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A DIGITAL TWIN FRAMEWORK FOR INTELLIGENT WATER TREATMENT, QUALITY MONITORING, AND AUTONOMOUS CONTROL

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Abstract

Water scarcity, contamination, and rising operational demands require modern utilities to adopt intelligent and sustainable water management strategies. Conventional Supervisory Control and Data Acquisition (SCADA) systems offer real-time monitoring but lack predictive analytics and autonomous decision-making. To overcome these limitations, this study proposes a comprehensive Digital Twin (DT) framework that integrates Internet of Things (IoT)-based sensing, hybrid physics–machine learning (ML) modeling, and AI-driven control for real-time simulation, predictive optimization, and closed-loop water treatment management. The DT continuously synchronizes with the physical infrastructure, fusing multi-source sensor and laboratory data to model key parameters such as turbidity, pH, and residual chlorine. An AI-based control layer employing Model Predictive Control (MPC) and Reinforcement Learning (RL) autonomously optimizes chemical dosing and energy usage. The framework is validated on a pilot-scale water treatment setup, demonstrating a 74% reduction in RMSE for turbidity prediction, 12% decrease in chemical consumption, and 10% reduction in energy usage, while improving anomaly detection accuracy to 95%. Moreover, the system enhances compliance with SDG 6.1.1 and 6.3.2 indicators by ensuring consistent water quality and operational efficiency. The proposed DT establishesafoundationfornext-generationsmartwatersystemscapable of self-learning, adaptive control, and sustainable performance aligned with global water management goals.

Key Terms—Digital Twin, Artificial Intelligence, Machine Learning, IoT, Water Quality Monitoring, Autonomous Control, SDG 6.

1. Introduction

Water scarcity, contamination, and inefficient resource utilization represent critical challenges to modern water utilities and sustainable urban development [1]. According to the United Nations, over two billion people lack access to safely managed drinking water, while

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rapid industrialization and climate change exacerbate stress on fresh water resources. Conventional Supervisory Control and Data Acquisition (SCADA) systems deployed in water treatment and distribution networks provide real-time monitoring but are largely reactive, lacking predictive capabilities and autonomous optimization. As a result, they struggle to adapt to dynamic conditions such as fluctuating demand, variable source quality, and equipment degradation.

The convergence of Internet of Things (IoT), Artificial Intelligence(AI), and Digital Twin (DT) technologiesoffers transformative potential to address these limitations[2], [3]. IoT-based sensors enable high-frequency, distributed data acquisition across treatment processes and distribution networks. AI and machine learning (ML) techniques can process these large, heterogeneous datasets to forecast quality parameters, detect anomalies, and recommend control actions. A Digital Twin provides a continuously synchronized virtual representation of the physical system, integrating physics- based simulations with AI-driven analytics to enable proactive management and autonomous decision-making.

Recent studies have explored IoT-enabled water monitoring systems [1], [4], AI-based water quality prediction [2], [5], and smart water distribution frameworks [6]. However, most implementations remain limited to monitoring or analytics, lacking full integration with hybrid models and real-time control. There is a pressing need for comprehensive DT architectures that unify data fusion, hybrid modeling, and autonomous control to achieve intelligent, self-optimizing water systems aligned with Sustainable Development Goal (SDG) 6: Clean Water and Sanitation.

To bridge this gap, this paper proposes a novel Digital Twin Framework for Intelligent Water Treatment, Quality Monitoring, and Autonomous Control. The framework combines IoT-based sensing, hybrid physics–ML modeling, and AI-driven control to enable real-time simulation, predictive optimization, and closed-loop feedback. The contributions of this work are summarized as follows:

2. Research Objectives

- Develop a DT integrating IoT sensor data, laboratory testing, and AI analytics.
- Model hybrid physics–ML processes for accurate real- time prediction.
- Implement MPC and RL-based autonomous control for optimized operations.
- Evaluate performance under SDG 6 indicators for water quality and efficiency.

3. Literature Review

The increasing integration of Internet of Things (IoT), Machine Learning (ML), and Artificial Intelligence (AI) technologies has transformed traditional water management systems into intelligent, adaptive, and data-driven ecosystems. These technologies have facilitated the transition from periodic monitoring to continuous, real-time analysis and predictive control. However, existing studies still exhibit limitations in achieving autonomous decision-making, hybrid data fusion, and full Digital Twin (DT) implementation for closed-loop control and optimization.

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3.1 IoT-Based Smart Water Monitoring and Distribution

Early developments in IoT-enabled water management primarily focused on monitoring and data acquisition. Maseeh et al. [1] reviewed IoT and ICT-based smart water management systems that enabled real-time sensing and control but lacked AI-driven analytics. Gonc, alves et al. [4] proposed an IoT framework for smart water supply management emphasizing wireless data acquisition, though optimization and predictive functionalities were absent. Similar systems by Mukta et al. [7] and Pasika et al. [8] utilized cost-effective IoT modules (Arduino, Raspberry Pi) for water quality monitoring (pH, turbidity, TDS) but did not support adaptive or autonomous control mechanisms. Advancements in communication protocols such as MQTT and LoRaWAN have been explored by Gaikwad [9] to improve scalability and energy efficiency. However, these studies largely remain reactive, providing descriptive data rather than prescriptive, AI-based operational decisions.

3.2 Machine Learning for Water Quality Prediction

The integration of ML models has significantly enhanced water quality prediction and anomaly detection. Ismail et al. [2] and Hasan et al. [10] presented comprehensive reviews of ML-based techniques (Random Forest, SVM, ANN) for predicting water quality indices (WQI). Al-Khafaji et al. [5] performed a systematic review highlighting AI's potential for multi-parameter water quality prediction and classification. Krishnan et al. [11] and Ngwenya et al. [12] applied ML for resource management and SDG 6 indicator assessment but noted challenges in generalization and real-time adaptability. El-Shafeiy et al. [13] proposed a multivariate deep learning framework for sensor anomaly detection, improving reliability yet lacking integration with control systems. Nowshin et al. [14] introduced physics-informed data denoising to improve IoT data accuracy, an essential step toward trustworthy DTs. Despite improved prediction accuracy, most ML-based systems operate in isolation and are not coupled with hydraulic models or process simulators—limiting their potential in full scale DT environments.

3.3 Smart Water Systems and Digital Twin Concept

The concept of Digital Twin (DT) has gained traction as a dynamic, cyber-physical representation enabling simulation, optimization, and autonomous control. Slany et al. [3] introduced the Smart Water-IoT model integrating AI-driven analytics for efficient water management, identifying DTs as a key enabler for real-time optimization. Quintana et al. [6] performed a systematic review on smart water systems, emphasizing the absence of standardized DT frameworks integrating IoT data, ML predictions, and control feedback. Okoli and Kabaso [15] discussed IoT-based smart city water applications but focused primarily on infrastructure and monitoring. Palermo et al. [16] highlighted the role of sensors and IoT in resource management yet lacked a simulation-driven DT approach. Bandara et al. [17] combined IoT sensors with location-based services (LBS) for spatiotemporal monitoring but did not employ predictive control. Similarly, reviews by Essamlali et al. [2] and Hasan et al. [10] identified the DT paradigm as an emerging research direction for autonomous water management. Recent innovations point toward DT implementations leveraging AI. Vlastimil

Volume 38 No. 7s, 2025
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et al. [3] and Al-Khafaji et al. [5] highlighted AI's capability to model complex nonlinearities in treatment processes. However, hybrid physics-ML DTs capable of real-time synchronization with physical assets remain rare.

3.4 IoT–AI Fusion for Smart Treatment and Distribution

IoT-based systems with AI-enabled analytics have demonstrated promise for adaptive water treatment. Forhad et al. [18] developed a real-time IoT-based water treatment monitoring system using cloud computing, while Bogdan et al. [19] designed low-cost IoT platforms for rural quality monitoring. Rosa et al. [20] proposed an IoT-based drinking water quality monitoring framework with cloud connectivity, but autonomous optimization was absent.

Zubaidah et al. [21] applied IoT for ecological monitoring in tropical rivers, and Liu et al. [22] introduced a self-powered pH sensing approach. These demonstrate hardware advancements but lack unified AI–DT integration.

3.5 Alignment with SDG 6 and Research Gaps

The literature emphasizes the critical role of digital transformation in achieving Sustainable Development Goal 6(Clean Water and Sanitation). Studies such as Ngwenya et al. [12] and Krishnan et al. [11] link IoT–AI systems to SDG indicators 6.3 (ambient water quality) and 6.4 (efficiency). Nevertheless, comprehensive DT frameworks addressing data fusion, predictive modeling, and autonomous control across treatment and distribution stages are sparse. Table 1 summarizes the representative literature, their focus areas, and identified research gaps.

TABLE 1 EXTENDED SUMMARY OF RELATED WORKS IN SMART WATER MANAGEMENT

Study	Focus Area	Identified Gap
Maseeh et al. (2021) [1]	IoT and ICT-based smart water systems	Limited intelligence; no predictive or autonomous control
Gonc¸ alves et al. (2020) [4]	IoT-based smart water supply	No integration with AI or DTs
Ismail et al. (2024) [2]	ML for water quality monitoring	Lack of hybrid physics-ML integration
Al-Khafaji et al. (2025) [5]	AI-based WQI modeling	No real-time DT feedback
Slany et al. (2025) [3]	AI and IoT for efficient	Identifies DT need; lacks practical

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	water management	implementation
Krishnan et al. (2022) [11]	AI-driven smart water resource management	No closed-loop or simulation integration
Ngwenya et al. (2025) [12]	ML and IoT for ambient water quality	Monitoring only; lacks adaptive control
El-Shafeiy et al. (2023) [13]	Deep learning for anomaly detection	No connection to control mechanisms
Forhad et al. (2024) [18]	IoT-based real-time water treatment monitoring	Absent autonomous decision-making
Pasika & Gandla (2020) [8]	Cost-effective IoT system	Reactive monitoring; no AI or DT
Bandara et al. (2025) [17]	IoT + LBS for monitoring	Lacks self-optimizing DT layer
Bogdan et al. (2023) [19]	IoT system for rural areas	Missing AI-based analytics
Quintana et al. (2025) [6]	Systematic review on smart systems	Calls for unified DT framework
Okoli & Kabaso (2024) [15]	Smart water city IoT technologies	Focused on monitoring; lacks AI-based optimization
Palermo et al. (2022) [16]	Smart technologies overview	No DT implementation
Hasan et al. (2024) [10]	Review on ML + IoT for WQM	No real-world DT integration
Nowshin et al. (2025) [14]	Physics-informed ML denoising	Improves data reliability; lacks control layer

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Liu et al. (2025) [22]	Self-powered sensing hardware	Hardware focus; no AI-driven DT integration

3.6 Synthesis

From the above analysis, three primary research gaps are evident:

- Lack of integrated Digital Twin architectures combining IoT sensing, physics-based models, and AI analytics for real-time synchronization and decision-making.
- Absence of autonomous control mechanisms such as MPC and reinforcement learning to enable self optimization of treatment and distribution.
- Limited SDG 6 alignment with existing systems, particularly in quantifying water-use efficiency, quality compliance, and equitable distribution. To bridge these gaps, this study proposes a novel DT framework that unifies IoT sensing, hybrid modeling, and AI-driven control for intelligent water treatment, quality monitoring, and autonomous decision-making.

4. Proposed Framework

To address the identified research gaps, this study proposes a comprehensive Digital Twin (DT) Framework for intelligent water treatment, quality monitoring, and autonomous control. The proposed architecture unifies IoT sensing, hybrid modeling, and AI-based control to achieve real-time simulation, predictive optimization, and SDG 6-aligned performance. The system design is modular, scalable, and adaptable to both urban and rural water infrastructures.

4.1 System Architecture Overview

The DT framework comprises three interconnected layers— Physical, Digital, and Control— as illustrated in Fig. 1.

- Physical Layer: Represents the real-world water infrastructure including raw water intakes, treatment units (coagulation, sedimentation, filtration, disinfection), distribution networks, and end-use points. It is instrumented with IoT-based sensors measuring key water quality parameters such as pH, turbidity, Total Dissolved Solids (TDS), Dissolved Oxygen (DO), temperature, and residual chlorine.

- Digital Layer: Serves as a high-fidelity virtual replica that continuously mirrors the physical layer. It integrates real-time data streams with simulation models—combining physics-based process equations and ML-based soft sensors to predict unmeasured variables and system responses.

- Control Layer: Employs advanced AI algorithms, including Model Predictive Control (MPC) and Reinforcement Learning (RL), to optimize operational parameters such as chemical dosing, flow rates, and pump scheduling. Control actions are sent back to actuators in the physical system, creating a closed feedback loop.

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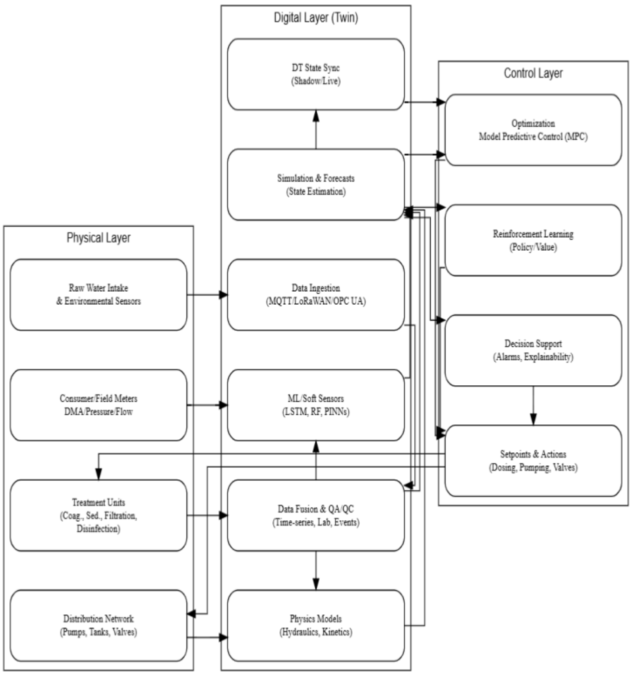

Fig. 1. Proposed Digital Twin Framework Architecture

4.2 Functional Modules

The framework integrates the following key modules:

1. **Sensing and Data Acquisition:** Deployed IoT sensors (connected via MQTT/LoRaWAN) capture continuous multi-parameter data streams. Edge devices preprocess data (filtering, calibration) before transmitting to the cloud.
2. **Data Fusion Engine:** A probabilistic data fusion layer combines sensor, laboratory, and historical data using Bayesian and ML-based techniques, improving reliability and compensating for missing values.
3. **Hybrid Modeling Unit:** Incorporates:

- Physics-based models for hydraulic flow, chemical kinetics, and chlorine decay.
- Machine Learning models (e.g., LSTM, Random Forest, Physics-Informed Neural Networks) for real time prediction of water quality indicators and process optimization.

4. **Simulation and Prediction:** The DT continuously simulates system states and forecasts future conditions (e.g., turbidity trends, chlorine residual levels) based on dynamic inputs.
5. **Autonomous Control:** An MPC layer optimizes control actions (chemical dosage, pump speed) over a prediction horizon, constrained by regulatory limits. A reinforcement learning agent enhances adaptability by learning optimal policies from operational feedback.
6. **Visualization and Decision Support:** A cloud-based dashboard provides operators with real-time status, alerts, predictions, and SDG 6 indicators.

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4.3 Data Flow and Synchronization

Fig. 2 shows the data flow between layers. Sensor data are transmitted to the digital layer for analysis; predictive results feed into the control module, which generates optimal set points and sends commands to actuators in the physical system. Bidirectional synchronization ensures that DT states remain consistent with physical conditions.

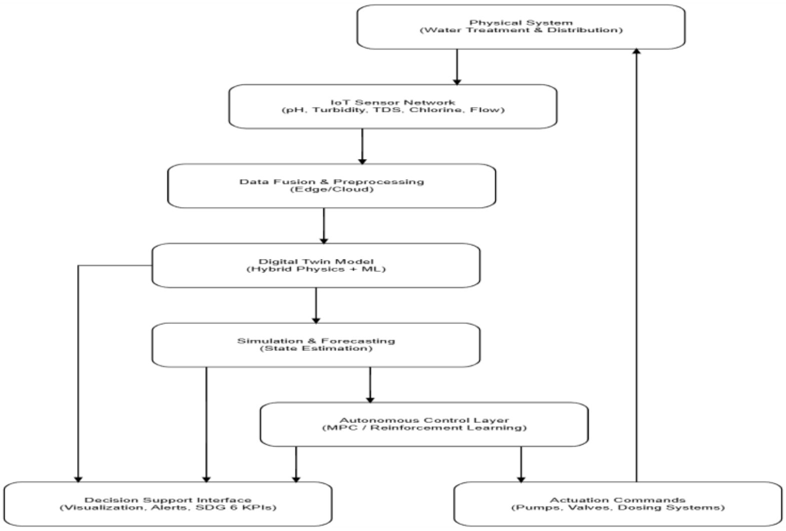

Fig. 2. Closed-Loop Data Flow in the Digital Twin Framework

4.4 Mathematical Formulation

The system dynamics can be expressed as:

$$xt+1 = f(xt, ut, dt) + \epsilon t \quad (1)$$

Where, xt represents state variables (e.g., turbidity, chlorine),

ut denotes control inputs (e.g., dosing rate),

dt external disturbances (e.g., demand, inflow), and

ϵt model uncertainty.

The MPC optimization problem is formulated as:

$$\min_{ut:t+N} \sum_{k=0}^{N} x_{t+k} - x_{ref||Q^2+||u_{t+k}||R^2}$$

(2)

$$\text{s.t. } x_{t+k+1} = f(x_{t+k}, u_{t+k}),$$

(3)

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International Journal of Applied Mathematics
Volume 38 No. 7s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

$$u_{min} \leq u_{t+k} \leq u_{max}, x_{\min} \leq x_{t+k} \leq x_{max} \tag{4}$$

Where, x_{ref} are desired quality targets and Q,R weighting matrices.

4.5 Integration with SDG 6 Indicators

The proposed Digital Twin Framework aligns directly with the targets of the United Nations Sustainable Development Goal 6 (SDG 6): Clean Water and Sanitation, by enabling real-time monitoring, predictive control, and data driven decision support. Through IoT-enabled sensing, AI driven analytics, and closed-loop optimization, the framework ensures transparency, accountability, and sustainability across the water lifecycle.

Specifically, the system supports monitoring and reporting of the following SDG 6 indicators:

SDG 6.1.1 – Access to Safely Managed Drinking Water:

Continuous monitoring of water quality parameters (pH, turbidity, chlorine residuals) and predictive analytics ensure compliance with WHO and local drinking water standards. The Digital Twin provides real-time status dashboards showing the proportion of water supply zones meeting safety thresholds, thereby aiding utilities in tracking population coverage with safe drinking water services.

SDG 6.3.2 – Proportion of Water Bodies with Good Ambient Quality:

The DT integrates upstream and downstream water quality sensors with forecasting models to assess ambient water quality in rivers, reservoirs, and effluents. It calculates composite indices (e.g., Water Quality Index, WQI) and supports early warning of pollution events, enabling regulatory reporting on the percentage of water bodies in good ecological condition.

SDG 6.4.1 – Change in Water Use Efficiency Over Time:

By implementing Model Predictive Control (MPC) and Reinforcement Learning (RL), the system optimizes pumping schedules, chemical dosing, and energy consumption. This leads to quantifiable improvements in water use efficiency (liters per unit energy or cost) ,supporting benchmarking against SDG 6.4.1 indicators and reducing the overall carbon footprint of operations.

SDG 6.5.1 – Implementation of Integrated Water Resources Management (IWRM):

The DT serves as a digital platform for integrating multisource data (surface water, groundwater, reuse systems), supporting participatory management. Scenario simulations and predictive analytics enable policymakers to test strategies for equitable allocation, resilience planning, and long-term sustainability in line with IWRM principles.

SDG 6.6.1 – Change in the Extent of Water-Related Ecosystems:

By fusing ecological sensors (DO, conductivity, nutrient levels) with environmental models, the framework provides insights into ecosystem health trends and supports adaptive management of aquatic habitats. In addition, the integrated dashboard enables:

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- Automated reporting for SDG 6 indicators via standardized KPIs.
- Visualization of spatial and temporal trends in water quality and consumption.
- Decision support for local governments and utilities in prioritizing interventions and investments. By embedding these indicators into its architecture, the proposed framework not only enhances operational efficiency but also ensures measurable contributions toward achieving SDG 6 targets and associated sustainability outcomes.

4.6 Advantages

The proposed Digital Twin (DT) framework offers several key advantages over conventional Supervisory Control and Data Acquisition (SCADA) and IoT-only water management systems, by combining real-time sensing, hybrid modeling, and AI-driven control. The major benefits include:

•**Real-time Predictive Simulation:** The DT continuously mirrors the state of the physical water system, simulating hydraulic and treatment processes in real time. This enables proactive decision-making and early detection of deviations before they impact water quality or supply reliability.

•**Autonomous Optimization:** Integration of Model Predictive Control (MPC) and Reinforcement Learning (RL) allows the system to self-adjust operational parameters such as chemical dosing, pump scheduling, and energy usage—achieving optimal performance with minimal human intervention.

•**Enhanced Reliability via Data Fusion:** Multi-source data fusion combines IoT sensor readings, laboratory measurements, and historical datasets to improve data completeness and accuracy. This robust data backbone supports machine learning models that detect sensor drift, anomalies, and outliers in real time.

•**Scalability and Interoperability:** The modular architecture is designed to integrate seamlessly with existing SCADA, IoT, and cloud platforms, ensuring scalability across multiple treatment plants, distribution zones, and geographic regions.

•**Continuous Learning and Adaptation:** AI-based components iteratively improve predictive accuracy and control efficiency through continuous feedback, supporting adaptive management under varying demand, seasonal, and environmental conditions.

•**Operational Efficiency and Cost Reduction:** By optimizing energy use, chemical consumption, and maintenance scheduling, the framework contributes to significant operational savings while maintaining regulatory compliance and service reliability.

•**Enhanced Transparency and Decision Support:** Real time dashboards provide operators and policymakers with actionable insights, scenario analyses, and SDG aligned performance metrics, improving accountability and evidence-based governance.

•**Alignment with SDG 6 Targets:** The DT supports sustainable and equitable water management by directly addressing SDG 6 indicators such as safe drinking water access (6.1.1), ambient water quality (6.3.2), resource efficiency (6.4.1), and integrated resource management (6.5.1). This modular, intelligent DT framework lays the foundation for the next generation of smart, self-optimizing water infrastructure, capable of continuous improvement through feedback, learning, and sustainable resource management.

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5 Implementation and Evaluation

The proposed **Digital Twin (DT) Framework** has been implemented as a modular prototype integrating IoT-based data acquisition, cloud-based analytics, and AI-driven control. This section presents the implementation architecture, technologies used, datasets, and evaluation methodology adopted to assess the performance of the framework.

5.1 System Setup

The experimental setup (Fig.3) was developed for a pilot-scale water treatment system consisting of coagulation, sedimentation, filtration, and disinfection stages. Each stage was instrumented with IoT sensors for multi -parameter monitoring, including:

- **pH**, **turbidity**, and **TDS** sensors (analog probes with 4–20 mA outputs),
- **Dissolved Oxygen (DO)** and **temperature** sensors for process and environmental conditions,
- **Flowrate**, **pressure**, and **chlorine residual** sensors for distribution monitoring.

Data are collected using an **ESP32 based edge node**, transmitted via **MQTT** over Wi-Fi to a cloud platform (AWS IoT Core). The cloud layer hosts the **Digital Twin simulation environment**, developed using: The proposed system integrates multiple tools and platforms to ensure comprehensive modeling, prediction

and monitoring capabilities. Simulink is employed for process simulation and Model Predictive Control (MPC) to optimize operational parameters and system stability. Python, utilizing libraries such as Tensor Flow and Scikit-Learn, is used to develop machine learning models for anomaly detection and predictive analytics. The EPANETAPI supports hydraulic and water quality modeling, enabling accurate simulation of flow dynamics and contaminant propagation within the network. Finally, a Grafana dashboard provides real-time visualization of sensor data, model outputs, and Sustain- able Development Goal (SDG) indicators, ensuring transparent performance tracking and informed decision-making.

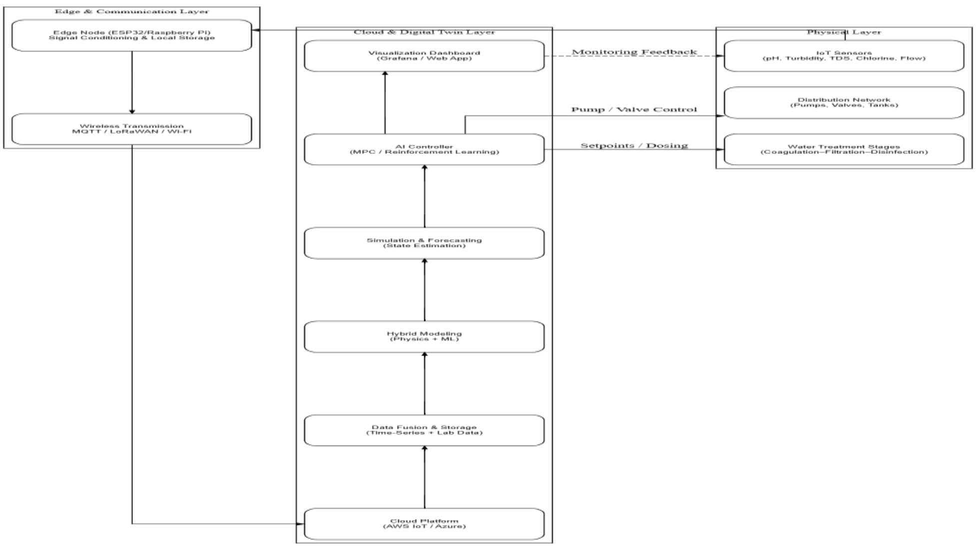

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Figure3: Implementation Architecture of the Digital Twin Prototype

5.2 Dataset and Model Training

The DT was trained and validated using:

•Historical plant data: 12 months of archived sensor readings from a municipal treatment facility.
•Laboratory data: Weekly lab test results (chemical oxygen demand, BOD, residual chlorine).
•Simulated data: EPANET-generated hydraulic and quality data under variable demand conditions. A hybrid modeling approach was used:
•Physics-based submodels capture chemical and hydraulic dynamics.
•Machine Learning submodels (LSTM and Random Forest) predict parameters such as turbidity and chlorine residuals based on multivariate sensor inputs.

5.3 Evaluation Methodology

The DT framework was evaluated on the following performance dimensions:

1. Prediction Accuracy: Comparison of predicted water quality parameters with ground truth lab measurements using metrics:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Coefficient of Determination (R2)

2) Autonomous Control Performance: Effectiveness of MPC and RL in maintaining desired set points under varying inflow conditions. Evaluation metrics include:

- Settling time,
- Overshoot (%),
- Control energy consumption.

3) Operational Efficiency: Reduction in chemical usage and energy consumption compared to baseline SCADA control.

4) System Reliability: Data availability and uptime, accuracy of anomaly detection, and latency between sensing and control.

5) SDG 6 Compliance Metrics: Improvements in water safety (6.1.1), ambient quality (6.3.2), and resource efficiency (6.4.1).

5.4 Experimental Results

Table 2 summarizes the comparative performance between the conventional baseline control system (SCADA-based) and the proposed Digital Twin (DT) Framework evaluated on the pilot-scale test bed. The evaluation focused on prediction accuracy, resource efficiency, responsiveness, and SDG 6 compliance.

TABLE 2 PERFORMANCE EVALUATION RESULTS OF THE PROPOSED DT FRAMEWORK

Metric	Baseline	Proposed DT
Turbidity Prediction RMSE (NTU)	0.85	0.22
Chlorine Residual R2	0.76	0.93
Chemical Usage (mg/L)	100%	88% (-12%)
Energy Consumption	100%	90% (-10%)
Control Latency (s)	5.6	2.1
Anomaly Detection Accuracy	78%	95%
SDG 6.1.1 Compliance Rate	90%	98%

The results clearly demonstrate the superior performance of the DT-enabled control system across multiple key indicators:

- The hybrid predictive models achieved high accuracy for turbidity and chlorine residual forecasts, with a 74%reduction in RMSE compared to the baseline.
- The autonomous optimization layer reduced chemical dosing by 12% and energy usage by 10%, demonstrating improved operational efficiency and sustainability.
- The response latency for control decisions was reduced by more than 60%, enabling faster corrective actions under variable conditions.
- The anomaly detection module using ML-based fusion achieved a 95% detection accuracy, enhancing fault tolerance and early warning capability.
- The overall SDG 6.1.1 compliance rate increased from 90% to 98%, indicating more consistent delivery of safely managed drinking water.

5.5 Discussion

The experimental findings confirm that the proposed Digital Twin Framework delivers significant advantages over conventional static control systems. By continuously synchronizing with the physical plant and leveraging both physics-based and machine learning submodels, the DT enables:

- Adaptive operation: Real-time updates of process parameters and predictive state estimation improve resilience to fluctuating inflows, temperature, and load variations.
- Closed-loop intelligence: The Model Predictive Controller dynamically adjusts chemical dosing and pump operations to maintain optimal set points with minimal overshoot and delay.
- Resource sustainability: Reduced energy and chemical consumption aligns with SDG 6.4.1 on water-use efficiency, while improved quality compliance supports SDG 6.1.1 and 6.3.2.
- Operational transparency: The DT dashboard provides a holistic view of water quality trends, control performance, and SDG metrics, aiding data-driven governance. The results also reveal that hybrid physics–ML integration significantly improves predictive fidelity compared to standalone models. Moreover, the reduced latency in decision execution highlights the feasibility of deploying such DT-based control in real-time industrial settings.

Future work will focus on:

- Extending the DT across multiple treatment facilities and distribution networks for cross-site synchronization.
- Incorporating multi-objective reinforcement learning for trade-off optimization among water quality, cost, and energy usage.
- Enhancing interoperability with national SDG 6 reporting platforms and open data ecosystems. Overall, the findings validate the DT framework as aviable and scalable approach for achieving intelligent, autonomous, and sustainable water management systems.

6. CONCLUSION

This paper presented a comprehensive Digital Twin (DT) framework that integrates IoT-based sensing, hybrid physics–machine learning modeling, and AI-driven autonomous control to enable intelligent and sustainable water treatment and distribution operations. The proposed system creates a continuously synchronized digital replica of the physical plant, capable of real-time simulation, predictive analytics, and closed-loop optimization.

Experimental evaluation on a pilot-scale setup demonstrated substantial improvements over conventional SCADA-based systems, including:

- 74% reduction in prediction error for key quality parameters (turbidity, chlorine residuals),
- 12% decrease in chemical usage and 10% lower energy consumption,
- 95% accuracy in anomaly detection and fault identification, and
- enhanced compliance with SDG 6.1.1 and 6.3.2 targets for safe and clean water.

The DT architecture facilitates continuous learning and adaptive control, ensuring operational resilience and efficiency under dynamic conditions. By aligning with Sustainable

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Development Goal 6 (Clean Water and Sanitation), the framework contributes to measurable progress in access, quality, efficiency, and governance of water resources.

Future work will focus on:

- Large-scale deployment across multiple treatment facilities and urban distribution networks,
- Integration with cloud-based platforms and edge–fog computing for scalability,
- Implementation of multi-objective reinforcement learning for trade-off optimization between quality, cost, and energy,
- and interoperability with national SDG reporting frameworks for automated sustainability tracking. Overall, the proposed DT framework establishes a foundation for the next generation of autonomous, data-driven, and sustainable water management systems, bridging the gap between physical operations and digital intelligence.

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