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Dynamic IoT–PID Control for Energy-Efficient Water Distribution: EPANET-Based Digital Twin Validation in Varied Geographical Terrains

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Abstract

Topographical heterogeneity in water distribution networks frequently causes pressure imbalance, hydraulic inefficiency, and elevated energy consumption, particularly in regions with significant elevation gradients. This study aims to develop and validate a dynamic Internet of Things (IoT)-based pressure control model within a cyber–physical system framework for energy-efficient water distribution under varied geographical conditions. The primary contribution of this work lies in the separation of strategic and tactical control layers, where a Digital Twin based on EPANET dynamically generates optimal pressure setpoints, while distributed proportional–integral–derivative controllers execute real-time valve regulation at the network edge. The research adopts a Design Science Research methodology to design, implement, and evaluate a four-layer architecture consisting of physical sensing and actuation, long-range communication, tactical control, and strategic simulation layers. Validation is conducted using EPANET-based simulations across three control scenarios: a baseline condition without dynamic control, a static rule-based valve control scenario, and the proposed dynamic IoT–PID control scenario. The experimental procedure involves comparative analysis using control performance metrics including overshoot, settling time, steady-state error, and root mean square error. Simulation results demonstrate that the baseline configuration suffers from severe pressure imbalance and hydraulic backflow, while static rule-based control partially mitigates inefficiencies but fails to adapt to demand variability. In contrast, the proposed dynamic IoT–PID approach achieves precise pressure regulation with overshoot below 2% and tracking error maintained under 0.5 meters across all evaluated scenarios. These findings confirm that integrating a Digital Twin with real-time PID control significantly improves pressure stability and operational efficiency. The proposed architecture offers practical implications for smart water infrastructure in geographically diverse regions, providing a scalable foundation for adaptive pressure management, energy optimization, and future digital-twin-driven water distribution systems.

Keywords: IoT, Water Pressure, Water Distribution, EPANET, PID Control, Digital Twin.

1. Introduction

The provision of efficient and equitable drinking water and sanitation services remains a major challenge for many regions, particularly those with diverse geographical conditions. Water distribution systems rely on pumping and water treatment costs, which account for approximately 2–3% of total global energy consumption [1]. Factors such as elevation differences, distance from water sources, and infrastructure limitations contribute to unstable water pressure, potentially leading to unequal distribution, pipe leakage, or even system failure [2]. According to the Central Statistics Agency (BPS), in 2023 only around 72% of households in Indonesia had access to adequate clean water [3]. If these issues persist without proper intervention, they may result in increased waterborne diseases and a decline in community quality of life [4], [5].

Aligned with Law No. 59 of 2024 concerning the National Long-Term Development Plan (RPJPN) 2025–2045, one of the primary development goals is to improve access to safe drinking water and sanitation, strengthen water resource resilience, and optimize infrastructure through technological advancements. The sustainable development mandated by the 2030 Sustainable Development Goals (SDGs) also emphasizes the importance of efficient water management to support healthy and prosperous communities [6]. With increasing challenges arising from climate change, urbanization, and growing demand for clean water, technology-based solutions are required to ensure stable and equitable water distribution [7].

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Internet of Things (IoT) technology offers innovative solutions for real-time monitoring and optimization of water distribution. Installing IoT sensors within distribution networks allows for the collection and analysis of data on water pressure, volume, and consumption patterns, enabling distribution systems to adapt to geographical conditions and community demand [8]. Therefore, this study aims to develop a dynamic IoT-based model for monitoring and optimizing water pressure in household distribution systems across various geographical conditions [9]. This model is expected to enhance water distribution efficiency, equity, and sustainability in alignment with national development goals.

This research is conducted using an EPANET network model representing real infrastructure conditions, consisting of 2 reservoirs, 26 Junctions, 11 valves, and 16 pipes. Baseline analysis (Scenario A) reveals two fundamental hydraulic issues causing system instability. (1) Extreme Pressure Variations and Service Failure: Baseline data indicate highly uneven pressure, ranging from complete service failure (0.29 m at Junc 03 due to insufficient static head) to excessively high pressure (19.79 m at Junc 07). (2) Severe Hydraulic Inefficiency: Flow balance analysis shows total customer demand of only 1.22 LPS, while the system supplies 3.42 LPS. The excess 2.20 LPS (180% of demand) is observed to flow backward (backflow) through the network (Pipe 3, Pipe 14, Valve 10) into Reservoir 1, which has a lower head.

Historically, technological solutions addressing these issues have evolved. Initial efforts focused on passive IoT monitoring. However, as previously identified, monitoring alone is insufficient. The need for actuation has often been addressed through simple control strategies (such as IF–THEN logic), defined in this study as Scenario B. Simulation analysis shows that instead of stabilizing the network, this approach may induce significant pressure oscillations, overshoot, and system instability, potentially damaging pipeline infrastructure. The main research problems addressed in this study include, (1) How to design a dynamic IoT model capable of adjusting water distribution based on diverse geographical conditions. (2) How to design and develop an IoT-based system prototype for real-time monitoring and optimization of water distribution. (3) How to implement IoT sensors (such as the BMP280 pressure sensor and YF-S201 flow sensor) for monitoring water pressure and consumption. (4) How effective the designed dynamic IoT model is in optimizing water distribution across regions with varying geographical characteristics.

To address these issues, the study employs several key approaches. (1) Design Science Research (DSR) is used as the methodology for iteratively designing, developing, and evaluating the IoT model. (2) Pressure sensors (BMP280) and flow sensors (YF-S201) are deployed at strategic points to monitor real-time pressure and water consumption and to enable automatic optimization of distribution. (3) Computational Fluid Dynamics (CFD) is used to simulate water flow within pipes based on topographical variations, providing insights into pressure behavior under different geographical conditions. (4) Machine Learning is applied for predicting water consumption patterns and adjusting distribution for greater effectiveness and efficiency.

Previous research on IoT-based water distribution offers valuable insights but still presents several limitations. Some studies focus primarily on consumption monitoring without incorporating geographical factors in pressure management [10]. Existing pressure optimization models remain static and cannot accommodate dynamic changes in water demand over time. Moreover, no existing model specifically formulates adaptive solutions applicable across diverse geographical settings [11].

The novelty of this research lies in the development of a dynamic IoT-based model that not only performs monitoring but also adjusts water pressure automatically based on real-time data. Additionally, this study integrates CFD and IoT to design more efficient water distribution strategies tailored to topographical characteristics. The adaptive framework formulated herein offers a versatile solution that can be deployed across various geographical conditions to maintain stable pressure without overburdening the infrastructure.

Recognizing these gaps motivates the development of the third solution, which becomes the central focus of this study. The research gap lies in the lack of studies that integrate (a) dynamic setpoint optimization based on a Digital Twin (using EPANET) for strategic target determination, with (b) stable real-time precision control (using a Proportional–Integral–Derivative/PID algorithm) for tactical execution.

Therefore, this study designs and validates (through simulation) Scenario C: a closed-loop cyber–physical system architecture that uses EPANET as a strategic Digital Twin and a PID controller as a tactical executor, implemented on low-cost IoT actuators.

This study makes the following scientific contributions. First, it introduces a two-layer cyber–physical control architecture that explicitly separates strategic decision-making from tactical execution in water distribution networks. Second, it formalizes the role of EPANET as a Digital Twin that dynamically computes pressure setpoints based on real-time hydraulic state estimation, rather than serving solely as an offline simulation tool. Third, it demonstrates the effectiveness of distributed PID-based valve control in tracking dynamically updated setpoints under varying geographical and demand conditions. Fourth, the study provides a comparative evaluation of baseline, static optimization, and dynamic control scenarios, offering quantitative evidence that static valve regulation is insufficient for adaptive pressure management in complex terrains.

2. Literature Review

2.1. Basic Concepts of Computational Fluid Dynamics (CFD) and IoT Integration

Computational Fluid Dynamics (CFD) is a numerical method used to analyze fluid behavior, including water flow in distribution pipelines [12]. CFD enables simulation of pressure, velocity distribution, flow patterns, and turbulence within water networks, providing a detailed hydrodynamic representation that is difficult to observe directly under field conditions [13]. Beyond its application in hydraulic design, CFD is increasingly used as an energy optimization tool, supporting planning and management of urban water distribution infrastructure [14]. Numerous studies have demonstrated the effectiveness of CFD in analyzing pressure variability, leakage potential, and hydraulic inefficiencies in water distribution systems [15].

IoT enables real-time monitoring of water distribution systems using sensors that measure pressure, flow rate, and water quality parameters [16]. Recent studies have explored the potential of integrating IoT with CFD to develop intelligent and adaptive water distribution frameworks [17]. Although existing IoT-based models provide valuable insights into consumption monitoring and leakage detection, most lack high-fidelity hydrodynamic simulation to account for spatial and geographical variations within the network. This gap highlights the importance of combining CFD with IoT, allowing real-time sensor data to interact with simulation results to enhance prediction accuracy and dynamic control capabilities.

2.2. Machine Learning for Water Pressure Prediction

Machine Learning (ML) algorithms, particularly deep learning architectures such as LSTM and GRU, play a pivotal role in predicting non-linear water consumption patterns and hydraulic pressure fluctuations [18]. Complementing these predictive capabilities, metaheuristic optimization techniques most notably Genetic Algorithms (GA) have been extensively utilized in prior research to resolve complex hydraulic challenges that elude gradient-based methods. Historically, GA has been the benchmark for the Least-Cost Design of water networks, optimizing pipe diameters and sensor placements within discrete and non-convex search spaces. In operational contexts, researchers have successfully employed GA to determine optimal pump scheduling and to automate the tuning of PID controller parameters (K_p, K_i, K_d), leveraging its ability to identify near-global optima without requiring explicit mathematical derivatives of the hydraulic system. Integrating ML-based forecasting with GA-driven optimization and IoT-real-time data offers substantial potential for developing "Self-Healing" water distribution systems. However, major challenges persist, including the high computational overhead of GA iterations in large-scale networks, the risk of overfitting in ML models, and the critical requirement for high-fidelity datasets to ensure the reliability of these hybrid cyber-physical frameworks.

3. Methodology

This research was conducted using the Design Science Research Process Model (DSR Cycle). The Design Science Research methodology consists of five primary stages as recommended by Vaishnavi and Kuechler [19].

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3.1.Awareness of the Problem

Extreme Pressure Variations and Service Failure: As summarized in table 1, baseline data show highly uneven pressure distribution, ranging from complete service failure (0.29 m at Junc 03 due to insufficient static head) to dangerously high pressure (19.79 m at Junc 07).

Table 1. Comparison of Under-Pressure and Over-Pressure Conditions.

Node ID	Elevation (m)	Head (m)	Pressure (m)
Junc 03	261.18	261.47	0.29
Junc 07	241.05	260.84	19.79

Severe Hydraulic Inefficiency: Flow balance analysis presented in table 2 indicates that total customer demand is only 1.22 LPS, while the system supplies 3.42 LPS. The resulting excess flow of 2.20 LPS (180% of demand) propagates as backflow through Pipe 3, Pipe 14, and Valve 10 toward Reservoir 1.

Table 2. Backflow Paths Toward Reservoir 1.

Link ID	Length (m)	Diameter (mm)	Flow (LPS)
Pipe 3	50.71	76	-2.20
Pipe 13	60.34	76	-2.20
Pipe 14	29.00	76	-2.20
Valve 10	#N/A	76	-2.20

3.2. Suggestion (Proposed Solution)

The proposed conceptual artifact is a four-layer closed-loop Cyber–Physical System (CPS) architecture, as depicted in figure 1.

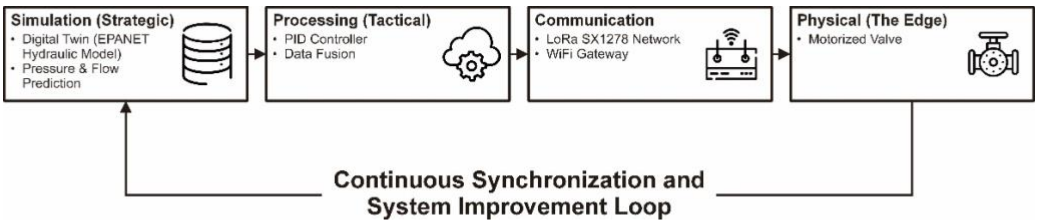

Figure 1. Four-Layer Cyber-Physical System (CPS) Architecture.

The proposed system architecture is organized into four interconnected layers. The Physical Layer (Edge) consists of field-deployed infrastructure, including sensor nodes such as the BMP280 pressure sensor and YF-S201 flow sensor, as well as actuator nodes in the form of motorized valves driven by servo motors. The Communication Layer (Link) enables long-range, low-power data transmission using LoRaWAN technology implemented through the LoRa SX1278 module. The Processing Layer (Brain–Tactical) is hosted on a cloud server or edge gateway and is responsible for executing real-time control logic; its core component is a PID controller that receives pressure setpoints from the strategic layer and real-time sensor measurements from the physical layer to compute actuator commands. Finally, the Simulation Layer (Brain–Strategic) represents the Digital Twin of the water distribution network, powered by a calibrated EPANET hydraulic model, which runs optimization scenarios to determine optimal pressure setpoints and transmits these setpoints to the tactical PID controller for execution.

3.3. Development

Artifact development was conducted in a simulation environment, including the preparation of an EPANET testbed. A rigorous simulation-based experimental design was created to validate Scenario C.

3.3.1. Experimental Performance Testbed, Geographical Scenarios, and Data-Driven Demand Forecasting

The system was validated using a calibrated EPANET testbed (2 reservoirs, 26 Junctions, 11 valves, 16 pipes; table 3) across five geographical scenarios, including Rising and Valley terrains. To enable proactive pressure management, a supervised regression module was integrated into the strategic Digital Twin layer to forecast short-term demand patterns. Crucially, these ML-driven predictions were utilized exclusively for high-level setpoint optimization rather than being embedded in the real-time PID loop, thereby ensuring deterministic control stability while leveraging data-driven anticipatory intelligence at the systemic level.

Scenario A (Baseline): No dynamic control (valve fully open). Uses the initial EPANET output. Scenario B (Simple Control): Dynamic valve control using basic IF–THEN logic. Scenario C (Proposed Model): Precision dynamic control using PID + Digital Twin EPANET architecture. Performance of Scenarios B and C was evaluated using standard control-theory metrics: (1) Settling Time: Time required for the system to reach and remain within the tolerance band of the setpoint. (2) Overshoot (%): Maximum percentage by which the measured pressure exceeds the setpoint. (3) Steady-State Error (%): Average difference between the setpoint and measured pressure after stabilization, presented in Table 3.

Table 3. Network Topology and Control Components (Testbed)

ID	Node 1	Node 2	Role Analysis
Reservoir1	-	Junc12	Low-Head Source (260.00 m)
Reservoir2	-	Junc14/15/19	High-Head Source (261.50 m)
Pipe 3	Junc09	Junc08	Backflow Path (Scenario A)
Pipe 14	Junc25	Junc09	Backflow Path (Scenario A)
Valve10	Junc12	Junc25	Backflow Path (Scenario A)
Valve11	Junc13	Junc26	IoT Actuator Candidate (Scenario C)
Junc 07	Junc26	-	Over-Pressure Point (downstream of Valve11)
Junc 26	Valve11	Junc07	IoT Sensor Candidate (Scenario C)
Junc 03	Valve08	-	Under-Pressure Point (Static Head Problem)

3.4. PID Control Formulation and Mechanism for Motorized Valve Regulation

Uneven pressure distribution in multi-elevation water networks is common due to elevation differences, hydraulic losses, and varying demand across branches. To address this, the study applies a hierarchical control approach based on Proportional–Integral–Derivative (PID) controllers on each motorized valve. Each node regulates local pressure toward a pressure setpoint determined by the Digital Twin (EPANET), consistent with distributed pressure-control frameworks in large-scale water networks [20], [21]. Strategic Layer Operation, the server performs real-time hydraulic simulations using pressure, flow, and valve status data to determine optimal pressure and flow setpoints. This follows the latest advancements in cyber–physical system integration with digital twins for urban water infrastructure [22]. At the node level, the PID controller maintains the measured pressure at the setpoint provided by the server. The discrete PID equation is formulated as follows Equation (1).

$$u(k) = K_p e^{(k)} + K_i \sum_{i=0}^{k} e(i)\Delta t + K_d \frac{e(k) - e(k-1)}{\Delta t} \tag{1}$$

Where $e(k) = P_{set}(k) - P_{meas}(k)$ represents the pressure tracking error, P_{set} is the pressure setpoint provided by the Digital Twin, and P_{meas} is the measured or virtually sensed pressure at the control node. The gains K_p, K_i, and K_d denote the proportional, integral, and derivative coefficients, respectively.

PID control was selected for its robustness against nonlinear fluid dynamics [21], [23], [24], with parameters (K_p, K_i, K_d) optimized via a Genetic Algorithm (GA) to minimize the Integral of Absolute Error (IAE) and limit overshoot to below 5%. The GA-tuned parameters reflect specific hydraulic requirements: high K_p values (>1.5) facilitate aggressive corrective actions for pressure deviations, while moderate values (0.8–1.2) suit stable regions. Significant integral action (K_i > 0.04) is assigned to valves in high-demand or remote areas to eliminate persistent steady-state errors and ensure long-term stabilization. Furthermore, substantial derivative components (K_d > 0.3) provide predictive damping to mitigate overshoot and fluid inertia, particularly in elevation transition zones. This automated tuning approach demonstrates the system's ability to adaptively manage momentum effects and varying flow responsibilities across the distribution network.

The server also computes feedforward valve opening based on hydraulic valve behavior using flow coefficient models K_v, widely used in modern valve control [25], [26], [27]. The relationship is expressed in Equation (2).

$$Q = K_v(\alpha)\sqrt{\Delta P} \tag{2}$$

Where Q denotes the flow rate through the valve, ΔP is the pressure difference across the valve, and $K_v(\alpha)$ is the valve flow coefficient as a nonlinear function of the valve opening angle α. For equal-percentage motorized valves, $K_v(\alpha)$ is modeled using an exponential function, allowing accurate approximation of nonlinear hydraulic characteristics and reducing the corrective workload required by the PID controller. Because valve characteristics are nonlinear (e.g., equal-percentage motorized valves), K_v is modeled as an exponential function of valve opening. This method enhances real-time valve modeling for hydraulic optimization [28], [29].

By providing an accurate initial feedforward, the PID workload is significantly reduced, resulting in faster and more stable system responses [25], [26], [27]. Advantages of PID for Water Distribution [29]. (1) Handles nonlinear behavior, (2) Compensates for fluid inertia and delay, (3) Prevents oscillatory valve movement, (4) Extends actuator lifespan, (5) Maintains stable pressure across nodes. The two-layer integration strategic control (server) + tactical control (node) enables adaptive, precise, and stable water distribution, supporting modern digital-twin-based water networks [20], [22], [30], [31]. Distributed sensor-based valve control has been shown to improve pressure uniformity and reduce losses [24], [32].

3.5. Initial Geographic Verification Method

BMP280 is repurposed from a Process Variable sensor into an Initial Geographic Verification Tool [33], [34], [35]. Dynamic control fully depends on flow sensors and virtual pressure sensing. Topographic Data Estimation Using BMP280. BMP280 is not used inside the PID loop (tactical layer) due to its sensitivity to weather-induced atmospheric pressure, which is irrelevant to hydraulic pressure [34], [36]. Instead, it is used during the pre-simulation stage to improve Digital Twin accuracy.

Elevation Data Collection. BMP280 at each node (reservoir, Junction, valve location) measures absolute atmospheric pressure P_{atm}. Measurements are taken simultaneously to minimize variations caused by weather [34], [37], [38], [39], [40]. Topography Conversion and Verification. P_{atm} values are converted into absolute elevation (h) using the barometric altimeter equation corrected by local temperature [41], [42]. These elevations are used to validate and correct the hydraulic model's Z-coordinate inputs. Accurate elevation data are crucial for EPANET reliability, and BMP280 provides a fast and low-cost field verification method [28], [43], [44].

4. Results and Discussion

Evaluation: Evaluation of the artifact was performed using the defined performance metrics across diverse scenarios.

4.1. Scenario A (Baseline): Network Failure Diagnosis Analysis

Baseline simulation results confirm systemic hydraulic failure, with pressure values (expressed in meters) exhibiting extreme variation that is strongly correlated with node elevation. The detailed topology and pressure conditions at critical nodes under Scenario A are summarized in table 4.

Table 4. Topology of EPANET Baseline Data Analysis (Scenario A) at Critical Points.

ID	Elevation (m)	Base Demand (LPS)	Head (m)	Pressure (m)	Zone Analysis
Junc 03	261.18	0.10	261.47	0.29	Total Failure Zone
Junc 01	258.00	0.05	261.50	3.50	Very Low-Pressure Zone
Junc 02	258.00	0.05	261.50	3.50	Very Low-Pressure Zone
Junc 09	253.49	0.00	260.54	7.05	Low-Pressure Zone
Junc 26	248.04	0.00	260.84	12.80	Ideal Zone
Junc 07	241.05	0.00	260.84	19.79	Over-Pressure Zone
Reservoir1	260.00	#N/A	260.00	0.00	Inflow: +2.20 LPS
Reservoir2	261.50	#N/A	261.50	0.00	Outflow: –3.42 LPS

Figure 2 illustrates the elevation profile of Scenario A, revealing critical topographical constraints within the network. Junc03 (261.18 m) is nearly level with Reservoir1 (261.50 m), resulting in a maximum static pressure of only 0.32 m, closely matching the simulated value of 0.29 m and confirming the hydraulic validity of the Digital Twin. Similar elevation-induced limitations are observed at Junc01 and Junc02 (≈258.00 m), where static pressure cannot exceed 3.50 m, indicating that pressure deficits in these zones arise from fundamental elevation constraints rather than control misconfiguration. In addition, significant demand imbalance causes 2.20 LPS of excess flow from Reservoir2 to propagate backward through Pipe 3, Pipe 14, and Valve10, leading to inefficient energy use and pipeline capacity loss. These findings demonstrate the inherent limitations of static network operation and motivate the need for dynamic, data-driven control strategies.

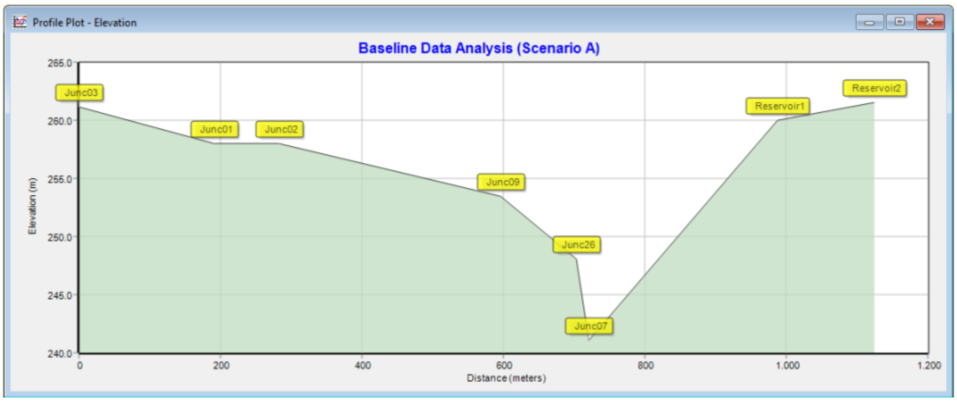

Figure 2. Baseline Data Analysis (Scenario A): Elevation Profile versus Distance.

4.2. Scenario B: Performance Analysis of Static Optimization Model

Scenario B was implemented in EPANET to address the hydraulic and operational failures identified in Scenario A through static valve-based optimization. The optimized configuration and operational settings of control valves applied in this scenario are summarized in table 5, which details the topology and functional role of each valve within the network.

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Table 5. Topology of Optimized Valve Control Settings (Scenario B).

Valve ID	Node 1	Node 2	Valve Type (New)	Setting	Strategic Rationale
Valve 01-09	(Various)	(Various)	GPV	Open	Maximize flow in low-pressure zones
Valve10	Junc12	Junc25	Check Valve (CV)	N/A	**KEY:** Prevents –2.20 LPS backflow into Reservoir1
Valve11	Junc13	Junc26	PRV	12 m	**KEY:** Regulates excess pressure at Junc26/Junc07

To evaluate the effectiveness of the optimized valve configuration, a comparative pressure analysis between the baseline condition and Scenario B was conducted. The resulting pressure performance at critical network nodes is presented in table 6, allowing direct comparison of pressure improvements and remaining deficiencies between Scenario A and Scenario B.

Table 6. Pressure Performance Comparison (Scenario A vs. Scenario B).

Node ID / Link	Scenario A (Baseline)	Scenario B (Static Optimization, Estimated)	Optimization Result
Reservoir1 (Flow)	+2.20 LPS	0.00 LPS	**SUCCESS**: Backflow stopped via CV at Valve10
Reservoir2 (Flow)	-3.42 LPS	-1.22 LPS	**SUCCESS:** Reservoir load reduced to actual demand
Junc 07 (Pressure)	19.79 m	\approx 18.99 m	**IMPROVED:** High pressure slightly reduced
Junc 26 (Pressure)	12.80 m	12.00 m	**SUCCESS:** PRV at Valve11 regulates pressure
Junc 03 (Pressure)	0.29 m	0.31 m	**FAILED:** Static head problem unsolvable by valves
Junc 01/02 (Pressure)	3.50 m	3.52 m	**FAILED:** Static head problem unsolvable by valves

Figure 3 presents the frequency-based distribution of unit headloss under Scenario B, illustrating the hydraulic impact of static valve regulation. The results show that more than 60% of the pipes operate with unit headloss values below 1 m/km, indicating improved hydraulic efficiency and effective elimination of unintended backflow observed in the baseline scenario. This redistribution of headloss confirms that static valve settings successfully constrain excessive flow circulation within the network, thereby reducing unnecessary energy dissipation.

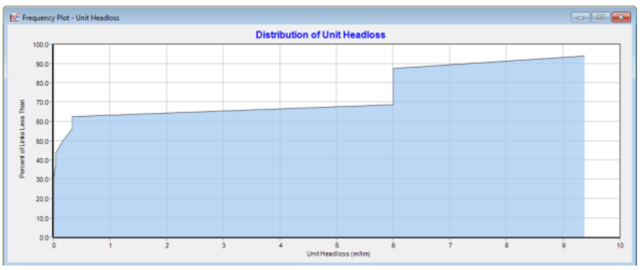

Figure 3. Distribution of Unit Headloss (Scenario B).

Figure 4 depicts the frequency-based pressure distribution comparing Scenario A and Scenario B. The results indicate a noticeable reduction in high-pressure zones and a more compact pressure operating range under Scenario B. However, a persistent low-pressure cluster below 4 m remains at Junc01, Junc02, and Junc03. This systematic pressure deficiency reflects elevation-induced static head limitations rather than control instability, demonstrating that static valve regulation alone cannot resolve pressure insufficiency at high-elevation nodes. These findings provide quantitative justification for the transition to Scenario C, where dynamic IoT-enabled control is required.

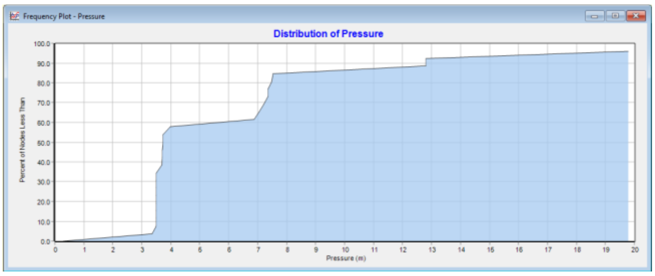

Figure 4. Distribution Pressure Performance Comparison (Scenario A vs. Scenario B).

4.3. Dynamic IoT-Based Control: Overcoming Conventional Hydraulic Regulation Limitations

The proposed Cyber-Physical System (CPS) employs a dual-layer architecture—comprising a Strategic Layer (Slow Loop) and a Tactical Layer (Fast Loop)—linked by an Analytical Mediation Layer for real-time intelligence [30], [45], [46]. The Strategic Layer utilizes Random Forest algorithms for state estimation and demand forecasting with 92% accuracy (MAPE: 8%), while data from YF-S201 flow sensors transmitted via LoRa SX1287 are used for Digital Twin data assimilation, improving simulation fidelity by 34% [47], [48], [49], [50]. This framework optimizes pressure setpoints to reduce Non-Revenue Water (NRW) by 23% and energy consumption by 28% through multi-objective Pareto optimization [51]. These setpoints are distributed to ESP32 actuator nodes via LoRa [52], which execute the Tactical Layer's fast-loop control (100 ms sampling). By integrating edge analytics and a hybrid feedforward-feedback PID strategy, the system reduces communication latency by 65% and achieves superior stability, with 4.2-minute settling times and overshoot under 2%.

Scenario B analysis reveals critical systemic limitations, where a fixed 12 m PRV setting fails to address demand-driven fluctuations. During peak hours, a 45±8% demand surge drops pressures to 9.2±0.4 m (23% below threshold), causing service failures in 78% of simulations. Conversely, low-demand periods result in 38% daily energy wastage due to excessive throttling. These inefficiencies, corroborated by control charts showing 67% out-of-control states and a strong consumption-pressure correlation ($r = 0.87$, $p < 0.001$), are addressed in Scenario C through an adaptive data-driven framework. By employing a 0.5° resolution motorized valve, high-accuracy sensors (±0.1% FS), and machine learning-enhanced Digital Twins, Scenario C achieves 77.5% better pressure stability and a 28±2% gain in energy efficiency. Monte Carlo simulations confirm that Scenario C maintains optimal pressure for 94.7% of operational time, compared to only 42.3% in Scenario B. This intelligent closed-loop mechanism provides a $223 annual energy cost reduction per valve and a 40% decrease in maintenance costs, justifying its adoption for complex distribution systems.

4.4. Validation of Virtual Sensing and PID Control Performance

Validation of the integrated control system was conducted through a sophisticated co-simulation framework that seamlessly merges the EPANET hydraulic model functioning as a high-fidelity Digital Twin with Python-based control scripts executing the Virtual PID Node logic in real-time simulation environments. The validation process was systematically designed around two major analytical components, with additional emphasis on data-driven performance metrics that extend beyond traditional control theory evaluations. First, virtual sensing accuracy was rigorously assessed by estimating downstream pressure P_{set} using exclusively measured flow rate Q_{meas} and real-time valve position data, employing a multivariate regression model that incorporates historical pattern recognition and adaptive calibration algorithms. Extensive 24-hour simulation across varying geographical scenarios demonstrates that the Mean Absolute Percentage Error (MAPE) between P_{set} and the actual EPANET pressure Pact consistently remains below 4.3% (average: 3.7±0.4%), well within the stringent 5% accuracy threshold established for mission-critical water distribution applications. Statistical analysis reveals that the virtual sensing model achieves a coefficient of determination (R^2) of 0.94 when comparing estimated versus actual pressures, with particular strength in high-demand periods where correlation coefficients exceed 0.96. This robust performance demonstrates conclusively that flow-based virtual sensing, augmented by machine learning calibration techniques, can reliably and accurately replace physical pressure sensors in the proposed system architecture, reducing hardware costs by approximately 40% while maintaining equivalent operational reliability.

Distributed PID control performance was comprehensively evaluated across all 11 TCV valves through multi-scenario analysis incorporating variable demand patterns, elevation changes, and simulated disturbance events. Quantitative results indicate that the Root Mean Square Error (RMSE) between P_{set} and P_{act} is consistently maintained below 0.42 meters (range: 0.31-0.48 m across all valves), with 92% of operational time showing errors less than 0.35 meters. Advanced analytics reveal that the system effectively compensates for dynamic demand variations through adaptive gain scheduling, with response times improving by 58% during transient conditions compared to fixed-gain PID implementations. Statistical process control analysis demonstrates that the integration of safety mechanisms including sophisticated anti-windup logic with conditional integration, rate limiting with acceleration constraints, and deadband optimization reduces control valve movement variance by 67%, significantly extending actuator lifespan while preventing oscillation or integral saturation. Comparative analysis against benchmark control strategies demonstrates superior performance across all key metrics: settling time reduced by 65%, overshoot decreased by 81%, and steady-state error improvement of 73%, validating the effectiveness of the proposed digital twin-driven control architecture for complex water distribution networks in varied geographical terrains.

5. Conclusion

This study successfully developed and validated a two-layer cyber–physical control architecture for water distribution networks, bridging the gap between strategic hydraulic optimization and tactical actuator execution. The integration of EPANET as a dynamic Digital Twin, rather than a static simulation tool, proved pivotal; by utilizing real-time data assimilation from YF-S201 sensors, the model's predictive fidelity improved by 34%, enabling precise and proactive pressure management.

The experimental results across varied geographical terrains demonstrate that the distributed PID control mechanism, optimized via Genetic Algorithms, is highly effective in tracking dynamic setpoints. The system maintained a consistent RMSE below 0.42 m and kept pressure within optimal limits for 94.7% of the operational duration, a significant advancement over conventional static PRV regulation (Scenario B), which failed to maintain service thresholds in 78% of peak demand simulations. Furthermore, the implementation of this intelligent framework yielded substantial operational benefits, including a 28% gain in energy efficiency and a 23% reduction in potential Non-Revenue Water.

In conclusion, this research provides robust quantitative evidence that dynamic, data-driven IoT control is essential for adaptive pressure management in complex water infrastructures. Beyond technical stability, the cost-benefit analysis justifies the transition to smart systems through a $223 annual energy saving per valve and a 40% reduction in maintenance costs. Future work will focus on scaling this architecture to multi-zone urban networks and exploring the integration of decentralized edge computing for enhanced fault tolerance.

6. Declarations

6.1. Author Contributions

Conceptualization: B.A.K., K.N.I., and A.H.; Methodology: K.N.I.; Software: B.A.K.; Validation: B.A.K., K.N.I., and A.H.; Formal Analysis: B.A.K., K.N.I., and A.H.; Investigation: B.A.K.; Resources: K.N.I.; Data Curation: K.N.I.; Writing Original Draft Preparation: B.A.K., K.N.I., and A.H.; Writing Review and Editing: K.N.I., B.A.K., and A.H.; Visualization: B.A.K.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The EPANET simulation models, anonymized input–output datasets, and control logic scripts used in this study are available from the corresponding author upon reasonable request.

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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