Journal of Engineering Technology and Applied Physics

IoT-Based Industrial Wastewater Monitoring System using ESP32 and Blynk

Jun Jie Choong and Kim Seng Chia*
Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Johor, Malaysia.
**Corresponding author*: kschia@uthm.edu.my, *ORCiD*: 0000-0003-0854-8954
https://doi.org/10.33093/jetap.2026.8.1.15
Manuscript Received: 9 July 2025, Revised: 6 October 2025, Accepted: 26 November 2025, Published: 15 March 2026

***Abstract*—Effective industrial wastewater management is essential to mitigate the environmental and public health risks posed by harmful contaminants e.g. high TDS, turbidity, abnormal pH, and temperature. A monitoring system is crucial in each related company to ensure its wastewater will be properly treated to meet regulatory standards as that can severely impact ecosystems, aquatic life, and water resources. However, traditional industrial wastewater monitoring methods like manual sampling and laboratory analysis fail to provide real-time data and are time consuming and labour intensive. Thus, this study evaluates an Internet of Things (IoT)-based monitoring system for industrial wastewater, focusing on the measurement of four parameters, including total dissolved solids (TDS), pH, temperature, and turbidity. The system consisted of a Durian ESP32 microcontroller, a TDS sensor (SEN0244), a pH sensor (SEN0161), a turbidity sensor (SEN0189), and temperature sensor (DS18B20). Real-time monitoring, data analysis, and visualization were facilitated via the Blynk cloud platform. The accuracy and reliability of the developed system were evaluated through functionality testing, performance testing, and system testing in actual environment using textile dyeing industrial water samples. Results show that the proposed monitoring system was able to achieve measurement accuracies of 87.76% for TDS, 93.28% for pH, and 95.35% for temperature. This shows that the system is feasible in continuously monitoring the TDS, pH, and temperature of water quality in industry.**

***Keywords*—IoT, Real-time monitoring, Industrial wastewater.**

I. INTRODUCTION

A. Problem Statement

The management of industrial wastewater is critical to mitigating environmental and health risks caused by harmful contaminants. Traditional methods of monitoring water quality rely on manual sampling and laboratory analysis, which are time-consuming, labour-intensive, and lack real-time insights. Industrial wastewater management is a crucial aspect of industrial operations [1]. Industries often discharge large quantities of wastewater containing harmful substances. Total dissolved solids (TDS), turbidity, pH and temperature are some of the parameters in reflecting the water quality. It will bring a significant risk to the ecosystem, public health, aquatic life and water resources if these parameters do not meet regulatory standards [2]. A successful wastewater management system can discharge water in a way that minimizes environmental impact.

With enabling the IoT system into the monitoring system with simply solve all the problem above. An IoT based wastewater monitoring system can continuously monitor through a network of connected sensor and devices [3]. It can collect data, transmit data and analyse data in real-time. The system will measure the key parameters mentioned in the wastewater to indicate the water quality. Consequently, a IoT system will provide a comprehensive approach for real-time data analysis, ultimately contributing to safer industrial waste management practices and environmental sustainability [4].

The introduction of strict environmental regulations, such as those outlined by the Environmental Quality Act in Malaysia, requires industries to continuously monitor and manage the quality of their wastewater before discharge [5]. Traditional methods of water quality assessment often involve manual sampling and laboratory analysis. This is time-consuming and low efficiency, it leads to poor wastewater management due to the time-consuming nature of manual sampling and laboratory analysis, the availability of critical information required for immediate action is delayed [6]. Without real-time monitoring, it becomes difficult to detect and respond promptly to changes in water quality, resulting in

Published by MMU PRESS. URL: https://journals.mmupress.com/index.php/jetap/index

inefficient control and potential environmental harm [7]. Thus, it urgently needs a solution that enables continuous and real-time water quality monitoring.

This study aims to design and develop an Internet of Things (IoT)-based real time monitoring system for industrial wastewater, focusing on the real-time measurement of key water quality parameters i.e. total dissolved solids (TDS), pH, temperature, and turbidity.

B. Water Quality Monitoring System (WQMS)

Water Quality Monitoring System (WQMS) is a tool for ensuring the safety and sustainability of water resources. These systems able to detect and monitor several water parameters such as temperature, pH value, turbidity, dissolved oxygen, and concentrations of contaminants for example heavy metals and nitrates [2]. With the growing of the industrial activities the amount of the industrial waste needed to discharge also increased. Therefore, an effective water quality monitoring system has become a global priority. Traditional methods of monitoring not able to provide real-time data [6]. Hence, automated and real-time monitoring system has become priority choice for water quality management. It able to provide continuous, accurate, and accessible data for the users.

Internet of Things (IoT) technologies had become the key component in developing water monitoring system. The IoT based system typically consist of sensors that can detect various water quality parameters, transmitted data using cellular or Wi-Fi and a cloud-based platform to store data and data analysis [8]. These systems also offer remote monitoring, low maintenance cost, and automated actions warning users while contamination happened helping user able to respond promptly to avoid the potential environmental and health hazards. In addition, this system also can be developed in various area such as rivers, lakes and water treatment plants to continuously monitor the water quality across large area.

Another critical component in modern water quality monitoring systems is data analysis. With the vast amount of data collected using the IoT based sensors and the advanced analytics techniques including machine learning and artificial intelligence, this system was able to predict potential hazards and offer decision support to increase the effectiveness of water management practices. For example, AI driven algorithms able to predict water quality trend based on historical data to improve accuracy and effectiveness of water quality monitoring system [9].

The water quality monitoring system also often applied in smart cities for better water quality management, thereby improve public health [10]. However, a lot of challenges still exist in the actual situation such as sensor durability and data accuracy to maximize the effectiveness of the water quality monitoring system. In conclusion, the advancement of water quality monitoring systems has greatly contributed to improved water quality management. Nevertheless, like any technology, it presents both advantages and limitations. Thus, addressing issues such as sensor lifespan, data accuracy, and cost-effectiveness is crucial for future enhancements of water quality monitoring systems.

C. Parameters of Industrial Wastewater Quality Monitoring

Monitoring water quality is essential for maintaining ecosystems and ensuring safe industrial activities. Parameters such as Total Dissolved Solids (TDS), pH, temperature, and suspended solids are critical indicators of water quality. TDS represents the combined concentration of organic and inorganic substances dissolved in water [11]. Research by Weber-Scannell and Duffy shows that increased TDS causes salinity-related toxicity, limiting biodiversity and affecting different life stages [12]. Hallock and Hallock also reported that elevated TDS nearly eliminated coontail and cattails [13]. The pH of water influences the solubility and bioavailability of nutrients and toxins. A pH below 7 indicates acidity, while above 7 indicates alkalinity. Low pH releases toxic metals from sediments, harming aquatic life, while high pH reduces dissolved oxygen availability [14]. Temperature affects chemical reactions and biological processes. Poor effluent management causes thermal pollution, which disrupts ecosystems and threatens cold-water species with limited mobility [15]. Turbidity, caused by suspended solids, reduces water clarity and carries pollutants such as heavy metals and organic compounds [16]. High suspended solids levels can cause aesthetic issues, increase water treatment costs, harm fisheries, and lead to ecological degradation [17]. Table I shows the summary of key water quality parameters including their definitions and environmental impacts.

D. Internet of Things (IoT) System and Related Works

Table I. Summary of key water quality parameters.

Parameter	Definition	Impacts on Water Quality & Ecosystems
Total Dissolved Solids (TDS)	Concentration of dissolved organic and inorganic substances in water.	High TDS increases salinity, causes toxicity, reduces biodiversity, and harms aquatic plants like coontail and cattails.
pH	Measures acidity or alkalinity.	Affects metal solubility and nutrient availability; extreme pH harms aquatic life by altering physiology, behaviour, survival.
Temperature	Regulates chemical and biological processes in water.	Thermal pollution affects ecosystems; elevated temperature stresses or endangers cold-water species with limited adaptability.
Suspended Solids (SS)	Undissolved particles affecting water clarity and quality.	High SS increases treatment costs, harms aquatic life, transports pollutants, and causes long-term sediment risks.

The Internet of Things (IoT) is a system that connects physical objects to the internet, enabling them to send, receive and process data in real-time [18]. The goal is to improve efficiency, comfort and productivity in various fields, such as smart homes, industrial, healthcare and agriculture. The architecture of IoT included few major components that work together to create intelligent system. The fundamental component is the thing or devices, which are physical devices that collects data from the environment using sensors such as temperature sensor, humidity sensor, pH sensor, turbidity sensor and light sensor. This device is the core of the IoT as it is the source of data [19].

The second major component of IoT is the gateway. The gateway server as a bridge that connects the devices and the cloud or a server. It is responsible for transmitted data from IoT devices to the cloud or central server for further analysis [19]. Gateway also manage the connection between devices using different communication protocols such as Wi-Fi, Zigbee, or Bluetooth, ensuring seamless interaction within the IoT ecosystem [20]. Other of that, gateway also ensure that the data being transferred is secure and protected from outside threats.

The next major component in the IoT system is cloud. After the data being transferred from the IoT devices to the gateway, it can be sent to the cloud, a server on the internet. It serves to store and manage the data collected by IoT devices. Then the data can be analysed, processed, and stored for long term [21]. The following components is analytics. Analytics refers to the process of collecting, analysing, and interpreting data coming from IoT devices, sensors, or other systems to gain useful insights [22]. Advanced analytics, including machine learning, artificial intelligence, and big data tools, process and analyse the data to extract valuable insights. These insights can help detect patterns, make predictions and automated actions, such as triggering alarms.

Finally, the user interface is crucial for enabling users to interact with the IoT system. This user interface can be an app on a smartphone, laptop, or other device that allows us to view the data collected such as the temperature of the house and giving commands for example turning on the lights. In short, five major components in the IoT system are devices, gateway, cloud, analytic and user interface, it enables real-time data collecting, processing and decision-making. However, the successful implementation of IoT also depends on overcoming challenges related to security, interoperability, scalability, and energy efficiency, which continue to be a focus of ongoing research and development in the field [23].

Recently, APAH - an autonomous IoT driven real-time monitoring and control system was proposed and validated using industrial wastewater in India. [4]. It addresses the shortcomings of conventional manual testing methods by integrating multiple sensors to continuously track key water quality parameters like pH, dissolved oxygen, turbidity, TDS, conductivity, and temperature. Using components like the ESP8266 microcontroller, cloud platforms (ThingSpeak, Firebase), and a custom-built Android app, the system collects, analyses, and displays data in real time. Machine learning models enhance its predictive capabilities, while automated valve controls help prevent contamination. The APAH system was field-tested in four different wastewater treatment plants, demonstrating its ability to improve treatment efficiency, ensure compliance with environmental standards, and provide a scalable, low-cost solution for industrial water management.

Another related work is IoT based Smart Water Quality Monitoring System [24] that was studied for drinking water quality monitoring application. The study presents an IoT-based Smart Water Quality Monitoring (SWQM) system that continuously measures water quality using four physical parameters: temperature, pH, electric conductivity, and turbidity. Four sensors are connected to an Arduino Uno to detect these parameters, with data transmitted to a desktop application developed on the NET platform. The system compares the measured data with WHO (World Health Organization) standard values. Based on the results, the SWQM system uses a fast forest binary classifier to determine whether the water sample is drinkable.

Next, Nurshahida *et. al.* proposed an IoT-based water quality monitoring system (WQMS) for Asian sea bass farming in aquaculture tanks [25]. Traditional monitoring water quality method often lacks real-time data, leading to improper feeding practices, reduced productivity, and potential environmental risks. To overcome these challenges, the study enhanced the accuracy of low-cost sensors using simple linear regression and validated the system by comparing its data with the YSI Professional Pro device over a three-month period. The system's real-time monitoring capabilities were achieved through the integration of a microcontroller, Thingspeak, Virtuino application, and ESP 8266 Wi-Fi module. This IoT-based system offers aquafarmers reliable insights into water quality conditions, potentially improving productivity, sustainability, and water quality management in aquaculture practices.

II. RESEARCH METHODOLOGY

A. *Concept and Project Idea*

Figure 1 shows the block diagram of the proposed IoT industrial wastewater monitoring system to measure four key wastewater parameters of temperature, pH, total dissolved solids (TDS), and turbidity. The system was powered with a power bank with USB-C cable and configured to collect data every 5 seconds. After the prototype was built, several tests would be conducted to evaluate the system's accuracy and reliability. These tests include functionality testing, system performance testing, and system testing in a real environment. Data were recorded and tabulated to calculate the accuracy of the system.

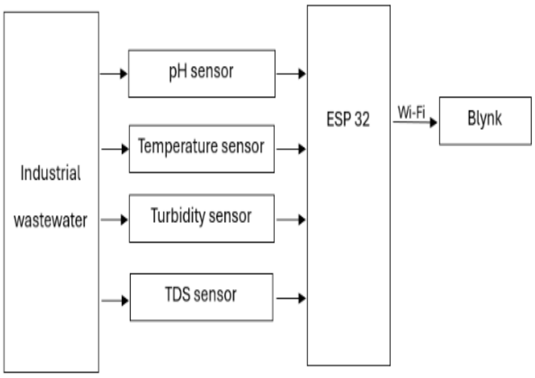

Fig.1. Block diagram of the system.

B. 3D Model and Prototype of the System

Figure 2 illustrates the design of the proposed measurement tank that would fix the positions of each sensor of the system. The sensor tank of the system was separated into two parts due to the electrical interfaces between the pH sensor and the TDS sensor. This is crucial to ensure accurate reading would be recorded.

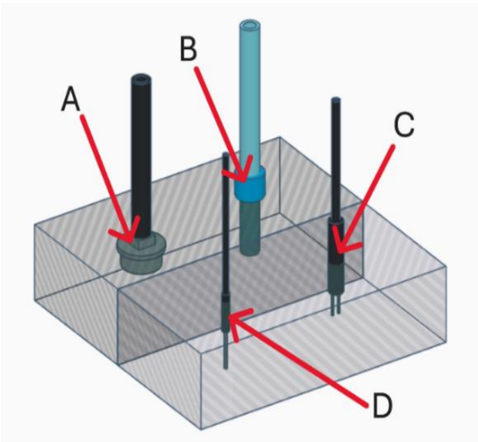

Fig. 2. The 3D model of the proposed measurement tank, with labelled components: A – turbidity sensor, B – pH sensor, C – TDS sensor, and D – temperature sensor.

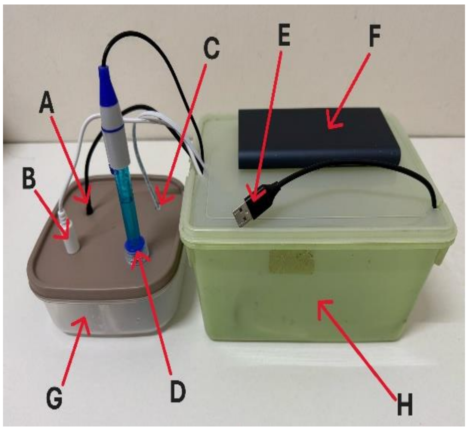

Fig. 3. Prototype of the system, with labelled components: A – temperature sensor, B – TDS sensor, C – turbidity sensor, D – pH sensor, E – USB cable, F – power bank, G – sensor tank, and H – embedded system enclosure.

Figure 3 presents the prototype of the system, highlighting key components including the temperature sensor (A), TDS sensor (B), turbidity sensor (C), pH sensor (D), USB cable (E), power bank (F), sensor tank (G), and the embedded system enclosure (H). The sensors are strategically positioned within the tank to ensure accurate and consistent water quality measurements. The embedded system enclosure houses the microcontroller and communication modules, enabling real-time data acquisition and transmission.

C. System Overview

The hardware of the IoT monitoring system was built using an ESP32 microcontroller and several sensors, including a temperature sensor (DS18B20), turbidity sensor (SEN0189), total dissolved solids (TDS) sensor (SEN0244), and pH sensor (SEN0161). On the software side, the system was developed using the Arduino IDE, and the collected data is sent to the Blynk cloud for display on mobile devices.

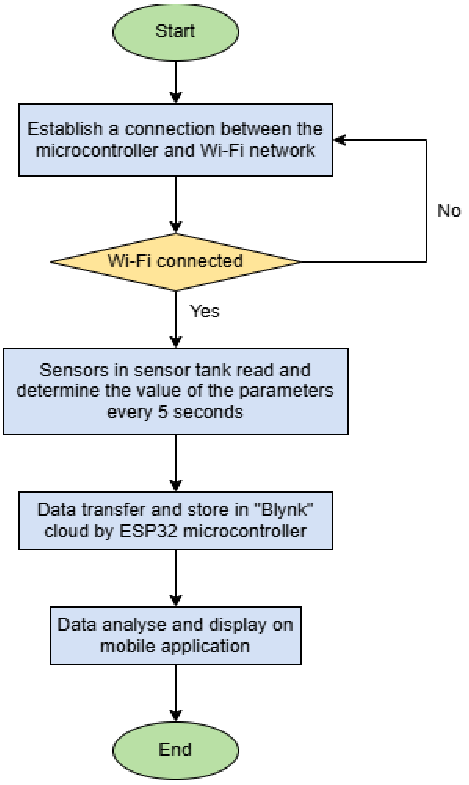

Fig. 4. Flowchart of the system.

Figure 4 shows the flowchart of the overall system. When the system is powered on, the microcontroller ESP32 establish a connection to Wi-Fi. This process was repeated until the Wi-Fi was successfully connected. Then, the sensor in the sensor tank was started to detect the parameters of the sample in the tank every 5 seconds. The data then transferred to the "Blynk" cloud platform to store and display. Users can remote monitoring all the parameters and the graph of those parameters. Figure 5 illustrates the user interface of the system that consists of the gauges and charts of the four key parameters. The gauges on the user interface displayed temperature in °C, TDS in ppm, turbidity in %, and pH value, all reading shown with two decimal points. In addition, the chart in the user interface can display the recorded values of each parameter over selectable time intervals: 15 minutes, 30 minutes, 1 hour, 6 hours, 1 day, and 3 days. Users can adjust the duration according to their needs. Besides that, the chart can also display live data for real-time monitoring.

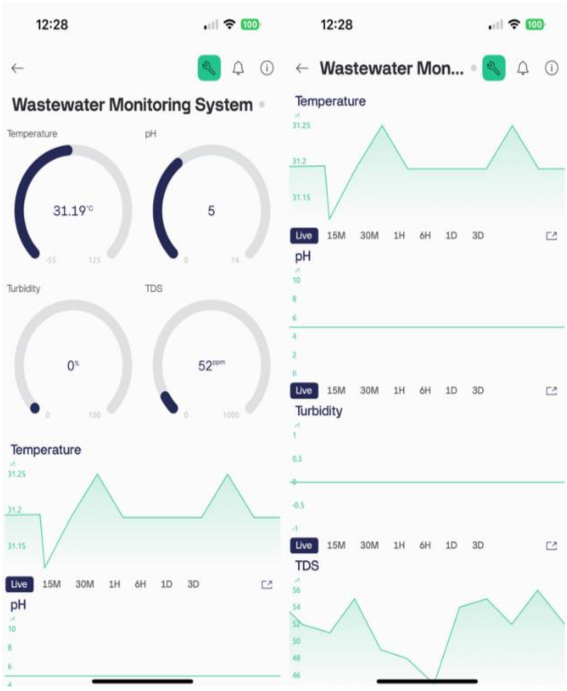

Fig. 5. User interface of the system.

D. System Evaluations

The system had been tested in three ways: functionality testing, system performance testing, and testing in a real environment. Firstly, in the functionality testing, the system had been tested with several samples to ensure it is functioning properly and capable of capturing different types of data. Secondly, in the system performance testing, the samples were regularly diluted into 5 different concentrations. Then, the system had been tested and compared with readings from other instruments available on the market such as pH meter and TDS meter with thermometer. The test data had been recorded and tabulated to calculate the system's accuracy. Lastly, in the real environment testing, the system was tested with several samples provided by the industry. The instrument used by the industry to detect the pH value is the APERA PH850 pH meter, TDS was measured using the Horiba LAQUAtwin TDS meter and temperature was measured using a thermometer. The industrial turbidity data were not provided, thus excluding this parameter from the comparison. The test data were recorded and tabulated, then compared with the actual data provided by the industry to evaluate the system's accuracy and reliability. This comparison helped assess how well the system performs relative to existing industrial methods, offering valuable insights into its effectiveness in monitoring and analysing wastewater quality.

III. RESULTS AND DISCUSSION

A. System Functionality Test

The system tested with 4 types of samples including lemon juice, liquid soap, cold cola soft drink and tap water. The data collected 5 times with the sensor to calculate the average data. Table II tabulates the average measurement collected from different samples. For soap, the TDS was 714.43 ppm, the temperature was 28.52°C, the pH measured 7.89, and turbidity reached 100%. Lemon had a TDS of 355.53 ppm, a temperature of 28.31°C, a highly acidic pH of 2.56, and 100% turbidity. Cola (cold) recorded a TDS of 163.17 ppm, a much lower temperature of 12.67°C, a pH of 5.47, and 79% turbidity. Tap water showed TDS at 50.89 ppm, a temperature of 27.89°C, pH of 6.96, and a turbidity of 100%. These values reflect the system successfully collect different value form different samples.

Table II. Average measurement collected from different samples.

Parameter	**Average measurement collected across different samples**			
	Soap	***Lemon***	***Cola (cold)***	***Tap Water***
TDS (ppm)	714.43	355.53	163.17	50.89
Temperature (°C)	28.52	28.31	12.67	27.89
pH	7.89	2.56	5.47	6.96
Turbidity (%)	100	100	79	100

TDS = Total Dissolved Solids

B. System Performance Test

The system tested with 3 types of samples including lemon, soap, cola soft drink. Each sample is regularly diluted into 5 concentrations: very high, high, medium, low, and very low. The data collected 3 times with the sensor to calculate the average data and compare with the instrument that available in the market.

Table III. Overall averaged accuracy of the measurement using different samples.

Parameter	**Averaged accuracy (%) across different concentrations**			**Overall averaged accuracy (%)**
	Soap	***Lemon***	***Cola***	
TDS (ppm)	96.98	97.33	98.90	97.74
Temperature (°C)	99.78	99.78	99.17	99.58
pH	99.11	98.59	98.62	98.77

TDS = Total Dissolved Solids

Table III summarizes the average accuracy of each sample of the system in detecting each parameter. Temperature accuracy is the highest among the three parameters, with values of 99.78%, 99.78%, and 99.17% for Soap, Lemon, and Cola, respectively, resulting in an average of 99.58%. This is followed by pH measurements, with values of 99.11%, 98.59%, and 98.62%, yielding an average of 98.77%. TDS showed the lowest measurement accuracy among the three, with values of 96.98%, 97.33%, and 98.90%, and an average accuracy of 97.74%.

C. System Test in Real Environment

The system was tested with five types of samples provided by the industry, including two types of raw water from river (Risda) and mountain (Simpang Kanan), filtered raw water, influent wastewater, and treated wastewater. Data was collected five times using the system, and the average values were calculated. These were then compared with the measurement was done using industrial instruments twice to obtain an average. The instrument used by the industry to detect the pH value was the APERA PH850 pH meter, and the TDS was the Horiba LAQUAtwin TDS meter. The standard deviation of the data collected by the system and data provided by the industry were calculated to determine the stability of the measurement. The smallest the standard deviation the stable the measurement. Although, the industry was using much expensive and trustable instruments to collect data, it also reached a standard deviation of 5.66 while measuring the TDS of the treated wastewater.

Table IV shows that the average measurement collected by the proposed system from five different samples. The raw water from Risda measured 38.64 ppm TDS, pH 6.98, and 24.00°C, while Simpang Kanan's raw water showed higher TDS 78.02 ppm, lower pH 6.68, and similar temperature 23.86°C. Filtered raw water had reduced TDS to 68.11 ppm, pH 6.78, and 24.19°C. Influent wastewater recorded 109.80 ppm TDS, pH 6.81, and 26.44°C. After treatment, TDS increased to 180.40 ppm, pH rose to 7.23, and temperature 26.24°C. These variations reflect the influence of source and treatment processes on water quality parameters, highlighting the system's capability to detect subtle changes across different water conditions.

Table IV. Average measurement collected by the system across different samples ± standard deviation.

Sample	Average measurement collected by system across different samples ± standard deviation		
	TDS (ppm)	***pH***	***Temperature (°C)***
Raw water (Risda)	38.64 ± 4.26	6.98 ± 0.03	24.00 ± 0.04
Raw water (Simpang Kanan)	78.02 ± 5.89	6.68 ± 0.06	23.86 ± 0.06
Filtered raw water	68.11 ± 1.02	6.78 ± 0.03	24.19 ± 0
Influent wastewater	109.80 ± 6.37	6.81 ± 0.05	26.44 ± 0
Treated wastewater	180.40 ± 5.64	7.23 ± 0.02	26.24 ± 0.03

TDS = Total Dissolved Solids

Table V shows the measurement that using analytic instruments that used in the company. Raw water from Risda measured 46.60 ppm TDS, pH 6.11, and 24.40°C. Simpang Kanan's raw water showed higher values at 91.05 ppm TDS, pH 6.13, and 25.45°C. Filtered raw water results were 76.50 ppm TDS, pH 6.88, and 26.00. Influent wastewater measurements recorded 119.00 ppm TDS, pH 6.31, and 27.20°C. The treated wastewater showed the highest values at 203.00 ppm TDS, pH 7.17, and 27.80°C. These reference values serve as a benchmark for evaluating the accuracy and reliability of the proposed IoT-based monitoring system.

Table V. Average measurement provided by industry across different samples ± standard deviation.

Sample	Average measurement provided by industry across different samples ± standard deviation		
	TDS (ppm)	***pH***	***Temperature (°C)***
Raw water (Risda)	46.60 ± 1.13	6.11 ± 0.12	24.40 ± 0.14
Raw water (Simpang Kanan)	91.05 ± 2.19	6.13 ± 0.11	25.45 ± 0.21
Filtered raw water	76.50 ± 0.71	6.88 ± 0.18	26.00 ± 0
Influent wastewater	119.00 ± 4.24	6.31 ± 0.02	27.20 ± 0.14
Treated wastewater	203.00 ± 5.66	7.17 ± 0.03	27.80 ± 0

TDS = Total Dissolved Solids

Figure 6 presents a comparison of the TDS measurement of IoT system and industrial instrument across five samples categories: influent wastewater, treated wastewater, raw water (Risda), raw water (Simpang Kanan), and filtered raw water. The data were visualized using boxplots. For example, in the influent wastewater the IoT system recorded TDS value ranging from 105.71 ppm to 121.06 ppm with an average of 109.8 ppm while the industrial instrument recorded TDS value ranging from 116 ppm to 122 ppm with an average of 119 ppm. In general, the TDS value ranging for all five samples recorded with the IoT system and the industrial instrument fell within the range of 0–25 ppm.

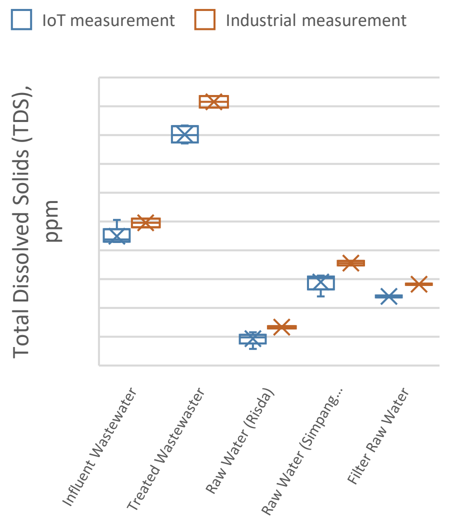

Fig. 6. The TDS measurement of IoT system and industrial instrument across 5 samples from industry.

Figure 7 shows the boxplot comparing the pH measurement recorded by both IoT system and industrial instrument. For influent wastewater, the IoT system recorded pH values ranging between 6.75 and 6.87, slightly higher than the industrial readings, which ranged from 6.29 to 6.32. In the treated wastewater, both methods reported highly consistent results. The IoT system measured pH values between 7.21 and 7.26, while the industrial instrument recorded values of 7.15 and 7.19. In the case of filtered raw water, the IoT system recorded values between 6.75 and 6.83, while the industrial instrument measured 6.75 and 7.00.

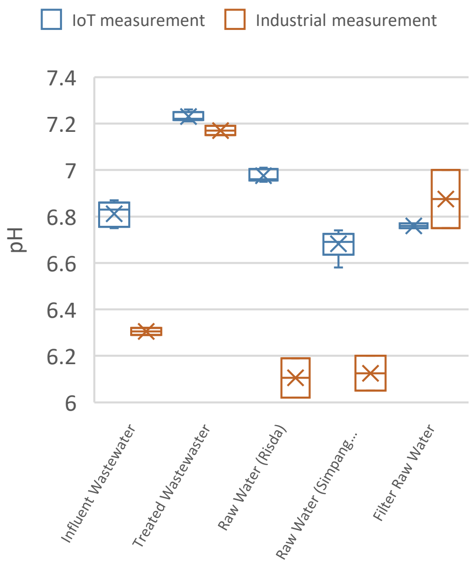

Fig. 7. The pH measurement of IoT system and industrial instrument across 5 samples from industry.

Figure 8 illustrates the comparison of temperature measurements obtained from the developed IoT system and the industrial instrument. According to Fig. 8, the temperature measurements obtained from both the IoT system, and the industrial instrument were generally consistent across all water samples. The largest variation was observed in the industrial measurements for raw water (Simpang Kanan), ranging from 25.3 °C to 25.6 °C with a difference of 0.3 °C.

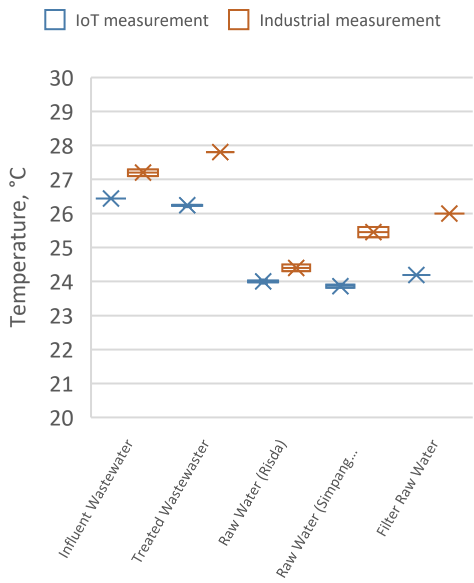

Fig. 8. The temperature measurement of IoT system and industrial instrument across 5 samples from industry.

Table VI tabulates the averaged accuracy of the system against the measurement using the instruments for each parameter. TDS measurement showed the lowest overall accuracy among the three parameters, with values of 82.91%, 85.69%, 89.04%, 92.27%, and 88.87% for River Water, Mountain Water, Filter Water, Influent Wastewater, and Treated Wastewater, respectively, resulting in an average accuracy of 87.76%. The accuracy of pH measurement drops between TDS and temperature with average accuracy of 93.28%, with recorded values of 85.73%, 90.91%, 98.62%, 91.96%, and 99.16% across the five water sources. The temperature measurement demonstrated the highest average accuracy of 95.35% with recorded values of 98.36%, 93.77%, 93.04%, 97.21%, and 94.38%. These results indicate that while all three sensors perform reliably, the TDS sensor may require further calibration or refinement to improve consistency across different water types. Overall, the system demonstrates strong potential for real-time water quality monitoring, particularly in measuring temperature and pH with high accuracy.

Table VI. Accuracy analysis of the measurement using water samples from industry.

Parameter	**Measurement accuracy (%) from samples that acquired from different locations**					**Average accuracy (%)**
	River Water	***Mountain Water***	***Filter Water***	***Influent Wastewater***	***Treated Wastewater***	
TDS (ppm)	82.91	85.69	89.04	92.27	88.87	87.76
Temperature (°C)	98.36	93.77	93.04	97.21	94.38	95.35
pH	85.73	90.91	98.62	91.96	99.16	93.28

TDS = Total Dissolved Solids

IV. CONCLUSION

This study successfully developed an IoT-based industrial wastewater monitoring system that is capable of real-time measurement of TDS, pH, temperature, and turbidity using the Durian ESP32 and various sensors. The findings of the experiments in both laboratory and industrial settings show that the system demonstrated reliable performance, achieving accuracies of 97.74% for TDS, 99.58% for temperature, and 98.77% for pH in the laboratory; and 87.76% for TDS, 95.35% for temperature, and 93.28% for pH in the industrial setting. Data was transmitted to the Blynk cloud for remote monitoring, improving efficiency and decision-making. The system offers a low-cost, scalable, and user-friendly solution that enhances environmental compliance and sustainability. Our future work is to investigate the implementation of machine learning algorithms to improve the system's data processing capabilities by filtering out sensor noise, increasing measurement accuracy, and enabling anomaly detection and trend prediction.

ACKNOWLEDGEMENT

This research was supported by the Universiti Tun Hussein Onn Malaysia (UTHM) through Multi Disciplinary Research Grant (MDR) (vot Q773). The authors would like to thank Mr Wayne Lian, Sincerely Dyeing & Finishing Sdn. Bhd. for generously providing the samples used in this research.

FUNDING STATEMENT

The authors received funding from Universiti Tun Hussein Onn Malaysia (UTHM) for the research and publication of this article.

AUTHOR CONTRIBUTIONS

Jun Jie Choong: Experimental Design, Methodology, Investigation, Data Curation, Formal Analysis, Validation, Visualization, Testing, Data Analysis, Implementation, Validation, Writing – Original Draft Preparation, Review & Editing, Manuscript Refinement, and

Kim Seng Chia: Project Administration, Conceptualization, Supervision, Resources, Technical Guidance, Investigation, Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflict of interests was disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

REFERENCES

[1] B. J. Singh, A. Chakraborty and R. Sehgal, 'A Systematic Review of Industrial Wastewater Management: Evaluating Challenges and Enablers,' *J. Environ. Manage.*, vol. 348, pp. 119230, 2023.

[2] M. B. Zanol, J. P. P. Lima, P. Assemany and A. Aguiar, 'Assessment of Characteristics and Treatment Processes of Wastewater from Slaughterhouses in The State of Minas Gerais, Brazil,' *J. Environ. Manage.*, vol. 358, pp. 120862, 2024.

[3] H. Taherdoost, 'Wearable Healthcare and Continuous Vital Sign Monitoring with IoT Integration,' *Comput., Mater. & Continua*, vol. 81, no. 1, pp. 79–104, 2024.

[4] N. Chavhan *et al.*, 'APAH: An Autonomous IoT Driven Real-time Monitoring System for Industrial Wastewater', *Digit. Chem. Eng.*, vol. 14, pp. 100217, 2025.

[5] *Environmental Quality (Industrial Effluent) Regulations 2009*, Department of Environment, Ministry of Natural Resources and Environmental Sustainability, Malaysia, 2009.

[6] H. S. Bhaskaran, M. Gordon and S. Neethirajan, 'Development of A Cloud-Based IoT System for Livestock Health Monitoring using AWS And Python,' *Smart Agricul. Technol.*, vol. 9, pp. 100524, 2024.

[7] M. N. A. Ramadan, M. A. H. Ali, S. Y. Khoo, M. Alkhedher and M. Alherbawi, 'Real-time IoT-powered AI System for Monitoring and Forecasting of Air Pollution in Industrial Environment,' *Ecotoxicol. Environ. Saf.*, vol. 283, pp. 116856, 2024.

[8] Md. M. Rahman, C. Bepery, M. Hossain, Z. Hassan, G. M. Hossain and M. Islam, 'Internet of Things (IoT) Based Water Quality Monitoring System,' vol. 2, pp. 168–180, 2020.

[9] M. Raparthi *et al.*, 'AI-Driven Decision Support Systems for Precision Medicine: Examining The Development and Implementation of AI-Driven Decision Support Systems in Precision Medicine,' *J. Artif. Intellig. Res.*, vol. 1, no. 1, pp. 11–20, 2021.

[10] D. Wu, H. Wang and R. Seidu, 'Smart Data Driven Quality Prediction for Urban Water Source Management,' *Future Generat. Comput. Syst.*, vol. 107, pp. 418–432, 2020.

[11] *Quality Criteria for Water (Gold Book)*, U.S. Environmental Protection Agency, Washington D.C., 1986.

[12] P. K. Weber-Scannell and L. K. Duffy, 'Effects of Total Dissolved Solids on Aquatic Organisms: A Review of Literature and Recommendation for Salmonid Species,' *Am. J. Environ. Sci.*, vol. 3, no. 1, pp. 1–6, 2007.

[13] L. L. Hallock, 'Detailed Study of Irrigation Drainage in and Near Wildlife Management Areas, West-Central Nevada, 1987-90; Part B, Effect on Biota in Stillwater and Fernley Wildlife Management Areas and Other Nearby Wetlands,' Water-Resources Investigations Report 92-4024-B, *U.S. Geological Survey*, 1993.

[14] S. K. Dewangan, S. Shrivastava, V. Tigga, M. Lakra, Namrata and Preeti, 'Review Paper on The Role of pH in Water Quality Implications for Aquatic Life, Human Health, and Environmental Sustainability,' vol. 10, pp. 215–218, 2007.

[15] H. Y. Li, J. Xu and R. Q. Xu, 'The Effect of Temperature on the Water Quality of Lake,' in *Advances in Textile Engineering and Materials III*, *Adv. Mater. Res.*, vol. 821, pp. 1001–1004, 2013.

[16] J. A. Mukarugwiro, S. W. Newete, F. Nsanganwimana and M. J. Byrne, 'Water Turbidity Affects The Establishment of Neochetina Eichhorniae (Warner) (Coleoptera: Curculionidae): Implications for Biological Control of Water Hyacinth', *Environ. Res.*, vol. 237, pp. 116946, 2023.

[17] G. S. Bilotta and R. E. Brazier, 'Understanding the Influence of Suspended Solids on Water Quality and Aquatic Biota,' *Water Res.*, vol. 42, no. 12, pp. 2849–2861, 2008.

[18] X. Mu and M. F. Antwi-Afari, 'The Applications of Internet of Things (IoT) in Industrial Management: A Science Mapping Review,' *Int. J. Prod. Res.*, vol. 62, no. 5, pp. 1928–1952, 2024.

[19] W. A. Jabbar *et al.*, 'Development of LoRaWAN-based IoT System for Water Quality Monitoring in Rural Areas,' *Expert Syst. Appl.*, vol. 242, pp. 122862, 2024.

[20] S. Madakam, R. Ramaswamy and S. Tripathi, 'Internet of Things (IoT): A Literature Review,' *J. Comput. and Commun.*, vol. 3, pp. 164–173, 2015.

[21] S. Neerputh, 'The Internet of Things (IoT),' in *Encyclopedia of Libraries, Librarianship, and Information Science*, 1st Edn., D. Baker and L. Ellis, Academic Press, pp. 301–307, 2025.

[22] M. Wu and X. Chen, 'Application of Internet of Things and Embedded Technology in Electronic Communication,' *Measurement: Sensors*, vol. 34, pp. 101246, 2024.

[23] J. S. Yalli, M. H. Hasan, L. T. Jung and S. M. Al-Selwi, 'Authentication Schemes for Internet of Things (IoT) Networks: A Systematic Review and Security Assessment,' *Internet of Things*, vol. 30, pp. 101469, 2025.

[24] M. Mukta, S. Islam, S. Das Barman, A. W. Reza and M. S. Hossain Khan, 'IoT based Smart Water Quality Monitoring System', in *2019 IEEE 4th Int. Conf. Comput. and Commun. Syst.*, Singapore, pp. 669–673, 2019.

[25] N. A. Mohd Jais, A. F. Abdullah, M. S. Mohd Kassim, M. M. Abd Karim, M. Abdulsalam and N. A. Muhadi, 'Improved Accuracy in IoT-Based Water Quality Monitoring for Aquaculture Tanks using Low-Cost Sensors: Asian Seabass Fish Farming', *Heliyon*, vol. 10, no. 8, pp. e29022, 2024.