode data	Computationally heavy on large data	Effective for varying flow regimes

This comparative table serves as a reference for selecting suitable models under different operational and data conditions.

Composite Ensemble Index. Since each algorithm captures different anomaly characteristics, their outputs were combined into a Composite Anomaly Index (CAI):

$$CAI = 0.3\, s'\{IF\} + 0.3\, s'LOF\} + 0.4\, s'\{EWMA\} \quad (11)$$

where (s') denotes normalised scores scaled to [0, 1].

This weighting prioritises global isolation while preserving local and gradual detection sensitivity. This study empirically selected the threshold (CAI > 0.5) (50th percentile) to balance sensitivity (true positives) and specificity (false positives).

RESULTS AND DISCUSSION

Model Description and Training Strategy. This study used unsupervised learning to detect anomalies. Unsupervised models discover the underlying structure of the data and spot cases that deviate from it, whereas supervised approaches require labelled examples of normal and abnormal states. This method works well for gas metering systems, where operational anomalies are uncommon but can be expensive, and historical fault data is limited [15].

Three primary models, Isolation Forest (IF), Local Outlier Factor (LOF), and Exponentially Weighted Moving Average (EWMA) combined into a single Composite Anomaly Index (CAI), comprise the unsupervised framework used in this study. The proposed framework balanced sensitivity (identifying real anomalies) and specificity (avoiding false alarms) through its ensemble design.

Isolation Forest (IF). By recursively dividing the data space, the tree-based Isolation Forest isolates anomalies [7]. Because anomalous points deviate from the bulk of the data, they are easier to separate according to the underlying principle. In this study, the IF model was configured with 200 trees, a contamination parameter of 0.1 (approximately 10% anomalies), and a random seed for reproducibility. The model produces an anomaly score for each observation, where higher scores indicate a greater likelihood of being an anomaly. The scores were normalised to a 0–1 scale for ensemble combination.

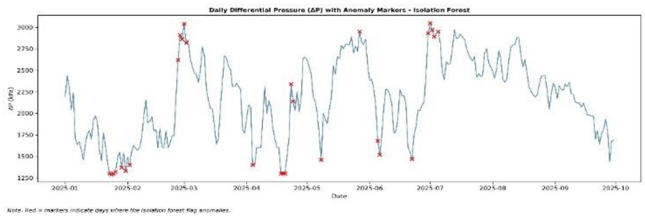

Figure 2 – Isolation Forest

Local Outlier Factor (LOF). The LOF method uses local density deviation to identify abnormalities. If a point's density is noticeably lower than that of its neighbours, it is deemed abnormal. This approach works well for identifying minute, context-specific variations that global approaches might miss [6].

LOF was applied with a neighbourhood size (k) of 10; novelty detection enabled evaluation on new, unseen data.

The resulting scores were inverted and normalised so that higher values correspond to stronger anomalies.

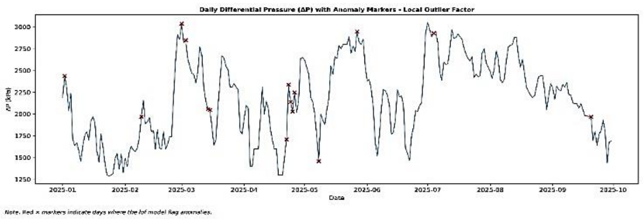

Figure 3 – Local Outlier Factor

Exponentially Weighted Moving Average (EWMA). The EWMA statistical process control method was used [11]. The normalised differential pressure (ΔP norm) weighted moving average is tracked over time, and deviations that exceed a dynamic threshold are flagged.

The proposed framework retained historical data and gave greater weight to newer observations by setting the smoothing factor (λ) to 0.2.

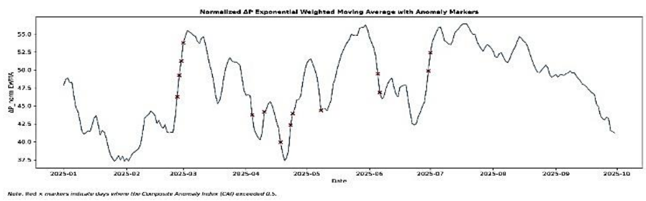

Figure 4 – Exponentially Weighted Moving Average (EMWA)

Composite Anomaly Index (CAI). To combine the strengths of the three models, their normalised outputs were aggregated into a weighted index:

$$CAI=0.3^{*}\ S_{IF}+0.3^{*}\ S_{LOF}+0.4^{*}\ S_{EWMA} \quad (12)$$

where each anomaly score is represented by (S_{IF}), (S_{LOF}), and (S_{EWMA}). This study empirically selected the weights based on the model's performance in the initial assessment.

Given its greater resilience to high-dimensional features, Isolation Forest was assigned the greatest weight. This study selected a cutoff point of 0.5 to categorise abnormalities. The proposed framework classified observations as possible anomalies when their CAI values exceeded this threshold. The analysis examined the score distribution and optimised the trade-off between missed detections and false positives to determine the threshold.

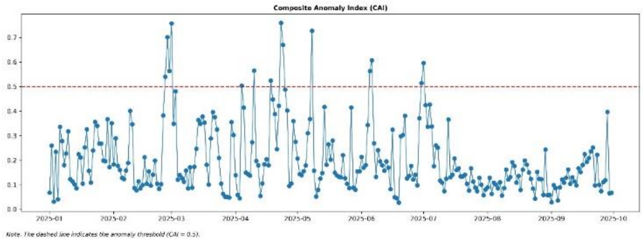

Figure 5 – Composite Anomaly Index (CAI)

Significance of the Anomaly Threshold (CAI = 0.5): The threshold line represents the decision boundary derived during model calibration. Crossing this threshold implies that the combined deviation across monitored parameters is statistically significant relative to baseline behaviour.

Key points: a) Values below 0.5 → Normal or acceptable variation; b) Values above 0.5 → Potential abnormal behaviour requiring investigation.

The fact that only a limited number of points exceed the threshold supports the model's robustness and indicates low false-alarm rates.

Relevance to Predictive Maintenance: This figure demonstrates that the proposed framework:

a) Detects early warning signs of abnormal behaviour,

b) Differentiates between transient disturbances and sustained degradation,

c) Provides actionable insight without requiring direct inspection data.

Rather than identifying exact failure modes, the CAI acts as a condition indicator, flagging periods when assumptions such as constant orifice geometry or sensor stability may no longer hold.

Interpretation of Key Anomalies

Early March 2025 – Transient hydraulic disturbance. The first significant anomaly occurs in early March 2025. The CAI briefly rises above its threshold, then quickly falls back to baseline. Signal analysis shows a short variation in differential pressure, while temperature and static pressure remain largely normal. In a traditional orifice metering system, this suggests a temporary flow disruption rather than a permanent fault.

Probable cause: sudden changes in flow velocity due to compressor load shifts, upstream valve actuation, or brief supply fluctuations; this distorts the velocity profile approaching the orifice plate, violating the fully developed flow assumption in standard orifice equations. No sustained temperature change confirms a hydraulic, not thermodynamic, origin. Once upstream conditions stabilise, the DP–pressure–temperature relationship realigns. While transient, frequent repetition could, over time, increase mechanical stress on the orifice plate edge and the impulse lines.

Late March 2025 – Early-stage impulse line restriction. The analysis identified a cluster of moderate CAI elevations in late March 2025, characterised by relatively stable inlet pressure and temperature while the differential pressure signal exhibited reduced responsiveness to normal process variability. This pattern strongly hints at a partial impulse line blockage. In orifice metering installations, the differential pressure transmitter relies on two impulse lines connected upstream and downstream of the orifice plate.

The accumulation of condensate, hydrates, corrosion products, or fine particulates can restrict one of these lines, causing the transmitter to sense an artificial or damped pressure differential. Hence, the measured ΔP becomes partially decoupled from the actual process conditions. The lack of correlated changes in static pressure and temperature supports the conclusion that the anomaly originates from the measurement system rather than from the flow itself. If left unresolved, this condition would lead to a systematic bias in the calculated flow rate, persisting until maintenance intervention or recalibration is performed. The CAI's sensitivity to this subtle inconsistency highlights its suitability for early detection of instrumentation degradation.

Mid-April 2025 – Flow instability and entrained-phase effects: The anomaly observed around mid-April 2025 is one of the most pronounced CAI peaks in the dataset, accompanied by increased variability across differential pressure and, to a lesser extent, static pressure. Temperature exhibits minor fluctuations, though not at the same magnitude as the pressure signals. This behaviour is consistent with flow instability, potentially caused by entrained liquids, rapid changes in gas composition, or upstream compressor dynamics. Entrained liquids or density fluctuations alter the effective flowing density through the orifice, directly affecting the differential pressure signal and increasing turbulence intensity at the plate edge.

Such conditions temporarily violate the single-phase flow assumption inherent in standard orifice metering theory. The resulting mismatch between DP, pressure, and temperature inputs amplifies the composite anomaly index. From a mechanical perspective, repeated exposure to such conditions accelerates erosive wear at the orifice plate edge, even if no immediate failure is observed. Hence, this anomaly represents not only a measurement deviation but also a potential precursor to long-term mechanical degradation, reinforcing the value of CAI-based monitoring for predictive maintenance.

Early May 2025 – Progressive mechanical or metering drift. Around early May 2025, the CAI displays a series of elevated values over an extended period rather than a single isolated spike. Unlike earlier transient events, this anomaly exhibits persistence, indicating a gradual deviation from baseline behaviour.

This pattern is characteristic of orifice plate wear or transmitter drift. Mechanical erosion of the plate edge leads to bore enlargement or rounding, altering the effective discharge coefficient and beta ratio. These changes introduce a systematic bias into the DP–flow relationship without necessarily producing abrupt signal excursions. The static pressure and temperature signals remain relatively stable during this period, suggesting that the observed anomaly is not driven by process fluctuations but by changes in the metering system itself. This type of deviation is particularly critical in fiscal metering applications, as small systematic errors accumulate into significant volumetric and financial discrepancies. The sustained CAI elevation demonstrates the framework's ability to detect incipient degradation, even when raw sensor data appears stable to operators.

Mid-July 2025 – Post-intervention or operational adjustment anomaly. An isolated CAI spike occurs in mid-July 2025 following a period of reduced anomaly activity. The event is short-lived, with all parameters returning to baseline behaviour quickly. This pattern is commonly associated with post-maintenance or operational adjustments, such as transmitter recalibration, impulse line purging, or temporary flow reconfiguration. During such interventions, short-term inconsistencies between pressure and temperature measurements may arise before full stabilisation. The brief nature of the anomaly and the absence of sustained deviation confirm that this event does not represent a fault condition. Instead, it demonstrates the model's sensitivity to short-term disturbances while maintaining robustness against false alarms.

Results of Ensemble Anomaly Detection. The ensemble anomaly-detection methodology produced a comprehensive description of the system's behaviour over the nine-month research period. The investigation identified different phases of irregular operation using the Composite Anomaly Index (CAI). These anomalies are examples of situations in which the overall relationships between the process variables were substantially different.

The ensemble framework combined the results from the Exponentially Weighted Moving Average (EWMA), Local Outlier Factor (LOF), and Isolation Forest (IF) models.

Every algorithm made a distinct contribution to sensitivity to deviations: EWMA detected slow changes in pressure differentials, LOF captured local density anomalies, and IF successfully identified global outliers. Together, these models offered a strong depiction of anomalies that were both sudden and progressive.

Over the entire dataset, approximately 4.8% of the observations were classified as anomalous by the ensemble system. This value is consistent with the pre-selected contamination threshold (≈2–5%) and aligns with realistic expectations in a stable process system, where anomalies are rare events.

CONCLUSIONS

This study has successfully developed and validated a predictive maintenance framework for orifice gas metering systems that relies exclusively on unsupervised machine learning. Using nine months of real field data, the research demonstrated that careful preprocessing and physics-informed feature engineering enable robust anomaly detection without the need for labelled fault histories. The Composite Anomaly Index, formed by ensemble integration of Isolation Forest, Local Outlier Factor, and Exponentially Weighted Moving Average algorithms, provided a sensitive yet specific indicator capable of distinguishing transient disturbances from progressive degradation.

Detected anomalies aligned closely with physically meaningful events such as impulse-line restriction, transmitter drift, plate wear, and operational transients, achieving high interpretability and low false-alarm rates. The framework offers clear practical advantages, including earlier fault identification, reduced maintenance costs, improved measurement accuracy, and greater asset reliability. Theoretically, the work advanced reliability engineering by reframing equipment health assessment around continuous deviation from learned normal behaviour rather than discrete failure events.

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