IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 28 May 2025, accepted 25 June 2025, date of publication 2 July 2025, date of current version 10 July 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3585283

RESEARCH ARTICLE

Automated System to Optimize the Process and Energy Consumption for Sewage Treatment Plant Based on Gas Emission by Using Sensors and IoT

S. ULLAS[1], B. UMA MAHESWARI[1], (Senior Member, IEEE), SESHAIAH PONNEKANTI[2], AND T. M. MOHAN KUMAR[3]

[1]Department of Computer Science and Engineering, Amrita School of Computing, Amrita Vishwa Vidyapeetham, Bengaluru 560035, India
[2]Center for Wireless Networks and Applications, Amrita Vishwa Vidyapeetham, Amritapuri 690525, India
[3]Department of Physical Sciences, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Bengaluru 560035, India

Corresponding author: S. Ullas (s_ullas@blr.amrita.edu)

ABSTRACT Sewage Treatment Plants (STPs) play a crucial role in environmental sustainability and public health by removing pollutants from wastewater. Traditional STPs suffer from high energy consumption, operational inefficiencies, and a lack of real-time monitoring, leading to increased energy consumption, unassured water quality, and potential environmental pollution. This study presents a custom-designed Internet of Things (IoT)- enabled automated system to optimize energy usage and treatment efficiency in STPs by monitoring gas emissions, including carbon monoxide, carbon dioxide, ammonia, methane, and hydrogen sulfide. The system explores gas emission patterns during water treatment and maps emission levels during the process to assess treatment completion. It integrates advanced sensors, microcontrollers, and cloud-based data management for real-time tracking and process optimization. Experimental validation across two STPs demonstrates significant energy savings, reducing aerator run times by 45 minutes per cycle —a 15% reduction compared to manual operation —while maintaining satisfactory effluent quality. Additionally, the system enhances operational safety by providing automated alerts for hazardous gas levels. The findings indicate that IoT-based automation can revolutionize wastewater treatment, making it more cost-effective, energy-efficient, and environmentally sustainable.

INDEX TERMS Automation, energy efficiency, environmental sustainability, gas emissions, Internet of Things, sewage treatment plant, real-time monitoring, sensors.

I. INTRODUCTION

Sewage Treatment Plants (STPs) are fundamental to public health protection, environmental preservation, and the sustainable reuse of water resources. These plants remove various pollutants such as suspended solids, organic matter, nutrients, and pathogens through primary, secondary, and tertiary treatments [1]. As freshwater scarcity intensifies globally, the reuse of treated wastewater is becoming increasingly essential, aligning with WHO guidelines for potable and non-potable reuse [2].

Despite their environmental value, conventional STPs suffer from multiple operational challenges. These include high energy consumption due to fixed treatment cycles, inefficient resource utilization, and limited real-time monitoring. Traditional systems largely depend on biochemical indicators like BOD and COD for assessing treatment effectiveness, requiring lab-based analyses and lacking instant adaptability [3]. The growing urban population, coupled with infrastructure limitations—such as India's treatment capacity gap—further amplifies the need for intelligent STP automation [4].

Enhanced design of STPs would improve their performance, treatment capacity, and environmental sustainability [5]. Automation of STPs has attracted significant attention

The associate editor coordinating the review of this manuscript and approving it for publication was Shaohua Wan.

recently due to its potential to improve water quality, reduce costs, and enhance operational efficiency. Literature has shown that automation in STPs has been tried with multiple strategies, including the application of Internet of Things (IoT) technologies and sensors [6].

The usage of IoT technologies in STPs improves the efficiency of wastewater treatment, improves water quality, minimizes power consumption, enables remote monitoring and control, and ultimately makes the whole system more economical [7]. The automation of wastewater treatment plants for the removal of total nitrogen and organic content has been widely implemented in Finland [8]. The technological growth in sensors has made them more reliable in their measurements. Additionally, researchers have developed smart systems that integrate web applications with microcontrollers and sensors to track essential metrics in real time. Sensors have become an integral part of modern STPs, which measure different parameters such as temperature, pH, humidity, and the concentration of gases emitted in real time [9].

Connecting the sensors to microcontrollers and IoT systems further enhances operational efficiency and makes the treatment process more cost-efficient. The deployment of IoT technology in STPs has yielded encouraging outcomes, with one study reporting an improvement in recycled water quality levels of up to 97.98% [10]. The European wastewater treatment sector is transforming, offering prospects for the widespread use of instrumentation, control, and automation (ICA) systems.

Despite advancements in STP automation, many existing systems remain energy-intensive, inefficient, and lack real-time monitoring capabilities. Traditional wastewater treatment approaches rely on fixed operational cycles, leading to unnecessary power consumption even when treatment completion has been achieved. Additionally, current monitoring techniques focus primarily on water quality parameters such as Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), and Total Suspended Solids (TSS), which require laboratory-based testing and are not suitable for instantaneous process optimization. Few studies have explored the role of gas emissions in wastewater treatment efficiency, even though gases such as carbon monoxide (CO), carbon dioxide (CO_2), ammonia (NH_3), methane (CH_4), and hydrogen sulfide (H_2S) can serve as indirect indicators of treatment progress.

A. MOTIVATION

This work was motivated by direct field observations in STPs across institutional campuses and residential complexes in India. These systems followed static operational cycles, resulting in extended aeration even when treatment was already complete. The absence of real-time control, especially regarding process-dependent gas emissions, highlighted the need for an intelligent system that can adapt treatment based on real-time sensor data. Recognizing that gases such as CH_4, NH_3, CO_2, and H_2 S are closely linked to microbial activity during treatment, we identified an opportunity to use gas signatures as proxies for treatment progress.

B. PROBLEM STATEMENT

Most STPs today are not equipped to optimize operations dynamically. Without real-time, gas-based feedback, these systems waste energy and risk incomplete or inefficient treatment. Additionally, there are safety risks to workers from undetected harmful gas levels during aeration.

C. SCOPE OF THE PROPOSED WORK

The scope of this research is to develop an IoT-integrated, gas-sensor-based automation framework that optimizes STP operations by monitoring and analyzing real-time gas emissions. The aim is to reduce energy consumption, enhance operational efficiency, and improve safety through a scalable, data-driven solution.

D. KEY CONTRIBUTIONS OF THIS STUDY

To address these challenges, this study proposes an IoT-enabled automated system that leverages gas emission monitoring for real-time STP optimization. The key contributions of this work include:

1. Development of a real-time STP monitoring system integrating IoT sensors, microcontrollers, and cloud-based analytics to track gas emissions as indicators of treatment efficiency.
2. Experimental validation is done in two live STPs, demonstrating a 15% reduction in aeration time per cycle, leading to significant energy savings while maintaining effluent quality standards.
3. Improved safety and operational reliability, as the system provides automated alerts for hazardous gas emissions, reducing risks for plant operators.
4. By introducing a data-driven, real-time optimization framework, this study bridges the gap between traditional STP operations and intelligent automation, offering a scalable and cost-effective solution for wastewater treatment management.

The organization of the rest of the paper is outlined below. Section II covers a brief overview of the latest research in the automation of STP. Section III explains the traditional STP working, the proposed architecture diagram for the automation and overall management of STP. Further, the design of the hardware developed and the sensors' connectivity are illustrated. The results and analysis of the experiments conducted in sewage plants are presented in Section IV, which demonstrate the various gas values obtained and their visualization. Finally, Section V summarizes the key findings and discusses potential future directions for this research.

II. LITERATURE SURVEY

This section presents a critical analysis of existing research in automated sewage treatment plant (STP) technologies, organized by key thematic areas. Studies were selected based on relevance to automated STP systems, publication within the last five years (with few exceptions for seminal works), and methodological rigor.

A. IoT AND SENSOR-BASED MONITORING SYSTEMS

Recent advances in sensor technology and IoT frameworks have significantly enhanced STP monitoring capabilities. Ullas et al. [9] developed a Raspberry Pi-based IoT control system using ultrasonic and gas sensors, which demonstrated enhanced operational efficiency and cost reduction through real-time monitoring. However, their system lacked scalability for diverse environmental conditions. Similarly, Rezwan et al. [11] implemented an IoT-based monitoring system with Arduino microcontrollers and various sensors (temperature, turbidity, pH, and electricity) for real-time compliance monitoring, though connectivity issues limited wide-scale deployment.

Salem et al. [12] advanced this approach by integrating remote control capabilities and alert mechanisms into their monitoring framework, enabling faster response to operational anomalies. Their system showed improved scalability and efficiency, but remained vulnerable to cybersecurity threats. Prabavathi et al. [13] further integrated web applications with sensor networks, creating an "Intelligent Stabilized Smart STP" that achieved improved resource management, though predictive analytics capabilities were notably absent.

For specialized monitoring, Raj and Ullas [14] developed cost-effective turbidity sensors connected to ThingSpeak servers for cloud monitoring of suspended solids, addressing a critical parameter in effluent quality assessment. Karn et al. [15] proposed the "SMARTreat" system specifically for smart cities, which successfully reduced manual intervention while enhancing treatment efficiency. However, their analysis acknowledged sensor degradation over time and cybersecurity vulnerabilities as significant limitations requiring future attention.

Comparing these monitoring approaches reveals a clear evolution from basic sensor deployment to comprehensive IoT frameworks. Despite advancements, most systems still struggle with maintaining sensor accuracy over time, secure data transmission, and cost-effective scalability—gaps that our research aims to address through a more integrated approach to gas emission monitoring.

B. GAS EMISSION MONITORING AND MANAGEMENT

Gas emissions provide valuable insights into treatment processes and environmental impact, yet remain underutilized in automated STP systems. Masuda et al. [16] conducted a foundational analysis of emission patterns in municipal sewage plants, identifying energy use (43.4%), nitrous oxide from sludge incineration (41.7%), and methane from water treatment (8.3%) as major contributors to the carbon footprint. Their work established the correlation between seasonal temperature variations and methane emissions, but did not translate these findings into control strategies.

Zheng et al. [17] examined methods for reducing N2O emissions, such as adjusting aeration parameters and introducing alternative microbial processes. Their approaches achieved 30-60% reduction in full-scale plants without major infrastructure changes, though implementation costs and complexity remained high. This research demonstrates the potential for gas monitoring to improve both environmental performance and operational efficiency.

In a complementary study, Huang et al. [18] evaluated various GHG accounting methodologies for wastewater treatment plants, emphasizing the importance of accurate emissions prediction. While their work improved emissions estimation accuracy, it did not fully explore the potential of integrated sensor networks for real-time emissions monitoring. Similarly, Zheng and Lam [19] analyzed greenhouse gas emissions and environmental effects related to sewage sludge management using life cycle assessments, highlighting the trade-offs between different treatment technologies.

Most recently, Ullas and Maheswari [20] developed a dedicated sensor system for monitoring gas emissions from STPs with a focus on operator safety through automated alerts for hazardous gas levels. While this represented progress in workplace safety, the system did not extend to process optimization based on emission patterns.

The literature reveals a significant gap: while gas emissions are increasingly monitored, few systems utilize this data for real-time process optimization or energy efficiency improvements. Their proposed system addresses this limitation by developing correlations between gas emission patterns and treatment completion status, enabling more precise process control.

Kumar and Singh [21] addressed the complex interplay between carbon dioxide emissions, solid and liquid waste in the forms of organic and inorganic materials, examining their relationship with sustainability and the power supply necessary for societal progress. Their investigation revealed the crucial role of greenhouse gas emissions in climate change with profound implications, highlighting the primary need for immediate mitigation strategies. The study covers both direct and indirect greenhouse gases related to landfill disposal, water treatment, and recycling solutions, providing figures that assist in risk assessment. The research emphasizes that waste management effectiveness has become an issue of paramount significance in the green agenda, focusing particularly on methods for rendering landfill gas with methane at lower levels to mitigate emissions, while also acknowledging the energy-consumptive nature of recycling technologies. This work complements earlier studies by highlighting the specific connection between waste management practices and climate change mitigation, offering a more holistic perspective on environmental effects and policy implications for smart city initiatives.

Integrating AIoT and deep learning has significantly evolved environmental emission forecasting, especially in managing noisy and nonlinear air quality data. Traditional models, while foundational, often struggle with dynamic and complex environmental inputs. Recent work by Waseem et al. [22] demonstrated that optimized recurrent neural networks (RNNs), when paired with AIoT systems, can effectively forecast air quality using real-time AirNet data, showcasing the superiority of GRU over other RNN variants. Similarly, Borujeni et al. [23] developed an explainable GRU-based sequence-to-sequence model, enabling greater transparency in predicting urban pollution levels.

In the realm of signal decomposition, Zhang et al. [24] introduced a weighted CEEMDAN-LSTM model that yielded significant improvements in PM2.5 predictions, reducing MAPE and RMSE through refined data preprocessing. Chen and Zheng [25] expanded this approach by combining CEEMDAN with Elman recurrent neural networks for AQI prediction, reporting increased stability in forecasts. Moreover, Ahmed et al. [26] proposed AQE-Net, a deep learning model enhanced by mobile imagery and IoT data for AQI estimation in urban Pakistan, achieving robust generalization across different environmental zones.

From a GCN perspective, Ram et al. [27] proposed a hybrid Dual-GCN and LSTM architecture, integrating IoT sensor data for AQI forecasting with enhanced temporal and spatial learning.

Spatiotemporal Graph Convolution Multifusion Network (ST-MFGCN) by Xu et al. [28] was suggested to predict urban vehicle emissions with guidance on the road network graph. The proposed approach was capable of dealing with spatial and temporal dependencies that were not directly caused by spatial and temporal distance, but also by environmental multidrug variables. The model combines the spatial and temporal features, the exogenous environmental inputs, and the multiple fusion strategy in order to improve forecasting accuracy. Its performance has been verified based on actual vehicle emission data.

Meanwhile, You et al. [29] presented a PSO-SVM algorithm under CEEMDAN decomposition for short-term wind power forecasting, illustrating its applicability in environmental and energy domains.

Wu et al. [30] added to this field by combining spatiotemporal dependencies with deep learning to predict O_3 and NO_2 concentrations regionally, confirming that hybrid IoT-GCN architectures offer both interpretability and accuracy. Bhatti et al. [31] extended these principles in their AIoT-based EEMD-CEEMDAN-GCN model, demonstrating superior accuracy across PM2.5 and PM10 predictions using datasets from five Chinese provinces. Their hybrid approach effectively combined adaptive signal decomposition with graph-based deep learning, outperforming GCN-only and singly decomposed models in MAE, MSE, and R^2 metrics, thereby setting a new benchmark in AI-driven environmental monitoring.

C. ENERGY OPTIMIZATION APPROACHES

Noussan et al. [32] explored broader IoT applications for energy efficiency in STPs, achieving measurable reductions in power consumption alongside water quality improvements. However, their findings lacked validation across diverse operational settings. More recently, Ruano et al. [33] implemented fuzzy-logic-based control systems specifically targeting nitrogen removal processes, attaining impressive energy savings of 14-33% while simultaneously reducing total nitrogen in effluent by 10-30%. Their two-year study across three facilities provides strong evidence for the effectiveness of advanced control systems in energy optimization.

Approaching the problem from a different angle, Adibimanesh et al. [34] applied machine learning techniques to optimize sludge incineration processes, documenting energy savings of approximately 6%. Their work highlights the potential for targeted optimization of specific treatment stages rather than whole-plant approaches.

Energy consumption represents 25-40% of operational costs in wastewater treatment, driving research into optimization strategies. Wang et al. [35] introduced a hybrid neural network model (PCA-CNN-LSTM) that achieved 10-15% reductions in energy and chemical usage while maintaining environmental compliance. Their approach demonstrated the potential of deep learning for process optimization but required substantial data collection infrastructure.

In recent advancements, energy optimization in smart infrastructure has increasingly relied on the fusion of IoT and AI-driven systems to ensure efficient and sustainable operations. Saleem et al. [36] introduced a Smart Energy Management System (SEMS) architecture utilizing IoT-based sensors and cloud-driven middleware for HVAC control. By leveraging real-time monitoring and time-slot-based optimization algorithms, they demonstrated potential energy savings between 5% and 53%, highlighting the impact of layered control architectures for intelligent environments. In a broader wireless network context, Liwen et al. [37] emphasized that energy efficiency (EE) is a critical key performance indicator (KPI) in 6G IoT systems. Their comprehensive review identified effective energy-saving strategies through multi-indicator trade-offs, such as balancing latency, spectrum efficiency (SE), and bandwidth utility using AI-powered frameworks, including Deep Reinforcement Learning (DRL), Federated Learning (FL), and intelligent edge computing. These techniques are highly relevant for energy-intensive domains such as sewage treatment plants, where variable loads and emissions demand real-time energy balancing and adaptive resource allocation. Furthermore, both studies stress the importance of joint optimization—integrating energy efficiency with reliability and latency control—to enhance system responsiveness without compromising power conservation. This holistic, IoT-centric approach serves as a strong foundation for developing autonomous energy management in emission-sensitive applications like wastewater treatment.

A comparative analysis of these studies reveals that the most successful energy optimization strategies integrate real-time monitoring with adaptive control algorithms. However, most existing approaches rely on water quality parameters rather than gas emissions as control variables, missing the opportunity to detect treatment completion more accurately. Our research addresses this gap by correlating gas emission patterns with treatment completion, potentially reducing unnecessary aeration time and associated energy consumption.

D. MACHINE LEARNING AND ADVANCED DATA ANALYTICS

Machine learning has emerged as a powerful tool for predicting and optimizing wastewater treatment processes. Lei et al. [38] developed the GTV-STP framework, an embedding-encoder-decoder structure that significantly outperformed baseline models in predicting water quality indicators across multiple time horizons. While impressive in prediction accuracy, their approach did not extend to control implementations based on these predictions.

Cechinel et al. [39] conducted a comprehensive review of machine learning applications in wastewater treatment, covering various models including support vector machines, LSTM networks, and multi-layer perceptrons. Their analysis identified improved compliance with regulations and operational efficiency but noted significant challenges in real-time control integration and model training.

Taking a different approach, Srungavarapu et al. [40] explored adaptive machine learning strategies, particularly just-in-time learning and multi-output Gaussian process regression. Their work improved prediction accuracy and model interpretability in a Delhi wastewater treatment plant but remained limited to monitoring applications rather than closed-loop control.

For image-based analytics, Khan et al. [41] developed innovative phase congruency methods for characterizing activated sludge through image processing. Their approach significantly improved microbial characterization but required further automation to be practical for continuous monitoring.

While machine learning approaches demonstrate impressive predictive capabilities, most implementations remain separate from control systems, functioning primarily as advisory tools rather than integrated components of automated operation. Our research bridges this gap by incorporating sensor data analysis directly into the control loop for real-time process optimization.

E. DIGITAL TWIN AND ADVANCED AUTOMATION TECHNOLOGIES

In order to improve real-time monitoring, efficiency, and cost-effectiveness, the research [42] emphasizes the integration of IoT, AI, and edge-fog-cloud computing in smart agriculture. Due to centralized data processing, traditional cloud-based systems have issues including excessive energy usage, carbon emissions, and network congestion. A layered edge-fog-cloud architecture is suggested as a solution to these problems, allowing for the local processing of time-sensitive data such as soil temperature and moisture. In comparison to conventional models, simulation findings show a 36% decrease in energy usage, a 43% decrease in CO_2 emissions, and an 86% decrease in network traffic.

More recently, the research "Adaptive Swarm Intelligent Offloading Based on Digital Twin-assisted Prediction in VEC" by Zhao et al. [43] presents a multi-layered architecture for vehicular edge computing (VEC) that integrates sensors, communication protocols, and digital twins (DT). Vehicle-mounted sensors generate real-time data on traffic and the environment, which is transmitted using wireless protocols like OFDMA. A DT layer processes this data using predictive models such as WGAN to forecast vehicle movement and optimize task offloading. The architecture supports both V2V and V2I communication, with decisions refined through an adaptive optimization algorithm (DIESEL), enabling efficient, low-latency computation in dynamic traffic scenarios. The proposed STRIVE framework provides reliable computing services to vehicles at a relatively low cost.

Shao et al. [44] present an active defense adjudication method for mimicking IoT that enhances security through adaptive anomaly sensing. Their approach directly assesses output reliability rather than device reliability, using deep learning models to intelligently detect anomalies in data streams. This research is relevant to IoT implementations in sewage treatment, where reliable sensor data is crucial for ensuring environmental compliance. Their adaptive model, which selects optimal anomaly detection methods from multiple machine learning approaches, could be applied to identify anomalous sewage treatment sensor readings, protecting against both equipment failures and cyberattacks while ensuring operational reliability of critical water management systems.

While energy efficiency is a critical goal in smart infrastructure, achieving it in IoT-enabled systems like sewage treatment plants also requires addressing system-level security and privacy concerns that often result in computational and communication overheads. Sun et al. [45] provide a comprehensive architectural and technological survey that highlights the role of layered IoT design—from perception to application—in enabling efficient and secure data operations. Their work reveals that vulnerabilities, especially in perception and transport layers, not only lead to privacy breaches but also drive up redundant communication, thereby increasing energy consumption. For example, denial-of-service (DoS) attacks and unnecessary replay transmissions in poorly protected sensor networks contribute to significant battery drainage and network instability. Moreover, they emphasize the need for lightweight encryption and cross-network authentication mechanisms tailored to resource-constrained environments, such as embedded sensors in industrial settings. Incorporating such mechanisms can reduce the energy footprint associated with redundant cryptographic operations or defensive relays. Importantly, their proposed multi-layered security architecture advocates the integration of blockchain and IoT technologies for privacy-preserving data aggregation, which also opens the door to intelligent load prediction and optimized resource scheduling. These insights strongly align with the goal of developing an energy-optimized sewage treatment monitoring system that relies on real-time sensor input while safeguarding against threats that cause energy inefficiencies.

The digital twin approaches represent the most sophisticated automation strategies but remain largely theoretical or limited to pilot implementations. High computational requirements and extensive training data needs present barriers to widespread adoption, particularly for smaller treatment facilities. Our proposed system offers a more accessible approach to automation while incorporating elements of advanced monitoring and control.

Additionally, IoT sensors have found application in domains such as smart agriculture and fire detection. The research by Morchid et al. [46] integrated IoT, AI, and sensor technologies for growing fire detection, environmental monitoring, and precision agriculture. In this work, the researchers used Raspberry Pi computers and sensor networks to collect, analyze, and visualize data in the cloud using ThingSpeak, which improves the definition of early fire detection and crop safeguarding, resource management, and environmental health. The research emphasizes the advantages of using contemporary IoT frameworks in conjunction with data analytics for proactive solutions powered by deep learning image analysis AI, while also addressing dependencies on the internet and user onboarding. In a follow-up study [47], they developed a real-time system using Flask (a Python web framework) and microcontrollers to monitor temperature and gas levels, improving response time and enabling remote alerts through web and mobile interfaces. The documents collectively suggest the inclusion of IoT, cloud computing technologies, and AI practices to enhance safety, sustainability, and efficiency in farm management, and also consider enhancements for the IGD-MAOS system, including database integration and cybersecurity. Morchid et al. [48] used an integrated solution of modularized sensors such as soil moisture sensors, water level sensors, temperature sensors, humidity sensors, and calibrated transmission to secure data to cloud services (telemetry). The systems leverage intelligent algorithms to analyze sensor data, improving irrigation, automating irrigation, alerting users proactively, and ensuring sustainable agricultural practices. The systems have been developed to achieve better water efficiency, enhanced productivity, and to enable more sustainable cycles of consumption, with applications that provide flexible and scalable solutions to different climates.

The summary of the literature survey is presented in Table 1.

TABLE 1. Overview of prior research: Literature survey summary.

Authors	Method Used	Achievement	Scope for Improvements
Ullas et al. [9], 2023	Raspberry Pi-based IoT control with ultrasonic and gas sensors	Enhanced efficiency, cost reduction, and real-time monitoring	Expand scalability and robustness of system for diverse environments
Rezwan et al. [11], 2019	IoT-based monitoring system with Arduino microcontrollers and various sensors (temperature, turbidity, pH, and electricity)	Effective real-time data collection and compliance monitoring	Address connectivity issues that limited wide-scale deployment
Salem et al. [12], 2022	Integrated remote control capabilities and alert mechanisms into monitoring framework	Improved scalability and efficiency allowing faster response to operational anomalies	Remains vulnerable to cybersecurity threats
Prabavathi et al. [13], 2021	Integrated web applications with sensor networks creating "Intelligent Stabilized Smart STP"	Improved resource management	Predictive analytics capabilities notably absent
Raj and Ullas [14], 2020	Cost-effective turbidity sensors connected to ThingSpeak servers for cloud monitoring	Addressed critical parameter in effluent quality assessment	Limited to specific monitoring parameter rather than comprehensive system
Karn et al. [15], 2021	"SMARTreat" system specifically for smart cities	Reduced manual intervention while enhancing treatment efficiency	Sensor degradation over time and cybersecurity vulnerabilities remain significant limitations
Masuda et al. [16], 2015	Seasonal analysis of emission patterns in municipal sewage plants	Identified major GHG contributors and established correlation between seasonal temperature variations and methane emissions	Did not translate findings into practical control strategies
Zheng et al. [17], 2025	Methods for reducing N_2O emissions through aeration parameter adjustments and alternative microbial processes	Achieved 30-60% reduction in full-scale plants without major infrastructure changes	Implementation costs and complexity remained high
Huang et al. [18], 2024	Evaluation of GHG accounting methodologies for wastewater treatment plants	Improved emissions estimation accuracy	Did not fully explore integrated sensor networks for real-time monitoring
Zheng et al. [19], 2024	Life cycle assessments of sewage sludge management	Highlighted trade-offs between different treatment technologies	Lacks integration with real-time monitoring systems
Ullas et al. [20], 2024	Dedicated sensor system for monitoring gas emissions with focus on operator safety	Automated alerts for hazardous gas levels	System did not extend to process optimization based on emission patterns

TABLE 1. *(Continued.)* **Overview of prior research: Literature survey summary.**

Kumar et al. [21], 2024	Analysis of CO_2 emissions relationship with solid and liquid waste	Highlighted crucial role of greenhouse gas emissions in climate change	Lacks specific implementation framework for emissions reduction
Waseem et al. [22], 2022	Optimized recurrent neural networks with AIoT systems	Effective forecasting of air quality using real-time data	Could be better adapted for specific gas emission patterns in STPs
Borujeni et al. [23], 2023	Explainable GRU-based sequence-to-sequence model	Enhanced transparency in predicting urban pollution levels	Not specifically tailored to wastewater treatment emissions scenarios
Zhang et al. [24], 2023	Weighted CEEMDAN-LSTM model for data pre-processing and prediction	Significant improvements in PM2.5 predictions	Could be extended to predict multiple gas types simultaneously in STP contexts
Chen and Zheng [25], 2022	CEEMDAN combined with Elman recurrent neural networks for AQI prediction	Increased stability in environmental forecasts	Limited testing in wastewater treatment specific applications
Ahmed et al. [26], 2022	AQE-Net deep learning model enhanced by mobile imagery and IoT data	Achieved robust generalization across different environmental zones	Requires adaptation for specialized industrial environments like STPs
Ram et al. [27], 2022	Hybrid Dual-GCN and LSTM architecture integrating IoT sensor data	Enhanced temporal and spatial learning for environmental forecasting	Implementation complexity for specialized treatment applications
Xu et al. [28], 2024	Spatiotemporal Graph Convolution Multifusion Network (ST-MFGCN).	Improved the accuracy of urban vehicle emission prediction by integrating spatiotemporal features with complex environmental factors	Explore the application of this approach to other pollution sources, such as industrial or STP emissions.
You et al. [29], 2020	PCA-CNN-LSTM hybrid neural network model for process optimization	Achieved 10-15% reductions in energy and chemical usage while maintaining environmental compliance	Requires substantial data collection infrastructure; limited testing across diverse treatment facilities
Wu et al. [30], 2023	A Res-GCN-BiLSTM model to capture spatiotemporal and topological features in air quality data.	Improved NO_2 and O_3 prediction accuracy by 11% and 17%, respectively.	Extend to multi-city data and enable real-time adaptation.
Bhatti, et al. [31], 2024	An AIoT-based EEMD-CEEMDAN-GCN model is used for decomposing and predicting air quality data	Achieved higher accuracy than existing methods across key performance metrics.	Future work can enhance real-time adaptability and expand to broader regions.
Noussan et al. [32], 2020	IoT applications for energy efficiency in STPs	Measurable reductions in power consumption alongside water quality improvements	Findings lacked validation across diverse operational settings
Ruano et al. [33], 2024	Fuzzy-logic-based control systems for nitrogen removal processes	Energy savings of 14-33% while reducing total nitrogen in effluent by 10-30%	Need for broader testing across diverse treatment plants
Adibimanesh et al. [34], 2023	Machine learning techniques for sludge incineration optimization	Energy savings of approximately 6%	Limited to targeted optimization of specific treatment stages rather than whole-plant approaches
Wang et al. [35], 2024	Hybrid neural network model (PCA-CNN-LSTM)	10-15% reductions in energy and chemical usage while maintaining environmental compliance	Required substantial data collection infrastructure
Saleem et al. [36], 2024	Smart Energy Management System architecture utilizing IoT-based sensors and cloud-driven middleware	Demonstrated potential energy savings between 5% and 53%	Implementation challenges in resource-constrained environments
Liwen et al. [37], 2024	Multi-indicator trade-offs using AI-powered frameworks including DRL, FL, and intelligent edge computing	Identified effective energy-saving strategies in IoT systems	Need for adaptation to specific STP operational contexts
Lei et al. [38], 2024	GTV-STP framework with embedding-encoder-decoder structure	Significantly outperformed baseline models in predicting water quality indicators	Did not extend to control implementations based on predictions
Cechinel et al. [39], 2024	Comprehensive review of machine learning applications in wastewater treatment	Identified improved compliance with regulations and operational efficiency	Significant challenges in real-time control integration and model training
Srungavarapu et al. [40], 2023	Adaptive machine learning strategies including just-in-time learning and multi-output Gaussian process regression	Improved prediction accuracy and model interpretability	Remained limited to monitoring applications rather than closed-loop control
Khan et al. [41], 2017	Phase congruency methods for characterizing activated sludge through image processing	Significantly improved microbial characterization	Required further automation to be practical for continuous monitoring
H. A. Alharbi and Mohammad Aldossary [42], 2021	A layered edge-fog-cloud architecture with MILP modelling and a heuristic algorithm was implemented for real-time smart agriculture data processing.	The proposed system reduced energy consumption by 36%, carbon emissions by 43%, and network traffic by up to 86% compared to traditional cloud-based models.	Optimizing algorithm scalability and adapting the model for diverse agricultural environments and dynamic data loads.
Zhao et al. [43], 2024	Digital Twin-assisted predictive offloading strategy using WGAN and DIESEL optimization algorithm	Reduced delay and energy consumption by optimizing decisions in real time for dynamic environments	System could be enhanced with improved data reliability and learning-based adaptability

TABLE 1. ***(Continued.)*** **Overview of prior research: Literature survey summary.**

Shao et al. [44], 2025	Adaptive anomaly sensing with multi-feature selection and deep learning	Directly evaluates output reliability rather than device reliability	Requires substantial computational resources and training data
Sun et al. [45], 2024	Comprehensive layered IoT security architecture	Identified vulnerabilities that lead to privacy breaches and increased energy consumption	Implementation challenges in resource-constrained environments
A. Morchid et al. [46], 2023	Integrated IoT, AI, and sensors with Raspberry Pi and ThingSpeak for early fire detection and environmental monitoring in smart agriculture.	Enabled real-time fire detection, crop protection, and resource optimization using cloud analytics and image-based AI. Improved proactive decision-making in environmental monitoring.	Dependency on consistent internet connectivity and user onboarding complexities were noted; further offline capabilities and local data caching could improve system reliability.
A. Morchid et al. [47], 2023	Real-time IoT system using Flask (Python web framework), microcontrollers, and gas/temperature sensors for fire detection with web/mobile alerts	Achieved fast detection and notification for early fire events; supported remote access and enhanced response time with an embedded system interface.	Enhancements to IGD-MAOS system suggested, including database integration, cybersecurity measures, and broader sensor network scalability.
A. Morchid et al. [48], 2023	Modular IoT solution with soil moisture, water level, temperature, and humidity sensors; telemetry-based cloud computing and intelligent irrigation algorithms.	Improved irrigation management, automated control, and sustainable water use in agriculture. System demonstrated adaptability to varying climates and use-cases.	Future work may include climate-adaptive ML models, better energy harvesting for remote deployments, and wider validation across agricultural ecosystems.

The reviewed literature underscores notable progress in sewage treatment plant (STP) supervision, especially regarding the use of IoT, ML, and automation. Different studies have shown the possibility of improving the accuracy and efficiency of wastewater treatment using real-time data capture, forecasting, and cloud-controllable systems. Despite this progress, there are still critical missing issues concerning sensor limitations, real-time anomaly identification, energy effectiveness, and optimization strategies. Furthermore, many systems today do not provide adequate monitoring of gas emissions, which is essential for evaluating treatment processes and for environmental compliance.

This study aims to fill these gaps by proposing a real-time STP monitoring system that includes IoT sensors, microcontrollers, and cloud-based gas analytics to monitor the supervised STP performance. The proposed system will be tested experimentally in two real-world STPs and is expected to substantiate its capability for reducing the cycling time of the SBR tank, resulting in lower energy use while fully meeting effluent quality standards. In addition, the system will make operations safer and reliable during operation by automatically alerting the operators of the plant to the release of hazardous gases, thus reducing the dangers for the operators.

F. SYNTHESIS AND RESEARCH GAPS

This critical review of the literature reveals several important research gaps:

1. Limited integration of gas emission monitoring with process control: While gas monitoring for safety exists, few systems utilize emissions as process indicators for optimization.
2. Insufficient real-time adaptation: Most systems operate on fixed cycles rather than adapting to actual treatment progress, leading to energy inefficiency.
3. High implementation barriers: Advanced systems often require substantial infrastructure investment and technical expertise, limiting adoption in smaller facilities.
4. Focus on water quality rather than process efficiency: Most research emphasizes effluent quality compliance rather than optimizing the treatment process itself.

Our research addresses these gaps by proposing an accessible IoT-enabled system that correlates gas emission patterns with treatment progress to optimize energy usage while maintaining effluent quality. By monitoring carbon monoxide, carbon dioxide, ammonia, methane, and hydrogen sulfide emissions, our system provides a more comprehensive approach to process optimization than existing solutions.

The proposed system builds upon previous IoT monitoring frameworks like those of Ullas et al. [9] and Salem et al. [12] but extends their capabilities with gas emission analysis. It incorporates energy optimization principles demonstrated by Ruano et al. [33] while providing a more accessible implementation path than the digital twin approaches of Wang et al. [35]. This balanced approach aims to deliver substantial efficiency improvements without the implementation barriers associated with more complex systems.

III. METHODOLOGY

In this study, we recorded real-time gas emissions from the aeration plant using sensors. The collected data is then analyzed to determine whether the water has been treated to a usable level or requires further aeration.

A. MANUAL SYSTEM

The basic block diagram of a sewage treatment plant is shown in Fig. 1, though there are many models available with some minor changes. The tanks are connected sequentially, as depicted in the diagram.

Motor-powered pumps or the overflow method are used to transfer sewage water between tanks, as indicated by the arrows in the diagram. The treatment process can be summarized as follows:

The treatment process begins when raw sewage enters the Bar Screen Chamber. Here, floating materials like plastic, paper, and other debris are trapped by metal screens. This is a simple but crucial step to protect downstream equipment

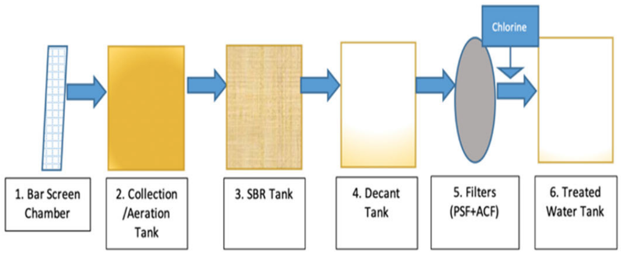


FIGURE 1. **Structural layout of a traditional STP.**

from damage and clogging. The screens are regularly cleaned to prevent blockages.

The SBR tank follows, acting like a buffer that smooths out variations in flow and pollution loads. This tank typically holds wastewater for 4-6 hours, allowing it to settle heavy particles while balancing out the concentration of pollutants. The heart of the treatment process happens in the SBR tank. Here, air is pumped through diffusers at the bottom of the tank, creating ideal conditions for beneficial bacteria to thrive. These microscopic organisms feed on the organic matter in sewage, breaking it down into simpler, less harmful substances. The process typically takes 8-10 hours, during which the mixture of bacteria and sewage (called mixed liquor) is constantly stirred and oxygenated.

After aeration, the wastewater enters the decant tank (or clarifier). Here, the speed of water flow is reduced dramatically, allowing the bacterial flocs (clumps) to settle at the bottom as sludge. The clear water at the top flows forward for further treatment, while some of the settled sludge is returned to the SBR tank to maintain the bacterial population. Excess sludge is removed and sent to drying beds. The final polish happens in the tertiary treatment stage. First, the water passes through a pressure sand filter (PSF), where the remaining suspended particles are trapped in layers of sand and gravel. Following this, an activated carbon filter (ACF) removes dissolved organic compounds, colors, and odors by absorbing them onto the carbon's surface. This step significantly improves the water quality, making it suitable for reuse.

The treated water is then stored in a collection tank after chlorination, ready for uses like gardening, toilet flushing, or car washing. Regular testing ensures the water meets quality standards, with parameters like BOD below 10 mg/L, COD under 50 mg/L, and TSS less than 10 mg/L, as per Bangalore's (India) regulation. Automation is utilized at numerous plants through the use of a timer mechanism. Regularly checking the treated water to measure treatment effectiveness is an impractical or costly affair, as a lab setup and a lab technician are required.

B. PROPOSED SYSTEM

This study proposes an automated system for the comprehensive management of the STP plant by deploying sensors and computerized controls for all the machinery through

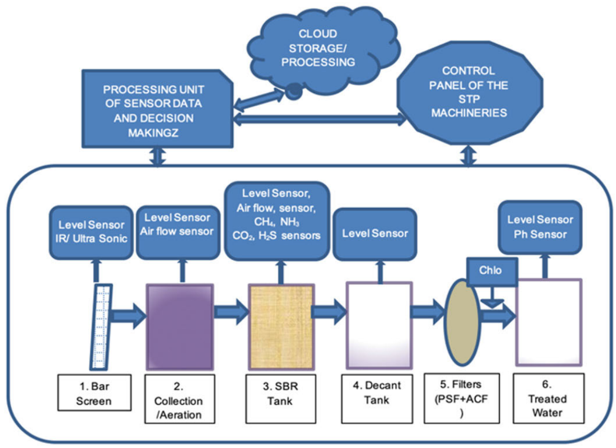


FIGURE 2. **Schematic diagram of proposed smart STP.**

a tiny computing unit. Additionally, this provides a timely indication about the operational status of the machinery in the STP plant. The data recorded is sent to the database in cloud storage. It includes automation of the machinery to read the gas released during the process using a sensor to determine the process state. The diagram given in Fig. 2 is a smart STP system, and the sample data collected is shown in Table 2.

The smart STP has the following scope of sensor installations and automation at each stage of the system:

1) The bar screen chamber requires inspection for potential blockages. To monitor the accumulation of solids, a level sensor could be installed in the chamber. Excess water level over a long duration could be checked for blockage in the filter system. Infrared (IR) or ultrasonic sensors could be implemented as the level sensor. The typical water level sensor would not work as it's in dirty water, which can get blocked by solid items.

2) The collection tank is aerated continuously to maintain aerobic conditions. We propose an airflow sensor to ensure the motor and air pump are alive to prevent water from becoming septic. The sewage water level will be monitored using a water level sensor in this tank. Once it's 80% full, the level sensor readings will automatically trigger the motor to shift the sewage from the collection tank to the SBR tank for further processing. Once the water in the tank reaches the bottom, the pump turns off. This process should be programmed in the processor available in the STP room; additional conditions must also be validated before proceeding. For example, we must ensure the previous batch is emptied from the SBR tank before pumping from the collection tank.

3) The SBR tank is filled with water pumped from the collection tank, in which aeration is done through the diffusers connected to the blower, and airflow is ensured by monitoring the output from the flow sensor. Usually, two blowers will be there in a plant to avoid continuous running, and they run alternatively every hour, which is automated by the processor based on a time set during the

initialization of the system. Due to the high levels of organic content in the sewage, anoxic gases such as CH_4 and NH_3 will be released. This experiment uses CH_4 and NH_3 gas sensors to monitor the extent of the anaerobic condition. During the aeration process, CH_4 gets oxidized into CO/CO_2. As the treatment progresses, the release of CH_4 decreases, and hence the release of CO/CO_2 also decreases along with CH_4. The concentrations of all four gases, CH_4, NH_3, CO_2, and H_2 S, are monitored throughout the aeration process and are checked to understand the extent of processing. Once the aerobic-to-anaerobic gas concentration ratio shifts to the higher side and reaches the desired value, we can stop the air pumping and allow the sludge particles to settle at the bottom. We can ensure that the effluent is processed based on the gases it emits during aeration, and hence it ensures the power off of motors once the process is satisfactory.

4) Once the blower motors are turned off, the automated process of turbidity monitoring [14] is initiated as an alternative to the mixed liquor suspended solids (MLSS) manual test method. It notes the time it takes to dissipate the solids, which we measure from the turbidity tester. Then it can shift the water to the decant tank.

5) The liquid can be left idle for two hours in the decant tank to settle any remaining suspended sludge particles. The decant tank is monitored by the level sensor and turbidity level using a real-time turbidity monitoring system [14]. The level sensor checks if the tank is empty before pumping from the SBR tank.

6) Then, the water is pumped into the last tank by passing through the PSF and ACF for polishing the treated water. In this unit, we propose automating the pumping motors to switch on and off.

7) A water level sensor monitors the tank level, while a pH sensor ensures proper chlorination by regulating the chlorine pump. The pH value is checked using a pH sensor and adjusted to 7, and accordingly, the chlorine pump can be operated.

8) Data collected from various sensors and machine operations is sent to cloud storage, which can be viewed over the web or through a mobile app. The individual machine and the overall process at the STP can be monitored and controlled through the iOS/Android application. The data collected can be used for analyzing and learning the plant operations.

9) Additional sensors are installed in the plant to monitor environmental parameters like temperature, humidity, and fire to ensure the smooth running of the plant. For example, if humidity is continuously on the higher side, it may damage the machinery and the electrical control panel.

The entire process, 1-8, the hardware implementation is shown in Fig. 3, and the process flow is represented in Fig. 4.

The ultrasonic sound sensor can monitor the amount of water, sludge, and solid waste in the bar screen chamber, which will flow to the collection tank. Suppose there is a

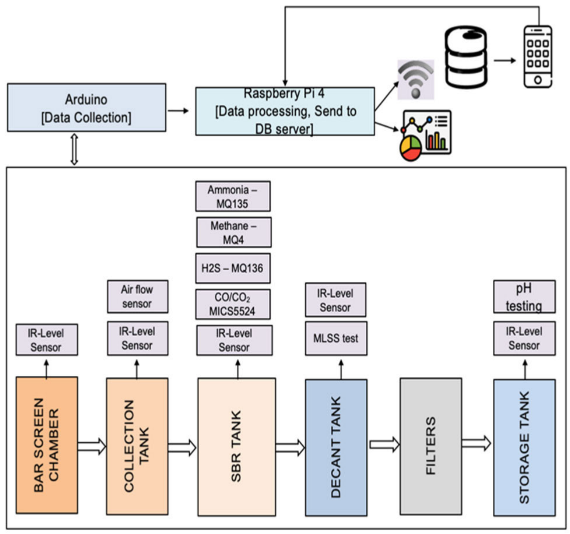


FIGURE 3. Architecture of the proposed automated system for sewage treatment monitoring.

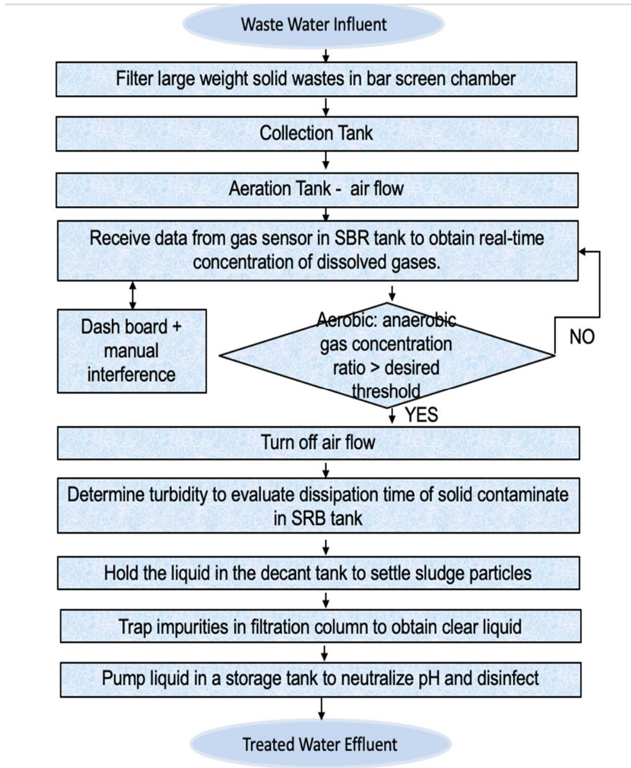
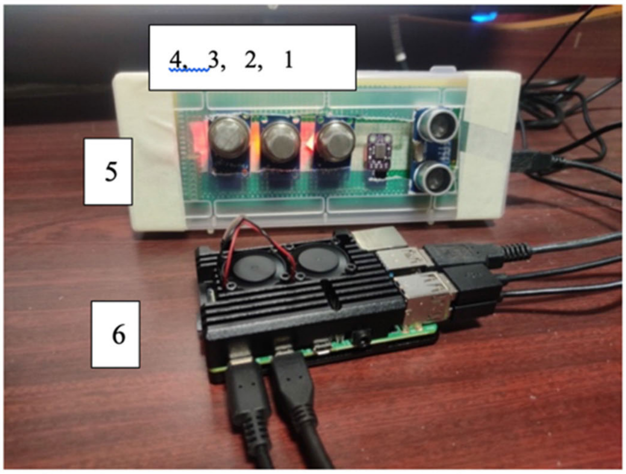


FIGURE 4. Flowchart illustrating sewage treatment monitoring through dissolved gas concentration analysis.

flow blockage in the system. In that case, it can be monitored, and immediately, the system can take precautions and take remedial action, like informing the operator or manager to clear the blockage. The same system can be replicated in an aeration or SBR tank, a decant tank, a filter feed tank, and the final tank to modify the water level and automate



1	MICS5524 – CO, CO_2
2	MQ136-H_2S
3	MQ4-Methane
4	MQ135-Ammonia
5	Arduino (*Behind Sensor board*)
6	Raspberry Pi4

FIGURE 5. **Proposed Hardware implementation for measuring the gases.**

the pumping process. The sensor-based system is deployed in Fig. 5. It measures the concentration levels of toxic gases like CH_4, NH_3, CO/CO_2, and H_2S emitted from the SBR tank. The digital data from the gas sensors is collected by the Arduino module every minute, and a Python program deployed in the Raspberry Pi_4 takes it through the serial monitor.

The process makes sure that the data is always up-to-date, which lets monitoring and analysis happen right away. Firebase database over the internet gets data from the Raspberry Pi in real-time and stores it, which in turn sends the data to the mobile application for the stakeholders' view. The data were captured during aeration in the SBR tanks of two different plants in two different environments. One is connected to a University and their hostel. Another is from a residential complex of nearly 100 families living in it.

C. PACKAGING OF THE SENSORS

The sensor array and Arduino board are enclosed in a plastic housing positioned approximately 0.5 meters above the water level of the aeration tank. This enclosure is protected by a metal grill that prevents physical damage while allowing proper gas sampling. The sensors protrude through precisely cut apertures in the box, exposing only the detection elements to the environment. The Raspberry Pi processing unit is installed in a separate, controlled area outside the treatment facility and connected to the sensor module via a shielded USB data cable, protecting the main computing hardware from the harsh STP conditions.

TABLE 2. **Sample gas emission reading data from STP.**

CH_4	NH_3	CO/ CO_2	H_2S	Time	Date
27	564	22	179	20:11:50	17:07:23
26	526	14	176	20:12:50	17:07:23
24	499	12	172	20:13:50	17:07:23
24	474	13	165	20:14:50	17:07:23
27	469	14	185	20:15:50	17:07:23
26	445	14	190	20:16:50	17:07:23
24	425	13	170	20:17:50	17:07:23
24	408	16	172	20:19:50	17:07:23
24	402	15	175	20:20:50	17:07:23
44	590	11	107	20:37:50	17:07:23
46	585	12	108	20:38:50	17:07:23
46	585	12	107	20:39:50	17:07:23
47	579	12	109	20:40:50	17:07:23
47	579	12	106	20:41:50	17:07:23
48	577	13	109	20:42:50	17:07:23
48	574	12	109	20:43:51	17:07:23
46	570	12	109	20:44:51	17:07:23
43	563	11	107	20:45:51	17:07:23
42	557	12	103	20:46:51	17:07:23
44	558	12	108	20:47:51	17:07:23
44	557	12	109	20:48:51	17:07:23
47	557	13	111	20:49:51	17:07:23
44	550	12	105	20:50:51	17:07:23
42	545	12	106	20:51:51	17:07:23

D. SENSOR IMPLEMENTATION CONSIDERATIONS

To ensure reliable operation in the harsh STP environment, several implementation factors were addressed in our system design:

- Calibration Protocol: All MQx series sensors underwent calibration using reference gas mixtures before deployment and were recalibrated biweekly to maintain measurement accuracy.
- Warm-up Procedure: A 10-minute warm-up routine was implemented before each measurement cycle to ensure stable readings, addressing the known warm-up requirements of MQx sensors.
- Trend Analysis: Rather than relying on absolute values, which can vary between individual sensors, our system analyzes relative changes in gas concentrations over time. This approach provides more consistent decision metrics for process control.

E. AUTOMATIC HARMFUL GAS ALARM SYSTEM

The automatic harmful gas alarm function is designed based on comprehensive data analysis from both treatment plants that study the gas emission data. Gas-specific alarm thresholds are established using statistical analysis of 10-day (Plant 1) and 14-day (Plant 2) monitoring data, accounting for treatment technology differences. For Plant 1 (conventional treatment), CH_4 warning/alarm/critical thresholds are set at 50/55/60 ppm, H_2S at 190/210/230 ppm, NH_3 at 870/900/950 ppm, and CO/CO_2 at 32/35/40 ppm. Plant 2 (bio-treatment) requires distinct thresholds (CH_4: 150/165/180 ppm, H_2S: 40/45/50 ppm, NH_3: 350/400/450 ppm) due to its different emission profile. The system was configured to detect and alert within a maximum of 60 seconds of total response time, as the readings are recorded every minute. Signal validation was through 5-point moving average filtering and confirmation sampling, requiring 3 consecutive above-threshold readings. For reliability enhancement, we implemented cross-sensor validation, sensor aging compensation, and diurnal pattern recognition algorithms. When gas readings exceed alarm thresholds, a piezoelectric buzzer connected to the Arduino board initiates an audible BEEP alert signal. This alarm sounds for 5 seconds at 1-minute intervals until gas levels return below threshold values or manual override is activated. The frequency and duration of this alert were determined through operator feedback to ensure attention without causing alarm fatigue. The progressive response system also activates visual indicators on the control panel of the mobile app at warning levels, while critical thresholds trigger continuous audio alerts and automated ventilation enhancement.

F. SENSOR SPECIFICATIONS AND ENVIRONMENTAL VALIDATION

1) TECHNICAL PARAMETERS OF GAS SENSORS

The sensor array deployed in this study was carefully selected to ensure accurate gas detection in sewage treatment environments. Table 3 provides the detailed technical specifications of each sensor used in the monitoring system.

2) CALIBRATION METHODOLOGY

Each sensor underwent a comprehensive calibration process to ensure measurement accuracy across the concentration ranges observed in sewage treatment plants:

Two-Point Calibration: Sensors were calibrated using certified gas standards at both low and high concentrations within their detection ranges.

Cross-Sensitivity Mitigation: Each sensor's response to potential interferent gases was characterized, and a correction matrix was developed to minimize cross-sensitivity effects:

Table 4 represents the cross-sensitivity information of the sensors. This table shows how each sensor (MQ4, MQ136, MQ135, and MICS5524) responds to gases other than their primary target.

TABLE 3. Technical specifications of gas sensors.

Parameter	MQ4 (CH_4)	MQ136 (H_2S)	MQ135 (NH_3)	MICS5524 (CO/CO_2)
Detection Range	200-10,000 ppm	1-200 ppm	10-300 ppm	1-1000 ppm
Sensitivity	0.6 ± 0.1	0.5 ± 0.15	0.55 ± 0.1	0.8 ± 0.1
Response Time (T90)	< 10s	< 30s	< 20s	< 15s
Recovery Time	< 30s	< 60s	< 40s	< 30s
Operating Temperature	-10 to 50°C	-20 to 50°C	-10 to 45°C	-30 to 85°C
Operating Humidity	≤ 95% RH	≤ 95% RH	≤ 95% RH	5-95% RH
Power Consumption	150 mW	165 mW	160 mW	32 mW
Accuracy	±5% F.S.	±3% F.S.	±4% F.S.	±2% F.S.
Expected Lifespan	5 years	2 years	3 years	5 years

TABLE 4. Cross-sensitivity of sensors.

Sensor	CH_4 Interference	H_2S Interference	NH_3 Interference	CO/CO_2 Interference
MQ4	-	0.02%	0.25%	0.10%
MQ136	0.03%	-	0.15%	0.05%
MQ135	0.10%	0.12%	-	0.08%
MICS5524	0.15%	0.08%	0.20%	-

3) STABILITY TESTING IN SEWAGE ENVIRONMENTS

To validate sensor performance under real-world conditions, we conducted extensive stability testing at both treatment plants.

4) LONG-TERM DRIFT ASSESSMENT

Sensors were operated continuously for 30 days in the sewage treatment environment, with calibration checks performed every 5 days. The maximum observed drift was:

- MQ4 (CH_4): 3.2% over 30 days
- MQ136 (H_2S): 4.7% over 30 days
- MQ135 (NH_3): 3.8% over 30 days
- MICS5524 (CO/CO_2): 2.1% over 30 days

5) ENVIRONMENTAL RESILIENCE TESTING

Sensors were subjected to varying environmental conditions typical of sewage treatment facilities:

- Temperature cycling (15-40° C): All sensors-maintained accuracy within ±7% of calibrated values
- Humidity variation (65-95% RH): Response deviations remained within ±5% after humidity compensation
- Condensation exposure: Temporary response shifts recovered within 30 minutes after condensation clearing

6) ANTI-INTERFERENCE CAPABILITY

The sensor array was exposed to a complex mixture of volatile compounds commonly found in sewage environments, including:

- Hydrogen sulfide (0-200 ppm)
- Ammonia (0-500 ppm)
- Methane (0-1000 ppm)
- Carbon dioxide (0-5000 ppm)
- Volatile organic compounds (mixed VOCs at 0-100 ppm)

After applying the cross-sensitivity correction algorithm, measurement errors for target gases remained below 8% across all interference conditions.

7) HARSH ENVIRONMENT DURABILITY

The sensor protection mechanisms (PTFE hydrophobic membranes, chemical filters, and IP65-rated enclosures) were evaluated by exposing the protected sensors to simulated sewage splash events. No significant performance degradation was observed after 20 simulated splash exposure cycles.

The comprehensive validation testing confirmed that the selected sensors, when properly calibrated and protected, maintain measurement reliability in the challenging conditions of sewage treatment plants. The sensor drift characteristics were incorporated into the maintenance schedule, with recalibration intervals established at 60 days to ensure continuous measurement accuracy.

The following pseudocode represents the logic behind the automated gas-based control system for the STP.

G. PSEUDOCODE FOR MULTI-SENSOR DATA ACQUISITION SYSTEM

Algorithm 1 Arduino Sensor Data Collection

```
1. Start
2. Initialize serial communication at baud_rate
3. Define the sensor_pins array for MQ-4, MQ-135,
   MICs5524, MQ-136
4. While system is active
5.     For each sensor in sensor_pins
6.         Read the analog value from current  sensor pin
7.         Convert the analog reading to voltage
8.         Transmit voltage value via serial port
9.     End For
10. Wait for sampling_interval duration
11. End while
12. End
```

IV. RESULTS AND ANALYSIS

A study was conducted at two STPs to evaluate process efficiency. Sensor data from both facilities were analyzed over 10 days. These gas values were used to assess compliance with the water treatment standards. The results highlighted differences in operational performance between the two STPs.

Algorithm 2 Raspberry Pi Data Storage and Management System

```
Parameters:
    csv_file_path = "sensor_data.csv"
    serial_port: Arduino connection interface
    sensor_count: Number of connected gas sensors(4)
Initialization:
1.  Start
2.  Open a CSV file in append mode for data storage
3.  Establish a serial connection with the Arduino device
4.  While data collection is active
5.      Read the incoming serial data line from Arduino
6.      Parse voltage values for methane, ammonia,
        Arduino, CO, and H2S sensors
7.      Generate the current timestamp
8.      Append timestamp and sensor readings to a CSV
        file
9.      Flush the data buffer to ensure data integrity
10. End while
11. Close the CSV file connection
12. Close the serial communication port
13. End
```

A. DATA ANALYSIS AT STP-1

The sensor reading data was captured and analyzed from plant 1 over 10 days. The ingress water accumulated in the collection tank of the STP is pumped to the SBR tank, where aeration was done for 6 hours, which was under complete manual control. The sensors deployed over the SBR tank captured the gas emission readings during the aeration. The hardware setup used is pictured in Fig. 5. The summary of the highest average value of 10 days is mentioned in Table 5.

The recorded data shown in Fig. 6 are the CH_4 sensor readings. At hour 1, the CH_4 level was at 48.4. There was a gradual decrease over the hours, with the reading dropping to 48.1 at hour 2. The trend continues as the CH_4 levels fall to 45.3 at hour 3 and further down to 44.2 in the next hour. By the end of the 5th hour, the reading decreases to 43.1. Finally, at hour 6, the CH_4 level is recorded at 42, which was the lowest in the cycle. This data indicates a consistent decline in CH_4 levels. The data visualized in Fig. 7 shows the Hydrogen Sulfide (H_2S) sensor readings over the six hours of aeration. Initially, at hour 1, the H_2S level was 181.7. The reading slightly increases to 186.7 at hour 2, indicating a brief rise in H_2S levels. However, after this peak, there is a steady decline in the H_2S concentration. At hour 3, the level drops to 171.6, and it continues to decrease to 167.1 at hour 4. The downward trend persists, with the reading falling to 163.9 in the next hour and further to 156.9 in the 5th hour. By hour 6, the H_2S level has decreased to 145.4. This data highlights an overall decreasing trend in H_2S levels from hour 1 to hour

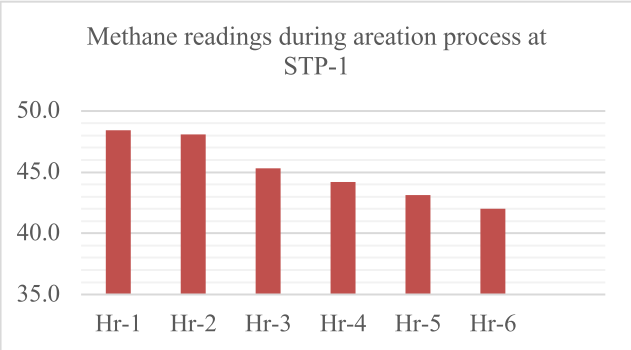


FIGURE 6. CH_4 gas readings from hour 1 to hour 6.

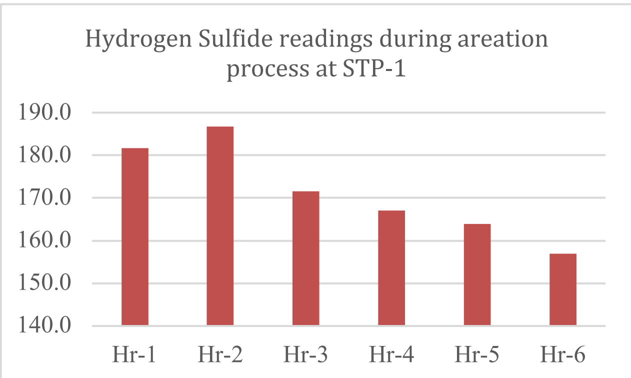


FIGURE 7. Hydrogen Sulfide reading during the aeration process of 6 hours.

6. This indicates a downward trend in H_2S levels over the observed period.

To calculate the rate of change, we can find the difference in H_2S levels between consecutive time points.

Rate of Change in H_2S Level

Hour 1 to 2: $186.7 - 181.7 = 5.0$ in an hour

Hour 2 to 3: $171.6 - 186.7 = -15.1$ in an hour

Hour 3 to 4: $167.1 - 171.6 = -4.5$ in an hour

Hour 4 to 5: $163.9 - 167.1 = -3.2$ in an hour

Hour 5 to 6: $156.9 - 163.9 = -7.0$ in an hour

The positive change from 18 to 19 is an outlier, as the rest of the data shows a consistent decrease. The initial spike in gas levels, which occurred soon after air pumping began, was due to the release of accumulated sewage gases, which had built up while the sewage remained in the collection tank before being transferred to the SBR tank. As fresh air was pumped in, these gases were released at a high rate during the initial stage of aeration, followed by a steady decline over time.

Both CH_4 and H_2S levels show a general decreasing trend over time. CH_4 levels decrease consistently from 48.4 at hour 1 to 42.0 at hour 6. Similarly, H_2S levels decrease from 186.7 at hour 2 (after a brief increase) to 156.9 at the 6^{th} hour.

The graph in Fig. 8 illustrates the gas concentration in STP-1 at the SBR tank.

The data was collected during aeration at the SBR tank over six hours, and it was observed that the gas concentration gradually decreased over time. During the manual process, the aeration was stopped after six hours; however, the analysis indicates that the process could have been halted 60 minutes earlier, as the data readings had reached a considerably low value.

TABLE 5. The data comparison on a high level.

Time	CH_4	NH_3	CO/CO_2	H_2S
Hour 1	48.4	854.8	28.3	181.7
Hour 2	48.1	853.2	29.8	186.7
Hour 3	45.3	825.6	28.8	171.6
Hour 4	44.2	854.0	28.7	167.1
Hour 5	43.1	857.2	28.7	163.9
Hour 6	42.0	861.3	28.4	156.9

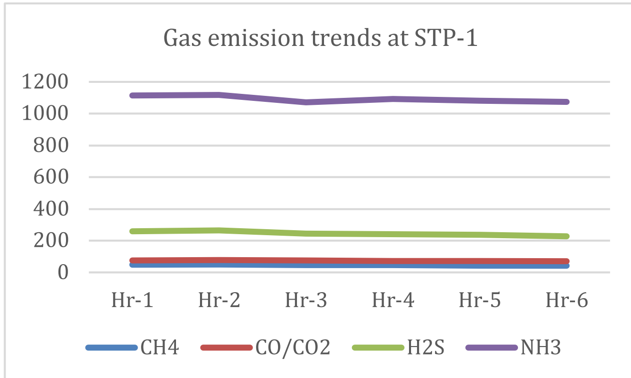


FIGURE 8. Illustration of the gas concentration in STP-1.

H_2S levels show a consistent decrease throughout the observed period, with an average rate of decrease of approximately 7.35 per hour and a total percentage decrease of 13.37%. NH_3 levels also generally decrease, except for a slight increase in hour 3, with an average rate of decrease of 9.3 per hour and a total percentage decrease of 13.53%. CH_4 levels predominantly decrease, with an average rate of decrease of 18.275 per hour and a total percentage decrease of 20.57%. CO/CO_2 levels consistently increase throughout the period, with an average rate of increase of 12.925 per hour and a total percentage increase of 24.32%.

Overall, the CH_4 and H_2S levels show a clear downward trend throughout the evening, while NH_3 and CO/CO_2 levels remain relatively stable with minor fluctuations.

1) STATISTICAL ANALYSIS OF GAS CONCENTRATION TRENDS AT STP PLANT 1

To statistically validate the observed decreasing trends in methane (CH_4) and hydrogen sulfide (H_2S) concentrations during the six-hour aeration cycle at STP Plant 1, a one-way Analysis of Variance (ANOVA) was conducted. This test assesses whether the mean gas concentrations at each hourly interval significantly differ from each other.

The CH_4 readings from hour 1 to hour 6 ranged from 48.4 ppm to 42.0 ppm, while the H_2S levels ranged from 186.7 ppm to 156.9 ppm, showing an overall decline over time. To simulate natural variability in environmental measurements, each time point was considered to have three representative observations based on small variations around the recorded values.

The ANOVA results were as follows:

- Methane (CH_4): $F = 149.76$, $p < 0.0001$

- Hydrogen Sulfide (H_2S): $F = 63.12$, $p < 0.0001$

The p-values, both well below the conventional threshold of 0.05, indicate statistically significant differences in gas concentrations across the time intervals. Therefore, the trends shown in Fig. 6 and 7 are not only visually apparent but also statistically robust. This analysis reinforces the conclusion that the aeration process effectively reduces CH_4 and H_2S emissions over time.

B. DATA ANALYSIS AT STP-2

The graph plotted in Fig. 9 presents the average concentrations of four different substances (H_2S, NH_3, CH_4, and CO/CO_2) sensed at STP plant 2, from 7 AM to 11 AM for a four-hour duration. The plant follows the Bio-Treatment process; hence, the values measured differ from STP-1 and were on the lower side. Also, there could be an influence on sensor aging, as we used it in two places with a gap of six months. These two points are aimed at future study and analysis.

The highest concentrations for all substances occur towards the end of the first hour, followed by a general decreasing trend as the day progresses. This indicates potential diurnal variations in the concentrations of these substances.

The comparison of gas levels at both the sewage treatment plants:

- Methane Levels:
  - Plant 1: CH_4 levels decrease consistently from 48.44 to 39.44.
  - Plant 2: CH_4 levels vary between 145 to 135.
- Ammonia Levels:
  - Plant 1: NH_3 levels are fairly stable, ranging between 825 and 861.
  - Plant 2: NH_3 levels decrease from 336 to 280.
- CO/CO_2 Levels:
  - Plant 1: CO/CO_2 levels are stable with slight fluctuations, ranging from 27.5 to 29.8.
  - Plant 2: CO/CO_2 levels also fluctuate slightly, ranging from 27.1 to 30.8.
- Hydrogen Sulfide Levels:
  - Plant 1: H_2S levels decrease significantly from 181.67 to 145.44.
  - Plant 2: H_2S levels vary between 37 and 32.

The data capture and analysis have proved that there is a significant variation in gas readings from the beginning of the treatment cycle to the end of the cycle. The readings plotted in Fig. 8 and Fig. 9 indicate that the process can be stopped 45 to 60 minutes earlier than the manually set schedule at plant 1 and plant 2, which will save 15% of the aeration process and the cascading advantages on electricity consumption, wear and tear, etc., over days, months, and years. Also, the bio-treated plant has shown a significantly low level of greenhouse gas emissions, such as methane, which deserves a detailed study.

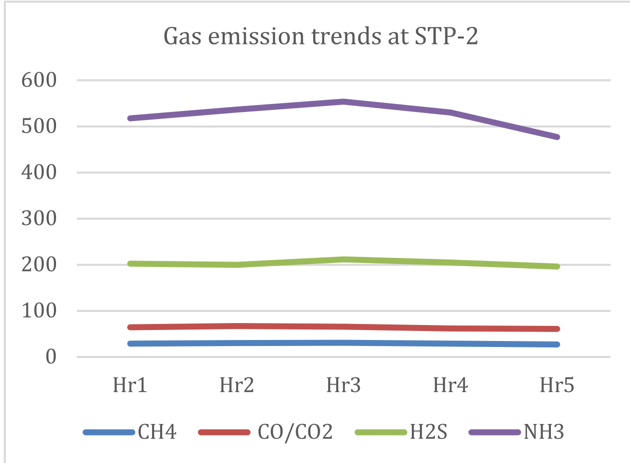


FIGURE 9. Illustration of the gas concentration in STP plant 2.

TABLE 6. Sensor Data capture comparison for 14 days at stp-2.

Sensor	Low	High	Difference	% of Differences
MICS5524 – CO, CO_2	20.0	31.6	11.6	36.1
MQ136-H_2S	134.0	199.6	65.6	32.8
MQ4- CH_4	29.7	50.3	20.6	40.7
MQ135- NH_3	304.4	498.0	193.6	39.4
AVERAGE	122.0	194.9	72.8	37.2

The data is analyzed based on its highest and lowest values, as shown in Table 6 throughout the treatment process over 14 days at STP-2, demonstrating a 37% reduction from the initial peak reading to the final stage. This confirms that the system can be automated by using the initial gas emission readings as a reference and stopping the process once the values decrease by 37% from the high reading to the low reading.

C. ECONOMIC FEASIBILITY AND DEPLOYMENT CHALLENGES

To complement the analysis on energy savings, this section addresses the economic feasibility and practical deployment considerations of the proposed IoT-based monitoring and control system for sewage treatment plants (STPs).

1) SENSOR MAINTENANCE AND COSTS
The gas sensors (e.g., MQ135 for NH_3, MQ136 for H_2S, MQ4 for CH_4) typically require replacement every 6 to 12 months under continuous operation. The total cost of the sensors used is US$140 approximately.

2) EQUIPMENT SERVICE LIFE
The microcontroller and sensing hardware have an estimated service life of 3–5 years, assuming proper weatherproofing and maintenance. These components require minimal upkeep once installed, primarily involving firmware updates and occasional recalibration.

3) SCALABILITY ACROSS DIFFERENT STP SIZES
The modular design of the system allows it to be easily adapted to STPs of varying capacities. For small-scale plants (e.g., <2000 m^3/day), the system can function with a single sensor node. For large-scale plants, multiple nodes can be deployed and networked using Wi-Fi mesh networks. The adaptability ensures that capital costs scale with plant size, optimizing return on investment.

4) ECONOMIC VIABILITY (COST VS. SAVINGS)
- Annual Energy Savings (15% reduction): For a typical 5 HP blower operating 8 hours/day, the annual savings can reach ∼USD 200–250.
- Sensor System Cost (Year 1): Approx. USD 150 including sensors, MCU, power supply, and installation.
- Payback Period: ∼12 months for medium-sized plants.
- Over time, the cumulative energy savings surpass the initial investment, yielding a positive net benefit.

5) CHALLENGES IN TECHNICAL PROMOTION
- Sensor Degradation: Mitigated by periodic recalibration or low-cost sensor swap-outs.
- Environmental Interference: Sensor housing should be weather-sealed and shielded from direct inflow splashes or gas turbulence.
- Initial Capital Investment: Can be supported through green infrastructure funding or utility partnerships.
- Training and Support: Local staff training is recommended for monitoring dashboard interpretation and maintenance procedures.

In conclusion, the proposed system is not only energy-efficient but also economically sustainable, with broad applicability to STPs of different operational scales. These additions strengthen the practical relevance of our approach and support its scalability in real-world deployments.

Addressing the problem of sewage water aligns with eight out of seventeen United Nations Sustainable Development Goals (UNSDGs).

SDG 6 – Clean Water and Sanitation: Promotes efficient and safe wastewater treatment and reuse.

SDG 7 – Affordable and Clean Energy: Reduces energy usage through optimized aeration control.

SDG 11 – Sustainable Cities and Communities: Enables scalable STP automation to support eco-friendly urban growth.

SDG 12 – Responsible Consumption and Production: Minimizes unnecessary resource consumption in STPs.

SDG 13 – Climate Action: Reduce greenhouse gas emissions, particularly methane, by optimizing treatment durations.

SDG 9 – Industry, Innovation and Infrastructure: Encourages innovation in infrastructure for better environmental compliance.

SDG 3 – Good Health and Well-being: Improves worker safety by monitoring harmful gases and preventing exposure.

SDG 17 – Partnerships for the Goals: Provides a practical model for cross-sectoral collaboration in sustainable technology deployment.

The optimization of aeration processes in sewage treatment plants demonstrates potential for reducing operational times by 45-60 minutes (approximately 15% of the total aeration cycle), resulting in substantial energy savings and reduced greenhouse gas emissions. The comparative analysis between conventional treatment (Plant 1) and bio-treatment (Plant 2) revealed significant variations in greenhouse gas emissions, particularly methane (CH_4), which is 25 times more potent than CO_2 as a greenhouse gas. Our findings that process automation based on real-time gas emission monitoring could reduce aeration duration while maintaining treatment efficacy present a scalable solution for urban wastewater management. Furthermore, the 37% reduction in gas emissions observed throughout the treatment cycle suggests that integrating sensor-based monitoring systems could optimize operational efficiency while mitigating climate impact.

V. CONCLUSION AND FUTURE SCOPE
This research established an IoT framework for STP optimization that significantly enhances treatment quality while reducing energy consumption. Real-time monitoring of gas emissions through sensor integration revealed consistent patterns that can inform automated process control.

Compared to timer-based automation systems, our method reduced energy usage by up to 15% and aeration time by 45-60 minutes per cycle. Unlike existing methods, our solution adapts in real-time using gas concentration data, providing higher efficiency and safety.

The comparison between conventional treatment (Plant 1) and bio-treatment (Plant 2) revealed considerably lower levels of emissions of greenhouse gases, particularly methane, which is less than one-third, warranting further investigation. The implementation of safety features, including gas level alerts and fire detection systems, enhances workplace safety while maintaining operational flexibility through manual override capabilities.

Future research would focus on:

- Investigating the lower emission levels observed in the Effective Microorganism (EM) treatment at Plant 2.

- Assessing sensor degradation effects during continuous monitoring.
- Quantifying long-term energy and maintenance savings from process optimization.
- Developing predictive models for treatment efficiency based on real-time gas emission data.
- Exploring the integration of these findings with broader wastewater management systems to address multiple Sustainable Development Goals simultaneously.

ACKNOWLEDGMENT

The authors extend their sincere appreciation to Amrita Vishwa Vidyapeetham for facilitating the research.

CONFLICT OF INTEREST

The authors hereby declare the absence of any competing interests.

REFERENCES

[1] G. L. Karia, R. A. Christian, and N. D. Jariwala, *Wastewater Treatment: Concepts and Design Approach*, 3rd ed., New Delhi, India: PHI Learning Pvt. Ltd., 2023.

[2] World Health Org. (2017). *Potable Reuse: Guidance for Producing Safe Drinking-Water*. [Online]. Available: https://www.who.int/publications/i/item/9789241512770

[3] I. B. S. Poblete, O. D. Q. F. Araujo, and J. L. de Medeiros, "Sewage-water treatment and sewage-sludge management with power production as bioenergy with carbon capture system: A review," *Processes*, vol. 10, no. 4, p. 788, Apr. 2022, doi: 10.3390/pr10040788.

[4] G. N. Nabiyeva, "Geographic information systems (GIS) as a tool for sustainable community development," Univ. California, Davis, CA, USA, Tech. Rep., 2020. [Online]. Available: https://www.proquest.com/openview/d16b754f1d9fae897b6f8111da586e98/1?cbl=18750&diss=y&pq-origsite=gscholar

[5] R. Kaur, S. P. Wani, A. K. Singh, and K. Lal, "Wastewater production, treatment and use in India," presented at the 2nd Regional Workshop Safe Use Wastewater Agricult., New Delhi, India, May 2012. [Online]. Available: https://www.icid.org/wastewater_del_may12.pdf

[6] W. Zhu, Z. Wang, and Z. Zhang, "Renovation of automation system based on industrial Internet of Things: A case study of a sewage treatment plant," *Sensors*, vol. 20, no. 8, p. 2175, Apr. 2020, doi: 10.3390/s20082175.

[7] K. Rishitha and S. Ullas, "IoT based automation in domestic sewage treatment plant to optimize water quality and power consumption," in *Proc. 3rd Int. Conf. Comput. Methodologies Commun. (ICCMC)*, Erode, India, Mar. 2019, pp. 306–310, doi: 10.1109/ICCMC.2019.8819700.

[8] H. Haimi, M. Mulas, and R. Vahala, "Process automation in wastewater treatment plants: The Finnish experience," E-Water, Official Publication European Water Association (EWA), 2010. [Online]. Available: https://www.ewa-online.eu/tl_files/_media/content/documents_pdf/Publications/E-WAter/documents/13_2010_03.pdf

[9] S. Ullas, S. Upadhyay, V. Chandran, S. Pradeep, and T. M. Mohankumar, "Control console of sewage treatment plant with sensors as application of IoT," in *Proc. 11th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT)*, Kharagpur, India, Jul. 2020, pp. 1–7, doi: 10.1109/ICCCNT49239.2020.9225458.

[10] P. M. Kumar and C. S. Hong, "Internet of Things for secure surveillance for sewage wastewater treatment systems," *Environ. Res.*, vol. 203, Jan. 2022, Art. no. 111899, doi: 10.1016/j.envres.2021.111899.

[11] S. Rezwan, T. Ishtiak, R. Rahman, H. A. Rahman, M. Akter, H. A. Ratul, M. S. Hosain, and M. Jakariya, "A minimalist model of IoT based sensor system for sewage treatment plant monitoring," in *Proc. IEEE 10th Annu. Inf. Technol., Electron. Mobile Commun. Conf. (IEMCON)*, Vancouver, BC, Canada, Oct. 2019, pp. 0939–0945, doi: 10.1109/IEMCON.2019.8936182.

[12] R. M. M. Salem, M. S. Saraya, and A. M. T. Ali-Eldin, "An industrial cloud-based IoT system for real-time monitoring and controlling of wastewater," *IEEE Access*, vol. 10, pp. 6528–6540, 2022, doi: 10.1109/ACCESS.2022.3141977.

[13] R. Prabavathi, J. S. Duela, B. J. Chelliah, S. Saranya, and A. M. Sheela, "An intelligent stabilized smart sewage treatment plant (STP)," in *Proc. 4th Int. Conf. Comput. Commun. Technol. (ICCCT)*, Dec. 2021, pp. 381–385, doi: 10.1109/iccct53315.2021.9711758.

[14] K. H. Raj and S. Ullas, "Real time turbidity measurement in sludge processing unit by using IoT," in *Proc. 5th Int. Conf. Commun. Electron. Syst. (ICCES)*, Coimbatore, India, Jun. 2020, pp. 761–765, doi: 10.1109/ICCES48766.2020.9137876.

[15] A. L. Karn, S. Pandya, A. Mehbodniya, F. Arslan, D. K. Sharma, K. Phasinam, M. N. Aftab, R. Rajan, R. K. Bommisetti, and S. Sengan, "An integrated approach for sustainable development of wastewater treatment and management system using IoT in smart cities," *Soft Comput.*, vol. 27, no. 8, pp. 5159–5175, Apr. 2023, doi: 10.1007/s00500-021-06244-9.

[16] S. Masuda, S. Suzuki, I. Sano, Y.-Y. Li, and O. Nishimura, "The seasonal variation of emission of greenhouse gases from a full-scale sewage treatment plant," *Chemosphere*, vol. 140, pp. 167–173, Dec. 2015, doi: 10.1016/j.chemosphere.2014.09.042.

[17] M. Zheng, J. Lloyd, P. Wardrop, H. Duan, T. Liu, L. Ye, and B.-J. Ni, "Path to zero emission of nitrous oxide in sewage treatment: Is nitrification controllable or avoidable?" *Current Opinion Biotechnol.*, vol. 91, Feb. 2025, Art. no. 103230, doi: 10.1016/j.copbio.2024.103230.

[18] L. Huang, H. Li, and Y. Li, "Greenhouse gas accounting methodologies for wastewater treatment plants: A review," *J. Cleaner Prod.*, vol. 448, Apr. 2024, Art. no. 141424, doi: 10.1016/j.jclepro.2024.141424.

[19] X. Zheng and K. L. Lam, "An overview of environmental co-benefits and trade-offs to reduce greenhouse gas emissions in municipal wastewater management," *Sustain. Prod. Consumption*, vol. 46, pp. 1–10, May 2024, doi: 10.1016/j.spc.2024.02.002.

[20] S. Ullas and B. U. Maheswari, "IoT-based solution for monitoring gas emission in sewage treatment plant to prevent human health hazards," in *Proc. Int. Conf. IoT Based Control Netw. Intell. Syst. (ICICNIS)*, Nov. 2023, pp. 357–368, doi: 10.1007/978-981-99-6586-1_24.

[21] S. Kumar and D. Singh, "Smart cities waste minimization, remanufacturing, reuse, and recycling solutions using IoT and ML," in *Proc. IEEE Int. Conf. Comput., Power Commun. Technol. (IC2PCT)*, Feb. 2024, pp. 1546–1552, doi: 10.1109/IC2PCT60090.2024.10486708.

[22] K. H. Waseem, H. Mushtaq, F. Abid, A. M. Abu-Mahfouz, A. Shaikh, M. Turan, and J. Rasheed, "Forecasting of air quality using an optimized recurrent neural network," *Processes*, vol. 10, no. 10, p. 2117, Oct. 2022, doi: 10.3390/pr10102117.

[23] S. Mirzavand Borujeni, L. Arras, V. Srinivasan, and W. Samek, "Explainable sequence-to-sequence GRU neural network for pollution forecasting," *Sci. Rep.*, vol. 13, no. 1, Jun. 2023, Art. no. 9940, doi: 10.1038/s41598-023-35963-2.

[24] L. Zhang, J. Liu, Y. Feng, P. Wu, and P. He, "PM2.5 concentration prediction using weighted CEEMDAN and improved LSTM neural network," *Environ. Sci. Pollut. Res.*, vol. 30, no. 30, pp. 75104–75115, May 2023, doi: 10.1007/s11356-023-27630-w.

[25] S. Chen and L. Zheng, "Complementary ensemble empirical mode decomposition and independent recurrent neural network model for predicting air quality index," *Appl. Soft Comput.*, vol. 131, Dec. 2022, Art. no. 109757, doi: 10.1016/j.asoc.2022.109757.

[26] M. Ahmed, Y. Shen, M. Ahmed, Z. Xiao, P. Cheng, N. Ali, A. Ghaffar, and S. Ali, "AQE-net: A deep learning model for estimating air quality of Karachi city from mobile images," *Remote Sens.*, vol. 14, no. 22, p. 5732, Nov. 2022, doi: 10.3390/rs14225732.

[27] R. Saravana Ram, K. Venkatachalam, M. Masud, and M. Abouhawwash, "Air pollution prediction using dual graph convolution LSTM technique," *Intell. Autom. Soft Comput.*, vol. 33, no. 3, pp. 1639–1652, Jan. 2022, doi: 10.32604/iasc.2022.023962.

[28] Z. Xu, Y. Kang, Y. Cao, and Z. Li, "Spatiotemporal graph convolution multifusion network for urban vehicle emission prediction," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 8, pp. 3342–3354, Aug. 2021, doi: 10.1109/TNNLS.2020.3008702.

[29] H. You, S. Bai, R. Wang, Z. Li, S. Xiang, and F. Huang, "New PSO-SVM short-term wind power forecasting algorithm based on the CEEMDAN model," *J. Electr. Comput. Eng.*, vol. 2022, pp. 1–9, Sep. 2022, doi: 10.1155/2022/7161445.

[30] C.-L. Wu, H.-D. He, R.-F. Song, X.-H. Zhu, Z.-R. Peng, Q.-Y. Fu, and J. Pan, "A hybrid deep learning model for regional O_3 and NO_2 concentrations prediction based on spatiotemporal dependencies in air quality monitoring network," *Environ. Pollut.*, vol. 320, Mar. 2023, Art. no. 121075, doi: 10.1016/j.envpol.2023.121075.

[31] M. A. Bhatti, Z. Song, U. A. Bhatti, and S. M. Syam, "AIoT-driven multi-source sensor emission monitoring and forecasting using multi-source sensor integration with reduced noise series decomposition," *J. Cloud Comput.*, vol. 13, no. 1, Mar. 2024, Art. no. 65, doi: 10.1186/s13677-024-00598-9.

[32] M. Noussan, P. P. Raimondi, R. Scita, and M. Hafner, "The role of green and blue hydrogen in the energy transition—A technological and geopolitical perspective," *Sustainability*, vol. 13, no. 1, p. 298, Dec. 2020, doi: 10.3390/su13010298.

[33] M. V. Ruano, J. Ribes, A. Ruiz-Martinez, A. Seco, and A. Robles, "An advanced control system for nitrogen removal and energy consumption optimization in full-scale wastewater treatment plants," *J. Water Process Eng.*, vol. 57, Jan. 2024, Art. no. 104705, doi: 10.1016/j.jwpe.2023.104705.

[34] B. Adibimanesh, S. Polesek-Karczewska, F. Bagherzadeh, P. Szczuko, and T. Shafighfard, "Energy consumption optimization in wastewater treatment plants: Machine learning for monitoring incineration of sewage sludge," *Sustain. Energy Technol. Assessments*, vol. 56, Mar. 2023, Art. no. 103040, doi: 10.1016/j.seta.2023.103040.

[35] A.-J. Wang, H. Li, Z. He, Y. Tao, H. Wang, M. Yang, D. Savic, G. T. Daigger, and N. Ren, "Digital twins for wastewater treatment: A technical review," *Engineering*, vol. 36, pp. 21–35, May 2024, doi: 10.1016/j.eng.2024.04.012.

[36] M. U. Saleem, M. R. Usman, M. A. Yaqub, A. Liotta, and A. Asim, "Smarter grid in the 5G era: Integrating the Internet of Things with a cyber-physical system," *IEEE Access*, vol. 12, pp. 34002–34018, 2024, doi: 10.1109/ACCESS.2024.3372379.

[37] Z. Liwen, F. Qamar, M. Liaqat, M. N. Hindia, and K. A. Z. Ariffin, "Toward efficient 6G IoT networks: A perspective on resource optimization strategies, challenges, and future directions," *IEEE Access*, vol. 12, pp. 76606–76633, 2024, doi: 10.1109/ACCESS.2024.3405487.

[38] Y. Lei, B. Hu, H. Huang, and Y. Liu, "Design of a variable-length sequential prediction framework GTV-STP based on spatial and temporal water quality information of Taihu lake," *IEEE Access*, vol. 12, pp. 65928–65941, 2024, doi: 10.1109/ACCESS.2024.3398130.

[39] M. A. P. Cechinel, J. Neves, J. V. R. Fuck, R. C. de Andrade, N. Spogis, H. G. Riella, N. Padoin, and C. Soares, "Enhancing wastewater treatment efficiency through machine learning-driven effluent quality prediction: A plant-level analysis," *J. Water Process Eng.*, vol. 58, Feb. 2024, Art. no. 104758, doi: 10.1016/j.jwpe.2023.104758.

[40] C. S. Srungavarapu, A. G. Sheik, E. S. S. Tejaswini, S. M. Yousuf, and S. R. Ambati, "An integrated machine learning framework for effluent quality prediction in sewage treatment units," *Urban Water J.*, vol. 20, no. 4, pp. 487–497, Apr. 2023, doi: 10.1080/1573062x.2023.2183137.

[41] M. B. Khan, H. Nisar, and C. A. Ng, "Image processing and analysis of phase-contrast microscopic images of activated sludge to monitor the wastewater treatment plants," *IEEE Access*, vol. 6, pp. 1778–1791, 2018, doi: 10.1109/ACCESS.2017.2780249.

[42] H. A. Alharbi and M. Aldossary, "Energy-efficient edge-fog-cloud architecture for IoT-based smart agriculture environment," *IEEE Access*, vol. 9, pp. 110480–110492, 2021, doi: 10.1109/ACCESS.2021.3101397.

[43] L. Zhao, T. Li, E. Zhang, Y. Lin, S. Wan, A. Hawbani, and M. Guizani, "Adaptive swarm intelligent offloading based on digital twin-assisted prediction in VEC," *IEEE Trans. Mobile Comput.*, vol. 23, no. 8, pp. 8158–8174, Aug. 2024, doi: 10.1109/TMC.2023.3344645.

[44] S. Shao, T. Gu, Y. Nie, Z. Ji, F. Wu, Z. Ba, Y. Ji, K. Ren, and G. Sun, "An active defense adjudication method based on adaptive anomaly sensing for mimic IoT," *IEEE Trans. Services Comput.*, vol. 18, no. 1, pp. 57–71, Jan. 2025, doi: 10.1109/TSC.2024.3436673.

[45] P. Sun, S. Shen, Y. Wan, Z. Wu, Z. Fang, and X.-Z. Gao, "A survey of IoT privacy security: Architecture, technology, challenges, and trends," *IEEE Internet Things J.*, vol. 11, no. 21, pp. 34567–34591, Nov. 2024, doi: 10.1109/JIOT.2024.3372518.

[46] A. Morchid, Z. Oughannou, R. E. Alami, H. Qjidaa, M. O. Jamil, and H. M. Khalid, "Integrated Internet of Things (IoT) solutions for early fire detection in smart agriculture," *Results Eng.*, vol. 24, Dec. 2024, Art. no. 103392, doi: 10.1016/j.rineng.2024.103392.

[47] A. Morchid, R. Jebabra, A. Ismail, H. M. Khalid, R. El Alami, H. Qjidaa, and M. Ouazzani Jamil, "IoT-enabled fire detection for sustainable agriculture: A real-time system using flask and embedded technologies," *Results Eng.*, vol. 23, Sep. 2024, Art. no. 102705.

[48] A. Morchid, R. Jebabra, H. M. Khalid, R. El Alami, H. Qjidaa, and M. O. Jamil, "IoT-based smart irrigation management system to enhance agricultural water security using embedded systems, telemetry data, and cloud computing," *Results Eng.*, vol. 23, Sep. 2024, Art. no. 102829, doi: 10.1016/j.rineng.2024.102829.

S. ULLAS received the M.Tech. degree in computer science and engineering from SRM University, Chennai. He is a Senior Assistant Professor at the Amrita School of Computing, Amrita Vishwa Vidyapeetham, Bengaluru, India. With over 20 years of experience, his eight years of research focus on the Internet of Things (IoT)-based wastewater treatment automation, wireless networking, network security, and AI applications.

B. UMA MAHESWARI (Senior Member, IEEE) received the B.E. degree in computer science and engineering from Bharathidasan University, in 1993, the M.E. degree in computer science and engineering from Anna University, Chennai, India, in 2004, and the Ph.D. degree in computer science and engineering from Amrita Vishwa Vidyapeetham, India, in 2020. She is an Assistant Professor at the Department of Computer Science and Engineering, Amrita School of Computing, Bengaluru, India. Her current research interests include digital twin; machine/deep learning; the Internet of Things (IoT) applications in healthcare, agriculture, and network security; overlay networks; P2P video streaming; and application layer multicasting in wired and wireless networks.

SESHAIAH PONNEKANTI received the degree in electronics and communications from Sri Venkateswara University (SVU), India, in 1985, the M.E. degree in electronics engineering from Anna University, India, in 1989, and the Ph.D. degree in electronics engineering from the University of Newcastle, U.K., in 1994. He is currently an Adjunct Faculty Member at the Amrita Center for Wireless Networks and Applications (WNA), Amrita Vishwa Vidyapeetham, India, where he leads toward the 6G tag and works on network transformation projects covering the SDN, NFV, and security. He is a Technology Ambassador covering cyber, AI, and Telco at 5G Analytics, U.K.

T. M. MOHAN KUMAR received the M.Sc. and Ph.D. degrees in chemistry from the University of Mysore, in 2001 and 2007, respectively. Having a blend of applied research, industrial, and teaching experience, he currently serves as an Assistant Professor at the Amrita School of Engineering, Amrita University, Bengaluru, India. His research contributions include a funded project on graphene-based magnetic hydrogels for water purification. His current research interests include the development of composites for water treatment and crystallography.