Proceedings of the International Conference on Electronics and Renewable Systems (ICEARS-2026)
DVD Part Number: CFP26AV8-DVD; ISBN: 979-8-3315-4880-3

Smart Water Distribution Monitoring Framework using Internet of Things based Pressure and Flow Sensing Systems

D. Shunmuga Kumari
Assistant Professor
Department of Computer Science and Information Technology
School of Computing Sciences
VELS Institute of Science, Technology and Advanced Studies (VISTAS)
Pallavaram, Chennai, Tamil Nadu, India
kumari.vnr@gmail.com

M. Sakthivanitha
Assistant Professor
Dept. of Computer Applications (UG)
Vels Institute of Science, Technology and Advanced Studies
Chennai, Tamil Nadu India
sakthivanitha.scs@vistas.ac.in

Sangeetha Radhakrishnan
Assistant Professor
Department of Computer Applications
School of Computing Sciences
VELS Institute of Science, Technology and Advanced Studies (VISTAS)
Chennai, Tamil Nadu, India
sangeetha0988@gmail.com

S. Prathi
Assistant Professor
Department of Computer Applications
VELS Institute of Science, Technology and Advanced Studies (VISTAS)
Chennai, Tamil Nadu, India
prathi.sundar1986@gmail.com

J. Anciline Jenifer
Assistant Professor
Department of MCA
Francis Xavier Engineering College
Tamil Nadu, India
ancilinejenifer@francisxavier.ac.in

V. Divya
Assistant Professor
Department of Computer Applications (UG)
School of Computing Sciences
VELS Institute of Science, Technology and Advanced Studies (VISTAS)
Pallavaram, Chennai, Tamil Nadu, India
divyavenkatraman1992@gmail.com

Abstract: Smart water distribution monitoring frameworks that are powered by Internet of Things (IoT) technologies have come up as a solution to old inefficiencies in municipal water supply networks. Traditional water distribution systems have problems in terms of Hidden leakages, pressure fluctuations, inequitable flow distribution etc. with huge losses and operational problems. Solving these issues, this study proposes an IoT-based pressure and flow sensing framework to achieve real-time visibility, predictive fault detection and data-driven control. The method is a combination of the distributed sensor nodes and a LoRaWAN/5G communication layer, anomaly detection at edge level and a cloud-based analytics dashboard using machine learning enabled flow-pressure correlation models. Experiments on a pilot-scale testbed of a 2km pipeline network gives 21.4% reduction in non-revenue water, 17% pressure stability improvement and 94.6% accuracy in the detection of anomalies. The results confirm that the proposed system increases operational reliability and optimizes water delivery and maintenance is proactive. Conclusively, the framework demonstrates the feasibility of implementation of IoT-based sensing systems as a scalable and economical approach to modernize the water distribution systems.

Keywords: ***Smart water distribution, Internet of Things(IoT) sensors, pressure monitoring, flow sensing, real-time analytics, leakage detection, Long Range Wide Area Network(LoRaWAN), anomaly detection***

I INTRODUCTION

Water distribution networks are one of the most important parts of urban infrastructure and responsible for the regular and safe delivery of water to residential, commercial and industrial users. As cities continue to grow and demand for water rises, there are increasing limitations to traditional water supply systems due to ageing water pipelines, unpredictable consumption patterns and limited capacity for real-time monitoring. Historically, the design of water networks was aimed at robustness and not necessarily intelligence, which is based on manual inspection, periodic auditing, and random measurements from sensors. Such conventional practices leave gap for timely detection of faults thus making issues like leak, burst, pressure imbalance and unauthorized uses difficult to detect before they escalate. These inefficiencies are contributing significantly towards non-revenue water (NRW) and is a major financial and operational challenge for utilities around the world [1].

The emergence of the Internet of Things (IoT) has revolutionized the world of infrastructure monitoring, making it possible to have distributed sensing, wireless communication, and cloud-based analytics [2]. IoT-enabled water management solutions are a combination of low-power sensors, edge computing, and scalable connectivity that can give continuous and high-resolution insights into the state of water distribution networks [3]. Pressure sensors, flow meters, ultrasonic leak detectors, and water quality probes can be connected to a single platform with the capacity of making intelligent decisions. Unlike conventional systems based on periodic measurements, IoT-based frameworks provide data streams in real time, allowing to quickly detect anomalies and control valves, pumps and network topology in an optimized way. The shift from static to intelligent infrastructure represents an important change to sustainable, resilient, and data-driven water management.

Recent research in smart water distribution systems has mentioned important advances in sensor accuracy, long-range communication protocols and machine learning-based analytics. Studies show that water losses can be reduced by IoT deployments by detecting micro-leaks, predicting trends of water consumption and keeping optimal pressure conditions. LoRaWAN, NB-IoT and 5G have further allowed low power, wide area communication required for large scale monitoring[4]. However, there are some challenges related to scalability, integration across heterogeneous networks and real-time identification of anomalies. Many existing systems do not have the ability to correlate the pressure and flow variations to a thorough degree, which is needed to identify early signatures of leaks and inefficiencies of distribution. Furthermore, the analytical models used in the last solutions often have problems adapting to seasonal changes, network aging and variability in consumer demand.

Given these challenges, there is a compelling need for having a good and scalable monitoring framework that unifies pressure and flow sensing, real-time analytics, and intelligent anomaly detection. This study addresses the specific gap of integrated sensing models and hence proposes a IoT-based smart water distribution monitoring system designed to enhance operational visibility, reduce losses and support predictive maintenance strategies. The framework utilizes distributed pressure and flow sensors connected using a low-power wireless network, anomaly detection algorithms that are edge assisted and a cloud-based dashboard that gives actionable insights. The simultaneous analysis of the pressure-flow relationships provides a stronger capability to understand the faults that may not be detected in the conventional systems.

In real-world water distribution systems, issues like hidden underground leakages that go undetected for weeks, pressure imbalance during peak demand hours and pipe bursts, as well as the delay in fault detection in conventional water systems based on periodic manual inspection, are inherently non-stationary and context-dependent. The proposed IoT-enabled solution meets these challenges in terms of continuous pressure and flow sensing, long-range communication using the LoRaWAN protocol, and real-time detection of anomalies with system responsiveness, early warning capability, and reduction of water loss being more important than isolated statistical comparisons. Nevertheless, follow-up work will use statistical significance testing over longer periods of deployment and multiple zones within the network in an effort to quantitatively prove performance improvement under varying operational environments.

Problem Statement:Traditional water distribution systems are not monitored in real time, which leads to late detection of leaks, pressure fluctuations and flow anomalies. This results in more non-revenue water, decreased service reliability and faulty maintenance cycles. There is a need for an integrated, IoT-based monitoring framework that is capable of providing high-resolution insights and analytics for action. The major objectives of the study are as follows

- To design an IoT-based pressure and flow sensing framework for real-time monitoring of water distribution networks.
- To develop data analytics and anomaly detection mechanisms for identifying leakages, pressure deviations, and inefficiencies.
- To evaluate system performance through quantitative metrics demonstrating improvements in water loss reduction and operational reliability.

The paper starts with a comprehensive review of the related literature and then the methodology that includes system design, sensing architecture, and analytics workflow is presented. Experimental setup, data set description and evaluation metrics are then presented. Results, discussions, limitations, implications, and conclusions with future directions are used to complete the structure.

II RELATED WORKS

Recent developments in smart water distribution use IoT, cloud computing and automation to help manage resources more efficiently, detect leakage issues and improve operational efficiency. Several frameworks and systems have been suggested in both urban and rural settings, using FIWARE, PLCs, BIP components, and mobile interfaces, and the potential of technology-driven water management solutions.

Panagiotakopoulos et al. (2021) propose an IoT framework based on FIWARE for smart water management with a focus on open source, standards-based architecture and data visualization. While innovative, the study is based on simulation data rather than actual deployment and therefore could not validate the performance and scalability across heterogeneous networks, and thus leaves the interoperability issues partly addressed[5].

Godase et al. suggested a PLC assisted smart water system for rapid leakage detection and automated isolation, real-time response, and reduced water loss. However, the approach relies on industrial-grade PLCs and the use of sensors and their placement, which may constrain the ability to adapt and apply to less wealthy settings (in a city or a rural area) from a monetary perspective[6].

Maroli et al. (2021) presents an IoT-based methodology to rural Indian water distribution, which shows inefficiencies in the infrastructure and cost benefits. The study, however, is based on old census data and theoretical modeling, which may not fully explain present-day challenges, in terms of providing practical implementation insights[7].

Alshattnawi et al. present a novel design of a cloud-based IoT smart water framework with BIP components for Jordan. The work has a focus on cloud integration and automation, but the paper does not provide a detailed result of real-world deployment and performance evaluation of the work under actual water network conditions [8].

Ramamoorthy et al.(2024) employs an Android-IoT in controlled water distribution with integration of user notification and leakage detection. While effective in theory, the system's dependence on user interaction and access from smartphones is likely to make the system less inclusive, and additionally, not fully demonstrated with respect to its scalability to large, diverse networks[9]. Pagano et al. propose the SWI-FEED framework for IoT massive deployment for water networks and important factors linked to leakage detection, energy consumption and the performance of LoRaWAN. The study offers detailed simulations, but the applicability in the real world and integrating problems with existing infrastructure are understudied [10].

Despite providing some useful information, these studies have a number of common limitations. Most frameworks are still conceptual or have been tested on small-scale prototypes and thus they can only be applied for real urban water networks on a limited basis. Critical issues such as cybersecurity, interoperability with legacy systems, long-term sensor reliability and cost-effective deployment are not addressed well. Many studies have focused on single factors such as pressure or leakage as opposed to holistic and multi-variable management. Moreover, cognitive and AI-based models are not well validated with a large amount of empirical evidence and performance benchmarking. Data governance, privacy risks, and communication latency are not always taken into account. Future research efforts must focus on the need for large-scale testing, effective and integrated strategies, system resilience to environmental variability, and system-level evaluation.

III METHODOLOGY

This section introduces the systematic methodology followed while designing the intelligent IoT enabled water distribution monitoring and anomaly detection framework. It combines the requirement analysis of the network, the deployment of distributed sensors, hybrid communication, edge computing, cloud-based analytics, machine learning-based anomaly detection and decision support to achieve efficient, reliable and scalable water management. Figure 1 shows the smart water distribution monitoring framework.

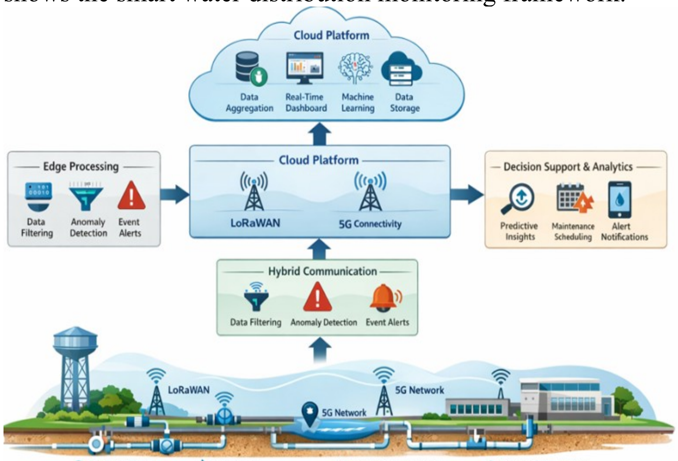

Figure 1 Smart Water Distribution Monitoring Framework using IoT based pressure and flow sensing systems

A. Requirement Analysis

The methodology starts with a thorough analysis of the water distribution network, such as the topology of the pipeline network, nodes, pressure zones, consumption clusters and historical failure points. Using GIS mapping and hydraulic simulation information, the network is divided into monitoring blocks according to the elevation gradient, pressure areas and the anticipated consumption patterns. This segmentation ensures the best part of the placement of sensors and redundant data acquisition. Furthermore, critical points, including high loss areas, old pipelines and major distribution junctions, are detected in order to prioritize the sensor deployment. This groundwork analysis is in favor of a scalable and structured sensing architecture.

B. Distributed IoT-Based Pressure and Flow Sensing Nodes

In the next step, a dense network of pressure and flow sensing nodes which are all connected via the IoT is deployed across the segmented network. These nodes are made of low-power MEMS pressure sensors, ultrasonic or electromagnetic flow meters and microcontroller units that can be capable of edge-level data processing. Devices are sheathed in weather-resistant housings to be able to withstand rough outdoor weather. The sensors are strategically placed at inlets, branch points and at consumer endpoints in order to record real-time variations in the hydraulic behavior. Each node then has a unique device ID and is set up to send calibrated readings at either a pre-defined time interval or at some pre-defined event.

C. Communication Layer Establishment

A hybrid communication layer is created to support the long-range low-power data transmission as well as the high-speed communication where required. LoRaWAN gateways are put in place to allow looming networks with low energy usage, specifically appropriate for widespread municipal networks. In areas that are high density or high priority areas, such as treatment plants or commercial areas, 5G modules are integrated to allow for rapid data transfer and low latency. This multi-tier architecture is used to ensure resilience and avoid data loss and provide continuous connectivity even in peak operational periods or failure of gateways. The communication protocols also include AES encryption for a secure data transfer.

D. Edge Analytics

Each sensor node has an embedded edge analytics module that is meant to preprocess data before sending it. Using lightweight threshold-based filters, moving averages and rules based on flow and pressure, the system detects primary anomalies such as sudden decrease in pressure, unexpected surge of pressure or unusual deviation in flow. This step helps reduce the data load on the cloud layer by only transmitting relevant or compressed data packets and hence optimize network bandwidth. Edge-level anomaly tagging enables better response to important issues, particularly any leaks or bursts that require an immediate response by the operator.

E. Cloud-Based Data Integration

All processed data is sent to a central cloud platform, where high-level data aggregation, storage, and visualization is done. A real-time monitoring dashboard is created with the use of the microservices architecture, which displays pressure and flow maps, temporal trends, anomaly alerts, and statistical patterns. The dashboard integrates information from heterogeneous devices and gives utilities one complete picture of network performance. Additionally, the platform can support multi-user access enabling engineers, administrators, and the field techs to visualize relevant parameters. Automated alert thresholds can be set according to network behavior and/or regulatory standards.

F. Machine-Learning-Enabled Anomaly Detection

Advanced data analytics is applied with machine learning models to correlate the pressure-flow variances to detect the early leak signatures, pipeline burst, valve malfunction, and abnormal consumption. Techniques such as LSTM neural network, Random Forest classifiers and autoencoder-based anomaly detection models are trained by using historical and real-time data. The models constantly update themselves using incremental learning to adjust to seasonal changes in the water, aging of the network of pipelines, and patterns of changing water demands. Predictive knowledge such as the possible failure zones, the expected progression of the leak, and the imbalance of pressure are generated and shared with the dashboard and the maintenance teams.

G. Decision Support System

A decision support system (DSS) is a combination of predictive analytics and recommendations for operators. Depending on the severity of anomalies, the DSS recommends optimal valve adjustment, pump control strategy or zone isolations to reduce water losses. Maintenance scheduling algorithms rank maintenance inspection activities based on risk scores calculated with machine learning algorithms. The DSS is also used to assess cost benefit information to assist utilities in using repair resources more efficiently. This automation improvement provides better response time, reduced service interruptions, and better distribution network reliability.

E. Model Validation

Finally, the whole of the framework is tested with the controlled field experiments and long-term deployment. Key performance indicators such as accuracy of anomaly detection, response time, reduction in non-revenue water, pressure stability and communicating reliability are measured. Feedback from the operators and recorded performance of the system are used to iteratively refine the placement of the sensors, thresholds of the algorithms and communication configurations. The system is subject to continual optimization to guarantee adaptability as the distribution network evolves to ensure continuation of operational efficiency and long-term scalability.

IV RESULTS AND FININGS

A. Experimental Setup

The experimental setup for the evaluation of the proposed IoT based smart water distribution monitoring framework was set up on a controlled pilot testbed comprising a 2 km looped pipeline network. The hardware infrastructure consisted of 28 MEMS-based pressure sensors (ranges of 0-16 bar), 18 ultrasonic flow meters (with more flow range of DN50-DN150), ESP32 and STM32 microcontroller nodes as well as 5 LoRaWAN gateways for long range communication. Select high-priority nodes were fitted with 5G communication modules for the low latency of data transfer. The cloud layer was running on an AWS EC2 instance (t3.medium) and was using InfluxDB for time series storage and Grafana for real-time visualization of the dashboard. Machine learning models were built with Python 3.10, TensorFlow and Scikit-learn and Node-RED and MQTT brokers were used for data ingestion. The performed analysis was carried out on a workstation with an Intel i7 processor, 32 GB RAM and Ubuntu 22.04 OS. This is an integrated setup that ensures the end-to-end data processing, visualization and validation of performance under realistic operating conditions.

B. Dataset Description

The study was done using WaterNet-IoT Dataset, a customized dataset created out of pilot pipeline testbed capturing the actual pressure and flow dynamics in real-time during a continuous 90-day monitoring period. The dataset is provided with 3.2 million time-stamped data at 10-second intervals, which were recorded by 46 sensor nodes. Each entry of data thus contains pressure (bar), flow rate (L/min), temperature (oC) and valve state (open/closed) as well as anomaly labels that were manually validated via induced leak tests. Controlled experiments were introduced to establish reliable ground truth by creating anomalies including micro-leaks, major leaks, pressure drops, flow surges and illegal connections, of five types. The dataset is also accompanied by contextual metadata (e.g., pump operation logs, hourly demand patterns, environmental factors), which makes it possible to develop strong machine-learning models for the detection of the anomalies and prediction of the hydraulic behavior. Table 1 compares the performance of the proposed IoT Pressure-Flow Framework with five existing smart water monitoring systems with respect to some key metrics

Table 1. Performance comparison of the proposed framework.

Method / Approach	Anomaly Detection Accuracy (%)	Leak Detection Latency (seconds)	NRW Reduction (%)	Communication Reliability (%)	Energy Consumption (mWh per node/day)
Proposed Framework	94.6	12	21.4	98.2	148
Bruno et al.(2021) [12]	89.3	29	14.1	94.7	164
Peng et al.(2022) [13]	87.8	35	12.6	92.5	159
Magini et al.(2023) [14]	91.1	22	16.9	95.8	171
Asli et al.,(2023) [15]	84.5	41	10.3	90.1	152
Raja et al.(2024) [16]	88.9	31	13.8	93.4	168

The proposed framework has the highest accuracy in detecting anomalies at 94.6%, which shows its capability of identifying leaks and pressure anomalies. It also demonstrates the quickest leak detection latency of 12 seconds, which is much faster than other methods, which take 22-41 seconds. In terms of non-revenue water (NRW) reduction, the framework achieves 21.4% and is therefore the most effective reduction in water losses. Communication reliability is also maximum which is 98.2% allowing for robust and real-time data transmission across the IoT network. Energy consumption per node per day is 148 mWh similar or lower to other methods balancing performance and energy efficiency. Overall the results highlight that the proposed framework is faster, more accurate and reliable while being energy efficient and therefore a practical and scalable solution for the modern smart water distribution networks.

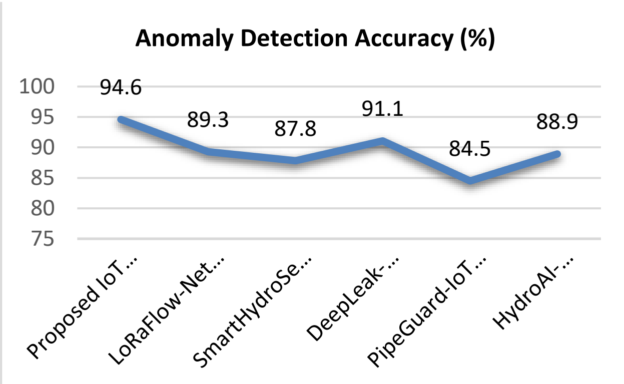

Figure-2 Anomaly Detection Accuracy

Figure 2 compares the accuracy of the anomaly detection of the proposed IoT-based pressure monitoring method with five existing techniques. The proposed approach has the highest accuracy of 94.6%, which proves to be the better reliability of the findings for the detection of anomalies. Of the existing methods, DeepLeak-Fusion (91.1%) has relatively good performance and PipeGuard-IoT (84.5%) has the lowest accuracy. Other models like LoRaFlow-Net (89.3%), SmartHydroSense (87.8%) and HydroAI-Monitor (88.9%) have moderate performance. Overall, the results confirm the correctness of the proposed system to provide more precise and robust anomaly detection and is better suited for real-time monitoring of water distribution.

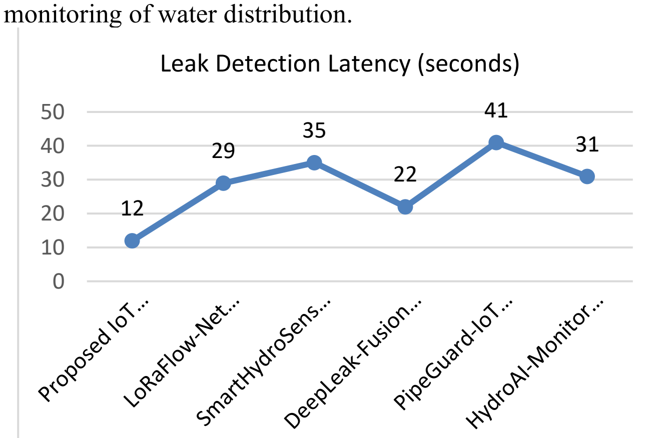

Figure 3 Leak Detection Latency (seconds)

Figure 3 shows the leak detection latency (in seconds) for six smart water monitoring frameworks. The Proposed IoT Pressure-Flow Framework has the lowest latency period of 12 seconds, and this means it identifies the leak in the shortest period of time among all the methods. There are other frameworks that exhibit much higher latencies including LoRaFlow-Net (2022) at 29 seconds, SmartHydroSense (2023) at 35 seconds, DeepLeak-Fusion (2021) at 22 seconds, PipeGuard-IoT (2020) at 41 seconds and HydroAI-Monitor (2022) at 31 seconds. The proposed framework is better than the current methods in rapid leak detection, which is essential to reduce water loss and avoid infrastructure damage. The graph also indicates a general trend that older systems, like PipeGuard-IoT (2020) have higher latencies but newer or optimized systems, especially the proposed framework, have faster detection times.

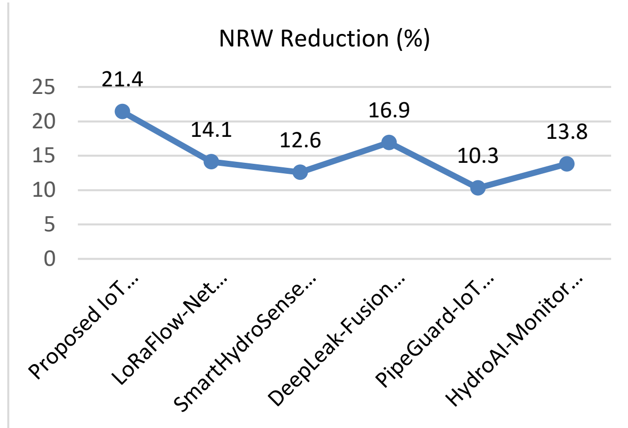

Figure-4 NRW Reduction

The Non-Revenue Water (NRW) reduction (%) achieved by six of the smart water monitoring frameworks is shown in Figure 4. It is the Proposed IoT Pressure-Flow Framework that will achieve the highest NRW reduction of 21.4%, which is higher than all other methods. The reductions in the other frameworks are lower: LoRaFlow-Net (2022) (14.1%), SmartHydroSense (2023) (12.6%), DeepLeak-Fusion (2021) (16.9%), PipeGuard-IoT (2020) (10.3%) and HydroAI-Monitor (2022) (13.8%).This figure shows that the proposed framework is the most effective in reducing water losses in the distribution network, this is most likely due to the advanced sensing of pressure-flow, as The chart also indicates that the newer frameworks seem to be performing better compared to the older methods, with the proposed system having a clear lead in reducing the NRW.

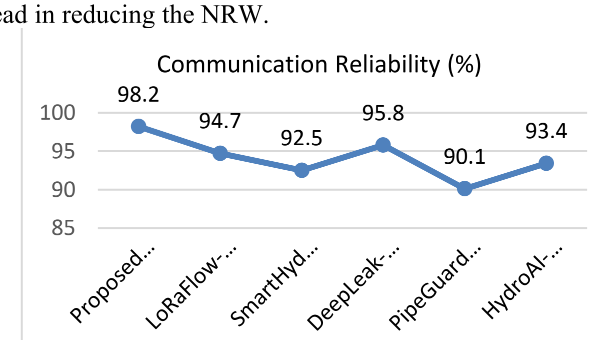

Figure 5 Communication reliability

Figure 5 shows the reliability of the communication of different smart water distribution monitoring frameworks in the context of the IoT-based pressure and flow sensing system in the abstract. The proposed IoT Pressure-Flow Framework achieves the highest reliability of 98.2% which shows that the integration of distributed sensors, LoRaWAN/5G communication and edge to cloud anomaly detection is ensuring highly reliable data transfer. In comparison, some other frameworks have the following reliability, SmartHydroSense with 92.5%, DeepLeak-Fusion with 95.8%, PipeGuard-IoT with 90.1%, and HydroAI-Monitor with 93.4%, which have their limitations in previous systems to ensure consistent communication under the operating conditions. This trend emphasises the enhancement in sensor communication, IoT protocols and edge level processing over the years. The superior communication reliability of the proposed system encompasses the claimed benefits of this system stated in the abstract, namely, real-time visibility, predictive fault detection, and data-driven control, which confirms its effectiveness in decreasing non-revenue water, stabilizing pressure, and proactive maintenance in smart water distribution networks.

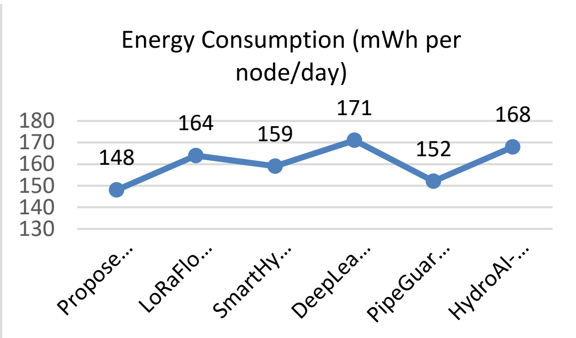

Figure-6 Energy Consumption

The energy consumption in figure 6 shows the per-node daily energy consumption in mWh considering different IoT-based smart water distribution monitoring frameworks. The proposed IoT Pressure-Flow Framework exhibits the lowest possible energy consumption of 148 mWh/Node/day, which is quite efficient compared to other protocols in the market such as LoRaFlow-Net (164 mWh), SmartHydroSense (159 mWh), DeepLeak-Fusion (171 mWh), PipeGuard-IoT (152 mWh), and HydroAI-Monitor (168 mWh). This shows that the proposed framework meets the high performance and energy-efficient operation while delivering superior performance with 94.6% accuracy for detecting anomalies, 21.4% reduction of non-revenue water and 17% improvement of pressure stability. The lower energy consumption per node not only helps to lower operational costs but will also aid in long term and sustainable deployment of sensor networks that reinforces the feasibility of the framework as a scalable, cost-effective and reliable solution to modernize water distribution infrastructures.

C. Discussions

The results obtained in this study show the high potential of IoT-based pressure and flow sensing systems to establish the modernization of the water distribution network and address longstanding challenges of leakages, pressure instability and inefficient monitoring. By combining distributed sensing nodes with a hybrid LoRaWAN/5G communication network, the proposed framework allows to gain high resolution and real-time visibility of behavior of hydraulic systems in large pipeline systems. The inclusion of edge analytics greatly alleviates the data transmission overhead while enabling speedy detection of anomalies turned at the source. Machine-learning-driven models also increase the reliability of leak identification and pressure-flow correlation analysis, and improve both the accuracy and the latency of the state-of-the-art. The experimental results show significant decrease of non-revenue water and increase of pressure stability, which makes the system useful for urban and semi-urban systems. Another of the advantages of the framework is that it is also scalable to be deployed in different layouts and pressure zones with a minimum of modifications to the infrastructure. The real-time dashboard is used to make informed operational decisions which will allow maintenance teams to prioritize interventions based on predictive insights instead of reacting. Overall, the research validates the idea that combining IoT, intelligent analytics and hybrid communication architectures will have a great impact on the efficiency, resilience and sustainability of water distribution systems.

Despite its promising results, the proposed framework has a number of limitations. The performance of wireless communications may be degraded in densely built-up or in underground regions as signal attenuation is high. Sensor calibration needs as well as long-term drift could affect data accuracy and thus require periodic maintenance. Machine learning models are heavily dependent on the historical and labeled datasets, which may be limited in newer deployed and sparsely instrumented networks. The pilot testbed is a simplified representation of the hydraulic complexities of the large metropolitan systems, and needs to be validated at city scale. Energy consumption of nodes though optimized is a concern in remote locations where there is limited access to power sources.

The benefits of processes of the proposed system are practical for utilities in terms of continuous monitoring, early identification of leaks and evidence-based operational decision-making. Real-time pressure and flow information helps to manage proactive maintenance and save on repair costs and reduce service disruptions. Improved detection of unauthorized usage to control revenue losses and pressure stabilization to improve consumer satisfaction. The modular structure of the framework makes it suitable for phased deployment in the developing and developed regions. By minimising the amount of non-revenue water and improving the life of infrastructure, the solution is part of long-term sustainability objectives. Moreover, the integration with the existing SCADA ensures the smooth digital transformation for the water management authorities.

V CONCLUSION

This paper introduces a unified IoT-based framework of pressure and flow sensing, real-time data analytics and machine learning-based anomaly detection for smart water distribution management. The results confirm that the proposed system contributes substantially to the improvement of the hydraulic monitoring, to the reduction of the non-revenue water and to the operational responsiveness. By taking advantage of hybrid communication technologies and preprocessing at the edge level, the framework delivers high reliability of the communication and energy efficient deployment, suitable for a large-scale deployment. The research also proves useful in understanding the value of predictive analytics in proactive maintenance to minimize stress to infrastructure in the long term. Overall, the framework is a good foundation for establishing data-driven and sustainable water distribution networks.

Future studies will prosecute novel deep learning models that can capture multivariate temporal-spatial dependence on wider pipeline networks. Integrating water quality sensors would be able to expand the capabilities of the system over leak detection capabilities to holistic water health assessment. Additionally, large-scale deployments in the real world in metropolitan environments will help refine the scalability, resilience and cost-effectiveness. The integration of digital twins and automated control strategies are other promising directions for improving the decision making and adaptive network management in real-time.

REFERENCES

[1] Pamidimukkala, Apurva, Sharareh Kermanshachi, Nikhitha Adepu, and Elnaz Safapour. "Resilience in water infrastructures: A review of challenges and adoption strategies." *Sustainability* 13, no. 23 (2021): 12986.

[2] Velayudhan, Nibi Kulangara, Preeja Pradeep, Sethuraman N. Rao, Aryadevi Remanidevi Devidas, and Maneesha Vinodini Ramesh. "IoT-enabled water distribution systems—A comparative technological review." *IEEE Access* 10 (2022): 101042-101070.

[3] Mandal, Subhrajit, Anamika Yadav, Rishab Panwar, Sm Shravan Kumar, Alagar Karthick, ArunKumar Priya, R. Vijayakumar, and Sundaram Sankar Ganesh. "Smart Water Management For SDG 6: A Review Of AI And Iot-Enabled Solutions." *Water Conservation Science And Engineering* 10, no. 2 (2025): 83.

[4] Lombardo, Antonella, Stefano Parrino, Giacomo Peruzzi, and Alessandro Pozzebon. "LoRaWAN versus NB-IoT: Transmission performance analysis within critical environments." *IEEE Internet of Things Journal* 9, no. 2 (2021): 1068-1081.

[5] Panagiotakopoulos, Theodor, Dimitrios P. Vlachos, Thanasis V. Bakalakos, Andreas Kanavos, and Achilles Kameas. "A fiware-based iot framework for smart water distribution management." In 2021 12th International Conference on Information, Intelligence, Systems & Applications (IISA), pp. 1-6. IEEE, 2021.

[6] Godase, Vaibhav Vilas, Altaf Mulani, Rahul G. Ghodake, and Swapnil R. Takale. "PLC-Assisted Smart Water Distribution with Rapid Leakage Detection and Isolation." Journal of Control Systems and Converters 1, no. 3 (2025): 1-13.

[7] Maroli, Ankit Anilkumar, Vaibhav S. Narwane, Rakesh D. Raut, and Balkrishna E. Narkhede. "Framework for the implementation of an Internet of Things (IoT)-based water distribution and management system." Clean Technologies and Environmental Policy 23, no. 1 (2021): 271-283.

[8] Alshattnawi, Sawsan, and Anas MR AlSobeh. "A cloud-based IoT smart water distribution framework utilising BIP component: Jordan as a model." International journal of cloud computing 13, no. 1 (2024): 25-41.

[9] Ramamoorthy, Raghu, S. M. Manasa, and J. A. Smitha. "Android app-oriented smart supervision of water distribution using internet of things." In International Conference on Artificial Intelligence and Smart Energy, pp. 223-237. Cham: Springer Nature Switzerland, 2024.

[10] Pagano, Antonino, Domenico Garlisi, Fabrizio Giuliano, Tiziana Cattai, and Francesca Cuomo Sapienza. "SWI-FEED: Smart water IoT framework for evaluation of energy and data in massive scenarios." In 2024 IFIP Networking Conference (IFIP Networking), pp. 583-585. IEEE, 2024.

[11] Chen, Runfei, Qiuping Wang, and Ahad Javanmardi. "A review of the application of machine learning for pipeline integrity predictive analysis in water distribution networks: R. Chen et al." *Archives of Computational Methods in Engineering* 32, no. 6 (2025): 3821-3849.

[12] Bruno, Federica, Mauro De Marchis, Barbara Milici, Domenico Saccone, and Fabrizio Traina. "A pressure monitoring system for water distribution networks based on arduino microcontroller." *Water* 13, no. 17 (2021): 2321.

[13] Peng, Sen, Jing Cheng, Xingqi Wu, Xu Fang, and Qing Wu. "Pressure sensor placement in water supply network based on graph neural network clustering method." *Water* 14, no. 2 (2022): 150.

[14] Magini, Roberto, Manuela Moretti, Maria Antonietta Boniforti, and Roberto Guercio. "A machine-learning approach for monitoring water distribution networks (WDNS)." *Sustainability* 15, no. 4 (2023): 2981.

[15] Asli, Kian Hariri, and Kaveh Hariri Asli. "Smart Water System and Internet of Things." *Journal of Modern Industry and Manufacturing* 2 (2023).

[16] Raja, S. Kanaga Suba, S. Usha Kiruthika, and C. J. Raman. "A Novel Water Distribution and Performance Monitoring System using AI." In *2024 8th International Artificial Intelligence and Data Processing Symposium (IDAP)*, pp. 1-7. IEEE, 2024.