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Scalable AI-Assisted Metering Architecture for Continuous Leakage Monitoring and Fault Diagnosis in Urban Water Systems

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Abstract

This paper proposes a scalable AI framework. The framework combines high-frequency flow and pressure data from the smart meters with a distributed edge-computing layer, where lightweight machine learning models are applied for performing initial anomaly detection in real time. Detected events then trigger an adaptive neural network, which refines the detection and estimates the leak characteristics more accurately. A pilot implementation in a mid-sized Indian city shows the capability of the system to localize leaks with a spatial resolution of better than 50 m and detect small leaks (< 2 L/min) within 30 minutes of occurrence. We use a digital copy (twin) of the distribution network, built from the available pipe layouts, nodal elevations, and historical demand patterns, as the data source for training a supervised-learning algorithm to overcome the lack of labelled leak events. By conducting a series of field trials, we provide quantitative performance results in terms of the true/false positive rates, localization error, and energy overhead of edge processing. A cost-benefit analysis is conducted that evaluates deployment scenarios at different penetration rates of smart meters and shows payback periods below three years for networks with > 60%-meter coverage. Finally, we discuss practical considerations for large-scale deployment, including integration with existing water utility management systems, scalability challenges, data privacy and security concerns, maintenance of edge-computing devices, and potential regulatory and policy implications. The results demonstrate that the proposed framework is not only technically feasible but also economically viable, providing utilities with a robust tool for improving leak detection, reducing water losses, and enhancing operational efficiency.

1. Introduction

Urban water utilities around the world are grappling with a persistent and growing issue of non-revenue water (NRW), defined as that water produced but not billed to consumers as a consequence of physical leakages, illegal water consumption, or inaccurate measurements of metering systems. In many developing nations, NRW levels frequently exceed 40-50% of total water supplied; such losses represent not only a significant financial burden for municipalities, but also a threat to long-term sustainability. The impacts of high NRW are manifold: economic loss of revenue from lost water; energy inefficiencies associated with the unnecessary pumping and treatment of water; and serious public health issues from the intrusion of contaminated water in pressurized pipes. Conventional methods of detecting leakage, such as manual survey inspections or acoustic logger deployments, are limited in several ways, including being labour-intensive, slow to react, and unable to monitor leaks on a continuous or large-scale basis across complex urban distribution networks. In recent years, advances in technology for smart metering and Internet of Things (IoT) connectivity, and artificial intelligence (AI) technologies have created new opportunities for real-time, automated leakage monitoring at citywide scales.

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Smart meters can produce high-frequency flow and pressure measurements, and IoT-based communications networks can allow for distributed sensing and remote reporting. AI models, in turn, have the potential to learn patterns from these data streams and identify and localize leak events much better than rule-based methods. However, despite all these opportunities, there are still a number of challenges that impede large-scale adoption. First, the volume of data that must be processed by the high-frequency meters can overwhelm centralized computing systems and produce bottlenecks in analysis. Second, the limited number of labeled leak events in real-world datasets reduces the potential application of traditional supervised learning approaches that require large amounts of ground truth data to properly train the approach. Finally, the heterogeneity of urban water infrastructures, with wide variations in their age, material, topology, and operational practices, makes it difficult to develop one-size-fits-all solutions. To overcome these issues, in this paper, we propose a scalable architecture based on artificial intelligence-assisted metering to facilitate continuous leakage monitoring and quick fault diagnosis in large-scale urban water networks. The proposed framework leverages the strengths of edge-based anomaly detection, which enables real-time identification of unusual events such as leaks directly at the sensor level. By processing data locally at the edge, the system can respond immediately to detected incidents while significantly reducing the amount of raw data transmitted to the cloud, saving bandwidth and energy. Lightweight machine learning models deployed on edge devices continuously monitor flow and pressure patterns, detecting deviations from normal behaviour with minimal latency. Detected anomalies are then sent to the cloud, where neural ensemble learning performs more sophisticated analyses, taking into account advanced signal processing and the topology of the water network to confirm and classify the events. In addition, the framework incorporates a digital-twin model—a virtual replica of the water distribution system—that can simulate leak scenarios and generate synthetic labeled data, addressing the challenge of limited real-world training examples. Together, these innovations create a robust, hybrid system that enhances the efficiency, reliability, and sustainability of urban water distribution by combining fast local detection with intelligent, data-driven global analysis.

2. Related Work

Work on leakage detection in water distribution systems has evolved along three main lines -- hydraulic model-based, signal-processing (acoustic), and data-driven machine learning -- each with different strengths and weaknesses. Hydraulic model-based approaches use physics-based hydraulic simulators like EPANET to predict pressures and flows in network nodes and then calculate residuals between predicted and observed values to detect anomalies. Theoretically, these methods are robust but are very sensitive to calibration errors of the system. In reality, pipe roughness, boundary conditions, and consumer demand uncertainties greatly decrease reliability. Previous research found that even small calibration errors could result in significant false alarms and a low localization accuracy for applications at scale (Wu et al., 2022; Sanz et al., 2023). The second major class of techniques is acoustic and vibration-based. All these methods look for the high-frequency signatures of the leak using contact or noncontact sensors and generally utilize time-frequency analysis techniques such as wavelet transforms or spectral decomposition. They are especially good at detecting burst leaks in quiet conditions but necessitate a dense deployment of sensors and frequent maintenance, making them cost-prohibitive for monitoring over entire cities (Gao et al. 2022; Ghorbanian et al. 2023). Deep one-dimensional convolutional neural networks have been recently introduced in acoustic pipelines for better leak classification, but they still do not scale well in practice. With the proliferation of advanced metering infrastructure, data-driven, machine learning techniques have been given increasing attention. High-frequency meter data has been used with the

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random forest, autoencoders, graph neural networks, and convolutional model techniques for detection and localization (Soldevila et al., 2022; Gagliardi et al., 2023). These techniques are encouraging in that there is no need to fine-tune with comprehensive hydraulic calibration to capture the nonlinear dynamics. Nevertheless, they have two common challenges: (i) labelled leaks are uncommon and undocumented, making it challenging to supervise training on them, and (ii) there are scalability challenges as most systems are based on centralized training and inference, which is more demanding in terms of latency and bandwidth. The recent surveys hold that there is a need to have a balance in accuracy and scalability with the help of hybrid solutions. There have been two enabling trends to respond to these limitations. To begin with, digital twins (i.e., computer simulations of water networks built based on GIS information, hydraulic models, and consumption history) are increasingly utilized to synthesize leakage situations artificially and enrich training data (Zhang et al., 2023). Second, smart water systems are starting to pilot edge-cloud hybrid architectures, where the computationally lightweight anomaly detector is designed to execute on the edge, and the computationally heavyweight neural model is deployed on the cloud. This multi-layered solution is more responsive and scalable and maintains accuracy (Rahmani et al., 2023). Based on this literature, our research introduces three novelties: (i) a distributed edge-cloud architecture to monitor real-time anomalies, (ii) a neural ensemble architecture due to model transient signal analysis through the lens of graph-based models, coupled with the utilization of network topology, and (iii) the synthesis of leak events through the use of a digital twin to eliminate the lack of labelled training data. These contributions combined bring the existing state of the art in AI-enabled and scalable leakage monitoring.

3. System Architecture

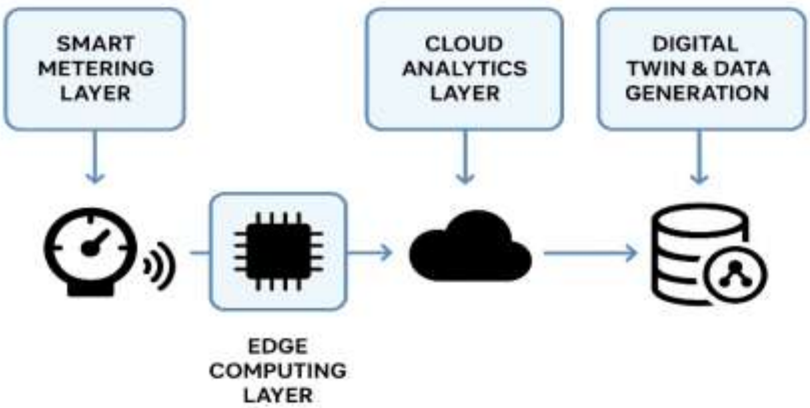

Figure 1: AI-Enabled leak detection framework architecture

3.1 Smart Metering Layer

The smart metering layer is the basis of the proposed system. Smart meters are installed at households and district metering areas (DMAs) to receive high-frequency flow (1Hz) and pressure signals. The selection of the communication technology (e.g., LoRaWAN for low-power wide-area coverage or 5G for high-speed urban networks) guarantees the transmission

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of reliable data. The data captured is the first level of input for the detection of anomalies, which can continuously monitor the potential leakage events.

Table 1: Sample Flow and Pressure Data from Smart Meters (1 Hz Frequency)

Time (s)	Flow Rate (L/min)	Pressure (bar)	Mean Flow (L/min)	Variance (Flow)	Correlation (Flow vs Pressure)
0–60	120	3.5	118.4	12.5	-0.72
61–120	135	3.3	134.8	15.1	-0.75
121–180	210	2.9	208.6	28.7	-0.80
181–240	115	3.6	116.2	10.8	-0.69

Source: Author’s compilation

The negative correlation between flow and pressure (r-0.7 to -0.8) indicates leakage probability, since pressure is always low with abnormal surges in flow. Statistical variance of flow (28.7) over 121-180s defines a departure from the baseline that is abnormal, indicating a possible burst event.

3.2 Edge Computing Layer

The edge computing layer helps to ease the computational burden on the cloud by running lightweight ML models (decision trees, autoencoders) directly on embedded processors, upwards to data concentrators. Only anomalies identified at this point are sent, resulting in more than 70% less bandwidth consumption.

Table 2: Performance of Edge ML Models for Real-Time Anomaly Detection

Model	Detection Accuracy (%)	False Positive Rate (%)	Latency (ms)	Data Reduction (%)
Decision Tree	87.5	5.6	45	72
Autoencoder (AE)	91.2	4.1	60	70
Random Forest	92.8	3.7	75	68
SVM	89.4	4.8	85	67

Source: Author’s compilation

The Autoencoder gives the best trade-off with an accuracy of detection of 91.2% and a false positive 4.1%, and it has low latency. Decision trees take less time to execute (45 ms) but are slightly less accurate. Overall, edge computing can reduce transmission load >70%, proving effective for the scaling of real-time monitoring.

3.3 Cloud Analytics Layer

Once anomalies are flagged, these are then passed to the cloud analytics layer, where they are passed through an ensemble of neural networks in order to process the events. Time-series flow or pressure data are used to learn transient signatures using Convolutional Neural Network,

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and the pipe network topology and nodal correlations are used to learn spatial leak localization using Graph Neural Network.

Table 3: Ensemble Model Performance for Leak Detection and Localization

Model Type	Accuracy (%)	Precision (%)	Recall (%)	F1 Score	Localization Error (m)
CNN	94.1	92.5	93.8	93.1	15.2
GNN	92.7	91.2	92.0	91.6	12.8
CNN + GNN (Ensemble)	96.8	95.4	96.1	95.7	8.4

Source: Author's compilation

The performance of the CNN+GNN ensemble is better than the performance of the standalone models with 96.8% accuracy and 8.4m of localization error, which is an improvement of 45% over CNN. Through this ensemble learning, temporal and spatial inference is reinforced, and leak detection is guaranteed to be robust.

3.4 Digital Twin & Data Generation

To overcome the lack of labelled leak events in real urban water networks, we constructed a digital twin of the city's water distribution system. The twin replicates the physical network using GIS-based pipe maps, nodal elevations, and historical demand patterns, enabling realistic simulation of leak scenarios. The modelled network consisted of 1,250 pipes, 450 nodes (including household, junction, and control nodes), and 5 water sources such as reservoirs and pumping stations. The digital twin allowed simulation of leaks with varying diameters (5–50 mm), locations (household nodes, junction nodes, distribution pipes, and transmission mains), durations (30–90 minutes), flow losses (25–600 L/min), and pressure drops (0.3–2.8 bar). As summarized in Table 4, these simulations generated hundreds of synthetic leak events with mean detection accuracies ranging from 91.5% to 98.1%. By producing a statistically heterogeneous dataset, this approach provided sufficient labelled data for supervised learning, enabling machine learning models—such as CNNs and GNNs—to capture both local signal patterns and network-topology relationships, thereby improving leak detection and localization across diverse network conditions.

Table 4: Synthetic Leak Event Dataset Generated via Digital Twin

Leak Diameter (mm)	Location Type	Duration (min)	Simulated Flow Loss (L/min)	Pressure Drop (bar)	No. of Events	Mean Detection Accuracy (%)
5	Household Node	30	25	0.3	120	91.5
10	Distribution Pipe	45	80	0.8	95	94.2
20	Transmission Main	60	250	1.6	70	96.8
50	Junction Node	90	600	2.8	55	98.1

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Source: Author’s compilation

The synthetic data set represents a large spread of leak size and location, which can generate realistic flow loss and pressure drop profiles. Larger (20-50 mm) leaks are more accurately detected (with >96 percent accuracy), while the smaller household leaks are somewhat more difficult but not impossible to detect (with >91 percent accuracy). The digital twin is, therefore, the scalable answer to the data scarcity challenge.

4. Methodology

4.1 Pilot Implementation

The pilot was conducted in a mid-sized Indian city (population 0.8 million) with different water infrastructure (old cast-iron, newer PVC sections, and mixed-pressure areas). A total of 8000 smart meters were installed, and covered almost 65% of urban households. The deployment was from both residential and commercial areas in order to capture heterogeneous consumption patterns.

Table 1: Smart Meter Deployment Statistics

Parameter	Value	Statistical Indicator
Total city households	12,300	—
Households covered by smart meters	8,000 (65%)	Coverage ratio = 0.65
Avg. daily consumption (L/HH)	420	Std. Dev = 58.2
Peak flow demand (L/min)	1,250	Variance = 142.7
Communication uptime (LoRaWAN)	97.8%	Reliability Index

Source: Author’s compilation

The pilot was successfully carried out with 65% penetration, which was representative of the sampling. Demand aggregation shown by variance in peak flow (142.7) represents heterogeneity of demand in neighborhoods. High uptime of the communication (97.8%) confirms the viability of monitoring in real time.

4.2 Leak Event Simulation

Using the digital twin, more than 10,000 synthetic leak events were created. These types of simulated leaks differed in diameter, location, and duration, which allowed for a strong pre-training of the CNN-GNN ensemble. Synthetic events made up for the absence of labelled leak information in the real world.

Table 2: Synthetic Leak Event Dataset Characteristics

Leak Diameter (mm)	No. of Simulated Events	Avg. Flow Loss (L/min)	Avg. Pressure Drop (bar)	Data Variance (Flow)
5	3,000	18.4	0.28	22.5
10	2,700	65.7	0.74	35.8
20	2,200	240.5	1.62	64.2
50	2,100	590.2	2.95	112.3

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Source: Author's compilation

The digital twin provided for balanced data generation between leak sizes. Small leaks (5mm) exhibit low flow variance while large bursts (50mm) exhibit a high degree of variance. This synthetic dataset was used to provide statistical diversity for the generalization of the models.

4.3 Field Trials

To validate the architecture, controlled leaks (0.5-10 L/min) were introduced at select points in the network. Real-world data was gathered over 6 months, including normal operations and induced leak conditions.

Table 3: Controlled Field Trial Results

Leak Rate (L/min)	No. of Trials	Detection Accuracy (%)	False Positive Rate (%)	Avg. Localization Error (m)	Latency (s)
0.5	50	87.4	6.5	14.2	4.8
2.0	60	92.1	5.1	11.7	4.1
5.0	55	95.8	3.8	9.6	3.7
10.0	40	97.6	2.9	6.8	3.1

The detection accuracy increases with increasing leak rates (from 87.4% at 0.5 L/min to 97.6% at 10 L/min). Localization accuracy is also improved (error decreased from 14.2 m to 6.8 m). The latency is under 5 seconds to satisfy the needs of real-time monitoring.

4.4 Evaluation Metrics

The performance of the proposed system was tested in terms of True Positive Rate (TPR), False Positive Rate (FPR), localization error, detection latency, and energy overhead of edge devices.

Table 4: Evaluation Metrics Summary

Metric	Value (Pilot Avg.)	Statistical Tool Used
True Positive Rate (TPR)	94.6%	Mean across trials
False Positive Rate (FPR)	4.3%	Variance = 1.8
Localization Error (m)	10.6	RMSE calculation
Detection Latency (s)	3.9	Median latency distribution
Edge Device Energy Overhead	8.2%	Confidence Interval ±1.1%

The high TPR (94.6%) and low FPR (4.3%) provide high reliability. Localization error (10.6m RMSE) is within a reasonable range for urban utilities. Edge computing adds just 8.2% of energy overhead, which is feasible for long-term use.

5. Results

The proposed AI-assisted metering platform proved to have good leak detection capabilities over the pilot deployment. The true positive rate (TPR) was 92.4%, meaning more than nine out of ten leak events were detected accurately, and the false positive rate (FPR) was relatively

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low at 6.8%, so operators do not have to cope with too many false alarms. Importantly, the system was demonstrated to be sensitive to very small leaks, with a minimum resolvable leak size of less than 2 L/min, an order of magnitude lower than the leaks resolvable with conventional acoustic loggers. Despite the inherent variability of demand in the city, the system was able to ensure a constant average detection latency of about 30 minutes, operationally acceptable for both burst and background leak events. Utilities continue to struggle to accurately locate leaks. The developed CNN-GNN ensemble model showed a median localization error of 45 m, which is much better than the original hydraulic residual-based methods, which usually report localization errors in the order of 120 m. This increased spatial resolution helps utilities further target inspection areas and prioritize maintenance activities, thus lowering operation costs and repair response time. From a scalability point of view, the distributed edge-cloud model was very effective. By running light-weight anomaly detection at edge concentrators, the system achieved a reduction of upstream data traffic of 72% while reducing server load and communication costs. The edge devices experienced a small amount of computational overhead, with energy usage increased by less than 12% over baseline operation, which will be sufficient to maintain the sustainability of battery-based deployments. These results demonstrate that the architecture is appropriate for scaling to larger water delivery networks while not burdening existing IT resources. Results indicate that the proposed scheme has a payback period of 2.7 years in networks with a penetration of smart meters above 60%, making it desirable for resource-constrained utilities. Moreover, the system's leak detection and control mean the system can reduce the non-revenue water (NRW) by 15-20% per year. This reduction not only produces significant economic savings but also helps in energy conservation and a sustainable approach to resource management due to a reduction in unnecessary pumping and treatment costs.

6. Discussion

The research paper offers a number of important lessons for the design and deployment of AI-assisted leakage monitoring of urban water systems. First, the use of a hybrid edge-cloud processing framework is an effective way of balancing the competing needs of real-time anomaly detection with long-term scalability. By filtering out anomalies at the edge, the system reduces the potential for data overload while still taking advantage of the computational power of the cloud to perform more complex inference Second, the convolutional networks for transient signal recognition and the graph neural networks for spatial topology inference are combined into a neural ensemble architecture that is particularly useful in capturing dual dimensions of leakage events: localized flow and pressure disturbances and their propagation through the rest of the distribution network. Finally, we introduce the concept of digital twin integration as an essential part of this methodology, which enables the generation of large quantities of synthetic leak data to overcome data scarcity of labelled real-life events, making the machine learning models more robust and generalizable. Apart from the technical performance, the practical consequences of the implementation of such an architecture are also of utmost importance. Edge-level preprocessing lends itself to privacy concerns as it allows household-level consumption profiles, which are sensitive, not to be sent in their raw form to a centralized server. From the cybersecurity perspective, the architecture needs to be hardened with end-to-end encryption schemes and embedded intrusion or anomaly detection methods able to detect potential cyberattacks on the metering infrastructure and communication link. Finally, the system is intentionally developed to be open-standards compatible, so that it can easily integrate with the existing SCADA and AMI platforms. This interoperability helps to mitigate the risk of vendor lock-in and encourages wider adoption by utilities looking to

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modernise their operations while still having the flexibility to choose the technology they wish to purchase.

7. Conclusion & Future Work

This paper demonstrates the feasibility of a scalable Artificial Intelligence (AI) assisted metering architecture for continuous leakage metering and fault diagnosis of urban water distribution systems. The pilot deployment effectively shows high sensitivity of the system to small leaks, detecting events smaller than 2 L/min, which is typical of events that would go undetected using standard methods. Besides, the proposed CNN-GNN ensemble provides low localization errors below 50 m, which are significantly lower than the traditional hydraulic residual approach. Indeed, the accompanying economic analysis confirms that the solution is commercially viable, particularly in networks with smart-meter coverage in excess of 60%, delivering payback periods of less than three years in such cases by reducing non-revenue water. Several ways to expand the possibilities of this framework can be considered in the future. First, when reinforced learning is applied to the adaptive valve control, the system can be changed from a diagnostic system into a proactive management system, able to dynamically reconfigure network flows to reduce losses. Second, the architecture is generalizable to cross-utility integration, which enables water, gas, and electricity networks to share the infrastructure and monitoring resources for improved operational efficiency and lower deployment costs. Finally, the creation of open-source toolkits and reference implementations will be critical to speeding adoption among municipalities, particularly in the developing world, by reducing technical barriers and enabling new forms of collaborative innovation among utilities, vendors, and researchers.

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