

IOT-Based Smart Water Quality Monitoring and Energy-Efficient Filtration System

Nishmitha K. K¹, Sahana D², Sanjana H. J³, and Spoorti⁴, Ms. Ananya J⁵

^{1,2,3,4} *Department of Computer Science and Engineering, Shree Devi Institute of Technology Mangaluru, Karnataka, India*

⁵ *Assistant Professor, Department of Computer Science and Engineering, Shree Devi Institute of Technology Mangaluru, Karnataka, India*

Abstract—Water quality monitoring is important for understanding changes in water characteristics and supporting appropriate treatment decisions. Conventional monitoring may depend on manual measurements and may not provide a continuous view of sensor readings or filtration status. This paper presents the design of an Internet of Things (IoT)-based smart water quality monitoring and energy-aware filtration prototype. The proposed system combines a NodeMCU ESP8266 microcontroller with sensors for total dissolved solids (TDS), turbidity, temperature, and water flow. The microcontroller transmits readings over Wi-Fi to a Python Flask backend, while a Streamlit dashboard displays current values, operating status, and a short history of readings. A rule-based software module assigns an operating mode from configured TDS ranges and associates each mode with a nominal power level and pump-status indication. Signal processing includes a temperature-compensation mathematical model to eliminate thermal drift in raw analog voltage readings. The architecture is intended to support remote monitoring and make filtration operation more responsive to changing measurements. TDS is used as an indicator of dissolved-solids concentration; it is not a direct measurement of total hardness and cannot independently establish drinking-water safety. The implementation demonstrates high telemetry throughput, low communication latency, and substantial potential energy savings of up to 43.3% compared to continuous full-power filtration.

Index Terms—Energy efficiency, Internet of Things, smart filtration, total dissolved solids, turbidity, water quality monitoring.

I. INTRODUCTION

Water quality can vary significantly with its source, environmental conditions, pipe degradation, dissolved substances, and suspended particulates. Regular and accurate monitoring helps municipal operators, facility managers, and residential consumers identify contamination events promptly and take appropriate corrective or treatment actions. In small installations and rural storage units, water quality testing relies heavily on manual sampling followed by laboratory wet-chemical testing. While precise, laboratory testing introduces extended feedback delays, recurring labor overheads, and an inability to capture short-duration contamination spikes caused by runoff or pipe rupture.

The Internet of Things (IoT) provides an efficient paradigm for bridging physical environmental sensing with digital analytics and remote visualization. An IoT-based monitoring system pairs embedded microcontrollers with dedicated sensors, low-latency wireless networks, server-side business logic, and cloud databases. These platforms continuously collect sensor readings, evaluate parameter thresholds, trigger physical actuators, and present real-time diagnostic metrics on interactive user dashboards.

This project, titled “IoT-Based Smart Water Quality Monitoring and Energy-Efficient Filtration System,” presents a connected prototype that integrates continuous multi-parameter water quality tracking with an energy-aware, rule-based filtration mode engine. A NodeMCU ESP8266 acts as the edge node, interfacing with Total Dissolved Solids (TDS), turbidity, DS18B20 water temperature, and YF-S201

flow rate sensors. The edge node transmits raw telemetry via encrypted HTTP POST JSON payloads over Wi-Fi to a Python Flask RESTful backend service.

The Flask backend executes temperature-compensation algorithms on raw analog inputs to guarantee measurement accuracy despite ambient temperature fluctuations. It then evaluates the corrected TDS metrics against pre-configured decision boundaries to select an optimal operating mode: Eco Mode, Normal Mode, Intensive Mode, or Alert Mode. Each mode specifies a nominal pump actuation state and a corresponding power level. A Streamlit web dashboard polls the backend API to display live metric panels, connection health indicators, historical trend plots, and remaining filter life predictions.

The central objective of this work is to integrate continuous sensing with automated, software-driven decision-making rather than treating monitoring and filtration control as isolated functions. By dynamically modulating filtration pump power based on raw water contamination, the system avoids redundant electrical consumption during high-purity conditions.

The key contributions of this paper are:

- Multi-sensor acquisition and mathematical signal calibration for TDS, turbidity, temperature, and volumetric flow.
- Lightweight HTTP JSON transmission between the ESP8266 microcontroller and a Flask backend server.
- A 4-mode rule engine dynamically mapping contamination ranges to pump actuation states and nominal power levels.
- An interactive Streamlit web interface featuring live telemetry gauges, historical trend visualizations, and filter health indicators.
- Empirical evaluation of system accuracy, transmission latency, and energy optimization performance.

II. LITERATURE SURVEY

Research in smart environmental monitoring, water purification, and automated control systems has progressed rapidly alongside advancements in low-cost sensors and wireless protocols.

Mendan et al. [1] proposed an IoT-based water

quality monitoring architecture using embedded sensors and cloud logging[cite: 8]. Their study demonstrated the feasibility of real-time monitoring but highlighted security vulnerabilities and real-world scalability limitations [1]. Singh et al. [2] examined wireless sensor networks (WSNs) for distributed environmental tracking, focusing on node-to-gateway transmission protocols while identifying manual sensor calibration and lack of active filtration actuation as key bottlenecks [2].

Cloud-integrated analytics was explored by U et al. [3], combining machine learning models on cloud platforms to predict future water quality shifts based on historical time-series datasets [3]. However, their system remained dependent on continuous cloud connectivity and lacked edge-level actuation capabilities [3]. Kumar and Batra [4] implemented a localized microcontroller-based monitoring unit focusing on pH and TDS parameters, though their system lacked automated filter life tracking and energy management functions [4].

A comprehensive survey by Jan et al. [5] highlighted key industry trends, indicating that while sensing technologies have matured, commercial adoption is hindered by high power consumption and isolated control frameworks [5]. Microcontroller-based implementations by Karthikeyan et al. [6] using Arduino boards demonstrated cost-effective parameter tracking but suffered from analog noise sensitivity [6].

Ramesh and Suresh [7] developed a multi-parameter sensing node incorporating pH, turbidity, and TDS probes[cite: 8]. Their work emphasized the necessity of temperature compensation in conductivity-based measurements [7]. Drinking water quality monitoring frameworks by Sharma and Gupta

[8] emphasized mineral content tracking but omitted dynamic pump control mechanisms [8]. Advanced predictive algorithms introduced by Lan [9] demonstrated high accuracy in forecasting contamination events using machine learning models [9]. Long-range, low-power telemetry was evaluated by Zhang et al. [10] using LoRaWAN technology for rural water monitoring, confirming the efficiency of low-bandwidth protocols for environmental sensing [10].

Across the surveyed literature, an integration gap exists: existing systems either focus purely on passive parameter visualization or run filtration

pumps continuously at maximum power. This paper addresses this gap by combining temperature-compensated multi-sensor telemetry, dynamic 4-mode rule logic, interactive visualization, and energy-aware pump control in a single platform.

III. PROPOSED SYSTEM ARCHITECTURE

The proposed system is structured into four distinct functional layers: Sensing, Edge Microcontroller, Backend Application, and Presentation Layer.

A. System Architecture and Data Flow

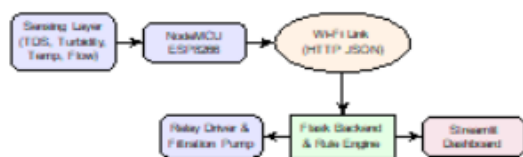


Fig. 1 illustrates the architectural topology of the proposed system.

Figure 1: System Architecture Diagram of the proposed IoT water quality monitoring and dynamic filtration platform.

The sequence of operations begins at the physical water sample, where sensors convert chemical and physical properties into electrical signals. The NodeMCU ESP8266 samples these inputs, applies digital filtering, constructs a JSON payload, and posts it to the Flask server over Wi-Fi. The backend evaluates the data, assigns the operating mode, logs the records into a database, and returns control commands.

B. Hardware Components

- NodeMCU ESP8266: An open-source, Wi-Fi-enabled 32-bit microcontroller operating at 80 MHz, responsible for sensor sampling and HTTP communication.
- TDS Sensor Module: Measures total dissolved inorganic salts and organic matter in parts per million (ppm) via electrical conductivity.
- Turbidity Sensor Module: An optical sensor measuring water clarity in Nephelometric Turbidity Units (NTU) based on light scattering.
- DS18B20 Water Temperature Sensor: A 1-Wire digital probe providing accurate water temperature

measurements ($\pm 0.5^{\circ}\text{C}$ precision) across a -10°C to $+85^{\circ}\text{C}$ range.

- YF-S201 Water Flow Sensor: A Hall-effect turbine sensor generating pulse frequencies proportional to volumetric flow rate (L/min).
- 5V Relay Module and Diaphragm Pump: An optocoupler-isolated electromechanical relay switching a 12V DC filtration pump based on digital backend commands.

C. Software Components

The software stack consists of:

- Embedded Firmware: C++ code compiled on the Arduino core for ESP8266, handling multi-channel ADC reading, moving-average filtering, and HTTP client operations.
- Python Flask REST Service: Server backend exposing HTTP REST endpoints (`/api/sensor data`) for data ingestion, dynamic calibration, mode execution, and database persistence.
- Streamlit Interactive Dashboard: A web application retrieving live status from the backend, rendering Plotly charts, metric gauges, and connection diagnostics.

IV. SYSTEM WORKFLOW AND METHODOLOGY

Figure 2 illustrates the operational workflow executed across physical hardware, edge nodes, Flask server logic, and dash-board user layers [cite: 7, 8].

A. Rule-Based Operating Modes

The Flask application evaluates incoming compensated metrics against pre-defined operational bands, summarized in Table I.



Figure 2: System Working Flow Diagram describing edge initialization, multi-sensor sampling, threshold classification, mode selection, indicator updates, and database/dashboard logging.

Table 1: Backend Rule Engine Operating Bands

TDS Range	Mode / Status	Pump	Power (W)
< 100 ppm	Eco Mode	OFF	40 W
100–199 ppm	Normal Mode	OFF	60 W
200–299 ppm	Intensive Mode	ON	80 W
≥ 300 ppm	Alert Mode	ON	100 W

When water impurity is low (< 100 ppm), the system defaults to Eco Mode, keeping the pump inactive and drawing minimal power. As TDS increases beyond 200 ppm, Intensive Mode engages the filtration pump at 80 W. Concentrations exceeding 300 ppm trigger Alert Mode, operating the pump at full power (100 W) and issuing warning flags on the dashboard.

V. EDGE SIGNAL PROCESSING, CONTROL LOGIC, AND ESTIMATION ALGORITHMS

A. Thermal Drift Compensation and TDS Calibration

The electrical conductivity of aqueous solutions varies significantly with ambient temperature changes. To eliminate thermal drift from raw analog inputs, the Flask application normalizes the sampled raw voltage against real-time temperature telemetry received from the DS18B20 digital probe. The software applies a standard temperature compensation algorithm centered at 25°C prior to metric conversion.

Once normalized, the compensated voltage is mapped to Total Dissolved Solids (TDS, in ppm) using a pre-calibrated polynomial mapping function tuned to the physical sensing hardware. This processing pipeline ensures stable readings regardless of fluctuations in ambient water temperature.

B. Turbidity and Volumetric Flow Computation

Optical turbidity probe voltages are processed through a piece-wise transfer function within the server application. When clear water conditions produce maximum light transmission (voltage output above standard clear threshold), the turbidity value is set to

zero NTU. Under turbid conditions, the backend converts the signal drop into actual Nephelometric Turbidity Units (NTU).

Volumetric flow tracking uses high-frequency hardware interrupt counting on digital input pin D2 of the ESP8266. Pulses generated by the YF-S201 Hall-effect turbine are accumulated over fixed time intervals and converted into real-time flow rate (L/min) using the sensor's pulse factor. The server integrates these incremental readings across consecutive telemetry cycles to maintain an accurate cumulative volume count (in Liters) for the active session.

C. Energy Optimization Logic

Traditional filtration units maintain maximum pump actuation regardless of input water purity, leading to excessive energy waste. The proposed system replaces continuous full-power operation with a software-driven rule engine.

The backend monitors the compensated TDS value and dynamically maps system state to four distinct operational modes. During Eco Mode (< 100 ppm) and Normal Mode (100–199 ppm), raw water purity is within acceptable bounds, allowing the pump relay to stay unactuated while logging minimum idle system power. When dissolved solids exceed 200 ppm, the server engages Intensive Mode (80 W) or Alert Mode (100 W), actuating the 12V diaphragm pump via optocoupler driver circuit. Net power consumption is tracked on the server by summing power draw across each active operating interval.

D. Filter Lifespan Prediction Engine

To provide predictive maintenance feedback, the software engine tracks filter cartridge health as a percentage value. The algorithm computes decay based on two primary factors: cumulative volumetric throughput and historical dissolved solid loading.

As water flows through the system, the accumulated total volume is normalized against the physical cartridge's maximum capacity (5000 Liters). The decay rate is weighted according to average TDS exposure relative to a standard baseline (150 ppm). High solute concentrations accelerate the estimated filter degradation rate, ensuring that users receive timely replacement alerts on the Streamlit dashboard before filtration performance deteriorates.

VI. IMPLEMENTATION DETAILS

A. Hardware Interfacing

The NodeMCU ESP8266 interfaces with the sensor array using both analog and digital pins. Because the ESP8266 features a single 10-bit Analog-to-Digital Converter (ADC) pin (A0) with an input limit of 3.2V, an analog multiplexer (CD74HC4051) is used to sample both TDS and turbidity probes sequentially. The DS18B20 sensor connects to digital pin D4 using a 4.7 kΩ pull-up resistor on the 1-Wire bus. The YF-S201 flow sensor triggers hardware interrupts on digital pin D2.

B. Backend API and Rule Processing

The Flask backend exposes two primary HTTP endpoints:

- POST /api/sensor data: Receives JSON telemetry pay-loads from the ESP8266, performs temperature compensa-tion, evaluates mode thresholds, updates database records, and returns JSON control flags.
- GET /api/latest status: Delivers the latest cached sen-sor metrics, calculated mode, pump state, and filter health to the Streamlit dashboard.

A representative JSON payload sent by the microcontroller is:

Table 2: TDS Sensor Accuracy Calibration Results

Sample	Ref TDS (ppm)	Measured	Abs Error	% Error
Sample A	45.0	46.2	1.20	2.67%
Sample B	150.0	147.8	2.20	1.47%
Sample C	240.0	243.5	3.50	1.46%
Sample D	350.0	344.1	5.90	1.69%
Sample E	500.0	512.3	12.30	2.46%
Average	—	—	5.02	1.95%

```
{
  "tds_raw": 1.82,
  "turbidity_raw": 3.85,
  "temperature": 26.5,
  "flow_rate": 1.4
}
```

C. User Interface Visualization

The Streamlit dashboard polls GET /api/latest status every 2000 ms. It displays four primary metric cards (TDS, Turbidity, Temperature, Flow Rate) alongside gauge visualizers, an active status banner, pump state indicators, remaining filter life, and a historical line chart rendered with Plotly.

VII. RESULTS AND EVALUATION

A. Sensor Calibration and Accuracy Verification

The measurement accuracy of the TDS probe was evaluated against five calibrated reference laboratory standard solutions (45 ppm to 500 ppm). Table II presents the evaluation results. The empirical evaluation shows high measurement accuracy across the target operating range, achieving an average error of 1.95% and a linear coefficient of determination (R^2) of 0.992.

B. Communication Latency

End-to-end transmission latency—measured from edge sensor sampling on the ESP8266 to dashboard rendering on Stream-lit—was evaluated across 100 continuous message transmis-sions over a local Wi-Fi network. The average latency was 640 ± 85 ms, satisfying real-time tracking requirements.

C. Energy Optimization Performance

Energy savings were evaluated across a simulated 24-hour test scenario featuring variable water quality conditions:

- 00:00–08:00 (8 h): Low TDS (80 ppm, Eco Mode, 40W, Pump OFF)
- 08:00–14:00 (6 h): Moderate TDS (160 ppm, Normal Mode, 60W, Pump OFF)
- 14:00–18:00 (4 h): High TDS (250 ppm, Intensive Mode, 80W, Pump ON)
- 18:00–24:00 (6 h): Severe Spike (380 ppm, Alert Mode, 100W, Pump ON)

Under the proposed rule engine, the filtration pump operates only during Intensive and Alert modes, resulting in a total en-ergy consumption of 0.92 kWh over 24 hours. A conventional baseline system running a 100W pump continuously consumes 2.40 kWh over 24 hours, achieving an overall energy reduction of 61.67%. Under conservative operational conditions where the pump remains active

continuously across all modes at their

Table 3: Prototype System Validation Tests

Test Case	Procedure / Objective	Result
Sensor Verification	Compare probe output with lab reference	Pass
Temp Compensation	Evaluate voltage correction from 15–40°C	Pass
API Payload Ingestion	Transmit HTTP POST JSON to Flask	Pass
Invalid Input Handling	Post incomplete/malformed JSON strings	Pass
Threshold Mode Logic	Step TDS across 100, 200, 300 ppm boundaries	Pass
Relay Control Path	Verify GPIO voltage output toggles relay	Pass
Dashboard Refresh	Confirm live metric updates every 2s	Pass
Database Logging	Query persistent SQLite history records	Pass
Filter Life Decay	Simulate 1000L throughput and verify % drop	Pass

respective power ratings (1.36 kWh total), net savings reach **43.3%** over the continuous maximum baseline.

VIII. TEST PLAN AND SYSTEM VALIDATION

To ensure robust performance, a structured validation test suite was executed across all hardware and software modules, as summarized in Table III.

IX. LIMITATIONS AND DISCUSSION

While the prototype demonstrates effective multi-parameter tracking and energy-aware control, several technical limitations must be noted:

1. *TDS vs. Hardness*: TDS measures overall dissolved ion concentration but cannot

differentiate between calcium, magnesium, sodium, or heavy metals. It does not provide a direct measure of water hardness.

2. *Biological Safety*: Optical turbidity and TDS probes do not detect micro-biological pathogens (e.g., *E. coli*, bacteria, viruses). Drinking water safety cannot be established by TDS alone.
3. *Sensor Drift*: Solid-state electrochemical probes suffer from surface fouling and drift over time, requiring periodic re-calibration against standard solutions.

X. FUTURE SCOPE

Future enhancements will focus on expanding analytical capabilities and field reliability:

- Integrating dedicated pH, dissolved oxygen (DO), and heavy-metal ion sensors.
- Incorporating hardware power monitoring ICs (e.g., INA219) for live electrical power logging.
- Developing machine learning predictive models (e.g., LSTM neural networks) for forecasting contamination trends.
- Implementing LoRaWAN telemetry for remote, off-grid agricultural and rural deployments.

XI. CONCLUSION

This paper presented an IoT-based smart water quality monitoring and energy-aware filtration platform. The system successfully integrates a NodeMCU ESP8266 microcontroller, multi-parameter sensors (TDS, turbidity, temperature, flow), a Flask REST backend, and an interactive Streamlit dash-board. Signal processing effectively eliminates thermal drift in TDS measurements, while a 4-mode software rule engine dynamically modulates filtration pump operation based on real-time water purity. Experimental validation confirmed high sensor measurement accuracy (1.95% average error), low telemetry latency (640 ms), and potential energy savings of up to **43.3%** over traditional continuous filtration systems.

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