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Smart IoT-based water treatment with a Supervisory Control and Data Acquisition (SCADA) system process

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ABSTRACT

Water treatment is necessary to ensure the availability of clean and safe water for various uses. Integrating Internet of Things (IoT) technology with water purification systems has shown enormous potential in recent years for enhancing the efficiency and efficacy of the treatment process. Monitoring the disposal of sewage in treatment facilities is the primary obstacle. As a result, a Supervisory Control And Data Acquisition (SCADA) system, including the IoT, has been proposed to ensure the proper operation of these sewer systems and limit the risk of overflow and malfunction. In this paper, we suggest a novel approach that blends Deep Belief Networks (DBNs) with an IoT-based water treatment system equipped with a SCADA system for increased monitoring and control. An IoT–SCADA system can be implemented at various wastewater collection and treatment phases. Secondly, incorporating DBNs enhances the system's predictive capabilities, enabling proactive maintenance and decision-making to prevent potential failures and optimize resource allocation. The proposed technique computes the efficacy of the effluent treatment facility and ensures that chemical emissions do not exceed permissible limits. Furthermore, Complex Event Processing (CEP) can be utilized to evaluate and analyze the massive influx of real-time data sets provided by IoT sensors.

Key words: Complex Event Processing (CEP), Smart Internet of Things (IoT), Supervisory Control and Data Acquisition (SCADA), water treatment

HIGHLIGHTS

- IoT–SCADA system can be implemented at various wastewater collection and treatment phases.
- An intelligent water sensor powered by the Internet of Things monitors water quality, pressure, and temperature.

1. INTRODUCTION

Water is a precious resource that sustains life on Earth, yet it is becoming increasingly scarce and polluted. There is a greater need than ever for effective and efficient water treatment solutions. As Internet of Things (IoT) technology progresses, intelligent water treatment systems are being developed to optimize water treatment processes and reduce waste. Smart IoT-based water treatment, in this context, is a cutting-edge technology that employs IoT to build an intelligent and self-contained water treatment system. This technology increases treatment efficiency and efficacy by integrating sensors, data analytics, and machine learning algorithms to continuously monitor and control several aspects of the water treatment process. In this article, we will examine the main characteristics and advantages of intelligent IoT-based water treatment and how it might revolutionize the water treatment sector.

Many different types of living things rely greatly on water to survive. There are growing worries about water shortage due to increased water use brought on by a rise in the human population (Ma *et al.* 2020). In addition to the widespread concern about freshwater shortages for drinking, there are growing worries about water shortages for agriculture (Rosa *et al.*

2020). A strong water management system is necessary to address the issues caused by water scarcity. Real-time monitoring of water quality and equality is essential for effective water management. Real-time water level monitoring can significantly reduce the water wasted by a tank overflow. The water management system can help find water leaks in an intelligent home by monitoring water levels throughout the day. Making the world a better place requires a cutting-edge water management system. One of the foremost reasons for the low adoption of intelligent water management systems is their high cost (Singh & Ahmed 2021).

The development of IoT for smart cities has resulted in a sharp decline in prices in recent years (Vallino *et al.* 2020). An interconnected system of objects known as the 'Internet of Things' transmits and receives data. Low-cost IoT-based water management technology has become more well-liked recently. IoT devices are perfect for monitoring water levels in real-time since they can exchange data without assistance from a human. Scientists have recently explored a range of markers of water quality, including temperature, conductivity, pH, biochemical oxygen demand, and total dissolved solids (TDS). In smart cities, real-time water quality monitoring is becoming more prevalent. The IoT-based water management system is shown in perspective in Figure 1. A typical setup might include a controller, sensors, and data visualization software. The controller can monitor variables like pH and turbidity with the help of sensors. The data for the measurement are gathered by sensors and transmitted to the organizer.

An organizer is a little computer that can run applications and associate with them a network. It can be set up to gather sensor data and send it online for archiving and analysis. An application is a program that runs online and provides data through a user interface in response to input from a controller. IoT-based systems for water management are low-cost and easy to scale. It is straightforward to verify the water's quality for the presence of various impurities thanks to reasonably priced sensors. Communication technologies that are readily accessible enable deployment in an existing system with little configuration. Monitoring and controlling equipment from a distance is straightforward when IoT platforms are used (Hammi *et al.* 2018).

The Supervisory Control and Data Acquisition (SCADA) system is utilized to manage the filtering process. A plant can be monitored and controlled, and data can be collected using a group called SCADA. Computers have rapidly advanced over the past few decades and are now an essential component of a contemporary SCADA system (Anshori 2015). The water treatment facility's filtering procedure will use this system. This technology will make the filtering process more accessible by automatically controlling and monitoring the process without human involvement. The filtration process can also be

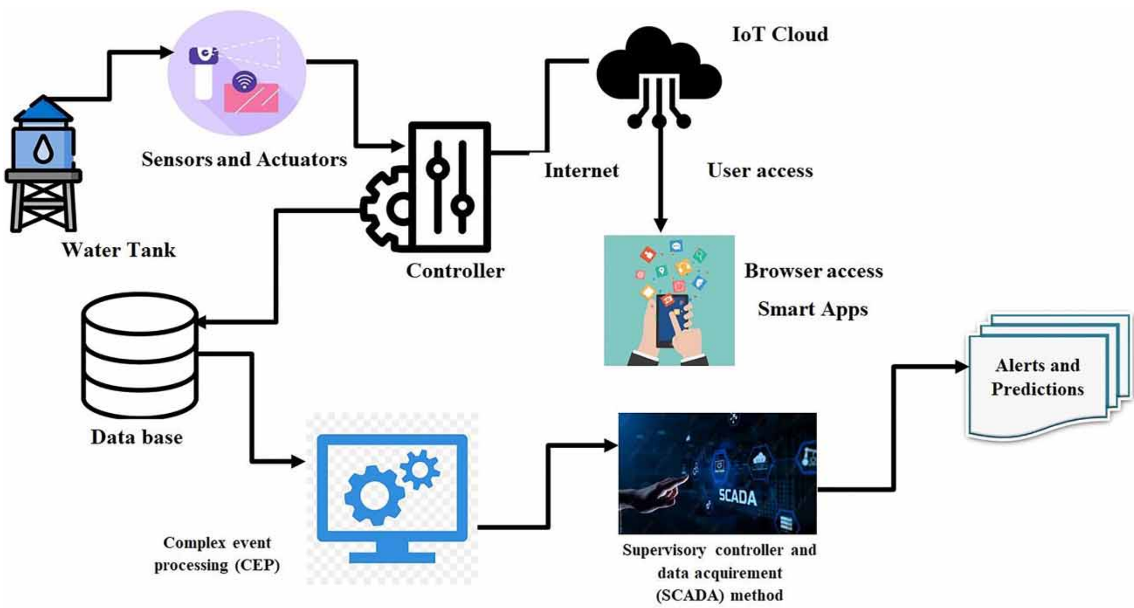

Figure 1 | The proposed method of IoT–SCADA.

observed across vast distances without constant visits. SCADA systems provide the necessary infrastructure for real-time monitoring, control, data acquisition, alarm, and remote access in a smart water treatment system. They enhance operational efficiency, ensure system integrity, and enable informed decision-making for effective water treatment processes.

There is one system, called DCS, that is comparable to SCADA. The distributed control system (DCS), centered on a control room with various control, monitoring, and optimization functions, distributes numerous tasks that govern different process variables and operation units. The integrated DCS system is designed to control manufacturing processes that are batch- or continuous-oriented, like paper production, petrochemical production, central station operations, and oil refining (Hamidi *et al.* 2019). DCS and SCADA operate similarly to one another in terms of how they perform control and monitoring. However, there are some distinctions between the two systems. DCS can only be accessed by specific operators within a particular range or communicate with operators within a limited range. Operators have unlimited access to SCADA at any time and from any location. Additionally, SCADA has data acquisition, whereas DCS merely monitors. Thus, the system has the most recent and earlier data in a process. In contrast to SCADA, which uses open-loop control, DCS uses closed-loop power, meaning that the output impacts the plant (feedback). While SCADA needs a low-speed communication system, DCS needs a high-speed, reliable one. According to the comparison above, SCADA is more helpful than DCS. However, SCADA and DCS each have advantages and drawbacks of their own. SCADA has advanced over time, become more valuable and affordable, and its general application can be used for both industrial and small-scale (prototype) processes. A Remote Terminal Unit (RTU) or other tool is needed to integrate a SCADA system infiltration.

The IoT concept builds on the existing vision of conventional SCADA and enables real-time data gathering and transfer across several protocols. The procedure entails connecting various physical components to digital representations and integrating them into information systems. The idea of the IoT makes it easier for advanced modules and services to be seamlessly integrated and compatible, enabling data aggregation and the preservation of historical data for analysis. This method improves our comprehension of the collected data by offering insightful information. Real-time information monitoring and process control are the cornerstones of SCADA. A thorough understanding of production quality can be attained by integrating an integrated SCADA architecture with an IoT platform that supports various network protocols.

1.1. Contribution

- This study recommends a supervisory control and data collection system based on the IoT to ensure the effectiveness of these sewer systems and lessen the likelihood of overflow and malfunction.
- Various stages of wastewater collection and treatment can use an IoT–SCADA system. An intelligent water sensor driven by the IoT analyses water dynamics. It continuously assesses water quality, pressure, and temperature to map the water flow across the whole treatment capability.
- The suggested approach determines the effluent treatment facility's efficacy and ensures that chemical emissions stay within permitted limits. Complex event processing (CEP) can also be used to analyze and handle the enormous stream of data sets produced in real-time by IoT sensors. The system also examines the gathered data and delivers insightful data using cutting-edge data analytics methods.
- These perceptions can help with treatment process optimization, prospective issue detection, and system maintenance and improvement choices.
- The system may also automate specific tasks thanks to the integration of IoT and SCADA, which lowers the need for manual intervention and boosts operational effectiveness.

The remaining portions of the article are organized as follows: agricultural, industrial, and residential uses are separated in Section 2's categorization of current publications on this topic. Section 3 recommended a SCADA organization that uses an IoT strategy. The results of the experiment are discussed in Section 4. The final section of the investigation is Section 5.

2. LITERATURE SURVEY

The necessity of practical, theoretical, and empirical development was underlined by Dhanwani *et al.* (2021) to comprehend how intelligent technology may help the ecosystem flourish without damaging it. The secondary goal was to ensure that an extensive study of Smart Environmental Pollution Monitoring Systems offers many opportunities to increase understanding of environmental management by applying cutting-edge international technology. By examining historical tendencies, they worked with other academics to promote various 'smart' solutions. As a result, research has a better, greener, and more intelligent future. Sustainable technology has also advanced, and a civilization free of pollution has been created.

Pujar *et al.* (2020) described an IoT-based business for real-time water quality monitoring. Water quality indicators for the Krishna River included pH, demand, temperature, biochemical oxygen, conductivity, and TDS. The controller was an Arduino Mega 2560. The system used one-way and two-way analysis of variance (ANOVA) to analyze the data. The outcomes demonstrated that one-way ANOVA was the most successful IoT system control strategy. The study also showed how many variables affect water quality throughout the year.

A wireless sensor network with IoT capabilities was utilized by Zin *et al.* (2019) to monitor water quality continuously. They used several parts, including a computer, an FPGA, a wireless Zigbee connection, and a protocol. In Curtin Lake in northern Sarawak on the island of Borneo, they employed the technology to track the pH, turbidity, temperature, water level, and carbon dioxide on the lake's surface. The technique cuts down on expenses and energy usage.

A thorough analysis of IoT device applications for intelligent irrigation systems was published by García *et al.* (2020). The study presented in-depth analyses of sensor networks for irrigation systems, soil monitoring, and weather monitoring. The survey indicates that the most popular IoT nodes for irrigation organizations are Arduino boards. Numerous IoT systems are carefully studied concerning their maximum data throughput and frequency spectrum. According to the report, Wi-Fi is the communication technology that is most widely used. The most commonly used database system is MySQL, and the most widely used cloud platform is discovered to be ThingSpeak.

Smart water meters with IoT integration from Nasser *et al.* (2020) automatically transfer data to the cloud after regular data collection intervals. The system's design used microservices and containers to manage real-time streaming and infrastructure effectiveness. The authors employed machine learning methods like Random Forest and Support Vector Regression for time series forecasting applications. Comparative investigation showed that the suggested model was superior and may be used as a benchmark for others.

Sengupta *et al.* (2019) leverage IoT to provide a low-cost method for controlling and monitoring water quality in real-time. Using an analog-to-digital converter, a Raspberry Pi is connected to sensors for temperature, turbidity, and pH. Instructions for the solenoid valve to turn on or off water flow from the overhead tank to the dwellings will be delivered based on data gathered by numerous sensors and processed by the Raspberry Pi. This entire method is carried out automatically, with no human intervention, saving time spent dealing with the issue manually. Finally, it decides whether or not the water quality parameters are within the acceptable range. All of these devices are inexpensive, versatile, and effective.

Woźniak *et al.* (2021) developed a fuzzy rules control model for a next-generation home environment with electronic components, infrastructure, and appropriate applications. The technology is being developed for the next stage of the IoT and is based on 6G network connectivity technologies. Through adaptive ventilation, the suggested control technique effectively manages water flow, windscreen monitoring, safety concerns, and carbon dioxide reduction. The latest 6G connectivity protocol was designed to interact with the technology, enhancing data flow, and dependability at the local area network and end-user interface levels.

The E-Sensor AQUA water quality monitoring system was created and tested in the Mekong Delta by IDanh *et al.* (Vinh *et al.* 2020). The instrument determined the temperature, water's salinity, dissolved oxygen, and pH. The solution utilized the IoT platform ThingSpeak to save data on the cloud server. Every minute, the master controller takes the data gathered from the sensor nodes and updates the information stored on the cloud server. Apps for Android and iOS smartphones may be used to access the system and view the data.

Luccio *et al.* (2020) have suggested a technique for obtaining coastal data using sensors and devices installed in naval equipment. The distributed pleasure boat sensor network for marine and atmospheric studies is the name of the technology. The results show that by including crowd-sourced bathymetry data in the process of computational model design, the end consequences' precision is improved, and a more exact spatial pattern of the sea current transporting the tracers is made possible.

A model developed by Gupta *et al.* (2021) automatically assesses water quality variables like turbidity, pH, and temperature. The ESP32 was chosen for underwater communication because of its built-in Wi-Fi and low battery consumption. The IoT-based model was built using communication modules, a turbidity meter, and a pH sensor. Additionally, based on previously computed data, a machine learning method based on K Means was used to examine water quality. The constructed locomotive model regularly assesses the water quality in large and small bodies of water. The central pollution control board can visit the webpage displaying the readings. A robot can monitor the quality of the water anyplace. This project is self-sufficient and effective because the designed model is affordable, and the robot can communicate underwater using high-speed Wi-Fi.

Demissie *et al.* (2021) suggested a surfactant-based method as an adequate but energy-intensive substitute for eliminating dangerous pollutants from water. The elimination of pollutants, including the recycling of concentrated aqua, was evaluated by the authors, who discovered no signs of degradation. The authors discussed various strategies for enhancing process efficiency and obstacles and opportunities for further study in wastewater treatment.

A low-cost intelligent irrigation system for farming is presented by Akhund *et al.* (2022). Agriculture is moving to automated, remote monitoring and IoT network-integrated fog, cloud, and automation technologies. With a hardware sensor and a microcontroller, we developed a prototype that can gauge the temperature, humidity, and water level. The purpose of this study is to identify whether to switch on or off the motor by using a variety of sensors to measure a variety of readings and values. We present the main algorithm and flowchart of the system. Our automated system, built on an IoT application, creates a self-contained irrigation system and notifies us remotely by SMS on our mobile devices.

Yousif & Abdalgader (2022) present a real-time monitoring and auto-watering system based on mathematical models that establish and control the required water rate. It helps with water saving by giving the plant the proper amount. Additionally, it ensures interoperability across many sensor data sources necessary for large-scale agricultural analytics. The Arduino Integrated Development Environment (IDE) provides access to the mathematical model for sensing soil moisture levels and calculating if they drop below a predetermined threshold value, at which time plant watering is automatically started. The suggested strategy boosts productivity through irrigation optimization while using less water (more than 70% less) to increase irrigation system efficacy (Yasin *et al.* 2021).

The need for water from competing economic sectors increases as the population rises. Because of this, it is impossible to meet human needs for water while maintaining the natural flows necessary to protect our ecosystems. Many areas are losing underground water, which increases the likelihood that present and future generations may experience more climatic fluctuation. Because of this, information technology techniques and internet communication technologies (ICTs) play a crucial role in water resource management by minimizing excessive freshwater wastage and managing and monitoring water contamination. In this paper, we will examine studies that use the IoT as a communication tool to regulate the preservation of available water and prevent it from being wasted by households and farmers.

2.1. Limitations of existing system

- Due to their reliance on the internet, intelligent IoT-based water treatment systems are susceptible to operational disruptions from connectivity failures, power outages, or other technical challenges. Additionally, fouling or calibration drift may impact the sensors' dependability to detect water quality.
- An innovative IoT-based water treatment system's implementation can be pricey because it calls for hardware, software, and maintenance expenditures. For smaller or less financially secure organizations, these fees can be exorbitant.
- Cyber-attacks could lead to data breaches or system failures in intelligent IoT-based water treatment plants. These systems need more resources and knowledge to ensure their security.
- Qualified operators and maintenance workers must operate and maintain intelligent IoT-based water treatment systems. For these systems to function well, people must be adequately taught and competent to manage them.
- More extensive or sophisticated water treatment facilities won't readily scale up intelligent IoT-based water treatment systems. As a result, they might work better in smaller systems or as an addition to more conventional water treatment techniques.
- Smart IoT-based water treatment systems may need specialized analysis tools and knowledge to properly analyze and utilize the massive amounts of data they create. False assumptions and errors in the decision-making process might result from a lack of comprehension of the evidence or inaccurate interpretation.

2.2. Problem identification of existing system

Despite being a fundamental human right, a significant section of the world lacks access to clean, safe drinking water. To ensure a sustainable water supply, addressing problems such as water pollution, the depletion of freshwater resources, and inadequate sanitization is crucial. Conventional water treatment methods employ chemicals, which could harm the environment and people's health. Additionally, the conventional approach to water treatment consumes many resources and energy, making it only seldom practical in locations with limited resources.

A cutting-edge IoT-based system for water treatment can effectively monitor, evaluate, and treat water in real-time to get past these problems. The system must identify water quality issues and react quickly to remove potential health risks. 'A Smart IoT-based water treatment system' aims to create a long-lasting, affordable, and adequate water treatment system that uses the most recent IoT technology to continually monitor, evaluate, and treat water. Through the system, which should be able to deal with challenges like water pollution, the depletion of freshwater supplies, and poor sanitation, everyone should have access to safe and clean drinking water.

3. PROPOSED SYSTEM

3.1. IoT-powered smart water management system

While estimating the effectiveness of the effluent treatment facility, the method described in this component makes sure that chemical emissions do not go over permissible limits. In addition, advanced event processing can be used to analyze and manage the massive influx of data sets generated in real-time by IoT devices. Additionally, the system employs cutting-edge data analytics methods to analyze the gathered data and produce insightful results. The treatment process can be optimized using these insights, which can also be used to spot possible issues and make decisions about system maintenance and improvement. Additionally, the system may automate specific tasks thanks to the integration of IoT and SCADA, which lowers the need for manual intervention and boosts operational effectiveness. The block diagram for the IoT–SCADA technique is shown in Figure 1. The ability to monitor, regulate, and optimize water treatment procedures is improved by using smart water treatment systems. This leads to improved water quality and safety, reduced risks of contamination, increased operational efficiency, and more effective water supply system management.

The enterprise of an intelligent water organization is suggested in this section while keeping in mind the main takeaways from the analyses of the various strategies that were previously described. A real-time, intelligent water management system based on the IoT is advised to monitor water levels and quality indicators. The suggested approach will be controlled by a controller in the Raspberry Pi manner and run programs written in well-known programming languages like PYTHON. The pH sensor and the HC-SR04 ultrasonic range sensor will be connected to the controller to provide data on the water's quality and level. The proposed system combined water quality sensors such as pH and temperature, turbidity, water distribution sensors such as ultrasonic water level and flow, and microcontrollers through an IoT system, allowing residents to control the incoming water quality level via an installed home-based water filter. Integrating IoT systems like Blynk (Blynk – IoT platform for businesses and developers n.d.) within the controller is crucial for real-time monitoring. These platforms can remotely administer Raspberry Pi and other IoT devices.

This integration lets the mobile app show the water level in real-time. Monitoring the water level and other quality indicators on a secure website is crucial. The Google Sheets API should allow the proposed solution to update Google Sheets in real-time (Sheets API | Google developers n.d.). A straightforward application programming interface called the Google Sheets API makes it easy to read and publish data from Raspberry Pi and other low-powered machines to Google Sheets. An API key is required for every read-and-write query to change data values securely and to thwart replay attempts. The stakeholders can be informed of the generated alerts and predictions to react appropriately. Figure 2 shows the IoT-based water management organization. Implementing a layered security approach that combines Data Encryption and Authentication access control, these measures help protect IoT-based water treatment systems from cyber threats and ensure the overall safety and integrity of the system. It is essential to regularly update and adapt security measures as new threats and vulnerabilities emerge to maintain a robust defense against potential attacks.

3.1.1. Essential qualities

After carefully examining the relevant studies in this field, we offer the following essential components for a successful, intelligent water management system:

Low cost: The system should not have a high overall price. Large-scale implementation is discouraged by the expensive cost, particularly in intelligent campuses and smart cities.

- Low energy consumption: The system must consume less energy in light of the rising energy demand and its environmental effects. Energy costs can be decreased by using renewable energy sources like solar energy.

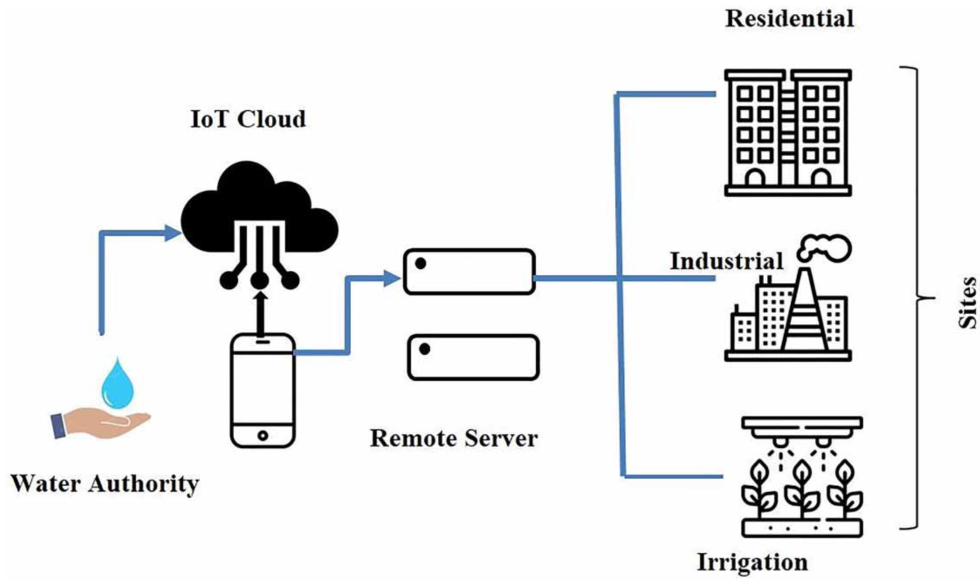

Figure 2 | Using the Internet of Things to manage water.

- Ease of deployment and upkeep: The system must be simple to set up and maintain. It should be able to reset and maintain software remotely.
- Water level and quality restrictions: It's critical to evaluate and record additional quality information in addition to water level for a comprehensive water management organization. Different sensors increase energy use, which raises the price.
- Real-time water monitoring is something that a smart water management system should offer. To find water leaks and overflows, real-time tracking may be helpful. Real-time monitoring necessitates a constantly connected network as well as heavy energy consumption. Cloud computing also makes it possible to make decisions instantly.
- Security: Protecting IoT messages and devices can be challenging, especially when dispersed over numerous physical locations. Hackers may take advantage of operating system flaws to steal sensitive data. Due to their constant Internet connection, these gadgets are good candidates for both infiltrations. To conduct DDoS attacks, many malwares, including Mirai (Antonakakis *et al.* 2017) and Hajime (Kolias *et al.* 2017), infect IoT devices in their network.

3.2. Complex Event Processing

Real-time behavioral patterns can be identified by recording and analyzing event streams using CEP (Bok *et al.* 2018). Smart meters, energy management, and agricultural irrigation are a few application areas where CEP is essential (Fardbastani & Sharifi 2019). The pressure and volume of water flowing through pipes are measured as part of water management systems to spot leakage patterns and foresee mishaps. A set of CEP rules specifies each design. The procedures for filtering, aggregating, correlating, and transforming data flows are limited by regulations. The architecture of the CEP is shown in Figure 3. When the event streams are received, the CEP engine applies the CEP rules to search for specific patterns. When a design is identified to alert human operators or other systems, the CEP engine delivers an alert. Data flows can be filtered, aggregated, correlated, and transformed using CEP rules, which are queries. The Event Processing Language (EPL) is used in this work to specify the CEP rules. Each CEP rule in this study identifies an active water management policy. For instance, once every 2 min, the rule checks to see if the 12-s average pressure is higher than a predetermined threshold. This work employs CEP principles in adding to water management instructions to spot unfavorable situations, such as a water storage tank's rapid decline or a critical water level (too high or too low), and warn water managers of the pattern (Gonçalves *et al.* 2020).

3.3. Supervisory controller and data acquirement method

SCADA schemes can be used for both distribution and wastewater treatment. Operators can monitor and carry out control activities at the PC-based workstation in a control room found in plants. In distribution plants, SCADA monitors various

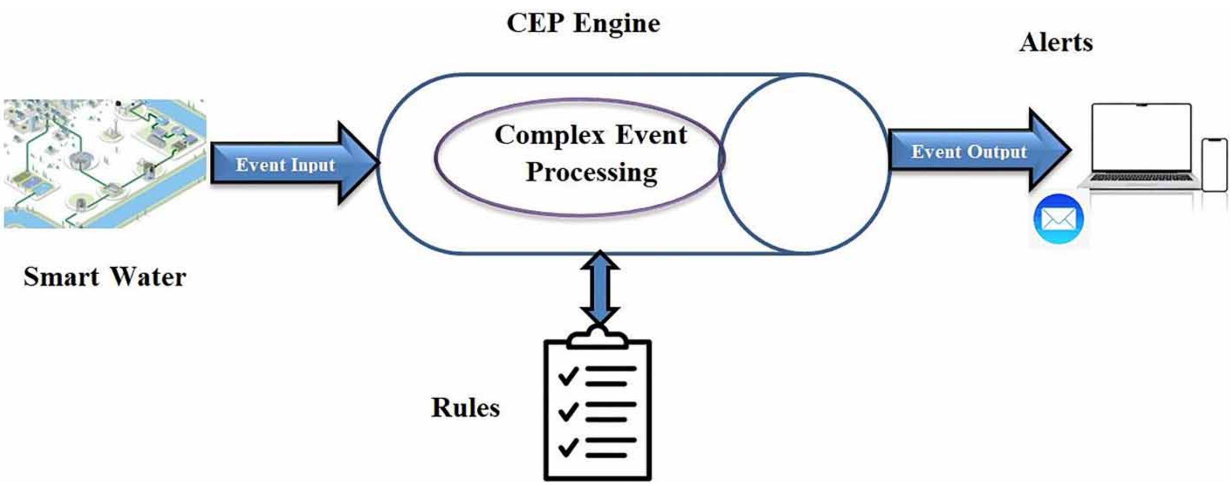

Figure 3 | Complex Event Processing (CEP) architecture.

processes, including chemical treatment, temperature control, filtration, sedimentation, and tank grades. In water control systems and facilities, SCADA also encourages corporate system integration, financial efficiency, and design safety (Metwally & Gupta 2022).

Wastewater collection, water treatment, distribution, and therapy may be monitored and managed thanks to computer-controlled systems (SCADA), which utilize several communication networks. The platform allows gathering data, controlling administration, and sending and receiving commands across a network. The communication system may employ telemetry, wireless, or cable links. SCADA systems worked together to boost water delivery to homes, companies, and industries while lowering service operating costs. The monitoring and control capabilities of SCADA will allow companies to safeguard and stop the significant deterioration of their infrastructure. Real-time control (RTC) ideal pump settings have been determined using data from various SCADA systems. Using mathematical models, the water distribution network designs simulate and approximate network statements and parameters under certain operating and loading conditions. The best mathematical models that have been applied to managing challenges in water delivery systems are covered in this section.

Proposition 1 (Stay-State and Dynamic Hydraulic Model). At each time step, the steady-state model determines the state variables of the hydraulic network. The water distribution system is shown in an illustration. Kirchhoff uses the first law to examine the conservation of flow (mass conservation) at the ends of a pipe network.

$$\sum_{v} q_{v,u} = Q_u \;\; u = 1, \;\ldots, I(junction\ nodes) \tag{1}$$

Equation (1) states that $q_{v,u}$ is the flow in the connection bridging nodes v and u, q_u is the demand at node i, and U is the total number of nodes.

The energy conservation law is another name for the second Kirchhoff conservation law. Any network loop has no total head loss.

$$\sum_{v,u \in n} h_{v,u} = 0 \;\; n = 1, \;\ldots N(loops) \tag{2}$$

This is shown in Equation (2), where N and H are the pip's loop count and head loss, respectively. Since there is only one accessible tank, there is no need for pseudo circles between fixed heads, which keeps things straightforward. Later, this was taken for granted. The relationship between flow-to-head loss and the network's third equation may be seen. Ohm's law is demonstrated on this page. The following acronym stands for the word:

$$h_{v,u} = S_{v,u}|q_{v,u}|^{m-1} q_{v,u} \tag{3}$$

The resistance of the nodes v and u connected by the pipe is denoted by $S_{v,u}$ in Equation (3), the fixed head loss exponent is denoted by m. The resistance coefficient of a valve can be affected by its local head loss coefficient and diameter.

A characteristic curve shows the relationship between head gain and flow in a pump. This can be approximated using the parabolic function.

$$h_{v,u} = b_l q_{v,u}^2 + a_u q_{v,u} + c_l \tag{4}$$

As seen in Equation (4), the features (1) through (4), where a_l, b_l, and c_l the pump supplier coefficients comprise a collection of nonlinear equations describing how water distribution networks maintain their constant state. The flows and heads in these water distribution networks can explain the calculations if all piping resistances, operational pump numbers, node specifications, valve opening degrees (working circumstances), speeds, and reservoir rates are understood.

The dynamic hydraulic model, the EPS, shows how water distribution network hydraulic behavior changes over time. The following has often been required of a node that has tanks or storage components by the mass preservation regulation:

$$\sum_v q_{v,u} - Q_u - \frac{dU_u}{dt} = 0 \tag{5}$$

Equation (5) can express the tan's storage capacity at Node i as X_u, where t stands for the passage of time. F_u and A_u are exhibited sequentially for each 'head,' 'total tank level and height,' and 'tank cross section area.' An illustration of the tank is

$$A_u \frac{dF_u}{dt} = Q_u^V = \sum_v q_{v,u} - Q_u \tag{6}$$

Extend Equation (6) to a network of multiple tanks. A dynamic network model can be expressed using a sequence of different comparisons.

$$A \frac{dF}{dt} = Q^V \tag{7}$$

dF/dt denotes the waste utilization rate per unit volume of digester, mass/volume-time. The cross-sectional areas in Equation (7) are symbolized by vector B, the tank heads by vector F, and the net inflows into the tanks by vector P^V. Numerical techniques (such as forwards Euler and enhanced Euler), hybrid transitional techniques, and direct integration approaches can all be used to solve the Tank Differential Equation. It is generally believed that the customer's water requirements are gathered in the nodes where the pressure heads are calculated. The distribution of water requirements along pipes is not uniform, though.

Proposition 2 (Graphs models connect). An efficient way to represent a water distribution network is as a linked graph with few connecting nodes. A graph element is a directed edge with two unique ends (often called a vertex). Each edge's diameter, length, and degree of roughness are provided. Bands could include pumps, valves, components, bends, pipelines, or other hydraulic apparatus where head loss and flow are known to be correlated. The endpoints are the data nodes or junction points that connect to water sources or storage tanks. The basic mathematical formulas for a network of interconnected nodes made up of edges (e), junction nodes (n), and date nodes (s) are more straightforward to understand because of the laws of mass and energy conservation. The following is the continuity idea's central idea:

$$\sum_{v=1}^{e} \lambda_{u,v} q_v + Q_u = 0; \ \lambda_{u,v} \in \{-1, 0, 1\} \mathit{and}\ u = 1, \ \ldots .m \tag{8}$$

In compact form,

$$[\wedge]\{q\} + \{Q\} = \{0\} \tag{9}$$

This suggests that each junction node's total inflows and outflows, ($\lambda_{u,v} = 1$) and ($\lambda_{u,v} = -1$), should equal zero. q stands for edge rate, Q for external demand at the junction, and it stands for matrix incidence reduced to junction nodes.

$$\sum_{v=1}^{e} \delta_{n,v} h_v + \Phi_n = o;\ \delta_{n,v} \in \{-1, 0, 1\}\ and\ n = 1,\ \ldots N + \omega + 1 \tag{10}$$

According to the Law of Conservation of Energy, in a closed loop, the algebraic total of the head losses h must be zero, while in an open loop, the difference in the heads at each endpoint must be equal. As such, we can divide it up as follows:

$$[\Gamma]\{h\} + \{\Phi\} = \{0\} \tag{11}$$

For fundamental circuits, components are zero, as stated in Equation (11). It is a loop matrix.

Edges can be distinct hydraulic characteristics with a recognized link between head loss and flow, as was already established. Head loss, denoted by the variable h, is shown here as a nonlinear function of flow rate.

$$h = S|q|^{m-1} porbp^2 + ap + c \tag{12}$$

Proposition 3 (Hydrostatic Models for Micro- and Macro-Scopy). Equations (1)–(7) describe the fundamental equations regulating water distribution networks and can be used to construct microscopic representations. These are comprehensive or standard recreation representations for the water distribution network, complete in that they include network topologies, well-defined nodes, and precise connection parameters (diameter, size, roughness). Nodal requirements must be calculated before usage.

Macroscopic modeling, on the other hand, relies on empirical modeling methods. Information is created and maintained for significant flows and heads linked to network storage tanks and pumping stations. Macroscopic models are adequate for tackling practical and optimal control problems in water distribution networks. These could use data-driven techniques like regression models or artificial neural networks. Even if these models have significant differences, creating a conceptual representation of a water supply network in a discrete period is still possible.

$$Y(o+1) = g(y(o), i(o), r(o), \varepsilon(o)) \tag{13}$$

Equation (13), in which $y(o)$ stands for the state vector, illustrates this. Tank depth, pipe flow, and nodal pressure are a few signs of progress. The additional numbers provide more clarity than the l-state variables defining the $o+1$ status variables. A vector control variable, $V(o)$. Discharge, in the form of flow control valves, Outlet Pressure, and Pumping Station Pressure, are some of the controllable variables. The demand at each node in a network is spread out using a vector called $r(o)$. The nonlinear network function portrays the stochastic disturbance as (o). The water management mathematical model's flowchart is shown in Figure 4.

Proposition 4 (Hydraulic Transient Models). The following words can be used to depict the water distribution networks' transient flow as water-hammer equations:

In Equations (14) and (15), R stands for the pipe diameter, and t stands for gravitational acceleration. F stands for the hydraulic head, q for pipe flow, y for distance, s for speed, and g for friction factor. A signifies the pipe's cross-sectional area, and a represents the wave speed.

$$tA\frac{\partial F}{\partial y} + \frac{\partial q}{\partial t} + \frac{h = g}{2RB} q|q = 0 \tag{14}$$

$$\frac{\partial F}{\partial y} + \frac{b^2}{tA}\frac{\partial q}{\partial y} = 0 \tag{15}$$

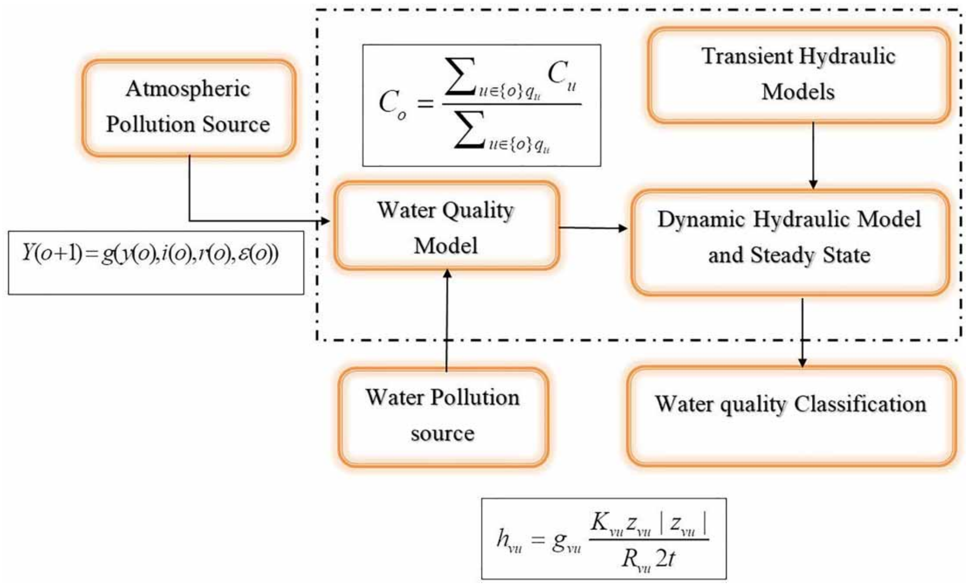

Figure 4 | Flow chart of water management.

The features $dy/dt = \pm a$ the approach can transform calculations (15) and (16) into a collection of normal difference reckonings along typical axes.

$$C^{+}:\begin{cases} tA\dfrac{\partial F}{\partial y}+\dfrac{\partial q}{\partial s}+\dfrac{h=g}{2RB}q|q=0 \\ \dfrac{dy}{ds}=+a \end{cases} \tag{16}$$

$$C^{-}:\begin{cases} -\dfrac{\partial F}{\partial y}+\dfrac{b}{tA}\dfrac{dq}{ds}+\dfrac{h=g}{2RB}q|q=0 \\ \dfrac{dy}{ds}=-a \end{cases} \tag{17}$$

where ds stands for time and dy for distance.

The grid locations of the network receive temporary heads and concurrent flow as a result of the approximations to Equations (17) and (18). If initial and boundary conditions are given (based on acknowledged network heads and flows), the finite difference approach can be utilized to identify solutions. Inputs used in calculating the pipeline friction factor, or h, are the length, K, diameter, head loss, and flow rate.

$$h_{vu} = g_{vu}\frac{K_{vu}z_{vu}|z_{vu}|}{R_{vu}2t} \tag{18}$$

Proposition 5 (Water Quality Models). The study of contaminant/disinfectant concentrations, simulating the water age, and maximizing operational water quality have all been appropriate for use in water distribution network representations. The location of the source impurities and the site for tracer studies have also been helpful. Organizations with expertise in hydraulics and water quality address water quality problems affecting the entire distribution system. These models are crucial for forecasting the direction and path of water quality along water distribution networks.

Chemical or other material diffusion in water distribution networks is influenced by pipeline advection, node mixing, and kinetic response processes. The persistent emissions in the pipe will be modeled using a one-dimensional mass conservation difference computation.

$$\frac{\partial C}{\partial s} = -\frac{q}{A}\frac{\partial C}{\partial y} + \theta(C) \tag{19}$$

In Equation (19), the concentration of pollutants in the pipeline is denoted by (C), where (A) is the transversal pipe area, (y) is the positively flowing pipe distance, (q) is the broad volumetric flow rate of the channel, and (C) is the reaction rate of the pipeline.

It is possible to interpret changes in the contaminants' focus using the first-order kinetic rate estimate in the following.

$$\theta(C) = oC \tag{20}$$

Equation (20), where C represents the bulk flow of pollutants, and o represents the first-order reaction rate coefficient, makes this observation clear. The coefficient is positive for operations that cause contaminants to increase, while it is harmful for activities that cause impurities to decrease.

The mass balance principle can be used to determine the node mixing:

$$C_o = \frac{\sum\limits_{u\in\{o\}q_u} C_u}{\sum\limits_{u\in\{o\}q_u}} \tag{21}$$

In Equation (21), the contaminated node O is represented by C_o, and the network of pipes entering the system is represented by l.

It is anticipated that active elements like pumps and valves will have identical amounts of contamination at the input and output (immediate advection of contaminants). The variable-level tank may display a reduction in pollutant levels.

$$\frac{d(C_W ZW)}{ds} = q_{in}C_{in} - q_{out}C_W + \theta'(C_W) \tag{22}$$

C_{in} represents the level of contamination in the input pipe, and the reaction rate inside the tank is represented by θ' (C_W), as can be seen in Equation (22), where C_W and Z_W stand for the thoroughly mixed tank concentration and tank volume.

Algorithm: Hybrid Algorithm

Input :v,u,o

Output :$q_{v,u}$ h_{vu}

For(u = 0)

$$\sum_v q_{v,u} = q_u$$

For(v-0)

$$h_{v,u} = T_{v,u}|q_{v,u}|^{m-1}q_{v,u}$$

For(o = 0)

$$h_{v,u} = a_o q_{v,u}^2 + b_o q_{v,u} + c_o$$

If(q = 0)

$$\sum_{v=1}^{e} \lambda_{v,u} q_v + P_u = 0;$$

Else

$$\frac{d(C_W Z_W)}{ds} = q_{in}C_{in} - q_{out}c_w + \theta'(C_w)$$

End for

End for

End for

End if

End

Return

The alleged thorough mixing of the nodes and tanks ought to facilitate the assessment of the water quality model. Computational fluid dynamics can be used to enhance the accuracy of additional types of mixing in water quality models.

The mathematical model used in the SCADA approach may accurately predict when water demand will surge, needing increased or ideal water distribution network operations. Water distribution networks' design, process, and management require water demand forecasting as a critical instrument. It is based on historical water consumption data, considering socio-economic and meteorological variables. The limitations include evapotranspiration, temperature, season, family size, precipitation, water quality, etc. SCADA systems provide real-time visibility, control, and data analysis capabilities that enable water treatment operators to monitor and optimize processes, detect, and respond to anomalies, and make data-driven decisions. By leveraging SCADA systems, water treatment operations can achieve higher efficiency, reduced operational costs, improved asset utilization, and enhanced overall performance.

This study shows that big data analytics, the IoT, data collection, and supervisory control can be used to implement novel water management. Hybrid strategies based on substitution models can be applied to managing water distribution networks. These models are used to simulate the performance of water distribution networks using computer software. For single- and multi-objective optimization problems, hybrid algorithms provide optimal global solutions with fewer function assessments. Using various methods, the researchers pinpointed the conduits that boosted single-cycle background leakage flow. Therefore, a multi-periodic leakage stream investigation will result in more helpful information. Water treatment facilities can achieve better control, monitoring, and management by integrating IoT and SCADA systems. This integration enhances data collection, enables real-time visibility, supports predictive maintenance, optimizes resource allocation, facilitates centralized data analysis, automates workflows, and ensures scalability. Ultimately, it leads to improved operational efficiency, reduced costs, enhanced system performance, and better overall management of water treatment facilities.

4. RESULTS AND DISCUSSION

4.1. Hardware implementation

The ESP8266 module, Arduino UNO, Ultrasonic sensor, and ThingSpeak server are used to implement this prototype. The hierarchical structure of hardware architecture places sensors, actuators, and Ardino UNO as control units and end devices, respectively. IoT is used for system communication. An ultrasonic sensor is fixed to the tank's top. We use the ultrasonic sensor to measure the water level in the tank. We regularly check the ultrasonic sensor reading and monitor the ultrasonic sensor's status by measuring the distance between the top of the tank and the water's surface. Start the water pump motor if there is water in the tank. A flow sensor is employed to measure the water flow rate through the pipe. When the flow rate exceeds the threshold, the water pump motor shuts off automatically. The Arduino UNO microcontroller is used to control all of these processes. These data were updated in the thing talk server using the ESP8266 Wi-Fi module. The platform is open-source. The data received and stored on the talk server can be continuously tracked. Here are some essential concerns for the scalability and practicality of applying the proposed system in real-world scenarios.

Cost-effectiveness: Cost is a significant factor in large-scale deployments. Research should focus on developing cost-effective solutions that can be scaled up without incurring prohibitive expenses. To do this, it may be necessary to investigate accessible sensor technologies, utilize existing infrastructure when possible, and optimize the data gathering and management procedures.

Scalability: Any water monitoring system designed for widespread use should be scalable to support a variety of monitoring locations. As the deployment expands, the system's architecture and design should make adding new sensors and monitoring sites simple. To achieve seamless integration across the monitoring network, interoperability, and standardized communication protocols should be considered.

Infrastructure Compatibility: To support the system's operations, large-scale deployments need compatible infrastructure. The current infrastructure, including communication networks and data storage capacities, must be evaluated to see if any upgrades or alterations are required. To guarantee widespread adoption, compatibility with various types of infrastructure, including urban, rural, and distant places, should be considered.

Research in water monitoring systems can significantly impact practical implementations and assist in overcoming challenges related to large-scale deployments when considering these practical implications, including cost-effectiveness, scalability, infrastructure compatibility, power supply, data management, long-term sustainability, and stakeholder engagement.

4.2. Challenges

Various issues arise in IoT-based water monitoring technologies. The key issues with IoT-based water monitoring technologies are covered in this section. Five significant problems have been found in the literature: water contamination, water management, agricultural management, conventional monitoring techniques, restricted water supplies, and population growth.

4.3. Limitations

Identification was difficult even though the database sources employed for the presented inquiry were numerous and reliable. The escalating progress in this region further affected the review's timeframe. Studies on a vital topic conducted at a specific time frequently do not accurately reflect the influence or application. But the information shows how the academic world has reacted to the issue.

4.4. Technology related

It is essential to create flexible, modular, expandable, and simple structures for people to erect. Future research should focus on enhancing real-time monitoring systems, including notifications and social media alerts. A mobile app is also advised to monitor red tides and scan the water's color using image processing (Dasig 2019). The method described by the authors in Narayanan *et al.* (2020) could be supplemented by creating a software agent-based model for underground pipe health and consumption monitoring that uses intelligent agents to inform the SCADA engineer for prompt control action and supply restoration. This intelligent agent would automate control during crucial times as a safeguard. The authors recommended concentrating on (Danh *et al.* 2020) assessing and enhancing measuring practices to increase the sensor probes' service life.

It is anticipated that a future machine learning technique could be created to evaluate the various physical properties of water and accurately predict the location of a water source that has undergone a sudden and abnormal change in water quality, according to speculation by the authors cited in Lalithadevi *et al.* (2019). This development may be beneficial in detecting and stopping the pollution or intrusion of dangerous compounds into water sources. To do this, the authors of Elijah *et al.* (2018) recommend that future research efforts concentrate on developing unmanned aerial vehicles (UAVs) tailored explicitly for river water quality sampling. These UAVs must consider river size, power consumption, payload capacity, and flight limits. For improved data transfer, scientists suggest using UAVs fitted with LPWA (Low Power Wide Area) communication technology. The significant impact of the load will raise interest in using tiny smart multi-parameter sensors for WQ, which will lead to further research on implementing a service composition algorithm with network awareness and several criteria.

4.5. Performance measure

The following measures are employed to assess the model's performance.

4.5.1. Security level analysis

Smart IoT-based water treatment security refers to the procedures and processes to secure the system and its connected devices from unauthorized access, data breaches, and malicious actions. Encryption, authentication, access limits, and regular monitoring protect the water treatment infrastructure and critical data. High security protects the intelligent IoT-based water treatment process's functioning, data, and privacy.

Figure 5 and Table 1 compare the IoT–SCADA strategy's security level with other recent technologies. The graph shows how the performance of the IoT approach has increased while keeping a high level of security. For instance, the IoT–SCADA model's security level with 100 data is 93.795%, compared to security levels of 84.763, 89.762, 70.865, and 73.876% for the Sewage Wastewater Treatment Systems (SWTS), Sewage Wastewater Farm Green (SWFG), IoT-Sewage Treatment Monitoring System (IoT-STMS), and Smart Farm-Scale Piggery Wastewater Treatment System (SFS-PWT) models, respectively. The IoT–SCADA model has, however, demonstrated its better performance with various data sizes. The security level for the IoT–SCADA is 95.484% under 300 data, compared to the values of 82.937, 91.641, 71.865, and 76.467% for the SWTS, IoT-STMS, IoT-STMS, and SFS-PWT models, respectively.

4.5.2. Flow rate analysis

The amount of water that passes through a cutting-edge IoT-based water treatment system in a specific time is known as the flow rate. It shows how fast IoT-enabled gadgets and technology clean water. Water treatment is optimized, and water quality is maintained by monitoring and adjusting the flow rate.

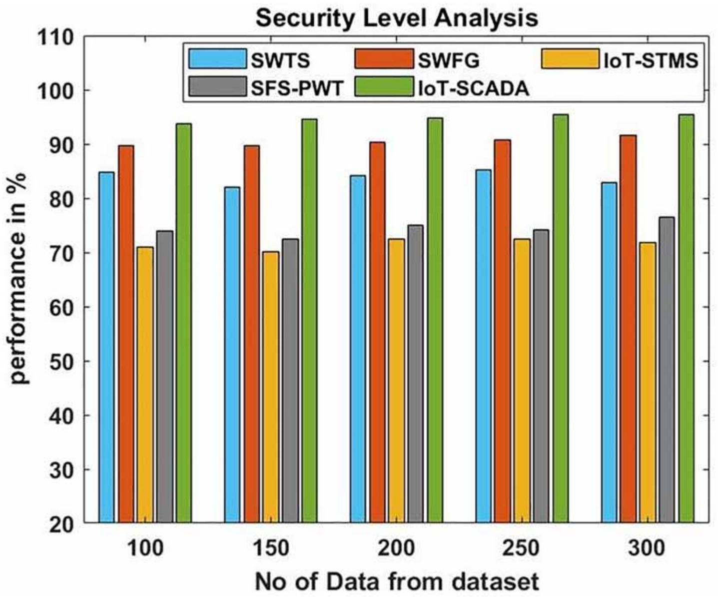

Figure 5 | Security level analysis for IoT–SCADA with existing systems.

Table 1 | Security level analysis for IoT–SCADA with existing systems

No. of data from dataset	SWTS	SWFG	IoT-STMS	SFS-PWT	IoT–SCADA
100	84.763	89.762	70.865	73.876	93.795
150	81.927	89.654	70.075	72.468	94.677
200	84.235	90.312	72.478	74.965	94.878
250	85.134	90.765	72.468	74.145	95.362
300	82.937	91.641	71.865	76.467	95.484

Comparative Flow rate Detection analysis of the IoT–SCADA methodology with other techniques is shown in Figure 6 and Table 2. The IoT–SCADA model's flow rate detection value at 50 psi is 39.571GPM, compared to the flow rate values of 28.234 GPM, 35.772 GPM, 33.433 GPM, and 25.455 GPM for SWTS, SWFG, IoT-STMS, and SFS-PWT, respectively. The IoT-OTT model has, however, demonstrated its better performance with various data sizes. Similarly, the Flow rate Detection value for the IoT–SCADA model under 250 psi is 41.894GPM, compared to the models for SWTS, SWFG, IoT-STMS, and SFS-PWT, which have values of 32.987 GPM, 38.548 GPM, 36.584 GPM, and 28.098 GPM, respectively.

4.5.3. Route failure rate analysis

The route failure rate for an intelligent IoT-based water treatment system is the frequency at which data or signals fail to transmit between system components. It evaluates information-transporting sensors, actuators, controllers, and communication networks. Data loss, delays, and disruptions may cause water treatment process inefficiencies or failures if route failure rates are significant.

The Route failure rate comparison of the IoT–SCADA approach with other methods in use is explained in Table 3 and Figure 7. The data unambiguously demonstrates that, in contrast to the different techniques, the suggested way has the lowest route failure rate. For instance, the recommended method's Route failure rate with 100 data is 46.365%, compared to SWTS, SWFG, IoT-STMS, and SFS-PWT's of 54.765, 63.548, 56.764, and 60.657%, respectively. The IoT–SCADA technique performs better with a lower Route failure rate. On the other hand, approaches like SWTS, SWFG, IoT-STMS, and SFS-PWT have a Route failure rate of 55.864, 63.548, 58.754, and 63.278%, respectively, whereas the suggested method has a Route failure rate of 49.303% with 500 data.

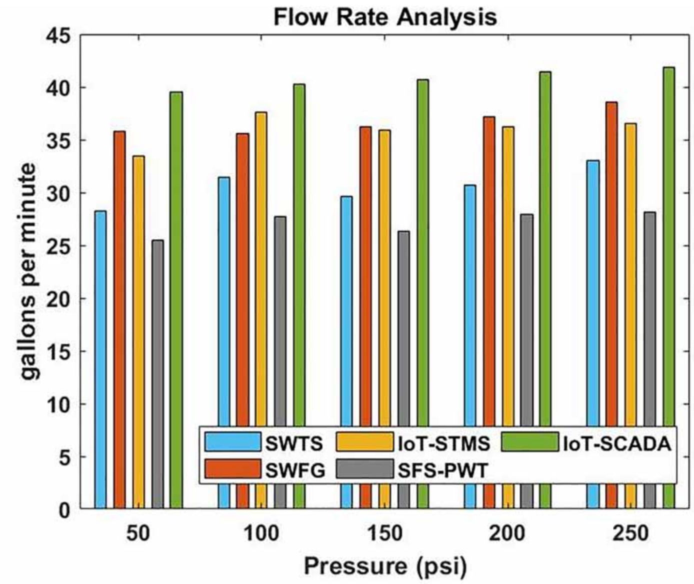

Figure 6 | Flow rate analysis for IoT–SCADA with existing systems.

Table 2 | Flow rate analysis for IoT–SCADA with existing systems

Pressure (psi)	SWTS	SWFG	IoT-STMS	SFS-PWT	IoT–SCADA
50	28.234	35.772	33.433	25.455	39.571
100	31.433	35.604	37.564	27.675	40.219
150	29.654	36.211	35.865	26.369	40.658
200	30.654	37.217	36.276	27.943	41.386
250	32.987	38.548	36.584	28.098	41.894

Table 3 | Route failure rate analysis for IoT–SCADA with existing systems

No. of data from dataset	SWTS	SWFG	IoT-STMS	SFS-PWT	IoT–SCADA
100	54.765	63.548	56.764	60.657	46.365
200	56.355	64.914	57.885	62.087	47.119
300	54.976	65.322	59.355	61.856	48.047
400	56.276	66.045	61.657	64.764	48.297
500	55.864	63.548	58.754	63.278	49.303

4.5.4. Efficiency ratio analysis

The efficiency ratio of an innovative IoT-based water treatment system quantifies how efficiently it uses resources and energy to treat water. It compares clean, safe water to power, chemicals, and operational costs. A more excellent efficiency ratio shows that the water treatment system is performing ideally, minimizing resource waste, and efficiently attaining treatment results. This ratio is usually estimated by comparing the amount of treated water generated to the total resources consumed during treatment.

In Figure 8 and Table 4, an efficiency ratio comparison of the IoT–SCADA strategy with other existing technologies is displayed. The graph shows how the IoT strategy has increased performance while preserving high efficiency. For instance, the

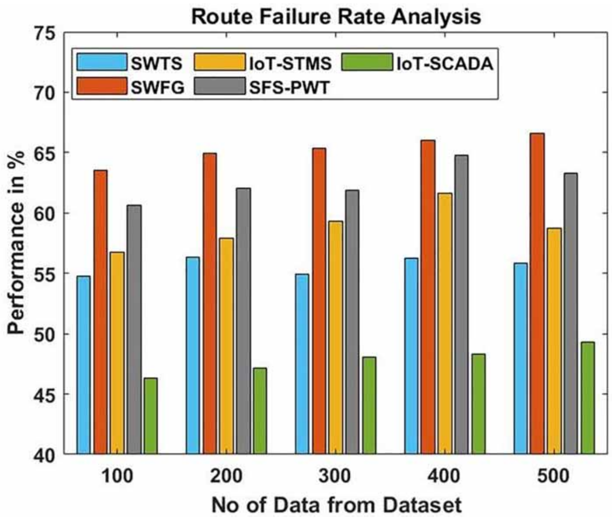

Figure 7 | Route failure rate analysis for the IoT–SCADA method with existing systems.

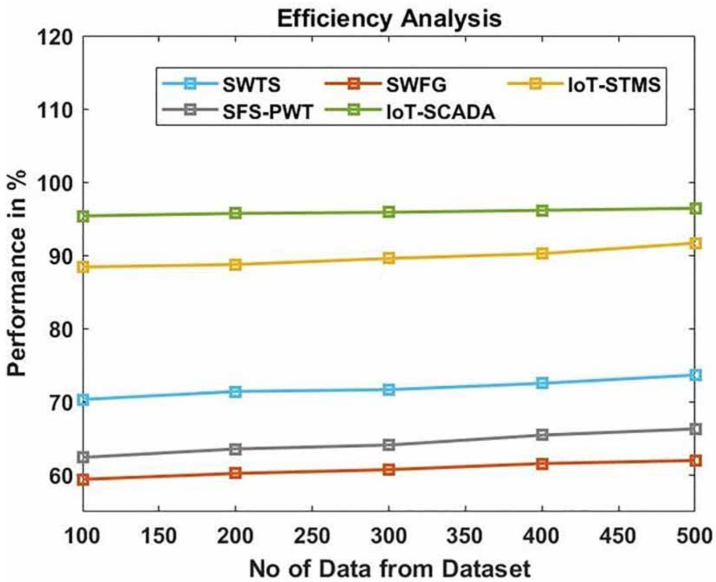

Figure 8 | Efficiency ratio analysis for IoT–SCADA with existing systems.

Table 4 | Efficiency ratio analysis for IoT–SCADA with existing systems

No. of data from dataset	SWTS	SWFG	IoT-STMS	SFS-PWT	IoT–SCADA
100	70.34	59.43	88.43	62.43	95.39
200	71.43	60.24	88.76	63.59	95.74
300	71.68	60.76	89.59	64.12	95.89
400	72.54	61.59	90.24	65.47	96.16
500	73.67	62.01	91.68	66.32	96.43

IoT–SCADA model's Efficiency ratio with 100 data is 95.39%, compared to Efficiency ratio of 70.34, 59.43, 88.43, and 62.43% for the SWTS, SWFG, IoT-STMS, and SFS-PWT models, respectively. The IoT–SCADA model has, however, demonstrated its better performance with various data sizes. The Efficiency ratio for the IoT–SCADA is 96.43% under 300 data, compared to the values of 73.67, 62.01, 91.68, and 66.32% for the SWTS, IoT-STMS, IoT-STMS, and SFS-PWT models, respectively.

4.5.5. Water quality detection analysis

Water Quality Detection for Smart IoT-based water treatment involves monitoring and analyzing water parameters and contaminants to ensure cleanliness, safety, and applicability. This uses IoT technology to capture real-time data on pH, turbidity, dissolved oxygen, temperature, and hazardous compounds. The collected data optimizes the water treatment, identifies faults, and ensures safe, high-quality drinking water.

Comparative Water Quality Detection analysis of the IoT–SCADA approach with other techniques is shown in Figure 9 and Table 5. The figure demonstrates that the IoT strategy has improved performance in water quality detection. For instance, the IoT–SCADA model's water quality detection value at 10 min was 50.879 mg/I, compared to the SWTS, SWFG, IoT-STMS, and SFS-PWT models' values of 44.766, 47.532, 39.263, and 41.287 mg/me, respectively. The IoT–SCADA model has, however, demonstrated its better performance with various data sizes. Similarly, the Water Quality Detection value for IoT–SCADA under 50 min is 54.165 mg/I, compared to SWTS, SWFG, IoT-STMS, and SFS-PWT models, which have values of 44.322, 51.675, 40.235, and 43.275 mg/I, respectively.

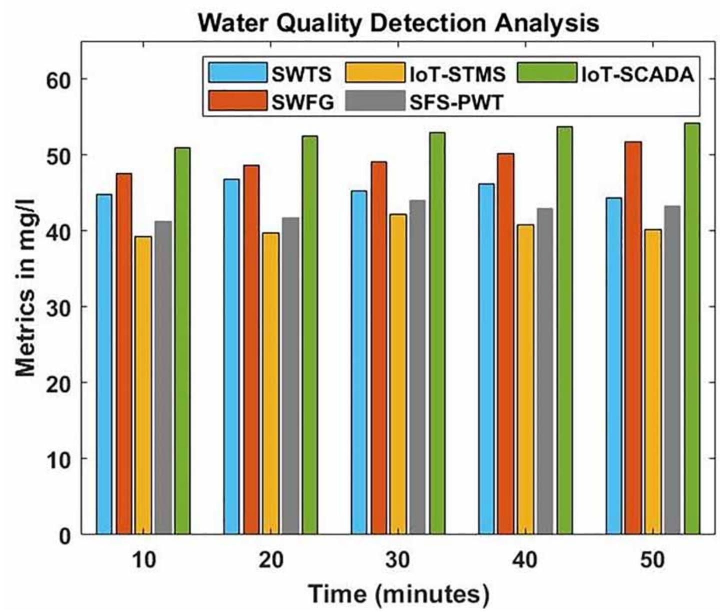

Figure 9 | Water quality detection analysis for IoT–SCADA with existing systems.

Table 5 | Water quality detection analysis for IoT–SCADA with existing systems

Time (min)	SWTS	SWFG	IoT-STMS	SFS-PWT	IoT–SCADA
10	44.766	47.532	39.263	41.287	50.879
20	46.754	48.671	39.675	41.754	52.438
30	45.187	49.054	42.234	43.975	52.956
40	46.234	50.178	40.865	42.964	53.781
50	44.322	51.675	40.235	43.275	54.165

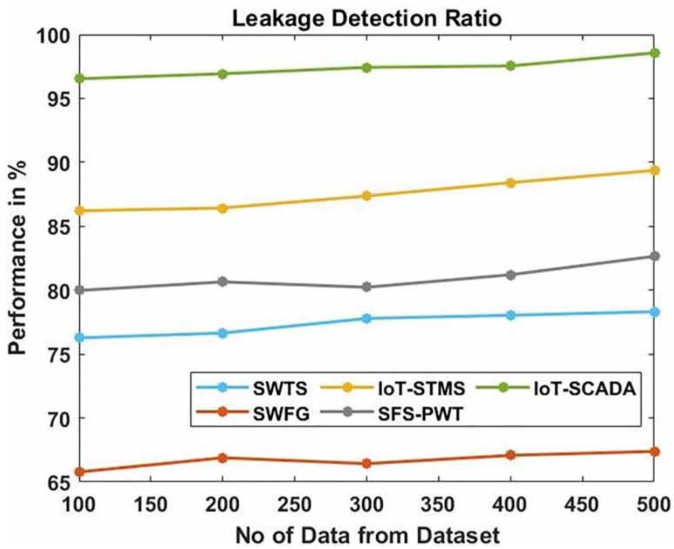

Figure 10 | Leakage detection analysis for IoT–SCADA with existing systems.

Table 6 | Leakage detection analysis for IoT–SCADA with existing systems

Time (min)	SWTS	SWFG	IoT-STMS	SFS-PWT	IoT–SCADA
100	76.27	65.78	86.21	79.98	96.54
200	76.65	66.89	86.43	80.65	96.93
300	77.79	66.43	87.37	80.23	97.43
400	78.04	67.08	88.41	81.21	97.54
500	78.32	67.39	89.37	82.65	98.56

4.5.6. Leakage detection ratio analysis

Smart IoT-based water treatment system's Leakage Detection Ratio measures its ability to find and quantify infrastructure leaks. It tests the system's IoT technologies and algorithms for water leak detection. A valuable measure for evaluating the effectiveness of the novel water treatment solution in reducing water loss and ensuring efficient operation is the ratio of precisely identified leaks to the total number of leaks.

Figure 10 and Table 6 compare the IoT–SCADA strategy's Leakage Detection ratio to other current technologies. The graph shows how the performance of the IoT strategy has increased while retaining a high level of leakage detection. For instance, the IoT–SCADA model's Leakage Detection ratio with 100 data is 96.54%, compared to Leakage Detection ratio of 76.27, 65.78, 86.21, and 79.98% for the SWTS, SWFG, IoT-STMS, and SFS-PWT models, respectively. The IoT–SCADA model has, however, demonstrated its better performance with various data sizes. The Leakage Detection ratio for the IoT–SCADA is 98.56% under 500 data, compared to the values of 78.32, 67.39, 89.37, and 82.65% for the SWTS, IoT-STMS, IoT-STMS, and SFS-PWT models, respectively.

5. CONCLUSION

The suggested experimental model solution provides a web-based SCADA platform that is of low cost, highly flexible, platform-agnostic, and modular. During the Industry 4.0 era, the SCADA platform was created using IoT concepts. An IoT–SCADA system can be implemented at various wastewater collection and treatment phases. An IoT-enabled intelligent water sensor maps water flow across the whole treatment plant by measuring pressure, temperature, pressure dynamics, and water quality. The suggested method ensures that chemical discharges do not exceed permitted limits while estimating the efficacy of the effluent treatment facility. In addition, CEP can evaluate and process the massive influx of data sets produced in real-time by IoT sensors. In addition, the system analyses the collected data and generates valuable insights using cutting-edge techniques for data analytics. These insights can aid in optimizing the treatment process, identifying potential problems, and making decisions regarding system maintenance and enhancement. In addition, integrating IoT and SCADA enables the system to automate particular operations, thereby reducing the need for manual intervention and increasing operational efficiency. The SFS-PWT, SWTS, and IoT-STMS are some of the models used in this study. The numerical outcomes of the suggested strategy demonstrate a security improvement (95.484%), efficiency (96.43%), and leakage detection (98.56%). Future research that incorporates all of these crucial factors and makes use of IoT-based predictions to increase the efficiency of the smart management system is what we recommend. Future studies can also use the IoT coverage factor to calculate measurement uncertainty. The authors recommend further research and fresh research partnerships to enhance IoT security, limit biological influence, use artificial intelligence (AI)/machine learning (ML) techniques, and lower system costs.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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