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Performance evaluation of a solar-driven IoT water quality monitoring system using descriptive and ANOVA analysis

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ABSTRACT

Water quality monitoring is vital for protecting aquatic ecosystems and ensuring sustainable water resource management. Traditional manual sampling methods are often costly, time-consuming, and unsuitable for real-time assessment. This study presents a newly designed solar-powered IoT-based water quality monitoring system for remote and continuous data collection. The system utilizes an ESP32 microcontroller integrated with pH, temperature, and total dissolved solids (TDS) sensors, powered by a 10W solar panel. Data is transmitted to a cloud-based platform wirelessly, enabling remote access and visualization via a mobile app. Performance evaluation included descriptive statistics and one-way ANOVA across four sampling sites. ANOVA results showed statistically significant differences ($p < 0.05$) in water quality parameters among locations, confirming the system's sensitivity. Sensor accuracy was validated against standard meters, revealing mean relative errors below 5% for pH and TDS. The system reliably provides real-time, accurate data, supporting proactive water quality management. Integrating IoT with renewable energy offers a cost-effective, scalable, and energy-efficient solution for environmental monitoring in remote or resource-limited areas.

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1. INTRODUCTION

The internet of things (IoT) is transforming various fields, including agriculture [1], [2], medical [3], [4], photovoltaic framewor management [5], and manufacturing [6], [7] by enabling seamless device connectivity and data sharing. In water quality monitoring [8]–[10], IoT provides real-time, accurate, and continuous data collection, revolutionizing environmental management. IoT-based systems use interconnected sensors to measure pH, turbidity, temperature, and dissolved oxygen, transmitting data to centralized platforms for automated analysis. Water quality monitoring must address diverse water bodies, including ponds [9], [11], freshwater sources [10], [12], mine water [13], and others, each with unique chemical and biological properties. These differences require specialized sensors and analytical methods to ensure accurate assessments. Water quality is typically evaluated based on physical, chemical, and biological parameters [8], [14], which determine contamination levels and overall water health.

Traditional methods rely on sample collection and laboratory testing [9]. While effective, these approaches are costly and time-consuming, often leading to delayed responses to contamination [10]. In contrast, IoT-based monitoring allows real-time data collection by deploying sensors directly in water bodies. These sensors continuously measure key water parameters, instantly transmitting data to cloud-based platforms for immediate analysis and response [9]. This enhances accuracy, efficiency, and proactive water quality management. By employing sensors and IoT technology, real-time water quality monitoring becomes possible, eliminating the need for manual sample collection. These sensors can be deployed directly in water bodies to continuously measure water key parameters [9], [10], [12] such as pH, turbidity, and pollutant levels. The data collected is instantly transmitted to a central system via the internet, enabling immediate analysis and response. This approach not only speeds up the assessment process but also enhances accuracy and allows for proactive management of water quality issues [9]. Various methods have been used in the water quality monitoring system in which to process data from sensors to assess water conditions such as ESP32 [9], [15], Raspberry [16], machine learning [17], meshlium device [18] and others. It manages real-time data collection and ensures accurate readings of parameters like pH, temperature, and turbidity. IoT-based monitoring systems enhance this process by transmitting data wirelessly to cloud platforms for analysis and visualization [15].

The performance evaluation of the IoT-based data is crucial in validating the system's reliability and usefulness. The development of a regression model [8], [10] further underscores the analytical potential of IoT-acquired data, enabling precise, data-driven decisions that are essential as presented in the previous work on the effectiveness greenhouse microclimate management [19]. In other hand, statistical methods such as analysis of variance (ANOVA) and water quality indices help quantify variations across different sampling locations, ensuring accurate classification of water quality levels [20]. Advanced techniques, including deep neural network [21], hybrid deep learning [22], machine learning [23], artificial intelligence [24] and remote sensing, further support accuracy measurement for water quality management. Combining traditional and modern analytical methods provides a comprehensive framework for assessing and managing water resources sustainably [25].

This study evaluates the performance of a solar-driven IoT-based water quality monitoring system using descriptive statistics and ANOVA. While many previous studies focus primarily on system design and implementation, sensor validation is often limited, solar integration is rarely addressed, and statistical analysis of system performance remains minimal. As a result, this important aspect has not been thoroughly explored.

2. RESEARCH METHOD

There are three primary steps in the proposed work's procedures. The first step is designing the hardware for the IoT monitoring system, which entails putting together the solar-powered supply module, integrating the ESP32 microcontroller, and connecting the total dissolved solids (TDS), pH, and temperature sensors in addition to the display and IoT communication components. The created IoT Monitoring System and a conventional market reference sensor are used in the second step to gather and measure data from water samples collected from many places. In order to evaluate the accuracy, dependability, and general performance of the suggested water quality monitoring system, the third stage entails evaluating the gathered data using descriptive statistics, ANOVA testing, and error evaluation. The work on a water quality monitoring system involves creating a sophisticated network of sensors and data analytics tools to track various parameters of water quality. This system enables real-time detection of contaminants, thereby enhancing the ability to manage and safeguard water resources effectively. Figure 1 shows the proposed IoT water quality monitoring system with the solar panel as its supply. The ESP32 is used as the main controller in which connected to solar system, sensors and IoT application.

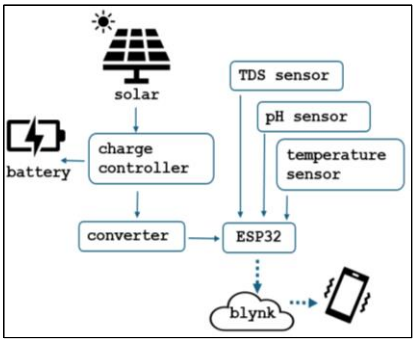


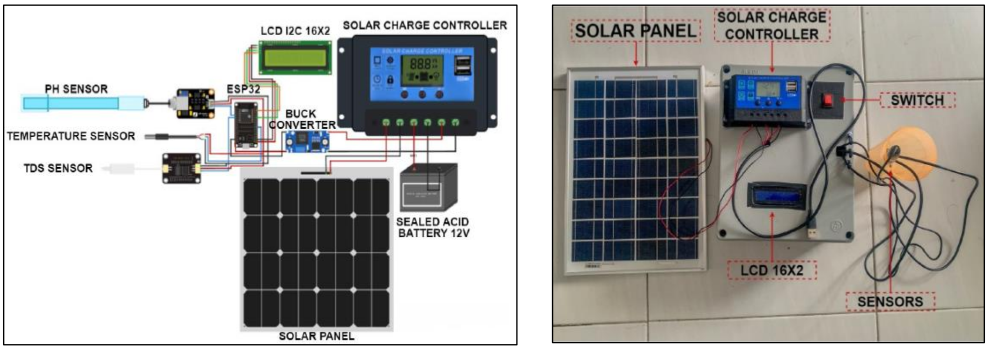
Figure 1. A solar-powered IoT-based water quality monitoring system

Solar energy is harnessed by panels and transformed into electrical power. A solar charge controller then controls the energy in which to ensure the battery is charged to the right level to avoid overcharging and increase its lifespan. The energy is stored by the battery for subsequent use. A buck converter reduces the voltage from the 12 V solar charge controller to the stable voltage of 3.3 V level at ESP32 input. The ESP32 is linked to multiple sensors, including a pH sensor that gauges acidity or alkalinity, a temperature sensor that tracks thermal conditions, and a TDS sensor that evaluates water quality. This configuration empowers the ESP32 to analyze and interpret data from these sensors, facilitating accurate environmental monitoring system. The water quality monitoring system is powered by a 10W polycrystalline solar panel with a current of 0.63 A and a voltage of 17.5 V, managed by a solar charge controller that supports 12 V or 24 V systems with a rated current of 10 A. It includes a 12 V, 7.2 Ah sealed lead battery for energy storage and operates using an ESP32 microcontroller. The system features an analog pH sensor, a DS18B20 digital temperature sensor, and an analog output TDS sensor, all of which are displayed on a 16×2 LCD screen for real-time monitoring. These parameters are presented in Table 1.

Table 1. Specification of system

Components	Specifications
Polycrystalline solar panel	10 W, Isc 0.63 A, Vmp 17.5 V
Solar charge controller	12 V/24 V, rated current 10 A
Sealed lead battery	12 V, 7.2 AH
Microcontroller	ESP32
pH, temperature TDS sensor	Analog type
LCD	16×2

A solar-powered water quality monitoring system setup is depicted in Figure 2 in which Figure 2(a) and Figure 2(b) for circuit diagram and hardware implementation respectively. Referring to Figure 2(a), the system uses a solar panel to collect sunlight and generate electricity, which is regulated by a solar charge controller to protect the battery. The sensors measure water temperature, TDS, and pH, the readings are shown on a 16×2 LCD, and a switch allows the system to be turned on or off, enabling continuous off-grid water quality monitoring. Figure 2(b) shows the hardware setup based on the circuit diagram in Figure 2(a), with several components neatly arranged inside the enclosure. The display is shown on the LCD as "Offline," which means it is not connected or in use. Once the device is online, the app allows users to monitor and evaluate the water quality in real-time. It shows temperature (29 °C), TDS at 53 ppm, and pH level at 5. Through the ESP32 module, data from the pH, temperature, and TDS sensors is transmitted to the Blynk IoT application. Blynk makes it easier for sensor data to be transmitted over the internet and enables real-time smartphone visualization.



(a) (b)

Figure 2. IoT Monitoring system with a solar system (a) circuit diagram and (b) hardware

Measurement and analysis on the water sample. IoT-based monitoring system was evaluated using four water samples collected from distinct locations: sample A, sample B, sample C, and sample D. The analysis focused on pH levels, temperature, and TDS, comparing the IoT monitoring sensor with a market sensor to assess accuracy and reliability. Descriptive statistics analysis was performed to summarize and describe the central tendency and the dispersion of the collected data. For this purpose, the mean, standard deviation, the skewness and kurtosis of the data were calculated for each pH levels and TDS in four locations of water sample. To determine the existence of significant differences in water quality across sampling locations, one-way analysis of variance (ANOVA) was applied. ANOVA is a statistical procedure that assesses the importance of one or more factors by comparing the response variable means at the different factor level. The analysis of variance (ANOVA) is based on two competing hypotheses: the null hypothesis (H_0) and the alternative hypothesis (H_1). The null hypothesis assumes that all group means are equal, whereas the alternative hypothesis suggests that at least one group mean differs among the sampling locations. The decision to accept or reject the null hypothesis is determined by the p-value obtained from the ANOVA test. Specifically, H_0 is rejected when the p-value is lower than the chosen significance level, $\alpha = 0.05$.

The significant value, α indicates a five percent deviation of the confidence level, and it is considered reliable to be used in the statistical analysis. The coefficient of determination, R^2 is an indicator used to describe how much variation is explained in by the water quality parameters and sampling locations. The (1) is the formula for R^2 in the ANOVA analysis.

$$R^2 = 1 - \frac{unexplained\ variation}{total\ variation} \tag{1}$$

One of the main objectives of this study is to assess the accuracy of sensors in the developed water quality monitoring system. Therefore, the measurement obtained from the pH sensor, temperature sensor and TDS sensor are compared to the standard readings via descriptive statistics and graphical error analysis. The relative error for each measurement is calculated by using (2). Where Re is relative error, $SensM$ sensor measurement and $STDread$ is standard reading.

$$Re = \frac{SensM - STDread}{STDread} \tag{2}$$

3. RESULTS AND DISCUSSION

This section presents the results of the water quality assessment conducted using an IoT-based monitoring system across four sampling locations: sample A, sample B, sample C, and sample D.

3.1. Descriptive statistics

Descriptive statistics of the data is presented in Table 2 in which it summarizes the descriptive statistical analysis of the measured water quality parameters for samples A, B, C, and D. The Table 2 presents key indicators, including mean, standard deviation, skewness, and kurtosis, to provide an overview of the distribution and variability of pH and TDS values across the samples.

Table 2. Descriptive statistics on the water quality for sample A, B, C, and D

Water sample	Measured	Mean	Standard deviation	Skewness	Kurtosis
A	pH	5.22	0.14	0.42	-1.95
B		4.68	0.08	0.08	-0.92
C		5.02	0.07	0.10	-0.14
D		5.80	0.15	0.09	-1.62
A	TDS (ppm)	61.5	2.95	0.19	-1.52
B		56.9	1.91	-1.14	0.30
C		207.1	5.07	0.81	0.06
D		103.4	1.07	-1.69	1.86

The mean pH values for all water samples range from 4.68 to 5.80, indicating slightly acidic conditions, with sample B identified as the most acidic. Sample C records the highest mean TDS value (207.1 ppm), reflecting a greater concentration of dissolved substances compared to samples A, B, and D. The relatively low standard deviation of pH across all samples suggests that the sensor measurements are closely clustered around their respective mean values. In terms of distribution, the pH data exhibit positive skewness with flatter (platykurtic) shapes relative to a normal distribution. For TDS, sample C shows greater variability, as indicated by a wider spread of data compared to the other samples. Additionally, TDS values for samples B and D are negatively skewed, while samples A and C demonstrate positive skewness. The kurtosis results further indicate that TDS in sample A has a flatter distribution, whereas samples B, C, and D display more peaked (leptokurtic) distributions compared to normal. Additionally, the temperature of the developed water monitoring system is recorded by the temperature sensor attached in the device. It is observed that the sensor managed to record the single value of temperature without the exact decimal place. This is probably due to limitations in the sensor's resolution, data conversion process, or the way the data is being rounded or displayed by the system. Nevertheless, the recorded temperature by sensor is still acceptable as the values is within the range of 29 ºC.

3.2. ANOVA test

The ANOVA test was conducted to evaluate the existence of significant different in mean of measurements for pH and TDS across four sampling locations. The hypothesis statement for the ANOVA are:

- H_o: all means of water sample at four sampling locations are equal.
- H_1: at least one of the means of water sample are different.

Table 3 presents the p-value and R^2 for pH and TDS based on ANOVA. The p-values for both pH and TDS are less than the significant level of 0.05, which lead to the rejection of H_o. Therefore, there exist significant difference in pH values and TDS for water sample collected from all sampling locations. The values of R^2 for pH and TDS are 93.13% and 99.76% respectively, indicates the percentage of variation in pH and TDS that is predictable by the water quality in sampling locations.

Table 3. Descriptive statistics from sensor and standard meter

Measurement	p-value	R^2
pH	0.0001	93.13%
TDS	0.0001	99.76%

3.3. Accuracy of the sensor

The water quality monitoring system developed in this study is powered by 10 W solar panel together with analog pH sensor and TDS sensor. The water pH and TDS measurement were collected at four different sampling locations for 3 consecutive days. To evaluate the accuracy of the sensors used in the developed device, measurement of pH and TDS were also recorded by using standard meter. Table 4 shows the descriptive statistics of pH values and TDS collected from the sensor and standard meter. Referring to Table 4, it is observed that the average values of pH and TDS collected from the sensor are slightly difference from the standard meter. The values of standard deviation for measurement recorded from the analog sensor suggested that the variability in sensor readings for both pH and TDS are higher than the standard meter. Nonetheless, the minimum values and maximum values of pH and TDS recorded from the sensor are just slightly different from the standard meter. Therefore, it is notable that the analog sensors used in the water quality monitoring system can provide measurements of pH and TDS that are close to the standard meter reading.

Table 4. Temperature recorded for water in sample A, B, C, and D

Parameter	Variable	Standard meter	Sensor
Mean	pH	4.96	5.18
	TDS	108.15	107.2
Standard deviation	pH	0.20	0.43
	TDS	59.38	61.29
Minimum value	pH	4.55	4.57
	TDS	51.0	53.0
Maximum value	pH	5.17	6.01
	TDS	209	217

Additionally, the relative error for pH and TDS were calculated to evaluate the accuracy of the measurements recorded by the analog sensors. Figure 3 and Figure 4 display the bar chart of the relative error for pH and TDS, respectively. The y-axis represents the relative error in the decimal form, while the x-axis represents the sampling data number. The histogram in Figure 3 exhibits that the fluctuation of the relative error of pH values which is fluctuate between -0.004 and 0.182. Most of the bar in Figure 3 are less than 0.05, with only 9 readings recorded from the sensors has high relative error of more than 0.10. The histogram of relative error in Figure 4 shows that the TDS relative error is between -0.16 and 0.094. The flatter spread of the histogram is supported by the high value of standard deviation for TDS measurements, that is 61.29 (Refer Table 4). Observing the histogram in Figure 4, it is likely that the value of negative relative error is approximately the same as the positive relative error. The developed system yields a positive relative error when its measured TDS value is higher than the standarf value, and vice versa.

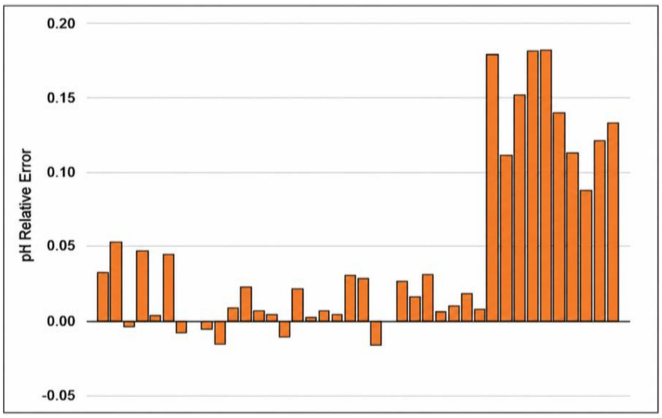


Figure 3. Histogram of relative error for pH values from sensor

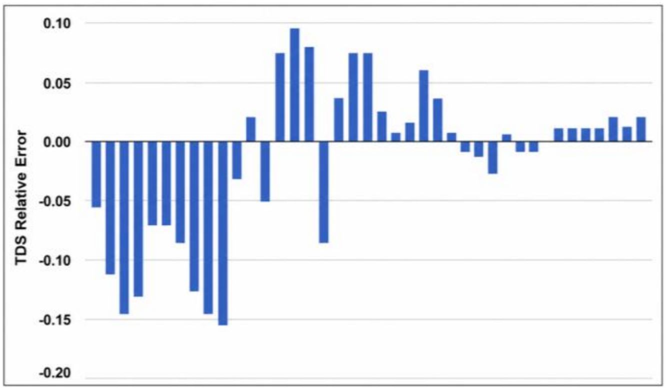
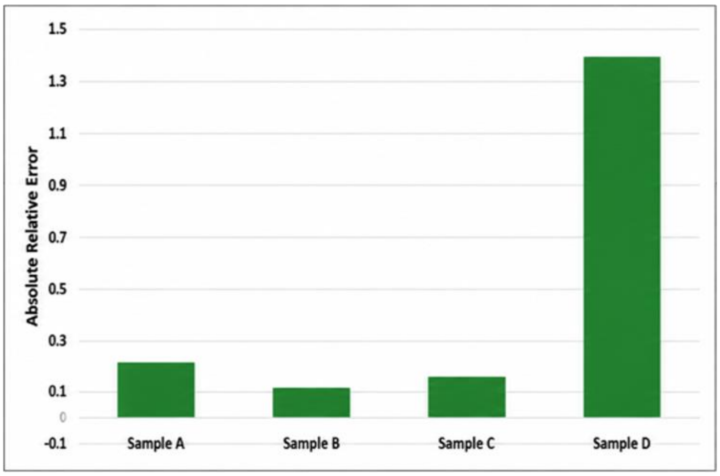


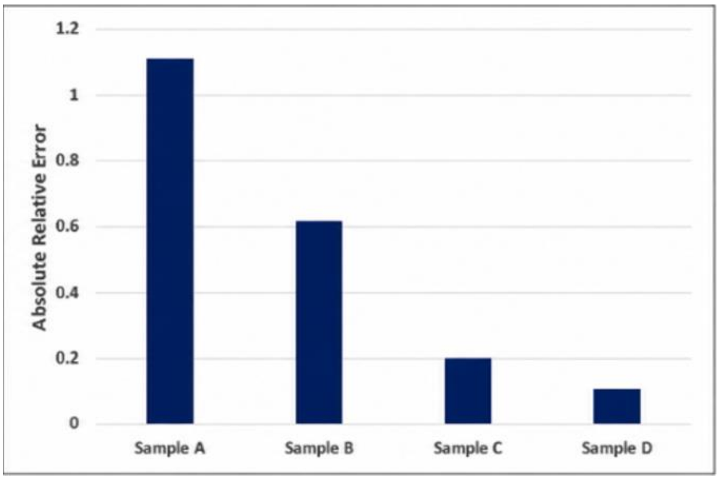
Figure 4. Histogram of relative error for TDS values from sensor

Figure 5 shows the histogram of relative error for both pH and TDS values from sensor. Figure 5(a) below displays the absolute relative error plot for pH based on water sample. The absolute relative error plot for pH values shows that the highest error in the sensor measurements is contributed by measurements of water sample D. Correspondingly, measurement of pH sensor from water sample A, B, and C give the much lower absolute error as compared to sample D. This finding is supported by the value of standard deviation for sample D as shown in Table 2. On contrary, the plot of absolute relative error for TDS sensor as in Figure 5(b) shows sample A gives the highest absolute error, followed by sample B, C, and D. The fluctuation of absolute relative error in TDS sensor is more evenly distributed as compared to pH sensors. Examine the error plots for pH sensor and TDS sensor, it is concluded that the measurement gains from both sensors are in the range of meter readings with no aberration from the recorded values of standard meter. Henceforth, it is proven that the sensors used in the water quality monitoring system are acceptably accurate in recording the pH values and TDS.

This study explored a comprehensive solar-powered IoT-based water quality monitoring system using analog pH and TDS sensors across multiple sampling locations. However, further in-depth studies may be required to confirm the long-term accuracy and stability of the sensors, particularly under varying environmental conditions, extended deployment periods and additional sensors such as dissolved oxygen, turbidity and others. The results show that IoT-enabled water quality monitoring systems are dependable and efficient for evaluating important water parameters in real time. To improve system resilience and predictive power, future studies might investigate the incorporation of more water quality indicators, more accurate digital sensors, and sophisticated data analytics methods with the benchmark of the other IoT system. In addition, beyond statistical significance, the system’s consistent performance and low measurement errors show that it can facilitate prompt decision-making and proactive water management in practical applications.



(a)



(b)

Figure 5. Histogram of relative error for both pH and TDS values from sensor (a) pH and (b) TDS

4. CONCLUSION

This study demonstrated the effectiveness of a solar-powered IoT-based water quality monitoring system for real-time assessment of pH, temperature, and TDS. The system successfully collected and transmitted data across four sampling locations (sample A, sample B, sample C, and sample D), enabling efficient analysis. ANOVA results showed significant differences in pH and TDS, indicating variations in water quality, while temperature remained relatively stable. Regression analysis further confirmed that TDS had the strongest relationship with location, suggesting environmental factors influence dissolved solids. Statistical analysis revealed notable variations in pH and TDS between locations, suggesting that environmental factors affect water quality. The system's low measurement error and steady sensor performance show its dependability, and it makes scalability, sensor calibration, and adaptation for broader real-world applications. Additionally, the gathered data can support future integration of either machine learning or artificial intelligence techniques for trend prediction, variance detection, and testing across various environmental conditions.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

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

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy.

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