A Robust Hybrid IoT Framework for Post-Disaster Water Leakage Detection under Uncertain Sensing Conditions

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***Abstract*— Water distribution networks are highly vulnerable during natural disasters, where pipe damage and hydraulic instability can lead to hidden leakages, service disruption, and increased flood risk. Conventional IoT-based leakage detection systems perform well under stable conditions but deteriorate when exposed to disaster-induced noise, missing data, and irregular pressure–flow behaviour. This paper presents a modular IoT-driven framework specifically designed for post-disaster environments. The framework augments benchmark leakage datasets with synthetic anomalies, such as pressure spikes, flow surges, sensor noise, and data outages, to emulate realistic flood- and earthquake-induced instability. A hybrid detection model combining rule-based logic with an unsupervised anomaly-detection module is then applied to extract and evaluate key hydraulic features. Experimental results from simulated disaster scenarios demonstrate that the hybrid model achieves higher detection rates, reduced false-alarm occurrences, and improved temporal stability compared to threshold-only detection. These findings indicate the effectiveness of the proposed approach for rapid leakage identification and early flood-risk mitigation in disaster-affected water networks.**

Keywords—IoT, Leak detection, Anomaly detection, Post-Disaster monitoring, Flood-risk mitigation.

I. INTRODUCTION

Water distribution systems are critical to community resilience but are highly vulnerable during natural disasters such as floods and earthquakes. Pipeline deformation, pressure shocks, and structural failures can lead to hidden leakages, service interruptions, and secondary flooding, amplifying both operational and societal impacts [1]. Rapid and reliable leakage detection is therefore essential for effective post-disaster recovery.

IoT-enabled monitoring systems have shown strong potential for real-time leak detection by leveraging pressure, flow, and vibration sensors to identify abnormal hydraulic behaviour [2]. Existing studies demonstrate high accuracy under stable operating conditions, where sensor readings follow predictable baseline patterns. However, most IoT-based leakage detection systems implicitly assume continuous sensing, low noise, and consistent pressure–flow relationships [3]. These assumptions break down in post-disaster environments, where networks experience noise, missing data, sensor outages, communication instability, and irregular hydraulic dynamics. Benchmark datasets such as LeakDB provide structured leakage scenarios but do not capture the instability and unpredictable fluctuations typically induced by floods or earthquakes [4]. This lack of realistic post-disaster data limits the development and evaluation of robust leakage-detection frameworks.

To address these limitations, this paper proposes an IoT-based post-disaster leak-detection framework designed to operate reliably under unstable sensing conditions. The framework introduces a disaster-oriented simulation module that injects hydraulic disturbances, such as pressure surges, flow irregularities, noise, and sensor outages, into existing IoT leakage datasets. A hybrid detection architecture combines rule-based thresholds, which capture clear hydraulic deviations, with an unsupervised anomaly-detection module capable of identifying subtle or irregular patterns that emerge when network behaviour becomes unpredictable [5]. This hybrid approach enhances robustness, reduces false alarms, and improves detection stability in the presence of disaster-induced irregularities. The key contributions of this paper are as follows:

- A disaster-oriented data simulation module that injects realistic anomalies, pressure spikes, pressure drops, flow surges, sensor noise, and missing data, into existing IoT leakage datasets.
- A hybrid leak-detection framework that integrates threshold-based rules with an unsupervised anomaly-detection module to enhance robustness under noisy, unstable, or disrupted sensing conditions.
- A comparative performance evaluation under simulated flood and earthquake scenarios, demonstrating improved detection rate, reduced false alarms, and resilience to partial sensor outages.
- A proof-of-concept demonstration showing the feasibility of IoT-based analytics for rapid leak detection and early flood-risk mitigation in post-disaster water networks.

The remainder of this paper is organized as follows: Section II provides the related work. Sections III and IV explains the system design and the implementation of the IoT-based post-disaster leak detection framework respectively. Section V outlines the results and relevant discussion. Finally, the conclusion of the paper is presented in section VI.

II. RELATED WORK

IoT-enabled water leakage detection has been widely explored in recent years, with numerous studies demonstrating the effectiveness of sensor-driven monitoring for identifying abnormal hydraulic behaviour. Prior work has shown that flow, pressure, and vibration sensors can detect leakage patterns and that integrating IoT sensing with AI-based models can improve leak localisation accuracy and outperform traditional monitoring techniques [2], [5]. Low-cost systems such as iWaLDeL further highlight the feasibility of scalable IoT deployments across diverse regions [3]. However, these

solutions are typically developed and evaluated under stable operating conditions, where sensor readings follow predictable baselines and communication remains uninterrupted.

Beyond leakage detection, several studies have examined the role of IoT systems in broader disaster-management contexts. Research has shown that distributed sensor networks can improve situational awareness, enable real-time environmental monitoring, and support post-disaster coordination efforts by providing continuous updates on critical infrastructure conditions [6], [7]. These works demonstrate the value of IoT in improving disaster resilience, but they do not focus on water distribution networks, nor do they address the specific hydraulic instability that arises following floods and earthquakes. In disaster settings, sensors frequently experience noise, intermittent connectivity, and abrupt pressure–flow fluctuations, factors not accounted for in the existing IoT leakage detection literature.

Recent developments in intelligent water networks have introduced digital-twin-based simulation and resilience analysis frameworks [8]. Digital twins allow virtual replicas of water systems to be used for prediction, planning, and stress-testing under different scenarios. While these models provide sophisticated infrastructure-level analysis, they rely on structured and stable sensor data and therefore do not mimic the nonlinear or irregular hydraulic responses typical of post-disaster environments. Such approaches remain largely theoretical when applied to rapidly changing network conditions, as they do not incorporate the sensor interruptions, noise spikes, or flow instabilities common during real disaster events.

Public datasets such as LeakDB have supported progress in leakage detection by providing controlled leakage scenarios for benchmarking algorithms [4]. However, these datasets lack representations of disaster-related disturbances, such as pressure surges, flow anomalies, missing readings, or sensor outages. This limitation restricts researchers to evaluating models under idealised conditions that do not reflect the unpredictable behaviour of damaged water systems. As a result, existing datasets do not allow researchers to explore how detection methods perform when exposed to the types of instability typical of flood or earthquake events.

Overall, prior work has advanced IoT-based leakage detection, disaster monitoring, and intelligent water network modelling, but these research areas have remained largely disconnected. Studies on leakage detection rarely consider disaster-induced instability, while disaster-monitoring research does not address leakage identification within water networks. Likewise, existing datasets do not capture the conditions necessary to evaluate detection performance in post-disaster environments. Furthermore, most current detection frameworks rely either on strict rule-based thresholds, which are sensitive to noise, or machine-learning approaches that depend on stable training distributions. These limitations underscore the need for adaptive, lightweight, and disaster-oriented leak detection frameworks capable of maintaining accuracy and reliability under noisy, irregular, and partially missing IoT data, conditions that are unavoidable in real post-disaster scenarios. Recent studies have also explored machine learning approaches such as autoencoders, Local Outlier Factor (LOF), and One-Class SVM for anomaly detection in IoT-based monitoring systems. While these methods demonstrate strong performance under stable conditions, their effectiveness often degrades when data distributions shift significantly, as occurs in post-disaster environments. This limitation motivates the use of hybrid detection approaches that combine interpretable rules with adaptive anomaly models.

III. System Design of the IoT-Based Post-Disaster Leak Detection Framework

A. Data Modelling and Post-Disaster Simulation

The framework integrates multiple IoT-based leakage datasets, including LeakDB and the Water Leak Dataset, to serve as the baseline input for hydraulic analysis. These datasets contain pressure, flow, and auxiliary sensor readings collected under controlled leakage conditions. However, as they reflect stable operating environments, they do not represent the disruptions typical of post-disaster systems. To address this limitation, the proposed framework generates synthetic anomalies that emulate realistic disaster-induced behaviour. The aim is to create a dataset capable of representing the nonlinearity, instability, and operational irregularities commonly observed after floods or earthquakes.

The system injects five categories of synthetic disturbances to replicate disaster-driven effects: (1) pressure spikes originating from pipe strain, obstruction, or sudden hydraulic shock; (2) pressure drops characteristic of bursts, ruptures, and structural failures; (3) flow anomalies resulting from unexpected surges caused by pipe cracks or sudden water escape; (4) missing intervals, representing sensor outages, communication failures, or power interruptions; and (5) sensor noise, introduced to emulate electrical interference or unstable wireless transmission. These anomaly types were selected based on typical hydraulic failure modes documented in IoT sensing environments and are summarised in Table I, which specifies the disturbance thresholds, deviation ranges, and corresponding sensor modalities.

TABLE I. SYNTHETIC ANOMALY SIMULATION RULES

Synthetic Condition	**Description**	**IoT Monitors**
Pressure Spike	Sudden surge from pipe strain or blockage	+30–50% deviation above baseline
Pressure Drop	Abrupt loss indicating rupture or burst	15–30% decrease from baseline (randomized)
Flow Anomaly	Sharp increase in flow suggesting leakage	10–25% increase from baseline (randomized)
Missing Intervals	Simulated data loss or sensor outage	Random removal of 2–5% of timestamps
Sensor Noise	Unstable transmission or electrical noise	Gaussian noise ($\mu = 0$, $\sigma = 0.05$)

To prevent bias between anomaly generation and detection, the disturbance parameters are randomized within defined ranges and intentionally differ from the fixed thresholds used in the rule-based detector. This design ensures that injected anomalies do not exactly match the detection conditions, enabling a more realistic and unbiased evaluation of detection performance under post-disaster uncertainty.

The perturbation rules preserve the temporal continuity of the original datasets, ensuring that only the hydraulic behaviour, not the sampling structure, is altered. This reflects post-disaster conditions where temporal patterns remain intact, but signals become irregular and noisy, enabling evaluation of detection stability under disrupted sensing.

After anomaly injection, the dataset contains both normal and disaster-affected segments. From these time series, the system computes key hydraulic features, including pressure deviation from baseline, flow rate variation, temperature fluctuation, vibration magnitude (where available), and anomaly persistence, defined as the number of consecutive windows exceeding expected thresholds. These features capture transient and sustained disturbances while preserving inter-sensor correlations.

This simulation-enhanced dataset forms the basis for the detection engine. By incorporating instability, noise, and missing readings, it allows the hybrid model to be evaluated under conditions that approximate post-disaster sensing environments. Although anomalies are synthetically generated, the randomized perturbation design provides a practical and controlled evaluation basis for evaluating detection robustness in the absence of real-world post-disaster datasets.

B. Hybrid Detection Architecture

The core of the proposed framework is a hybrid detection architecture that integrates a rule-based detector with an unsupervised anomaly-detection module. This combined design addresses the limitations of using either approach independently, particularly under the unstable sensing conditions typical of post-disaster environments. Rule-based detectors are efficient and interpretable, capturing characteristic hydraulic signatures such as sustained pressure decreases accompanied by elevated flow levels. However, they are highly sensitive to noise and may generate false alarms when signals fluctuate irregularly. Conversely, anomaly-detection methods can identify subtle or nonlinear deviations, but their performance degrades when baseline patterns shift abruptly, as occurs when pipes rupture or hydraulic behaviour becomes unpredictable after a disaster.

In the proposed framework, the rule-based detector evaluates pressure and flow readings against calibrated thresholds, identifying potential leakage only when deviations persist across multiple consecutive intervals. This temporal persistence requirement reduces the risk of false alarms caused by short-lived spikes or sensor noise. The enhanced rule-based logic is summarised in Algorithm 1 and incorporates checks for multi-sensor agreement to ensure that detected deviations reflect genuine hydraulic abnormalities rather than isolated sensor artefacts.

ALGORITHM I. ENHANCED RULE-BASED LEAKAGE DETECTION

```
# Initialise tracking variables
consecutive_count = 0
leak_flag = False

for each time_interval in dataset:

    # Evaluate pressure and flow deviations against thresholds
    if pressure_drop > 0.20 * baseline
       and flow_increase > 0.15 * baseline:

        leak_flag = True
        consecutive_count = consecutive_count + 1

        # Log raw anomaly data for auditing and model diagnostics
        record_anomaly(time_interval, pressure_drop, flow_increase)

    else:
        # Reset counters if current data does not indicate leak-like behaviour
        leak_flag = False
        consecutive_count = 0

    # Confirm leak only after persistent abnormal behaviour
    if consecutive_count >= 3:
        alert = "Confirmed Leak"
        log_event(time_interval, alert)
        trigger_response(alert)
```

To complement the deterministic rule-based mechanism, the anomaly-detection module analyses a multivariate feature set derived from pressure, flow, temperature, vibration, and anomaly-persistence metrics. By modelling deviations within this feature space, the module can detect irregular patterns that do not conform to fixed threshold rules. This is particularly important during post-disaster operation, where the underlying data distribution may shift significantly due to structural pipe damage, fluctuating pressure zones, or intermittent telemetry. The module assigns an anomaly score to each time window based on the magnitude and frequency of deviations, enabling the system to identify both subtle anomalies and atypical behaviour caused by sensor degradation.

A fusion mechanism integrates the outputs of the rule-based and anomaly-detection components to improve overall detection reliability. Leakage is confirmed only when either sustained rule-based deviations or statistically significant anomalies are observed, reducing the likelihood of missed detections while preventing spurious alarms caused by noise. The fusion process is illustrated in Algorithm 2, which combines threshold logic, anomaly-score evaluation, and temporal consistency checks to achieve a balanced detection decision. This hybrid approach takes advantage of the interpretability and stability of rule-based methods while leveraging the adaptability and sensitivity of unsupervised detection models.

ALGORITHM 2. ENHANCED HYBRID DETECTION FUSION

```
# Hybrid confirmation requires both rule-based and statistical indicators

if leak_flag == True:

    # Assess anomaly score produced by the unsupervised detector
    if anomaly_score > threshold:

        confirm_alert("Hybrid Leak Detected")

        # Optional: maintain logs for post-event analysis
        update_detection_log(anomaly_score, "hybrid")

        # Optional: escalate severity level for disaster-response workflows
        escalate_severity("hybrid_detection_event")
```

Figure 1 summarises the end-to-end hybrid workflow, beginning with data ingestion and simulated disaster perturbations, followed by feature extraction, rule-based evaluation, anomaly scoring, and final fused alert generation. Together, these components form a modular

and resilient detection architecture capable of maintaining high performance even when sensor continuity is reduced, noise levels are elevated, or hydraulic behaviour becomes irregular due to disaster-related disruptions.

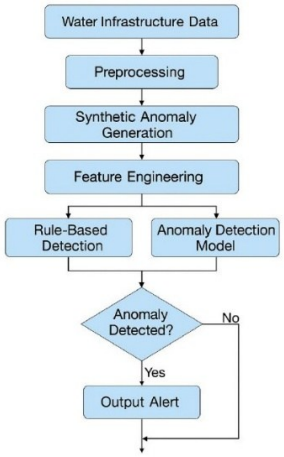

Fig. 1. System workflow for the proposed hybrid IoT-based post-disaster leak detection framework

IV. IMPLEMENTATION OF THE POST-DISASTER LEAK DETECTION FRAMEWORK

This section describes the implementation of the proposed IoT-based post-disaster leakage detection framework. The system follows the modular architecture presented in Section III, enabling the ingestion of sensor data, simulation of disaster-induced anomalies, extraction of diagnostic features, hybrid detection, and generation of structured leakage alerts.

A. System Integration and Processing Layers

The Implementation is organised into five sequential processing layers that correspond to the conceptual design described previously.

1) Input and Integration Layer

Sensor readings from LeakDB and the Water Leak Dataset serve as the initial input. These datasets are enhanced with synthetic anomalies to emulate post-disaster hydraulic disruptions. The anomaly types include missing intervals, Gaussian sensor noise, pressure spikes, pressure drops, and flow anomalies, each annotated with metadata for evaluation.

2) Preprocessing Layer

This stage performs data cleaning, removal of corrupted or duplicated readings, Min–Max normalisation of pressure and flow values, and segmentation into fixed 60-second windows. Preprocessing standardises the sensor data and produces temporally consistent inputs for subsequent feature extraction.

3) Feature Extraction Layer

A set of hydraulic and contextual features is computed, including pressure deviation from baseline, flow-rate variation, temperature changes, vibration magnitude, and anomaly-persistence scores. These features provide a compact, informative representation of operating conditions under both normal and disaster-affected scenarios.

4) Hybrid Detection Layer

This layer implements the hybrid leak-detection logic consisting of (i) a rule-based detector and (ii) an anomaly-detection module. The rule-based detector identifies clear pressure–flow deviations that match the thresholds defined during calibration. The anomaly detector evaluates the multivariate feature set to assign an anomaly score. Fusion logic confirms an anomaly when either the rule-based conditions persist across multiple intervals or the anomaly score exceeds its threshold. This combination maintains detection reliability despite noise, irregular fluctuations, or missing readings.

The anomaly detection component is implemented using an Isolation Forest model trained on normal data to learn baseline behaviour. The model uses 100 estimators, a contamination factor of 0.05, and a maximum sample size of 256. Anomaly scores are computed for each feature window, and thresholds are selected empirically to balance detection sensitivity and false alarms under varying post-disaster conditions.

5) Output and Alerting Layer

When a leak is detected, a structured alert is generated containing the timestamp of detection, anomaly type, confidence estimate, detection method (RBD, AD, or Hybrid), and associated metadata. These alerts support further analysis and can be integrated into visual dashboards or post-disaster decision-support systems.

The modular implementation enables calibration of thresholds, adjustment of anomaly-detection parameters, and inclusion of additional features or anomaly types without altering the overall pipeline. The lightweight structure maintains consistent performance even under sensor instability or data loss, ensuring that detection capability is preserved under simulated post-disaster conditions.

B. Hybrid Leak Detection Loop

At runtime, the hybrid detection loop sequentially executes the preprocessing, feature extraction, rule-based checks, anomaly scoring, and fusion stages described in Section III-B. For each incoming window of sensor data, the system evaluates both detectors and confirms a leak when either persistent rule-based deviations are detected or the anomaly score exceeds the defined threshold. Algorithm 3 reproduces the implementation used in this study, consistent with the hybrid architecture illustrated in Figure 1.

ALGORITHM 3. HYBRID LEAK DETECTION LOOP

```
for window in stream(data, window_size):

    # Extract hydraulic features for the current window
    feats = extract_features(window)

    # Rule-based condition
    rule_flag = (
        (feats["pressure_drop"]  > 0.20 * feats["p_baseline"]) and
        (feats["flow_increase"]  > 0.15 * feats["f_baseline"])
    )
    persist = update_persistence_counter(rule_flag)

    # Unsupervised anomaly detection
    ad_score = iso_forest.score_samples(feats.reshape(1, -1))
    is_anom  = (ad_score < ad_threshold)

    # Hybrid fusion logic
    confirmed = (persist >= 3) or (rule_flag and is_anom)

    # Alert generation
    if confirmed:
        emit_alert(
            node          = feats["node"],
            time          = feats["t_end"],
            pressure_drop = feats["pressure_drop_pct"],
            flow_increase = feats["flow_increase_pct"],
            method        = "Hybrid" if is_anom else "Rule-Based",
            confidence    = compute_confidence(rule_flag, is_anom, persist),
            response_time = compute_rt(feats)
        )
```

This loop operationalises the hybrid detection model defined in Algorithms 1 and 2, applying both the rule-based

and anomaly-detection components to each feature window. The logic ensures robustness under the simulated post-disaster conditions described in Section III-A, maintaining detection capability despite noise, irregular fluctuations, or missing sensor intervals.

V. RESULTS AND DISCUSSION

The proposed hybrid framework was evaluated under simulated post-disaster conditions to assess its performance in detecting leakage events in unstable water distribution networks. Two disaster environments, flood and earthquake simulations, were generated using the synthetic anomalies described in Section III-A.

A. Detection Performance under Simulated Disaster Conditions

To evaluate the detection behaviour of the rule-based detector (RBD) and the hybrid detector (RBD + AD), four performance metrics were used: Detection Rate (DR), False-Alarm Rate (FAR), Response Time (RT), and the F1-score. DR measures the proportion of true leak events correctly identified; FAR quantifies normal events incorrectly flagged as leaks; RT measures the time between anomaly onset and detection; and the F1-score captures the balance between precision and recall. These metrics are used throughout this section to compare performance under simulated flood and earthquake scenarios. Figure 2 presents the overall detection accuracy comparison for both detectors across the two simulated disaster environments. As shown, incorporating anomaly detection improves accuracy consistently across scenarios.

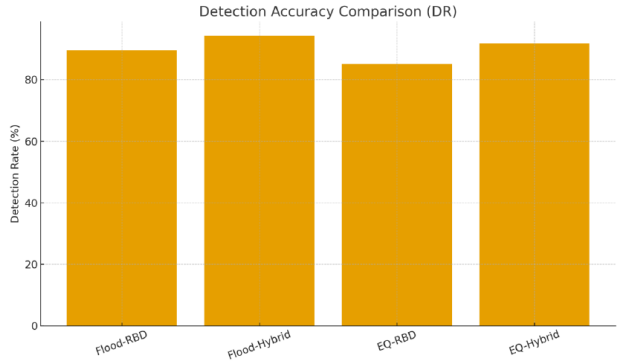

Fig. 2. Detection accuracy comparison for rule-based and hybrid models under flood and earthquake simulations

Representative alert logs captured during testing demonstrate how the hybrid model identifies both clear and subtle deviations:

```
[ALERT 01] Leak Detected at Node 3
Pressure Drop: 24.7%
Flow Increase: 17.2%
Detected via: Rule-Based Threshold
Response Time: 2.3 s
Confidence: 0.89

[ALERT 02] Leak Confirmed (Hybrid Model)
Pressure Drop: 28.4%
Flow Increase: 16.9%
Anomaly Score: 0.94
Response Time: 3.1 s
Confidence: 0.93
```

Quantitative performance results are summarised in Table II, showing DR, FAR, RT, and F1-score under flood and earthquake conditions. As seen in Table II, the hybrid model improves DR by approximately 5–6% and halves FAR compared to the RBD alone, with only a modest increase in RT.

TABLE II. SIMULATED PERFORMANCE COMPARISON ACROSS DISASTER SCENARIOS

Scenario	Model Type	DR (%)	FAR (%)	Avg RT (s)	F1-score
Flood	RBD	89.6	10.4	2.5	0.88
Flood	One-Class SVM	91	8.5	3.2	0.89
Flood	RBD+AD	94.2	6.3	3.0	0.91
Earthquake	RBD	85.1	12.9	2.7	0.84
Earthquake	One-Class SVM	88.2	9.1	3.3	0.87
Earthquake	RBD+AD	91.8	3.1	3.1	0.89

To further assess performance, a One-Class SVM baseline was included as a representative learning-based anomaly detector. It learns a boundary around normal data to identify anomalies. While it improves detection compared to the rule-based approach, it remains less effective than the hybrid model in reducing false alarms and maintaining stability under noisy and irregular condition.

B. Analysis of Detection Dynamics

To characterise the decision behaviour of the detectors under disaster-induced instability, we analyse the confusion matrix and the temporal anomaly-evolution plots shown in Figures 3 and 4. These analyses provide insight into how the rule-based and hybrid models behave across varying levels of noise, instability, and missing sensor data. Figure 3 presents the confusion matrix for the hybrid detector during flood simulations. The distribution of predictions shows a clear reduction in both false positives and false negatives compared to the rule-based detector, indicating that the anomaly-detection component contributes to more stable decision boundaries even when the hydraulic signals fluctuate. The confusion matrix explicitly includes true positives, false positives, true negatives, and false negatives, providing a complete evaluation of classification performance.

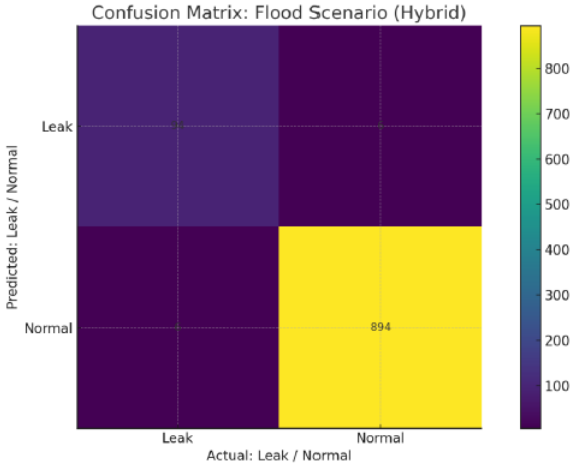

Fig. 3. Confusion matrix for the hybrid detector under flood-simulation conditions

Figure 4 illustrates a representative anomaly-timeline sequence for pressure and flow deviations. The hybrid detector identifies deviations earlier and maintains responsiveness across time, particularly in regions where noise is injected or where sensor outages occur. In contrast, the rule-based detector shows intermittent drops in sensitivity, highlighting its vulnerability to irregular fluctuations.

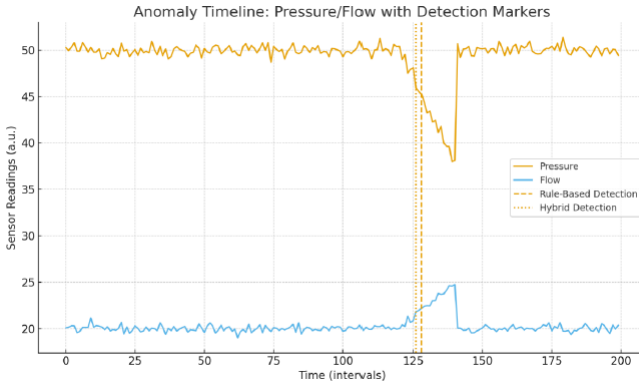

Fig. 4. Anomaly timeline showing pressure and flow deviations with detection outputs from RBD and hybrid models

These dynamic behaviours support three key observations:

1. Enhanced resilience to irregularity: The hybrid detector is less affected by transient fluctuations and partial data loss, enabling more reliable detection under unstable post-disaster conditions
2. Flood simulations exhibit smoother detection profiles: Flood-related anomalies generate more stable hydraulic patterns than earthquake-induced ones, resulting in more consistent hybrid detection outputs
3. Robustness to missing intervals: The hybrid model maintains effective performance even with up to 5% missing data, reflecting its suitability for disaster scenarios where sensing continuity cannot be guaranteed.

Overall, the detection-dynamic analysis in Figures 3 and 4 demonstrates that the hybrid detector offers superior temporal consistency, decision reliability, and resilience compared to the rule-based approach, confirming its suitability for real-world post-disaster leak identification. To ensure consistency, experiments were repeated across multiple simulated runs with varying anomaly injection patterns. Performance variation was minimal (approximately ±2%), indicating stable behaviour of the proposed framework. These results confirm that the proposed hybrid framework remains effective under mismatched and uncertain post-disaster sensing conditions.

VI. Conclusion

This study presented a modular IoT-based framework for detecting post-disaster water leakages under simulated flood and earthquake conditions. By integrating rule-based thresholds with an unsupervised anomaly-detection module, the system demonstrated reliable identification of both clear and subtle hydraulic deviations. The hybrid approach consistently outperformed the standalone rule-based detector, yielding higher detection rates, reduced false-alarm occurrences, and improved decision stability despite the presence of noise, missing data, and irregular sensor behaviour. These results highlight the potential of IoT-driven hybrid analytics to support rapid leakage identification and enhance post-disaster situational awareness within damaged water distribution networks. Although the framework provides a strong proof-of-concept, its evaluation relied on synthetic post-disaster anomalies due to the limited availability of real-world data. As such, real deployment in operational water systems remains an important next step. Future work will focus on testing the framework using on-site IoT deployments during controlled field experiments and exploring adaptive thresholding or learning-based optimisation methods to further improve real-time resilience and reduce dependency on manually defined parameter.

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