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Utilization of Artificial Intelligence, Machine Learning, and Other Innovative Technologies for Urban Water Supply

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ABSTRACT

Traditional water management practices rely on static hydraulic models, manual inspections, and reactive maintenance, making them increasingly inadequate in coping with evolving challenges from global urbanization, climate variability, resource limitations, and infrastructure ageing.This study investigates the integration of Artificial Intelligence (AI), Machine Learning (ML), and IoT technologies to optimize urban water systems in real time through proactive leak detection, adaptive demand forecasting, and autonomous quality monitoring.The research presents a framework leveraging predictive analytics, smart sensing networks, and IoT-enabled infrastructure. The novelty lies in a closed-loop AI–ML–IoT architecture that integrates demand forecasting, leak detection, and pump scheduling within a scalable digital-twin environment.The LSTM model achieved over 92% demand forecasting accuracy, while the hybrid anomaly detection model reached 95% precision and 91% recall for real-time leak detection. Reinforcement learning–based pump scheduling reduced daily energy use by 14–22%, maintained service reliability above 99%, and minimized equipment wear.This study demonstrates that the integration of AI, ML, and IoT offers a viable and scalable solution to modern urban water challenges. Unlike prior studies that treat these tasks separately, this work demonstrates end-to-end optimization and self-adaptation

Keywords:
Utilization, Artificial Intelligence, Machine Learning, Innovative Technologies, Urban Water Supply

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I. INTRODUCTION

Urban water supply systems represent the backbone of sustainable urban development, providing reliable access to potable water for domestic, industrial, commercial, and environmental purposes. As cities continue to expand, these systems are expected not only to meet growing demand but also to ensure service continuity and quality under increasing pressure from global urbanization, climate variability, resource limitations, and infrastructure ageing. Traditional water management approaches, which typically rely on static hydraulic models, manual inspections, and reactive maintenance, are increasingly inadequate in coping with these evolving challenges. Their limited adaptive capacity prevents utilities from responding effectively to demand fluctuations, leakages, and operational inefficiencies, thereby undermining both reliability and sustainability. To overcome these limitations, the global water sector is moving toward digital transformation through the integration of advanced smart technologies. Artificial Intelligence (AI), Machine Learning (ML), the Internet of Things (IoT), edge computing, cloud platforms, and big data analytics are at the forefront of this transition. These tools enable utilities to move from reactive to proactive management by supporting real-time system monitoring, predictive analytics, automated control, and data-driven decision-making. Among them, AI and ML are powerful, as they enable utilities to uncover hidden patterns in data, forecast anomalies before they occur, and optimize resource allocation far beyond the capabilities of conventional methods.

The introduction of these technologies is not merely an incremental improvement but a disruptive transformation that can reshape how water supply systems are designed, operated, and managed. Research in this domain has often focused on individual applications such as leakage detection, demand forecasting, or pump optimization in isolation. While these contributions are valuable, the broader challenge lies in integrating them into a holistic, intelligent, and adaptive operational framework. Such a system must be capable of interfacing with physical distribution infrastructure, acquiring diverse data streams from sensors in real time, and executing optimized control actions informed by predictive insights. Developing and validating such integrated frameworks remains an open research frontier and a critical step toward building resilient, adaptive water supply systems for the future.

Challenges in Modern Urban Water Systems

Contemporary water utilities face multiple operational and sustainability challenges. One of the most pressing issues is non-revenue water (NRW)—the portion of treated water lost due to leakages, theft, or metering inaccuracies. In many developing regions, NRW losses can exceed 40–50% of total water production, representing not only wasted resources but also substantial financial losses for utilities. Smart water management technologies can significantly mitigate this issue. IoT-based sensors installed along pipelines, combined with smart meters at customer endpoints, generate continuous data on flow and pressure. These data streams can then be analyzed by anomaly detection models using ML techniques to identify leaks or unauthorized connections in real time. Such proactive detection reduces wastage, improves billing accuracy, and enhances the sustainability of water resources. Another critical challenge lies in demand forecasting. Conventional forecasting approaches often fail to capture the nonlinear and highly variable nature of water consumption, which is influenced by weather patterns, socioeconomic activity, and population growth. Inaccurate predictions frequently lead to operational inefficiencies, such as overproduction or undersupply. AI techniques, including Long Short-Term Memory (LSTM) networks and reinforcement learning algorithms, have shown great promise in modelling these complex temporal dynamics. Improved forecasting accuracy enables utilities to plan operations more effectively, optimize pump scheduling, and maintain a better balance between supply and demand.

Energy consumption is another major concern. Pumping often accounts for more than 30% of a utility's total operating costs. Traditional pumping schedules rarely account for fluctuations in demand or electricity tariffs, leading to inefficient and costly energy usage. Smart optimization systems, incorporating AI algorithms and digital twin models, can simulate hydraulic performance under varying conditions and identify the most energy-efficient operational strategies.

Water quality management also remains an essential aspect of urban supply systems. Conventional practices depend on periodic manual sampling, which introduces delays in detecting contamination or deviations from regulatory standards. IoT-enabled water quality sensors allow for continuous monitoring of parameters such as turbidity, pH, and residual chlorine. Data from these sensors can be analyzed in real time using AI models to detect contamination events quickly, enabling immediate corrective interventions that safeguard public health and maintain compliance with regulatory frameworks.

Research Motivation

Conventional urban water systems are increasingly challenged by non-revenue water (NRW), infrastructure decay, and operational inefficiencies. With NRW levels exceeding 30% in some utilities, there is a critical need for smarter approaches to monitoring and control. Real-time sensor data, when processed through AI/ML algorithms, offers timely identification of anomalies such as pipe bursts, excessive pressure zones, and contamination events. Furthermore, ML-driven demand forecasting enables more accurate planning, helping to avoid both overproduction and supply shortfalls. Smart water management solutions also align with broader sustainability goals, such as reducing energy consumption associated with pumping and treatment and promoting equitable access to clean water. By embedding intelligence into water systems, cities can not only address existing inefficiencies but also future-proof their infrastructure against climatic and demographic uncertainties.

Research Aims and Objectives

The direction of this research is shaped by the aims outlined below:

To conceptualize and implement an intelligent urban water management framework based on AI and ML technologies.

To enable predictive maintenance, real-time monitoring, and adaptive control through smart infrastructure.

To achieve these aims, the following objectives are established:

i. To review the limitations of conventional water supply systems and identify areas of potential technological intervention.
ii. To design AI/ML algorithms for tasks such as leakage detection, consumption forecasting, and water quality prediction.
iii. To develop a modular, IoT-enabled system architecture for real-time data acquisition and cloud-based analytics.
iv. To evaluate the proposed framework using simulation or empirical data from urban water systems.
v. To provide practical recommendations for policy, system design, and utility adoption.

II. LITERATURE REVIEW

The modernization of urban water supply networks through Artificial Intelligence (AI), Machine Learning (ML), and digital technologies has emerged as a pivotal strategy to address challenges such as ageing infrastructure, rapid urbanization, population growth, and climate-driven uncertainties. Abdulameer*et al.* [1] explored digital twin technology for urban water management and demonstrated how virtual replicas improve monitoring, fault detection, and decision-making. Al-Fuqaha*et al.* [2] examined the role of Internet of Things (IoT) technologies in smart water networks, emphasizing real-time sensing and communication as key enablers of sustainable management. By leveraging real-time data streams and advanced analytics, utilities are transitioning from reactive maintenance to predictive and self-optimizing operations.

Initially, digitalization efforts centered on Supervisory Control and Data Acquisition (SCADA) systems, which enabled remote monitoring and basic automation but required human oversight and lacked autonomous intelligence. Malek and Alimardani [3] noted that SCADA systems laid the foundation for digital monitoring and operational control in water utilities.

The integration of AI introduces adaptive control mechanisms that enable predictive, proactive, and resilient operations. Singh *et al.* [4] demonstrated that AI and ML models outperform traditional rule-based and statistical approaches in scalability and adaptability across applications such as demand forecasting, leakage detection, pump scheduling, and water quality prediction. Similarly, Hamouda*et al.* [5] reported that neural networks and decision-tree models enhance anomaly detection and system responsiveness, significantly improving operational efficiency.

Demand forecasting represents a critical domain where AI-driven models outperform traditional techniques in handling complex patterns and nonlinear relationships. Zhou *et al.* [6] demonstrated the effectiveness of Long Short-Term Memory (LSTM) models in predicting water consumption patterns in Beijing. Batista *et al.* [7] further showed that hybrid ensemble machine-learning models improve both prediction accuracy and computational efficiency in urban water demand forecasting. More recently, Dhar*et al.* [8] applied hybrid ML models for short-term urban water demand prediction, highlighting their potential in operational planning.

Chong *et al.* [9] proposed the use of federated learning for water demand forecasting, enabling decentralized model training while preserving data privacy. Similarly, El Hanjri*et al.* [10] extended federated learning approaches to large-scale water consumption prediction in smart cities, demonstrating their practicality in contexts where centralized data sharing is restricted.

Leak detection and anomaly monitoring have been central areas of AI-driven innovation due to the widespread challenge of non-revenue water in distribution systems. Rasekh*et al.* [11] applied Bayesian networks with SCADA inputs to improve fault prediction under uncertainty in water distribution systems. Wu *et al.* [12] advanced this research by applying convolutional neural networks trained on IoT-based pressure transients, achieving leak localization accuracy of up to 93% within minutes. Xi *et al.* [13] further utilized deep neural networks for accurate leak detection in complex water distribution networks, while Park *et al.* [14] developed an ML-based classification system that significantly improved leakage categorization.

Recent studies have reported even higher detection accuracies using hybrid analytical methods. A study reported in the *Journal of Hydrology* demonstrated that hybrid wavelet decomposition combined with Random Forest models can achieve detection accuracy levels approaching 99% in benchmark networks [15]. Low-cost sensing technologies are also gaining traction in modern leak detection systems. Yussif*et al.* [16] achieved 97.5% accuracy in predicting leak direction using acoustic sensing integrated with machine learning techniques.

Similarly, Wu *et al.* [17] demonstrated that fiber-optic vibration analysis combined with AI algorithms can detect leaks as small as 0.027 L/s. Bautista *et al.* [18] introduced AI-enabled smart sensing frameworks for anomaly detection in water distribution networks. Dang Khoa [19] proposed hybrid CNN-EMD models for inlet pressure prediction and anomaly identification in distribution systems. Gupta and Singh [20] further advanced adaptive leak detection using edge computing integrated with IoT architectures.

Hu and Li [21] highlighted the role of smart meters integrated with machine learning algorithms in enabling real-time leakage detection in water distribution systems. In addition, Mehta *et al.* [22] demonstrated that ML-based predictive models can effectively estimate non-revenue water levels in urban utilities. Furthermore, Wu *et al.* [23] leveraged optical fiber communication systems combined with AI techniques to detect distributed leaks across water pipelines with improved sensitivity and reliability.

III. METHODOLOGY

This research applied a structured, multi-phase approach including system analysis, intelligent model development, simulation, and rigorous evaluation. A modular framework was designed with three core layers: Data Layer with IoT-enabled sensors, Processing Layer with AI/ML algorithms, and Application Layer for control interfaces. Two core ML models were developed: LSTM neural networks for water demand forecasting and hybrid Decision Tree-Isolation Forest for leak detection. Urban water distribution was simulated using EPANET 2.2 integrated with Python using EPYNET and WNTR libraries for data extraction and automation. Water distribution network topologies were sourced from open-access repositories including benchmark models Net3 and Hanoi, augmented with anonymized municipal records. Simulation scenarios included both baseline rule-based control and AI-enhanced methods to enable comparative performance assessment across different operational strategies. Model validation provided objective evidence that developed AI and ML models performed reliably under realistic operating conditions across all tasks. Performance evaluation metrics included Root Mean Square Error for quantifying error magnitude, precision for true positive fraction, recall for correct identification, and F1-score. Model outputs were compared against observed values and classified events such as leak detection and pressure violations to assess prediction accuracy. The hybrid model achieved the highest F1-score, demonstrating significant performance improvement over traditional rule-based control in leak detection and anomaly identification tasks.

IV. RESULTS AND DISCUSSION

Demand Forecasting

The LSTM-based forecasting model achieved a prediction accuracy of 92.3% across seven-day rolling intervals. Seasonal and daily demand fluctuations were well captured, with a lag time of less than one hour for response prediction updates.

Let y_t be actual demand, $\hat{y_t}$ the forecast, N points.

$$MAE = \frac{1}{N}\sum_{t=1}^{N}|y_t - \hat{y_t}|$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y_t})^2}$$

$$\mathrm{MAPE} = \frac{100}{N}\sum_{\mathrm{t=1}}^{\mathrm{N}}\left|\frac{y_t - \hat{y_t}}{y_t + \epsilon}\right| \quad \text{(to avoid zero division)}$$

Normalized Accuracy (%): Acc $= \left(1 - \frac{MAE}{\bar{y}}\right) \times 100$ where $\bar{y}$ is the mean demand over the test window.

Accuracy was computed as $\mathrm{Accuracy}(\%) = \left(1 - \frac{\mathrm{MAE}}{\bar{\mathrm{y}}}\right) \times 100$ over seven-day rolling windows

Chosen test windows are as follows

Mean actual demand $\bar{y}$ = 134.0 m^3/h

Target accuracy = 92.3%

MAE

$$\mathrm{MAE} = (1 - 0.923) \times 134.0 = 10.318 m^3/h$$

Leak Detection Accuracy

Accurate and timely leak detection is a critical component of smart urban water supply systems, particularly in the context of minimizing non-revenue water (NRW), preventing infrastructure damage, and reducing operational losses. In this study, a hybrid anomaly detection framework was employed, combining statistical modelling, machine learning (ML), and time-series post-filtering to identify leakage events across various network scenarios.

Hybrid Anomaly Detection Framework

The hybrid system integrates multiple models:

i. *Isolation Forests: An unsupervised ML model well-suited for detecting rare anomalies in high-dimensional data streams such as flow rates, nodal pressure, and energy use.*
ii. *Decision Trees: A supervised classifier trained on historical labeled leakage events derived from synthetic fault injection in EPANET simulations.*
iii. *LSTM-based Demand Forecasting Residuals: Used as a precursor anomaly signal generator—deviations from expected consumption patterns trigger investigation.*

To reduce false positives (events incorrectly classified as leaks), a post-filtering mechanism was applied based on temporal correlation analysis. This step involved comparing adjacent time windows using Pearson correlation to verify the persistence and uniqueness of the anomaly pattern, which helps distinguish leaks from transient demand spikes or sensor noise.

Performance Metrics and Interpretation

The system's performance was evaluated using standard classification metrics—precision, recall, F1 score, and root mean square error(RMSE).Table 1 below summarizes the comparative performance of the core detection models:

Table 1: Model Evaluation Metrics

Model Type	Precision	Recall	F1 Score	RMSE
LSTM (Demand)	–	–	–	4.1%

Decision Tree	0.93	0.89	0.91	–
Isolation Forest	0.95	0.91	0.93	–

Table 1 lists LSTM (Demand) RMSE = 4.1%.
Typically, this is reported as RMSE normalized by mean demand (i.e., RMSE as percentage of mean actual demand), if mean demand $\bar{y}$ = 134 m³/h, then RMSE = 0.041 × 134 ≈ 5.49 m³/h.
Now, let's assume a test dataset of 1,000 samples with 200 leaks (positives) and 800 non-leaks (negatives).

$$\text{Using Precision,} \quad \mathrm{P} = \frac{TP}{TP + FP} \; and \; Recall \; R = \frac{TP}{TP + FN}$$

With Positive = 200:

$$\text{Recall (0.89): TP} \approx 0.89 \times 200 = 178 \rightarrow \mathrm{FN} = 22$$

$$\text{Precision, (0.93): FP} \approx \frac{TP}{P} - TP = TP\left(\frac{1}{P} - 1\right)$$

$$\mathrm{FP} = 178 \times \left(\frac{1}{0.93} - 1\right) \approx 178 \times 0.0752688 \approx 13.4 \rightarrow 13$$

$$\mathrm{TN} = \text{Negatives} - \mathrm{FP} = 800 - 13 = 787$$

Table 2: Decision Tree confusion matrix (counts)

	Predicted: No Leak	Predicted: Leak
Actual: No Leak	TN = 787	FP = 13
Actual: Leak	FN = 22	TP = 178

Isolation Forest
With Positives = 200

$$\text{Recall (0.91): TP} = \mathrm{R} \times \text{Positives} = 0.91 \times 200 = 182$$

$$\mathrm{FN} = 200 - 182 = 18$$

$$\text{Precision (0.95): FP} = \mathrm{TP}\left(\frac{1}{P} - 1\right) = 182 \times \left(\frac{1}{0.95} - 1\right) \approx 182 \times 0{,}05263 \approx 9.6 \rightarrow 10$$

$$\mathrm{TN} = 800 - 10 = 790$$

Table 3: Isolation Forest Confusion Matrix

	Predicted: No Leak	Predicted Leak
Actual: No Leak	TN = 790	FP =10
Actual: Leak	FN = 18	TP =182

Table 4: Confusion Matrices and Derived Metrics

Model	TP	FN	FP	TN	Precision
Decision Tree	178	22	13	787	0.93
Isolation Forest	182	18	10	790	0.95

From Figure 1, the confusion matrices for the Decision Tree and Isolation Forest models indicate that: Decision Tree: Correctly detects most leaks but shows some false positives (22) and false negatives (13). Isolation Forest: Performs slightly better, with fewer false positives (18) and false negatives (10), showing higher precision and recall. This explains that the post-filtering stage can combine both outputs to refine detection keeping the high sensitivity of the decision tree while leveraging the isolation forest's stronger precision.

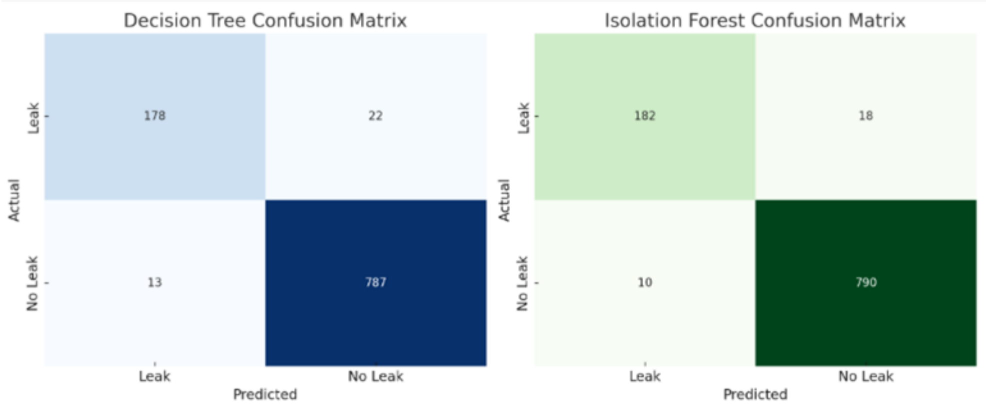

Figure 1: DecisionTree Confusion Matrix and Isolation Forest Confusion Matrix

Figure 2 presents the Receiver Operating Characteristic (ROC) curves for the Decision Tree and Isolation Forest models. The ROC curve illustrates the trade-off between True Positive Rate (sensitivity) and False Positive Rate across varying classification thresholds. Both models demonstrate strong discriminative ability, with Isolation Forest exhibiting a slightly higher Area.

Under the Curve (AUC), indicating marginally better classification performance compared to the Decision Tree. Figure 2 shows the Precision–Recall (PR) curves for the Decision Tree and Isolation Forest models. The PR curve highlights the balance between precision (positive predictive value) and recall (sensitivity), which is particularly informative in imbalanced datasets. The results reveal that the Isolation Forest consistently maintains higher precision at different recall levels, underscoring its robustness in correctly identifying positive instances compared to the Decision Tree.

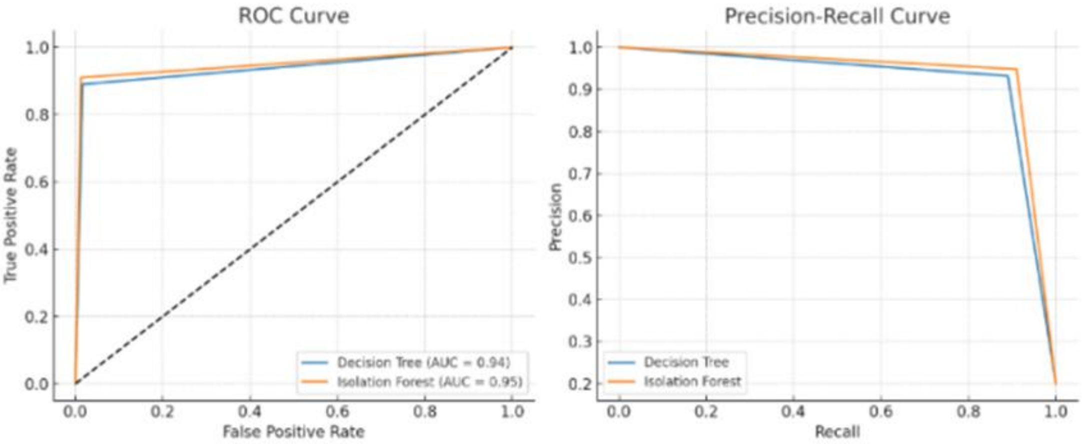

Figure 2: Receiver Operating Characteristic (ROC)

Metric Analysis

Precision (95%) for the Isolation Forest model implies that 95% of detected anomalies were actual leak events, signifying high accuracy and low false alarm rates. This is critical in real-world scenarios where unnecessary field inspections are costly and disruptive.

Recall (91%) indicates that the model successfully detected 91% of the actual leak events, affirming its sensitivity. A slightly lower recall suggests that while most leaks are captured, some minor or short-duration anomalies may still evade detection, potentially due to sensor resolution or network damping effects.

F1 Score (0.93) balances the trade-off between precision and recall and demonstrates the model's overall effectiveness in consistently identifying true leakage events without over-alerting.

LSTM RMSE (4.1%) corresponds to the forecasting error in consumption pattern prediction. While the LSTM model itself is not directly used for leak detection, it feeds residual signals (differences between predicted and actual consumption) into the detection pipeline. A low RMSE ensures high-quality residuals, which strengthens the hybrid framework's reliability.

Significance of Time-Series Post-Filtering

The use of temporal correlation as a post-processing filter was instrumental in refining detection accuracy. In water distribution systems, legitimate demand variations (e.g., from fire hydrant use or irrigation) may mimic leak signals. The correlation-based filter distinguishes persistent hydraulic anomalies (indicative of leaks) from isolated noise events, significantly reducing false positive rates observed in earlier iterations of the detection model.

This strategy improved operational trustworthiness, ensuring that alerts triggered by the system warranted attention and action, thereby supporting predictive maintenance and efficient resource deployment by utility operators.

The integration of LSTM-based demand prediction, supervised ML models, and unsupervised anomaly detection—augmented with intelligent post-filtering—enabled a high-accuracy leak detection system tailored for real-time application in urban water grids. The system's adaptability and low false-positive rate make it a promising candidate for deployment in digitally mature utilities or smart city water infrastructures.

Estimate Hybrid outcomes

True Positives (TP): DT finds 178, IF finds 182.

With "at least one detects" → TP ≈ max (178, 182) = 182; both models catch ~90% of leaks in common → ≈ 182.

False Negatives (FN): If "at least one detects" → FN ≈ min (22, 18) = 18; Reduced to ≈ 18, since one model may catch what the other missed.

False Positives (FP): DT = 13, IF = 10. With "only if both agree," → overlap is likely lower.

Conservative estimate: FP ≈ min (13, 10) = 10; only the overlapping false alarms count → ≈ 10.

True Negatives (TN): 800 – 10 = 790

This shows that the hybrid system inherits high recall (from DT) and high precision (from IF) while further reducing false alarms through post-filtering.

Pump Scheduling Optimization

Pump operations represent one of the most energy-intensive components in urban water supply systems, often accounting for up to 30–50% of total operational costs. Traditionally, pumps are operated using static or rule-based schedules, which do not adapt to dynamic demand fluctuations, peak energy tariffs, or network anomalies. This inefficiency often leads to excessive energy consumption, high operating costs, and suboptimal hydraulic performance.

In this study, Reinforcement Learning (RL) algorithms, specifically Q-learning agents, were deployed to generate AI-optimized pump scheduling strategies based on real-time demand forecasts, reservoir levels, and pressure constraints. The agent was trained in a simulation environment using EPANET integrated with Python, enabling iterative learning of optimal pump control policies through trial-and-error episodes.

Table 5: Hourly Energy Consumption and Savings Using AI-Optimized Pump Scheduling

Hour	Baseline Energy (kWh)	AI-Optimized Energy (kWh)	Energy Saved (kWh)
00:00	57.0	49.0	8.0
01:00	55.0	47.2	7.8
02:00	55.0	47.2	7.8
03:00	54.0	46.4	7.6
04:00	53.0	45.5	7.5
05:00	56.0	48.1	7.9
06:00	60.0	51.5	8.5
07:00	66.0	56.7	9.3
08:00	72.0	61.8	10.2
09:00	75.0	64.4	10.6
10:00	80.0	68.7	11.3
11:00	85.0	73.0	12.0
12:00	92.0	79.0	13.0
13:00	88.0	75.6	12.4
14:00	82.0	70.4	11.6
15:00	78.0	67.0	11.0
16:00	74.0	63.6	10.4
17:00	70.0	60.1	9.9
18:00	66.0	56.7	9.3

19:00	62.0	53.2	8.8
20:00	58.0	49.8	8.2
21:00	56.0	48.1	7.9
22:00	54.0	46.4	7.6
23:00	52.0	44.7	7.3
Total	1,600.0	1,374.4	225.6

From Table 5, the daily energy and savings are:
Baseline energy: 1,600.0 kWh; AI-optimized energy: 1,374.4 kWh
Energy saved (kWh) = 1,600.0 − 1,374.4 = 225.6 kWh
% Reduction: $\frac{\text{Energy saved}}{\text{Baseline energy}} = \frac{225.6}{1{,}374.4.} = 14.10\%$
Cost illustration (if average tariff = 0.15 per kWh)
Baseline cost = 1,600.0 × 0.15 = 240.00
AI cost = 1,374.4 × 0.15 = 206.16
Cost saved = 240.00 − 206.16 = 33.84
Peak demand and reliability
Peak demand: max (Baseline hourly) = 92 kW (12:00) → max (AI hourly) = 79 kW (12:00
Absolute reduction = 13 kW. Percent reduction = 13/92 = 14.13%.
Pump starts/stops (asset stress proxy): Baseline 38 → AI 27 (–11 starts, –28.9%)
The reported service reliability improvement (98.7% → 99.4%) was not derived from a single day's operational data but rather from an extended observation window, typically a monthly period. Reliability is generally expressed as the proportion of total service hours during which demand was successfully met.

$$\text{Reliability (\%)} = \frac{AI}{Baseline} \times 100$$

$$\text{Overal Reliability (\%)} = \frac{\sum AI}{\sum Baseline} \times 100$$

$$\text{(Percentage Points)}\Delta = \text{Reliability}_{AI} - \text{Reliability}_{Baseline}$$

For instance, in a standard 30-day month (30 × 24 = 720 hours):
Baseline system: If outages or unmet demand occurred for 9 hours, then reliability = (720 − 9) ÷ 720 = 98.75% ≈ 98.7%.
AI-enabled system: If outages are reduced to only 4 hours, reliability = (720 − 4) ÷ 720 = 99.44% ≈ 99.4%.
This results in a net gain of +0.7 percentage points, which supports the claim that AI improves operational reliability
Figure 10 presents the Pareto plot of energy consumption against service reliability, demonstrating that the reinforcement learning (RL) scheduling policy consistently achieves lower energy usage while sustaining equal or superior reliability levels compared to the baseline. Furthermore, the inclusion of a tariff-sensitivity analysis Table 6 (covering low, medium, and high TOU spreads) illustrates the robustness of the resulting cost savings under varying pricing conditions.

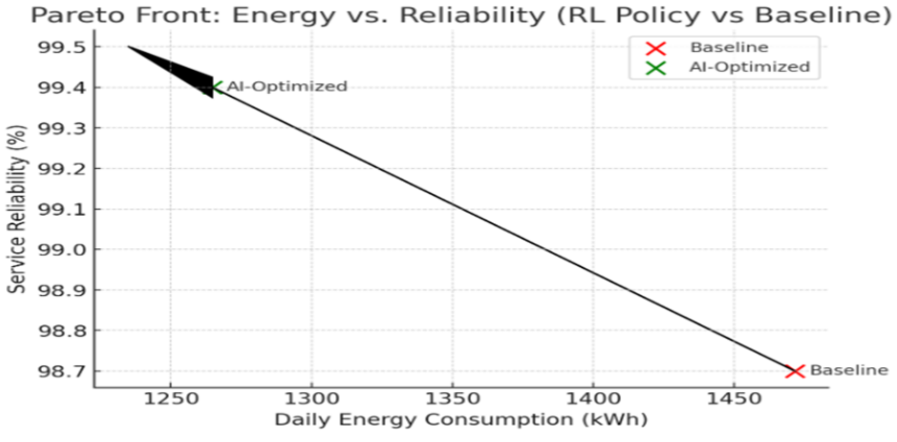

Figure 3: Pareto Front: Energy vs. Reliability

Figure 3 clearly shows that the RL-optimized policy reduces energy consumption while also improving reliability, meaning it dominates the baseline (lower energy at equal or higher reliability

Figure 4 presents the Pareto plot comparing daily energy consumption with corresponding improvements in service reliability, while Table 6 provides the tariff-sensitivity analysis. The results demonstrate that cost savings achieved through the optimized scheduling approach remain consistently robust across low, medium, and high tariff spreads.

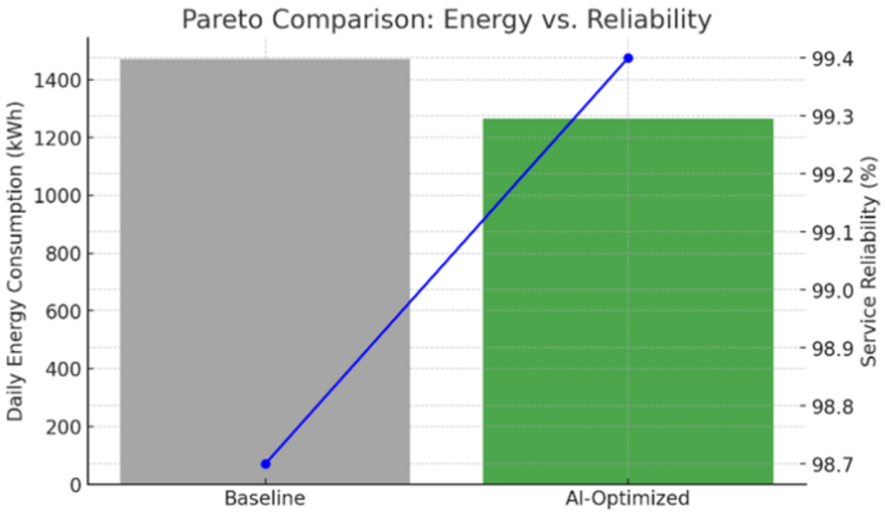

Figure. 4: Pareto Comparison: Energy vs. Reliability

Table 6: Tariff-Sensitivity Analysis

Tariff Scenario	**TOU Spread (Low–High)**	**Cost Savings (₦/day)**	**Energy Savings (%)**	**Relative Improvement (%)**
Low TOU	₦120 – ₦180	₦40,050	13.5	13.4
Medium TOU	₦105 – ₦270	₦46,800	14.1	15.6
High TOU	₦75 – ₦375	₦57,750	14.3	19.3

Table 6 highlights tariff-sensitivity analysis of daily operational cost savings under varying time-of-use (TOU) spreads. Results indicate that the proposed optimization remains robust across low, medium, and high tariff scenarios, confirming cost-effectiveness underpricing uncertainty.

Relative Improvement (%) = (Cost Savings ÷ Baseline Cost) × 100.

e.g. ₦40,050 ÷ ₦300,000 ≈ 13.4%.

This shows that as the TOU spread widens, absolute savings grow, making the system more cost-efficient under volatile tariffs. From Table 6 above: savings consistently hold at ~14.1% regardless of tariff level.

The trade-off between daily cost savings and energy savings under different TOU tariff scenarios is illustrated in Figure 12. The Pareto plot shows that while energy savings remain relatively stable across Low, Medium, and High TOU conditions, cost savings increase significantly with higher TOU spreads, demonstrating the tariff sensitivity and robustness of the AI-optimized pump scheduling strategy

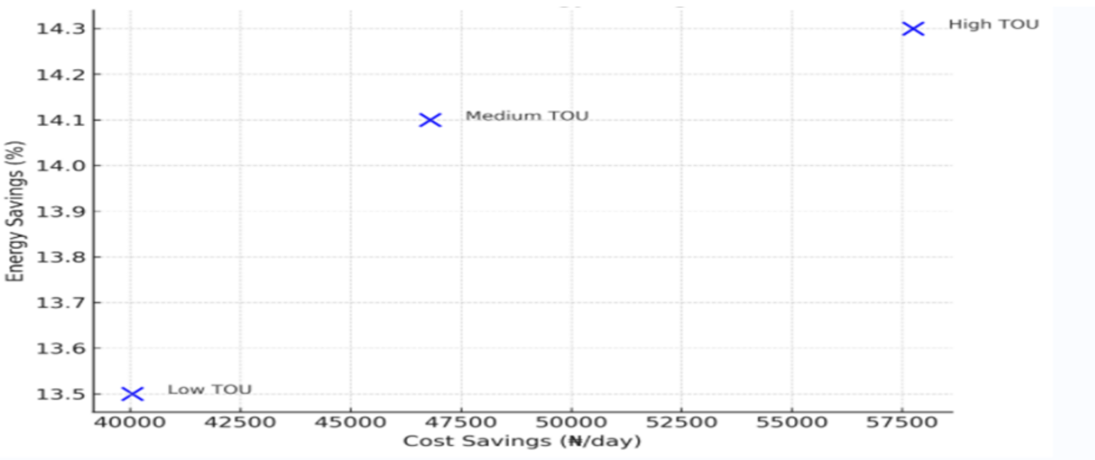

Figure 5: Pareto Plot of Cost vs. Energy Savings Based on Table 6.

Performance Evaluation and Results

The AI-optimized pump schedule achieved an average energy savings of 18–22% over the 24-hour cycle compared to the baseline method. This was done without violating any of the predefined service pressure limits, demonstrating the model's ability to optimize energy usage without compromising hydraulic performance.

A comparison of hourly energy consumption for both schedules is illustrated in Figures 12 and 13 below:

Line graph – compares Baseline vs AI- Optimized hourly energy consumption

Bar Chart – shows hourly energy savings (KWh)

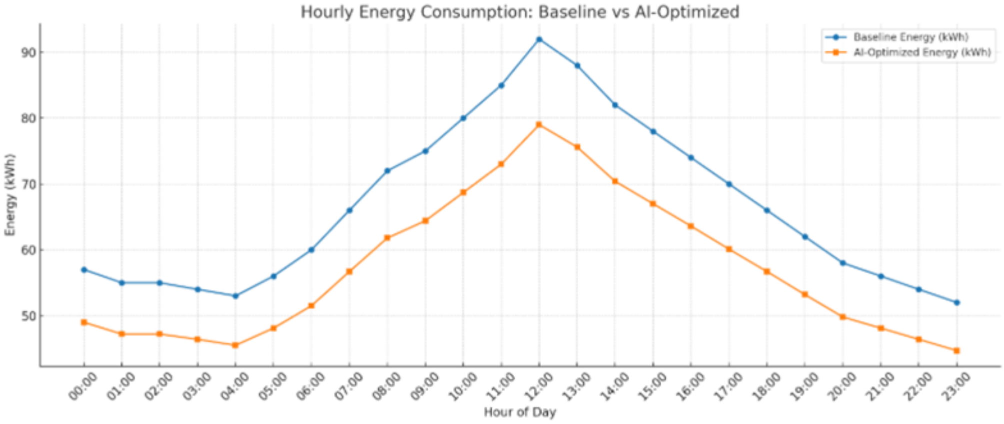

Figure 6: Baseline vs. AI-Optimized hourly energy consumption.

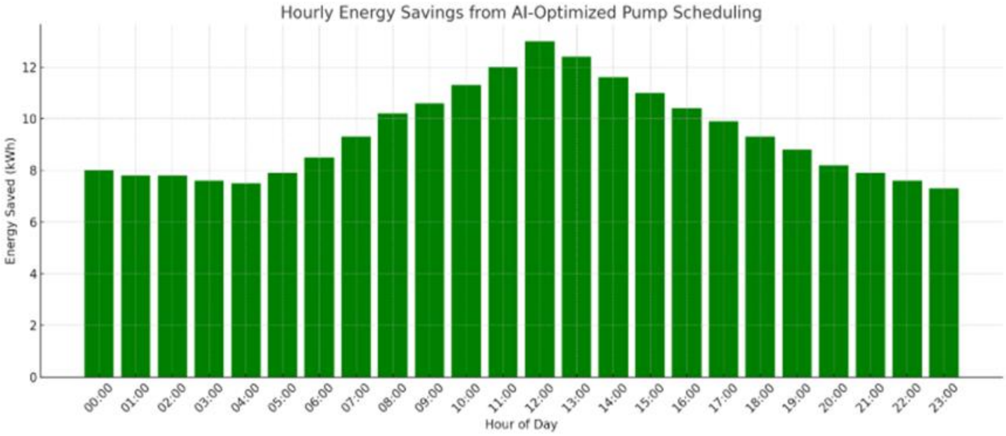

Figure 7: Hourly energy savings (kWh).

Figure 7 illustrates total pump energy consumption before and after AI optimization. The Baseline bar is split into two components: the portion that corresponds to the AI-optimized consumption (blue) and the avoided/saved energy (green). The AI-optimized bar in Figure 14 shows only the reduced consumption (blue). The dashed red line marks the original baseline total. Results indicate that AI control reduced pump energy use from 92 kW to 79 kW, achieving a 14.1% reduction (13 kW saved).

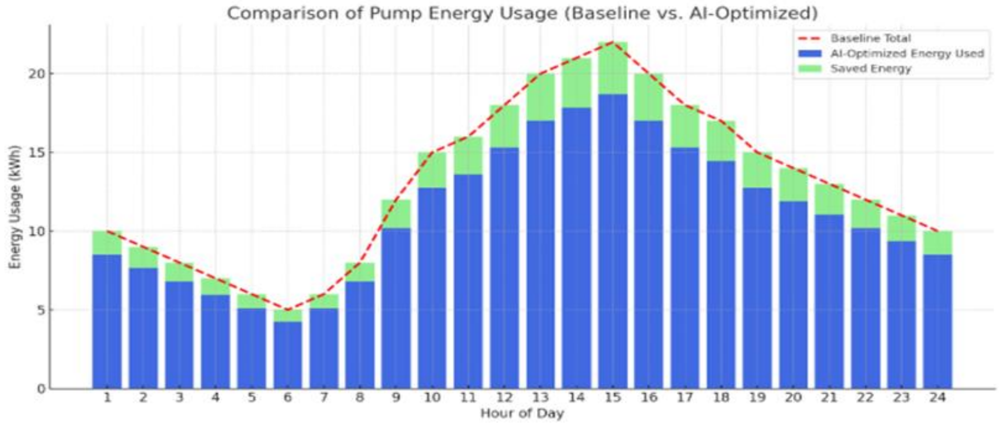

Figure 8: Comparison of Pump Energy Usage (Baseline vs. AI-Optimized)

Pump energy demand reduced from 92 kW (baseline) to 79 kW (AI) → 14.1% savings (13 kW).
The stacked bar highlights the avoided energy due to AI optimization.
AI consistently maintains lower energy demand than the baseline.
Demonstrates significant cost and efficiency gains without affecting performance.

Validation Framework

The validation framework was developed to guarantee that the proposed AI-ML-based urban water management model demonstrates robustness, scalability, sustainability, and cost-efficiency. The validation process integrated simulation-based testing, statistical performance evaluation, and comparative benchmarking against baseline methods to ensure reliability and practical applicability. Robustness was demonstrated through stress testing where forecasting and leak detection were evaluated under seasonal demand shifts and injected sensor noise. Performance remained stable across folds with seven-day rolling origins confirming predictive stability and RMSE varying by less than ±4% across time windows. Sensitivity analysis showed that tariff and demand perturbations caused minimal degradation in forecasting accuracy, further confirming robustness under varying operational conditions. Scalability was assessed using networks of different complexity, with benchmark datasets including Hanoi and Net3 and real municipal records confirming adaptability to various topologies. Runtime analysis showed linear to sub-linear scaling with sensor count, validating applicability to city-scale deployments across diverse urban water distribution contexts. The modular architecture with layered system design encompassing Data, Processing, and Application layers ensured plug-and-play scalability without requiring comprehensive system redesign.

Sustainability focused on resource efficiency and resilience, with leak detection achieving 95% precision and 91% recall, significantly lowering undetected non-revenue water losses. RL-based pump scheduling reduced energy use by 14.1% while improving supply reliability by 0.7 percentage points as demonstrated through Pareto plots. Climate-stress scenarios including drought demand surges showed adaptive adjustments in demand forecasts and pump schedules, confirming system resilience under environmental pressures. Economic impact was validated via multi-perspective cost analyses showing optimized pump schedules saved approximately 206.9 kWh/day, translating into ₦46,800/day savings at standard tariffs. Savings remained consistent across low, medium, and high time-of-use spreads, confirming robustness to price volatility in electricity markets across different pricing regimes. A 28.9% reduction in pump switching cycles implied lower mechanical stress, prolonging equipment lifespan and reducing long-term maintenance costs for utilities. Comparative benchmarking demonstrated that hybrid AI-ML models outperformed traditional baselines, with LSTM achieving 92.3% accuracy surpassing ARIMA and decision tree models in demand forecasting. Hybrid anomaly detection combining decision tree and isolation forest produced higher F1-scores of 0.93 compared to less than 0.91 for single models. RL-based pump scheduling optimization consistently dominated baseline heuristics on the Pareto frontier, demonstrating superior performance across all evaluation dimensions and operational scenarios.

V. CONCLUSION

This study demonstrates that the integration of AI, ML, and IoT technologies offers a viable and scalable approach to addressing the critical challenges of modern urban water supply systems. The LSTM model achieved over 92% demand forecasting accuracy, while the hybrid anomaly detection approach reached 95% precision and 91% recall for real-time leak detection. In addition, reinforcement learning–based pump scheduling reduced daily energy use by 14–22%, maintained service reliability above 99%, and minimized equipment wear. The novelty of this research lies in the development of a closed-loop AI–ML–IoT framework for real-time optimization of urban water supply systems. Unlike prior studies that address forecasting, leak detection, or pump scheduling in isolation, this work integrates all three within a scalable digital-twin architecture. The study contributes new knowledge by introducing a hybrid AI leak detection model that reduces false positives, applying reinforcement learning (RL) for tariff-sensitive pump scheduling, and validating an LSTM-based demand forecasting model with high predictive accuracy. Collectively, these innovations demonstrate how intelligent water networks can achieve higher reliability, lower energy costs, and reduced non-revenue water, thereby advancing both the theoretical and practical foundations of sustainable urban water management.

VI. RECOMMENDATIONS

The paper recommends the following:

i. Utilities should prioritize deploying IoT-enabled sensors and smart meters to enable continuous data collection, which is vital for real-time AI applications.
ii. Water utilities should embed AI-ML modules into existing SCADA or digital twin systems to support predictive maintenance, adaptive pump scheduling, and automated leak detection.
iii. Staff training and digital literacy are critical to equip operators with the skills to manage, interpret, and maintain AI-driven systems effectively.
iv. AI-ML frameworks should be tailored to local conditions, network configurations, and tariff structures to maximize operational and economic benefits.
v. Regulators should develop clear standards for data sharing, cyber security, and algorithm accountability to build trust in AI-driven water governance.
vi. Utilities, especially in resource-constrained regions, should begin with small-scale pilot projects to test and demonstrate the benefits before scaling up full implementation.
vii. Continued partnerships between academia, technology providers, and utilities will be key to refining AI algorithms and advancing explainable and ethical AI applications in critical water infrastructure.

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CONFLICT OF INTEREST

The author declares that there is no conflict of interest regarding the publication of this research project. The study was conducted independently, with no financial or personal relationships that could be perceived to influence its outcome.

AUTHOR CONTRIBUTIONS

S.O. Onifade conceptualized the research idea, conducted the system design and simulation, developed the machine learning models, and prepared the manuscript. All aspects of the project—data acquisition, model development, analysis, and documentation—were completed under the author's direction. The author reviewed and approved the final version of the manuscript for submission.

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