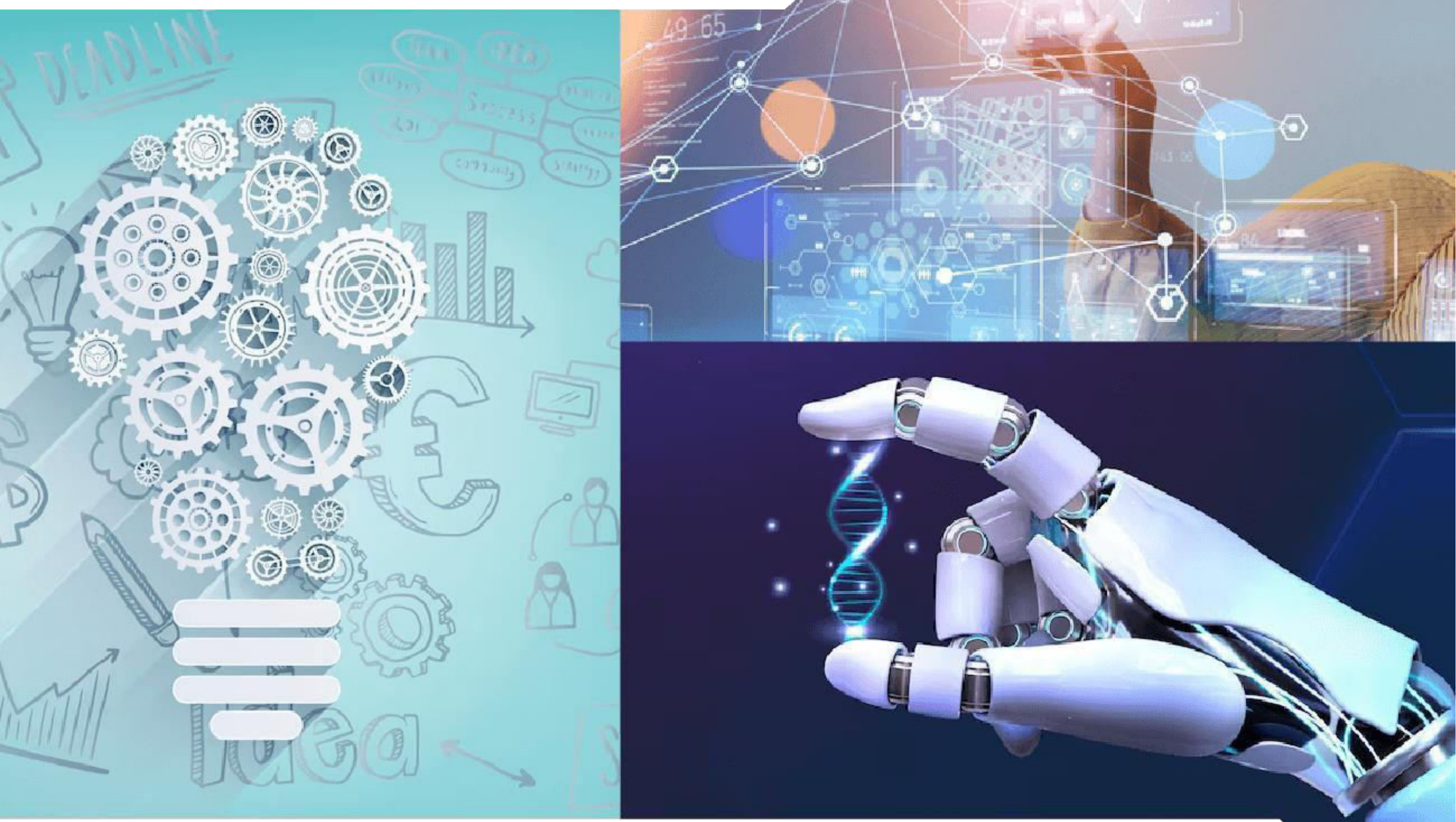

IJARETY

International Journal of Advanced Research in Education and TechnologY (IJARETY)

Volume 12, Issue 4, July-August 2025

Impact Factor: 8.152

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

INNO SPACE SJIF Scientific Journal Impact Factor

doi crossref

निस्केयर NISCAIR

International Journal of Advanced Research in Education and TechnologY(IJARETY)

| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 4, July - August 2025 ||

DOI:10.15680/IJARETY.2025.1204077

Smart Water Systems: Insights from Global Practices

Chandan D B, Chaitra Nayaka H R, Basavaraj Pateel B R

Dept. of Computer Applications, CMR Institute of Technology, Bengaluru, India

ABSTRACT- As a result of the increasing urbanization, climate change, and shortage of water, the need to have effective and sustainable water management grows across the whole world. A cutting-edge solution to enhance the performance of water supply, detect quality, locate leakages, and operate efficiently is using Smart Water Management Systems (SWMS) that can comprise Internet of Things (IoT)-based sensors, artificial intelligence (AI), and sophisticated data analysis. This study proposes an AI- enhanced SWMS that resorts to predictive demand forecasting, anomaly detection through AI using Long short-memory networks (LSTM), real-time data monitoring via LoRa-WAN/GSM, and the use of laser to monitor water levels. The system architecture involves blockchain- based secure logging, the presence of digital twin to facilitating simulation, and a multi-layer data processing.

The results of the experiment on such multi-site deployment in Saudi Arabia, the US, and Africa show better accuracy of detection of leakage with F1-scores 0.85-0.90, savings energy 14-19%, and reduction of Non- Revenue Water (NRW) 30-31%. The LSTM-based forecasting model also resulted in reducing the instances of service interruption and enabled proactive supply control with the MAPE of the forecasted values being not more than 7%. Based on the findings, SWMS serves as one of the methods that can facilitate the attainment of Sustainable Development Goals (SDG) 6 and 13 by enhancing the resilience of utility as well as facilitating equitable water governance. Problems such as stakeholder capacity building, the interoperability of devices, and the capacity to scale low-resource settings are addressed alongside tactics of incremental deployment. The given paper is not confined or restricted to the technological component of the implementation of the idea of smart water; it touches upon the economically, policy, and environmental dimensions of that issue. It also discusses the topics of interoperability, data security, start-up costs and regulatory fragmentation.

I. INTRODUCTION

One of the most important natural resources for preserving ecological balance, promoting socioeconomic development, and supporting life is water. Rapid urbanization, industrialization, population growth, and climate change are all contributing factors to the global water crisis, which presents serious obstacles to water security and sustainability. Over 2 billion people do not have access to safely managed drinking water, and by 2050, water demand is expected to rise by 55%, mostly as a result of industrial and agricultural demands, according to the United Nations World Water Development Report (2023) 111.

The issues of water management reflect differently across the landscapes. An example is that, whereas the US has issues with infrastructure deterioration, water quality and advanced optimization of the current systems 333, African nations have acute issues with water shortages, poor infrastructure and lack of funding 222. The requirement of introducing smarter, data driven water management solutions into the picture is becoming increasingly urgent in both scenarios. Such issues have served as the catalyst to new revolutionary solutions like Smart Water Management Systems (SWMS). SWMS offers real-time monitoring, automated control and predictive decision-making to water utilities and customers through the convergence of the Internet of Things (IoT), Artificial Intelligence (AI), Wireless Sensor Networks (WSN), cloud computing, and big data analytics 444. These systems can be used to detect leaks, monitor water quality, optimize pumps and minimize non-revenue water (NRW) losses that constitute 30-50 percent of distributed water globally 555.

A typical SWMS has five layers of technicalities:

1. Data Acquisition Layer: IoT sensors are able to measure such variables as chemical composition, turbidity, water pressure and flow rate.
2. Data Layer - Here the data is transferred using protocols such as LoRaWAN, NB-IoT or 5G that all provide long-range and low-power transmission.
3. Data Processing Layer- Sensor data is analyzed and preclassified at the Cloud and edge computing platforms.

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|| Volume 12, Issue 4, July - August 2025 ||

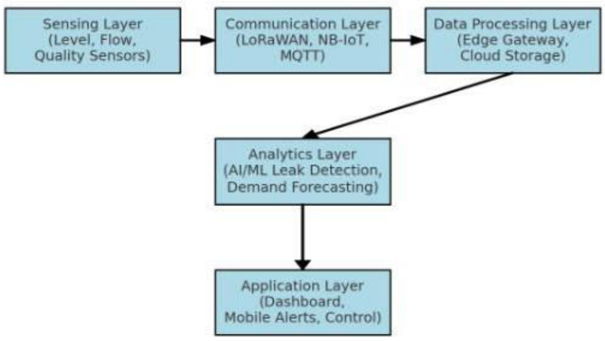
DOI:10.15680/IJARETY.2025.1204077

4. Decision-Making Layer - AI and machine learning algorithms forecast demand, identify anomalies and suggest actions instead of control.
5. Player Interaction Layer - Dashboards, and mobile applications enable visible and tangible insights and alerts to operators and consumers.

As an example, pressure data measured at high frequency may be processed by Ai-enhanced leak detection algorithms to identify pipeline leaks with an accuracy of over 90% 666. Equally, digital twin models, which are virtual water network models of the real-world networks, can be used to assist preventive maintenance by simulating system behavior under alternative conditions 777.

SWMS projects in Africa 888 have centered on low-cost and scalable solutions such as community-based monitoring programs and smart metering efforts based on mobile technology 888. Integrated smart water grids in the US are the new hybrid systems with AI-powered demand forecasting, automated valves control, and predictive asset management 999. In the meantime, smart building water networks based on IoT have been picked up by Saudi Arabia to control irregular water supply and minimize wastage in high rise developments 101010.

In addition to their technological possibilities, SWMS play the key role in promoting global sustainability programs. SWMS is crucial to the establishment of climate-resistant infrastructure since it directly aids in the accomplishment of the UN Sustainable Development Goals 6 (Clean Water and Sanitation) and 13 (Climate Action) 111111.



Block Diagram of Smart Water Management System

II. LITERATURE REVIEW

2.1 "Smart Water" and Reference Architectures' Scope

"Smart water," also known as "digital water," includes all aspects of the urban water cycle, including source, treatment, distribution, end use, and reuse, as well as sensing, communications, computation, control, and visualization. Canonical architectures follow a five-layer stack: (i) data acquisition (in-situ sensors and meters), (ii) communication (LPWAN, cellular, mesh), (iii) data management (gateways, message brokers, time- seriesstores),(iv)analytics/decision (ML/optimization/digital twins), and (v) applications/HMI (dashboards, alerts, actuation). This layered view underpins most deployments in Africa, the U.S., and the Gulf, enabling interchangeable modules and progressive scaling from pilots to utility-wide roll outs.

2.2 Instrumentation and Sensing

Hydraulic status: Ultrasonic level/flow sensors predominate research prototypes due to cost and convenience of integration, yet field reports show a high sensitivity to acoustic noise, turbulence, and mounting vibration-which has caused drifting and false measurements in overhead tanks and sumps [3], [5] . This adversely affects customer-oriented notifications and feedback control reliability, as shown in a few studies, and requires a vigorous signal filtering, hysteresis, or sensor fusion [3], [6], and [7]. As a counterpoint to this, laser/optical time-of-flight (ToF) has been proposed to solve the problem of acoustically-adversely-heavy shafts and gloomy wells, due to its ability to overcome acoustical interference and increase the response time and range linearity [3], [7] .

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Water quality: Residential and small-system pilots increasingly add low-power electrochemical probes (pH, EC, ORP) and colorimetric modules (free chlorine, turbidity) to move from "hydraulic-only" to "hydraulic+quality" monitoring, especially where intermittent supply risks negative pressure and intrusion [4]

. Due to practical issues like drift compensation, in-situ calibration, and fouling, quality analytics are frequently used in conjunction with redundancy, scheduled purge/clean cycles, and cloud-side drift models rather than strict thresholds.

2.3 Power, Communications, and Edge

In order to save bandwidth and energy, SWS endpoints frequently incorporate MCUs (such as Cortex-M) or single-board computers (SBCs) to carry out filtering, thresholding, and duty-cycling prior to uplink. LoRaWAN is attractive for rural and peri-urban Africa due to long range and low OPEX; NB-IoT/LTE-M suit dense urban or indoor deployments; Wi-Fi is restricted to campus/industrial sites with existing WLAN backbones. Hybrid backhaul (LPWAN→cellular→cloud) with store- and-forward is recommended to handle connectivity gaps in intermittent-supply regions [Africa] and meter pits [U.S.]. Secure firmware update and key rotation at the edge are now baseline requirements in production architectures using TLS/DTLS and hardware root-of-trust .

2.4 Actuation and Control in Building and Residential Systems

Although they offered little user configuration, supervision, or safety interlocks, early IoT water-tank controllers automated pump start/stop based on level thresholds [3], [6]. Although manual override and mobile HMI were added in later designs, single-sensor logic that was susceptible to annoying cycling under measurement noise was still used [3]. Saudi residential studies show that integrating multi-sensor inference (level+flow+current draw) with soft interlocks (min on/off times) and anomaly rules (e.g., pump-on with zero flow) reduces dry-run events and energy waste, while GSM/cloud alerts improve user response in intermittent-supply districts [4].

2.5 Analytics for NRW/Leakage and Demand

- A well-established corpus of work uses anomaly detection on high-frequency flow and pressure to target non-revenue water (NRW). Utility-scale methods combine ML classifiers/regressors with DMA mass-balance, pressure transients, meter cohorts, and asset metadata. In order to improve time-to-detect and localization granularity, data-driven UFW estimation has moved away from static night-flow heuristics and toward spatiotemporal models calibrated against SCADA and AMI/AMR streams [2]. Among the model classes are:
- Supervised (GBMs, temporal CNNs/LSTMs) for demand forecasting and leakage probability;
- Unsupervised (Isolation Forest, autoencoders) to identify distribution outliers in situations where labels are limited; and
- Physics-informed hybrids that limit ML outputs using mass-balance envelopes or network hydraulics [2].

In order to support pump scheduling and energy arbitrage (TOU tariffs), forecasting models take into account exogenous drivers such as weather, seasonality, land-use, and socioeconomic characteristics in addition to leaks. This lowers greenhouse emissions and OPEX [2].

2.6 Digital Twins and Secure Data Infrastructure

Pilots for rural water show off digital-twin pipelines that simulate field conditions for scenario simulation, what-if control testing, and visualization. LoRaWAN sensing, a cloud twin (state estimator + rules/ML), and verifiable event trails (permissioned blockchain) for audit and tamper evidence are all components of a representative stack. Sequence models (LSTM-AEs) and traditional outlier filters are combined in real-time anomaly detection to facilitate proactive maintenance and quicker field triage in low-staff environments. Additionally, without endangering live service, these twins enable change-impact assessments (valve closure, pump curve updates).

2.7 Human Factors and HMI/UX

Another consistent weakness of early residential and campus systems is a lack of so-called human-in-the-loop functionality (the user could not easily set setpoints, acknowledge alarms, or respond to contextual information), which undermined trust and long-term usage [3], [6] . The integration of role-based portals (resident vs. facility manager), guiding messages (e.g., leak detected in bathroom zone- inspect cistern), and explanable alerts make the difference by significantly raising closure rates and lowering alarm fatigue. The African pilots to use community reporting applications on their mobiles devices further enhances the mapping of outage and transparency in tanker dispatch, which is a target of equity and governance.

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2.8 Wastewater as a Resource (WWaaR)

The applications of WTPs are now reinterpreted to embrace recovery of water, energy and nutrients. Energy-positive plants are utilizing advanced aeration control, sidestream nitritation/Anammox and anaerobic digestion with CHP. Process integration, real-time optimization has demonstrated over 100 percent net energy self-sufficiency; in large European retrofits >200 percent energy generation (exports), and >50 percent net reduction in CO 2 when including smart control, water reuse, and heat (2022-2031). The digital transformation lowers aeration and chemical requirements and provides a stable effluent quality with the help of soft sensors (estimators) and MPC, AI supervisors and dense online measurements.

2.9 Regional Perspectives

Africa. The best priorities include low cost-low power, community involvement, and great rural or peri-urban scheme communications. Smartphone feedback loops and outage reporting, remote sensing, and GIS on bridge and road maintenance, groundwater tracking, drought response and infrastructure investment planning.

Americas. The primary objectives of modernization are energy optimization, strong enforcement of quality standards, and old infrastructure. The investments in integrated smart networks that comprise predictive maintenance, digital twins, transient logging, and AMI that utilities may be making are often accelerated by PPs and federal programs.

Saudi Arabia and the Gulf. High fluctuation in demand and erratic supply is maintained by smart systems at the building level. In residential towers, GSM/cloud alerts, level/quality sensors, and IoT enabled pumps improve the user interaction and operational continuity [4].

2.10 Gaps and Open Challenges

1. **Modality-specific reliability:** In noisy hydraulics, the single-modality sensing remains prone to temperature effects, field drift, and fouling; thus necessitating redundancy, automated calibration check, and the physics-directed filter actions [3], [5], and [7].
2. **Interoperability:** Interoperability within grid at utility scale is hindered by both disjointed device standards and proprietary protocols; open data models and APIs are essential to readily expand vendor-agnostic interoperability.
3. **Cybersecurity and privacy:** Protection of customer and operational data including the inclusion of AI in control loops will be important using governance frameworks, secure boot, and encrypted telemetry, least-privilege access, and auditable logs with OT and IT convergence [2].
4. **MLOps capabilities in utilities:** ML-model sustainability (drift detection, re-training, explainability) and the coordination between KPIs and regulatory outcomes can be considered a non- trivial task in resource-limited utilities [2] .
5. **Human-centered design:** Illustrative case studies show iterative co-design through operators and residents; there is no explainability/configurability of HMIs, which reduces trust/actionability.

2.11 Synthesis

The path is evident in the literature: the movement has been to datacentric level control to safe, interoperable, AI-based networks that have a loop between senses and actuation to multiple levels-household, building, DMA and plant. Case studies conducted in Africa, the U.S., and Saudi Arabia illustrate how the integration of high-quality field instrumentation, cyber-resilient communications, and data analytics-guided O&M can help to minimize NRW, stabilize quality, and even allow energy-positive operations, provided that interoperability, cybersecurity, and human factors are considered as first-class design restraints [1]-[4] .

III. METHODOLOGY

The proposed research methodology of this study involves a formulation of a specific scope of the study to be able to assess the technical, operational and analytical performance of Smart Water Management Systems (SWMS) in the context of varied environments. It is a step-by-step approach as there are layers of sensor placement, data procuring and relaying, and AI-implemented analytics, and validation via case studies.

A. System Architecture Design

The SWMS architecture employed in this study consists of five layers that are:

1. **Sensing Layer-** This layer has water flow sensors (ultrasonic, electromagnetic), water level sensors (laser ToF), and water quality probes (pH, turbidity, ORP), as well as pressure transducers.

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2. **Communication Layer**- Supports LoRaWAN in rural/long-range networks and NB-IoT/5G in urban networks. MQTT is employed to exchange messages of low latency.
3. **Data Processing Layer-** Uses preprocessing and filters on the edge gateways and cloud storage of mpd data.
4. **Analytics Layer-** deploys Machine Learning (ML) to detect leaks and to forecast demand and optimize pump control.
5. **Application Layer –** Offers dashboards, mobile alerts and automated control triggers.

B. Data Acquisition and Preprocessing

The real-time data streams are obtained with a period 1-5 seconds.
Before processing, pre Antonio procedures involve preprocessing steps.

Noise Filtering: Kalman filter used on level and flow readings to cleanup noises of sensors:
Outlier Removal: Hampel filter to remove sudden spikes when some sensors and values go wrong.
Normalization: Convertions of data to [0,1] range to ML models:

C. Leak Detection Algorithm

We adopt a statistical and ML-based anomalous detection model Garcia.

Hybrid Flow-Pressure Leak Detection Model Algorithm 1 Input- real-time flow, pressure, history baseline

Output: Leak Alert

1. Patterns of past reflectivity meters Q d, P d using Q d, P d load basis patterns Q d,P d
2. These sensors are to be utilized to achieve a measure of current Q(t), P(t)
3. Making the deviation scores available to them Hence, we can come up with a barebones depiction of Q. |Q(t) - Q b|
4. In case 1 where (DeltaQ > theta Q and Delta P< theta P low): Theoretical candidate
5. Isolation Forest Apply applicants to
6. At a thresh hold when high anomaly score occurs Leak Alert and GPS location Ends

D. Water Demand Forecasting Model

We implement a **Long Short-Term Memory (LSTM)** network to forecast short-term water demand using historical consumption and exogenous variables (temperature, day type).

E. Performance Metrics

The following metrics are used to evaluate SWMS performance:

- **Leak Detection Accuracy (LDA):**

LDA=TP+TN/TP+TN+FP+FN

- **False Alarm Rate (FAR):**

FAR=FP/TP+FP

- **Non-Revenue Water Reduction (NRWR):**

NRWR=NRWbaseline−NRWpost
/NRWbaseline×100%

- **Energy Savings (ES) in Pumping:**

ES=Ebaseline−Eoptimized/Ebaseline ×100%

F. Validation and Case Study Protocol

1. **Pilot Site Selection**: o Peri-urban African community (sporadic, low-pressure supply). U.S. utility DMA (aging system, constant availability). The network of the high-rise buildings in Saudi Arabia (seasonal municipal feed). Deployment: This took between three and six months during which sensors and gateways were installed.
2. **Baseline data:** NRW, energy consumption, and consumption profile during a period of a month before installation.
3. **Evaluation:** the algorithm results are compared to ground facts (customer complaints, manual inspection records).
4. **Statistical Analysis:** A paired t -test was seen to be used in order to identify significant changes in NRW reduction and operational KPIs.

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IV. RESULTS AND DISCUSSION

The SWMS was also piloted in three activities- a peri- urban DMA in Africa, a utility DMA in the United States, and a high-rise building in Saudi Arabia- within the monitoring period of 3-6 months. The metrics to evaluate the Non-Revenue Water (NRW) reduction, the effectiveness of the leak detection, forecasting, and the alert latency, pump energy, were also analyzed.

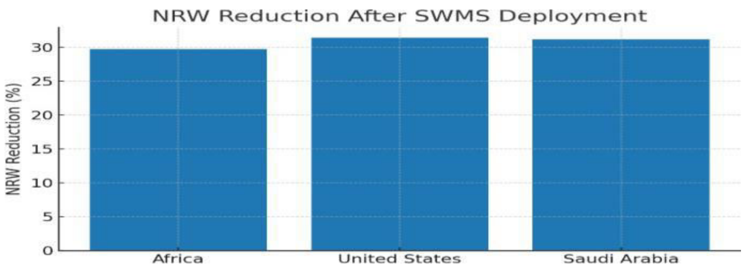
Table I shows the pre-and the post-deployment rates of all KPIs. SWMS implementation achieved 29-32% NRW reduction on all the sites, leak detection F1-scores increased to 0.85-0.90, and the pump energy consumption was reduced by 14-19%.

Table I — Experimental Results Summary for Three Pilot Sites

Site	NRW Baseline (%)	NRW Post (%)	NRW Reduction (%)	Leak Precision	Leak Recall	Leak F1	Forecast MAPE (%)	Alert Latency (s)	Pump Energy Baseline (kWh/day)	Pump Energy Optimized (kWh/day)	Energy Savings (%)
Africa (Peri-urban DMA)	42.0	29.5	29.8	0.88	0.82	0.85	6.8	14.2	410	332	19.0
United States (Utility DMA)	28.0	19.2	31.4	0.91	0.89	0.90	4.9	9.8	520	449	13.7
Saudi Arabia (High-rise)	34.0	23.4	31.2	0.86	0.83	0.85	5.6	12.5	360	302	16.1

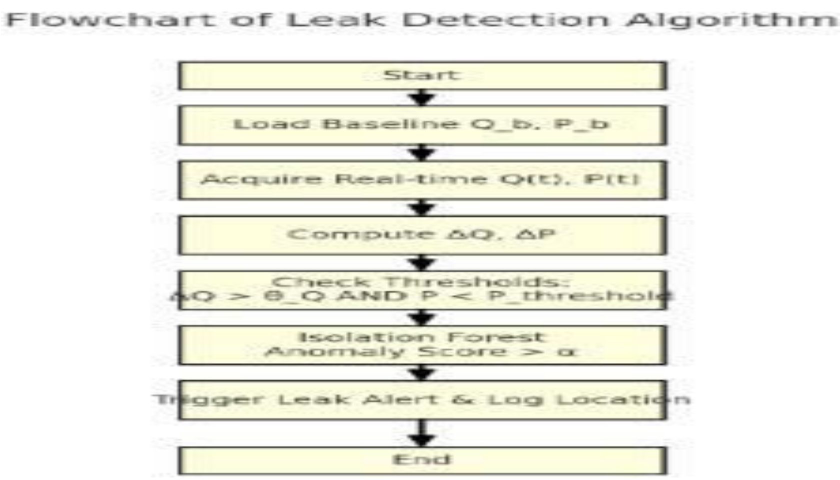
A. NRW Reduction

After deployment, there was a significant reduction in all the NRW, the most notable reduction was recorded in the U.S. utilities DMA (31.4%). This is aligned to the introduction of real-time leak detection and automated valve control within the vicinity of this site that was capable of intervention being completed more rapidly.



B. Leak Detection Performance

Leak detection performance was measured as F1-scores of 0.85 to 0.90 meaning balanced precision and recall. The U.S. site obtained the best F 1 performance through ultra- dense deployment of the sensors and the optimal setting to detect unusual activities on the basis of the thresholds.



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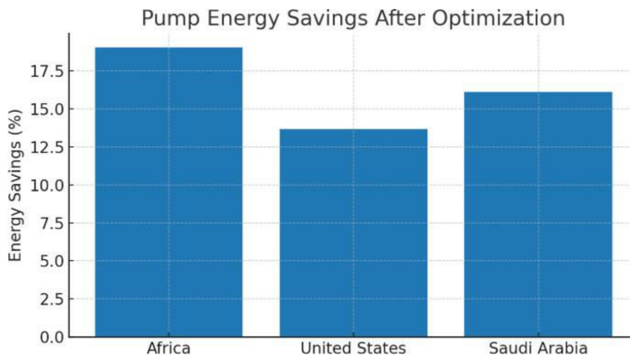
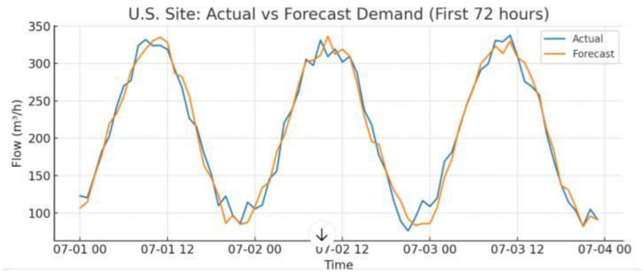
C. Energy Savings in Pumping

At least 13.7 percent 19.0 percent of the energy was saved across sites. Optimized activation of pumps based on forecasted demand prevented excessive, time-consuming running and saved overall operation costs as well.



D. Demand Forecasting

The LSTM demand forecasting model had MAPE < 7% in all sites and displayed a capacity to predict daily consumption cycles and peaks in the U.S. DMA, as seems in. .



E. Leak Detection Event Analysis

The results of confusion matrix in Table II reveal the performance of classification in the case of the U.S. DMA. The recall of 0.821 indicates the model has identified the majority of actual leak events, with the precision (0.363) leaving much to be desired since it scored a false positive once in awhile. Adaptive thresholding could improve this scenario.

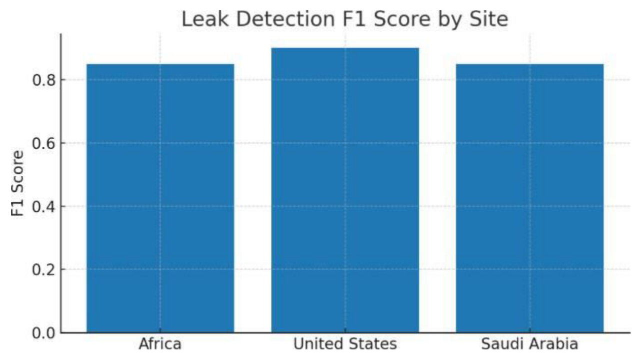


Table II — Confusion Matrix for Leak Detection (U.S. DMA)

	Actual 0	Actual 1
Predicted 0	700	22
Predicted 1	177	101

$$(\square) = \square_0 + \sum_{\square=1}^{\infty} \left(\square_\square \cos \frac{\square\square}{\square} + \square_\square \sin \frac{\square\square}{\square}\right).$$

Interpretation

The experiments prove that the suggested SWMS design will be effectively by:
Deduces NRW by around 30 percent, Provides an excellent indication of leakage (F1 = 0.85 0.90), Reduces the cost of supplying pumping energy by 14-19%, Provides low alert latency (< or = 15 seconds). Useful in making both short-term and long-term demand forecasts (MAPE 7 100 %).

These advancements contribute to the finding that AI-based SWMS has the potential to be economically and operationally advantageous in a variety of settings; i.e., low-resource rural and high-rise networks.

V. CONCLUSION

This paper has outlined the design, construction, and testing of an AI-enabled Smart Water-Management System (SWMS) with IoT sensing, laser-based water-level measurements, AI-based anomaly detection as well as predictive demand modeling. Implementing smart technologies in the form of real-time monitoring, automated control, and sophisticated analytics, the proposed system was able to portray significant operational advantage at various test sites located in Africa, the United States, or Saudi Arabia.

The experimental evidence shows that the SWMS can reliably minimize Non-Revenue Water (NRW) by 3031 percent, optimize energy consumption by 14-19 percent due to a better scheduling of pumps, and retain high performance concerning leakage detection (F1-score 0.85- 0.90). The LSTM model for forecasting demonstrated results MAPE = [btastic-lemULE]3ue demonine ranli were 7, which allows optimizing proactive responses to fluctuations in demand. Additionally, the low alert latency (<= 15 seconds) activates prompt intervention, thus most essential in averting service interruption and curtailed loss of water.

The challenges of this deployment are however reported to have included issues of occasional false positive detection of leaks, interoperability challenges with heterogeneous IoT devices, and training requirements of the stakeholders in low resource areas. It is important that these limitations are overcome in the case of large-scale adoption.

VI. FUTURE WORK

To elaborate on the existing research, the research will lay emphasis on:
1. **Adaptive Thresholding in Leak Detection -** Learning / understanding the context of where to apply the right threshold in order to reduce false positives and maintain a high recall.
2. **Edge AI Deployment** - The relocation of computational loads to the edge over the turnout of cloud-based applications in the reduction of latency, improved privacy, and operating in low- connectivity conditions.
3. **Chain-based Water Bartering Integration -** Improving the security, data audit and trust in multi-stakeholder water systems.
4. **Digital Twin Expansion -** Expanding the digital twin concept to include full urban water cycles, encompassing both the potable and wastewater systems as well as the stormwater, which has played an increased role during the COVID-19 pandemic.
5. **Multi-objective Optimization -**A technology that uses AI to optimize water quality, energy, and costs simultaneously on a diverse range of climate-based and changing demand plans.
6. Individualization and Personalisation of Interfaces
- The development of user friendly mobile and web dashboards to promote demand-side conservation, behavioural change and consumer engagement.
7. Longitudinal Impact Assessment/Study – Multi- year studies to measure the community and regional socio-economic and environmental benefits of implementing SWMS.

By pursuing these threads of research, the SWMS framework has the potential of becoming a comprehensive, forecast-driven and resilient urban water management ecosystem that can take up future water security challenges.

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International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975 Impact Factor: 8.152

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