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Variance of total dissolved solids and electrical conductivity for water quality in Sabak Bernam

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ABSTRACT

Water pollution is one of the most serious environmental problems in Malaysia. The most notable occurrence of pollution happened in Selangor. Currently, there are various water quality monitoring (WQM) methods to observe the quality of water. One of the methods used is the internet of things (IoT) for wireless sensor network technology to obtain real-time data measurement. In this study, the developed WQM system is equipped with a sensor that can measure total dissolved solid (TDS) and electrical conductivity (EC). Arduino UNO was used in this system as a microcontroller to interact with the sensor. The Wi-Fi module, ESP8266, was used to transfer the collected data to ThingSpeak, which acts as a cloud to store all the data. The results showed that both sample populations can be discriminated since the p-value is greater than 0.05 in the normality test, while in the paired sample t-test, the p-value is less than 0.05. In conclusion, this research provides an easier way to monitor water quality by taking up less time at less cost, as well as being reliable in giving real-time data reading.

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1. INTRODUCTION

Since the 1990s, there have been many water crises in Malaysia, resulting in lots of hardships and economic losses within the community. This has made it necessary for the government to have an awareness of the relevance of conserving water. Each year, hundreds of complaints about water pollution are issued to the Department of Environment from different sources, such as factories, businesses, farms, as well as individuals [1].

Over the years, water pollution has become a critical issue in Selangor, Malaysia. Water pollution that occurs in the rivers is mostly due to the dumping of wastewater from the factories located nearby [2], [3]. Many methods have been used in previous research to monitor the quality of water. Most of the current methods being used require a person to go directly to the river to monitor the water quality [4]. This method is not efficient since it is hard to obtain real-time data measurement [5]–[7]. Based on previous water quality measurements, most of the methods used to measure water quality do not include the electrical properties of water such as electrical conductivity (EC). Anna [8] conducted an experiment on the correlation between conductivity and total dissolved solid in various types of water, which shows that EC is an important parameter that can be used to indicate whether the water is clean or polluted. Based on the reviewed paper, it shows that the changes in EC values could affect the health of the consumer.

In this study, an IoT system was used in the proposed system design that enables the data to be collected and monitored in real-time through a personal computer (PC) or smartphone. A total set of 200 data were collected from the nearest river in Sabak Bernam, Selangor. The collected data were then sent to the cloud using ThingSpeak, which can store and retrieve data from a microcontroller using a standard protocol over the Internet or via a local area network (LAN). The data then were downloaded and tested using the statistical analysis method in IBM SPSS. The parameters that were observed in the proposed system were total dissolved solid (TDS) (unit in part per million, ppm) and EC (unit in milisiemens per centimeter, mS/cm). According to the National Water Standard for Malaysia, the maximum TDS and EC values for clean water are between 0 to 500 ppm and 0 to 1 mS/cm [9]. Hence, this project was introduced with the purpose of establishing a water quality monitoring (WQM) system that could discriminate between clean and polluted river water based on TDS and EC values.

The traditional water quality measurement involves three steps, which require the authority to do water sampling, sample testing, and investigative analysis [10]. This technique is not fully reliable and gives no indication beforehand of the quality of water. These methods mentioned above are also very expensive, difficult, time-consuming, require expert advice, and are less efficient. [11]. In order to use this technique, many instruments are needed, such as Secchi disks, which are used to measure water clarity, probes, nets, gauges, and meters. Besides impeding accurate water quality measurement, this technique also fails to predict sudden changes in the water.

Chowdury *et al.* [12] suggested building a system that is mainly composed of the main controller, sensor, and wireless communication module. The instruments used by the researchers to build a wireless WQM system were STM32, pH sensor, temperature sensor, turbidity sensor, and ESP8266. The system used a Microsoft SQL Server database to organize, store and manage the data collected. The data on water quality can be accessed by the user through a mobile phone application or web client. The researchers claimed that this system is low-cost, energy-saving, and has low power consumption. Furthermore, users can check the water quality problem in a timely manner.

A wireless WQM system with IoT has been developed in an effort to measure the water quality at Hyderabad Metropolitan City [5]. The instruments used were the Arduino Mega, four sensors which measure pH, turbidity, ultrasonic, and DHT-11, as well as the ESP8266 Wi-Fi module (NodeMCU). Although the parameters measured in this study were pH, turbidity, water level, temperature, and humidity of water, only two parameters were considered in the statistical analysis. The cloud used was ThingSpeak, which allows data to be stored and enables data to be visualized into graphical data. Besides that, ThingSpeak also provides an easier way for the user to access the data collected through their mobile phone and personal computer.

Electrical conductivity is one of the parameters that can be observed to determine the quality of water. Zhang *et al.* [13] have done a case study of determining the water pollution at Rudrasagar Lake by observing the EC. The researchers stated that the significant change in EC may be due to either natural flooding, evaporation, or man-made pollution, which can be very detrimental to water quality. The sudden increase or decrease in conductivity in a body of water may indicate pollution. There is also a linear relationship between TDS and EC.

Sulaiman and Hashim [14] discriminate latex between healthy and white root infected rubber trees based on dry rubber content using statistical analysis. The comparison of the DRC of latex from healthy rubber trees and white root infected rubber trees was initiated using a normality test to investigate whether the sample population followed a normal distribution or not. The data is considered normal if it is in a bell-curve shape. Then, the parametric test was applied using an error bar plot and followed by a paired sample test for conclusive numerical findings. Using statistical analysis, the result showed a very distinguishable value for both cases. There was no overlap in the error bar in both cases, and the p-value (0.001) indicated that there was a discrimination between both cases. This shows that statistical analysis is reliable and can be used to identify healthy and white root diseases in rubber trees.

Based on the above study, it can be concluded that there is an alternative way to monitor the quality of water by implementing modern technology in the system. TDS and EC are both indicators that can be used to identify clean and polluted river water [15]. Statistical analysis can be used to strengthen the proof that clean and polluted river water can be discriminated by looking at p-value results from the normality test and paired sample t-test. All these measurements can be made with the help of the Arduino Uno microcontroller and ThingSpeak for data collection.

2. METHOD

This section explains the process of the whole experimental work method of measuring TDS and EC properties using the Arduino Uno microcontroller. The methodology also explains the method of analyzing the results from the experiment. The overall process of the project is shown in Figure 1.

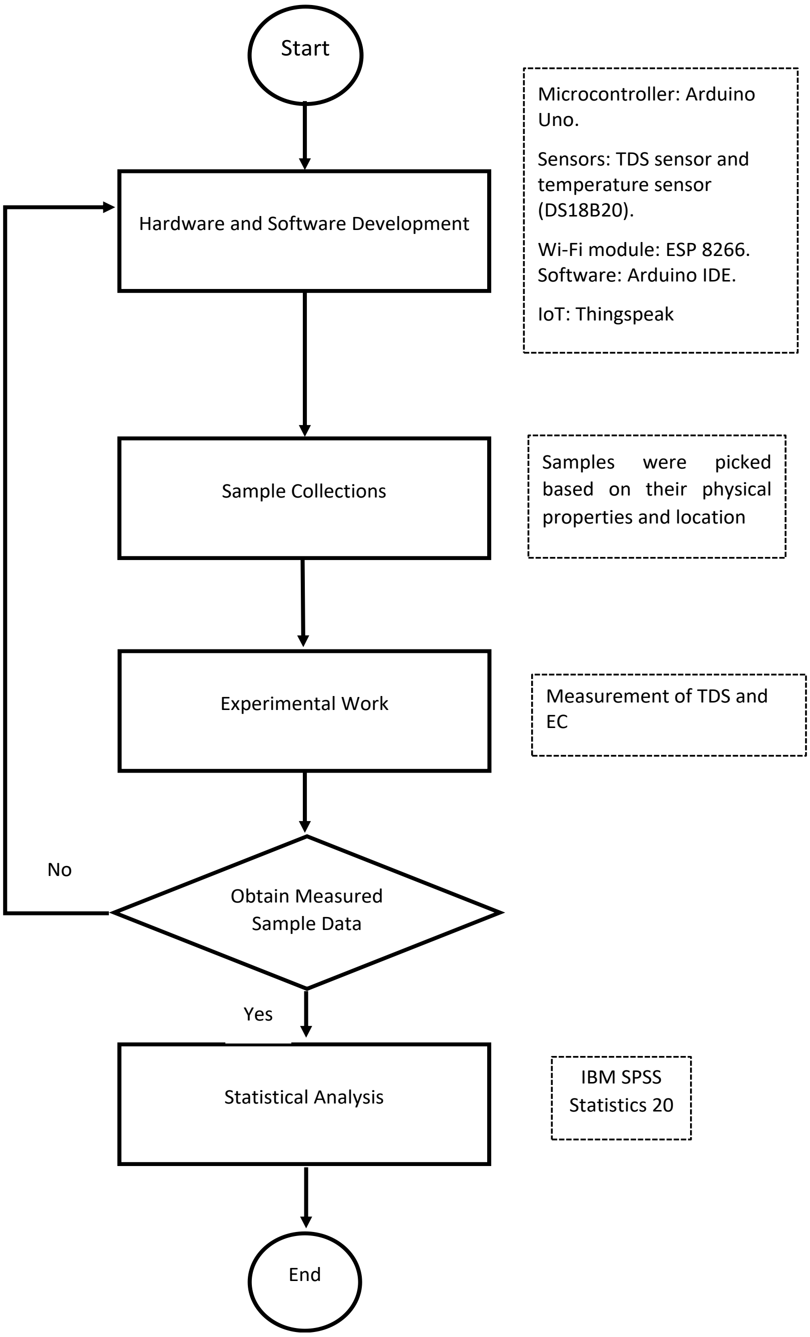

Figure 1. Overall flowchart of the research

2.1. Hardware development

In this project, the microcontroller was used as the system's central processing unit. The microcontroller was connected to all the sensors and the Wi-Fi module to process the collected and transferred data as shown in Figure 2. When sensors for the TDS received signals from the samples, these input signals were sent to the microcontroller for processing. The output signals from the microcontroller were then sent to the Wi-Fi module to provide access to the Wi-Fi network. Next, the transmitted data from the Wi-Fi module were sent to ThingSpeak for the process of storing and retrieving data.

The TDS sensor is an important device used to determine the quality of water. In this research, the TDS is not only used to obtain the TDS value of water but also the EC of the water. Furthermore, the sensor accepts an input voltage range of 3.3 to 5 V, which is compatible with the Arduino Uno, and the TDS measurement range is 0 to 1000 ppm, which is within the WQM system requirements. The sensor also has a high level of precision, and it is water resistant, which allows it to be used in water.

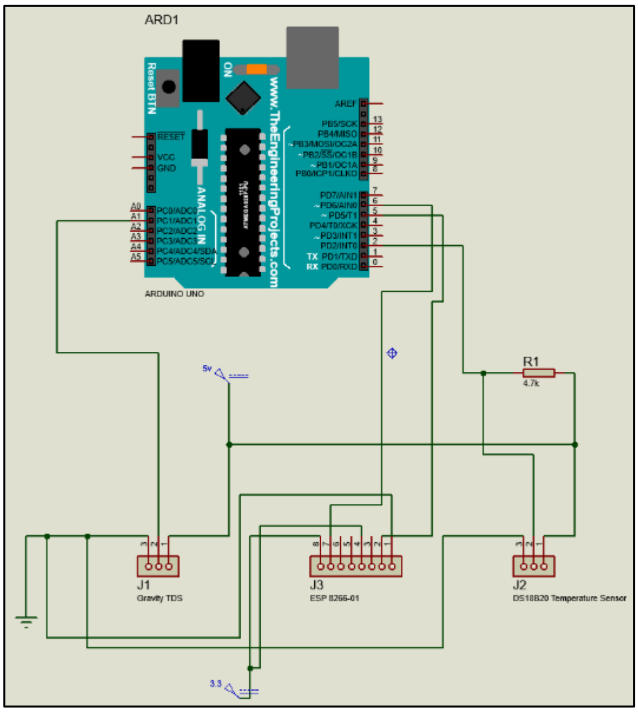

Figure 2. Microcontroller connection to Wi-Fi module and sensors

The ESP8266 module functions as both a data processing and a Wi-Fi networking server. The TDS and EC data collected were transmitted through the Wi-Fi network and sent to the web server. These data will be displayed on a web browser which can be accessed on an internet-connected computer [16]–[18]. The ESP8266 is a very user friendly and low-cost component that can be used to provide internet connectivity to the system. It is because the module can function as both a hotspot and a station (connecting to Wi-Fi). It can also use the application programming interface (API) to fetch the data from the internet, allowing the user to access any information available on the internet and making it smarter. Another appealing feature of this module is that it can be programmed with the Arduino IDE, which makes it even more user-friendly. However, due to the limited general-purpose input-output (GPIO) pins, a microcontroller like the Arduino Uno is needed to provide more GPIO.

The software used to program the Arduino Uno board is the Arduino integrated development environment (IDE). The languages that can be used by this software are C and C++ programming languages. This software is easy to use since it prepares two functions every time the user wishes to create a new project. The first function is the setup function, and the second function is the loop function.

Since this project uses an IoT system to store and display real-time data, the ThingSpeak application was chosen as its platform. ThingSpeak is an IoT analytic platform that allows the user to aggregate, visualize, and analyze live data in the cloud. The collected data can be analyzed graphically since the data can be represented using many types of graphs. The data that has been collected can also be downloaded as an Excel file for further analysis using a statistical tool (IBM SPSS). In addition, it shows that ThingSpeak can not only be accessed through a PC but also via a smartphone. Figure 3 shows the block diagram of the IoT WQM device, while Figure 4 shows the hardware of the circuit. The block diagram of the IoT WQM device is divided into 4 parts, which are the sensor network, microcontroller, Wi-Fi module, and IoT.

2.2. Sample collection

At the beginning of the project, 200 samples of clean and polluted river water were taken from different locations. The selection of this river is based on the factor of high-water consumption for agricultural activities such as palm oil, rubber tree plantations, and paddy fields. Samples of clean river water were taken from the tap water of houses located around the selected area in Sabak Bernam, Selangor. Meanwhile, the polluted river water samples were taken from the drains in Sungai Besar, Sabak Bernam, in Selangor. In order to verify the results, the data from the river at Pasar Jerami, Sabak Bernam were taken to test the reliability of the IoT WQM device. The location of the data collection was identified based on the criteria as mentioned in [19]. The location of the river for verification is shown in Figure 5.

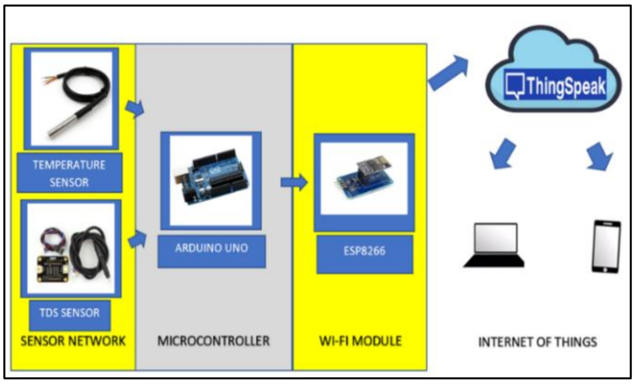

Figure 3. Block diagram of IoT WQM device

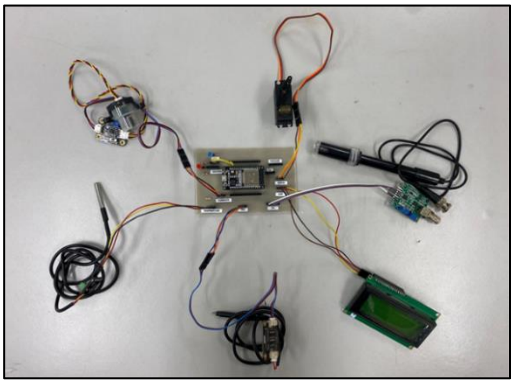

Figure 4. IoT WQM device hardware

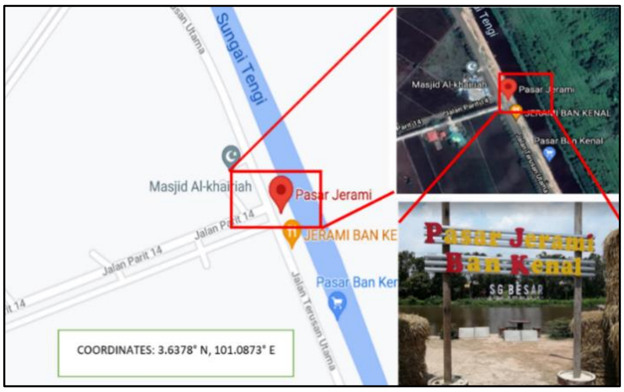

Figure 5. Location of Pasar Jerami River

2.3. Experimental work

Before the readings were taken from the samples, the TDS sensor must be calibrated using the TDS calibration method. A TDS calibration standard solution (from Netafarm Hydroproduct, Indonesia) is a calibration standard solution used in the calibration process. The reading for the TDS sensor needs to be the same as the TDS calibration standard solution. The value from the TDS sensor must not exceed the standard solution. In this calibration, the standard solution was set at 500 ppm. While for the EC value, the equation involved was based on the correlation equation between TDS and EC [8]. This is to ensure that the sensor is working perfectly.

There were 200 samples of clean water and polluted river water collected from the site. All these samples were tested using a water quality device. A total of 200 readings were taken from both water samples. All the collected data were stored in the Thingspeak cloud. In the beginning, the data were divided into two channels, which were tap water (clean river water) and drain water (polluted river water) in the Thingspeak platform. In both channels, the data were sorted into two fields, based on the measured parameter. There were two parameters collected during the research, the measured parameters in this study focused on TDS and EC values only. All the data that were stored in Thingspeak were displayed as a graph to provide an easy way for the user to observe the changes in water by using a graphical method. Lastly, the collected data were downloaded from Thingspeak into an Excel file. All the data from the Excel file were analyzed using the statistical analysis method in IBM SPSS software.

2.4. Statistical data analysis

In this project, statistical analysis was used to discriminate between clean and polluted river water [20]. The data obtained from the Thingspeak platform were used as input in IBM SPSS software for statistical data analysis. There were two tests involved in discriminating all the data. The normality test and paired sample t-test were used to see whether the data could discriminate between clean and polluted water.

It is widely known that the data must be normally distributed for a normally test. Normally distributed data can be evaluated using a particular set of statistics called parametric statistics. This statistical component includes the variance (s^2) and the standard deviation (s). The variance (s^2) for a sample can be represented in mathematical terms as in (1).

$$s^2 = \frac{\sum(x-\bar{x})^2}{n-1} \tag{1}$$

The symbol n represents the number of observations in the sample. Meanwhile, the standard deviation for normally distributed data (s) can be expressed as in (2).

$$s = \sqrt{\frac{\sum x^2 - \frac{(\sum x)^2}{n}}{n-1}} \tag{2}$$

If the data are normally distributed, then there would be a mathematical relationship between any one observation in the sample whereby x and y are the values calculated for any given x value. This mathematical equation is called the Gaussian equation, where:

$$y = \frac{1}{\sqrt{2\pi s^2}} e^{-\left(\frac{(x-\bar{x})^2}{2s^2}\right)} \tag{3}$$

Symbols e and π are particularly constant, and their values are 2.72 and 3.14 after being rounded to two decimal places, respectively. The mean for the sample observation is $\bar{x}$, while s^2 is the variance of the sample observation.

A paired sample t-test in statistics is a method of testing hypotheses about the mean of a sample drawn from a normally distributed population. The hypotheses are

- H_0: There is no difference between the means for the two observation samples, and
- *H1:* There is a difference between the means for the two samples.

In other words, in this research, the study seeks to investigate if there are any differences between the sample observations of drain and tap water.

The mathematical equations involved in the t-test are standard error of the difference between the mean, SE_D, the *t*-statistics or $t_{calculated}$, where it describes how closely the distribution of the data matches the distribution predicted under the null hypothesis of the statistical test, and lastly, the degree of freedom, df, which estimates or makes inferences about population parameters based on the sample data.
The mathematical equation for standard error is:

$$SE_D = \sqrt{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)} \tag{4}$$

where s_1^2 and s_2^2 is the variance, and n_1 and n_2 is the recorded number of observations for each sample. The mathematical equation for the *t*-statistic is:

$$t_{calculated} = \frac{\bar{x}_1 - \bar{x}_2}{SE_D} \tag{5}$$

where $\bar{x}_1$ and $\bar{x}_2$ are the mean of the sample observation. All these formulas [21] mentioned above were used automatically in the normality test and paired sample t-test in the IBM SPSS statistical tool. The results and discussions of the findings are described in the next section.

3. RESULTS AND DISCUSSION

This section presents the results and findings of the project. The analysis and discussion for each part of the results presented in this project are based on the findings from the data collection and measurement. In this research, only the values of TDS and EC were considered for analysis.

Figures 6 and 7 show that all the data collected throughout the experiment were stored in the cloud. From the graph, it can be seen that the range values of TDS and EC for clean river water were between (222 and 244 ppm) and (0.444 and 0.488 mS/cm) respectively. While for polluted river water, the range value of TDS and EC were between (506 and 528 ppm) and (1.012 and 1.056 mS/cm) respectively. The data that was stored in the channel for each field were downloaded and exported in Microsoft Excel via the ThingSpeak software. Table 1 illustrates an example of EC value data acquired for clean river water and polluted river water.

The collected data in the experiment were tested using the IBM SPSS software. A normality test was performed on the data to determine whether they were normally distributed or not. A normality test was performed on 100 datasets for clean river water and 100 datasets for polluted river water. The test was used for both TDS and EC properties for tap and drain water data as described in Tables 2 and 3.

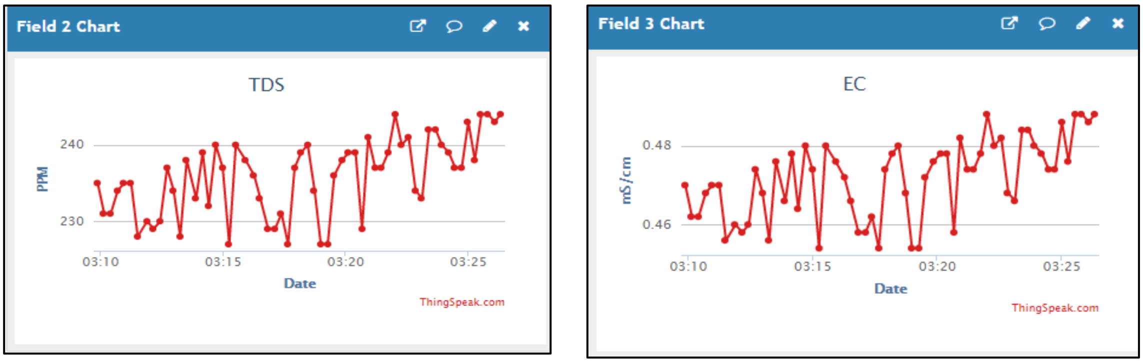

Figure 6. TDS and EC output from ThingSpeak server for tap water

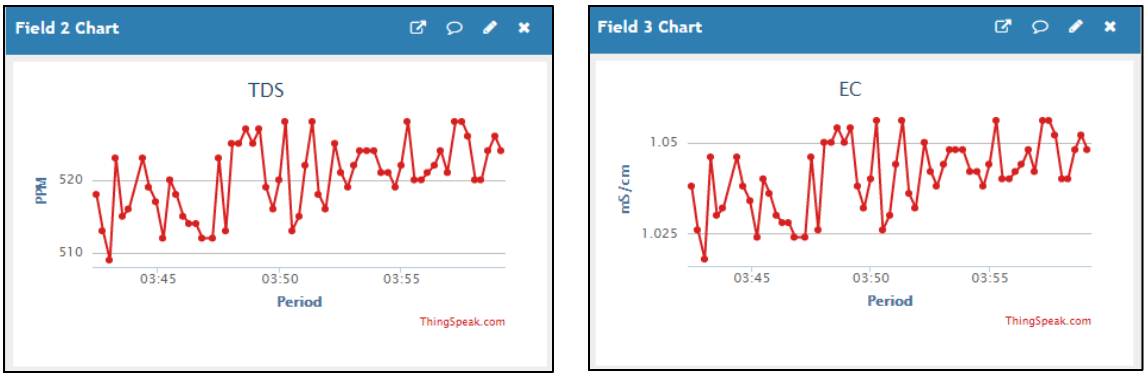

Figure 7. TDS and EC output from ThingSpeak server for drain water

Table 1. Example of EC value taken from IoT WQM device

Sample Number	Clean River Water (mS/cm)	Polluted River Water (mS/cm)
1.	0.444	1.018
2.	0.446	1.018
3.	0.450	1.014
4.	0.454	1.020
5.	0.458	1.030
6.	0.456	1.026
7.	0.444	1.012
8.	0.444	1.032
9.	0.448	1.028
10.	0.452	1.014

Given that the dataset is larger than 50, the Kolmogorov-Smirnov approach is highly effective for evaluating the results. Since the significant value (p-value) of clean river water in the TDS dataset and the significant value of polluted river water in the TDS dataset were both greater than 0.05, the data were normally distributed [22], [23]. The data for clean river water and polluted river water for EC properties also showed the same result as the data for TDS properties. Since the data for EC properties showed the same result as TDS properties, it can be said that the data were normally distributed. As the population for both TDS and EC was normally distributed, the parametric tests were then used to test both sets of data. Prior to testing the data with a paired sample t-test, an error bar plot was then used in order to differentiate between both data sets. An error bar plot was used to provide concrete evidence that the data could be discriminated against each other as shown in Figures 8 and 9 [24].

Table 2. Normality test for clean river water and polluted river water based on EC properties

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Clean river *water_ec*	.071	100	.200*	.976	100	.060
Polluted river *water_ec*	.076	100	.164	.971	100	.027

*. This is a lower bound of the true significance
a. Lilliefors Significance Correction

Table 3. Normality test for clean river water and polluted river water based on TDS properties

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Clean river *water_tds*	.071	100	.200*	.976	100	.060
Polluted river *water_tds*	.076	100	.164	.971	100	.027

*. This is a lower bound of the true significance
a. Lilliefors Significance Correction

The error bar plots for each dataset must not overlap in order to demonstrate that the dataset is discriminating against each other [25]. The error bar plots for tap water data and drain water data did not overlap, as illustrated in Figures 8 and 9. This demonstrates that the system can distinguish between tap and drain water data. As a result, it shows that an error bar plot can provide concrete evidence to show inequality between each population sample.

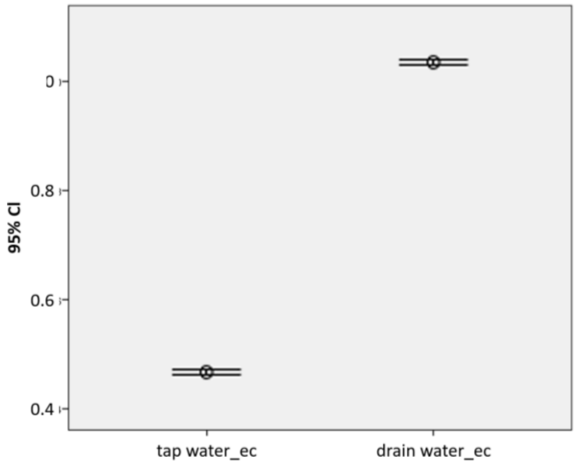

Figure 8. Error bar plot for clean river water and polluted river water based on EC properties

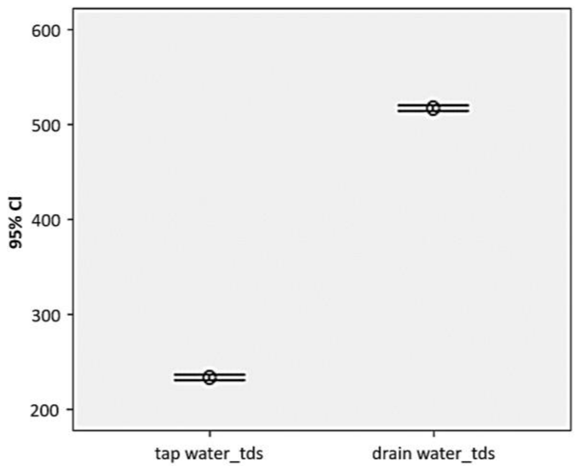

Figure 9. Error bar plot for clean river water and polluted river water based on TDS properties

The dependent t-test sample, also known as the paired sample t-test, is a statistical method for determining if the mean difference between two sets of observations is zero [26]. In a paired sample t-test, each subject or entity is examined twice, resulting in pairs of observations. The paired sample t-test is commonly used in case-control studies or repeated-measures designs. A paired sample t-test is a parametric test in which the data must first be subjected to a normality test to see if it is suitable for testing.

The data received from the system were valid to be examined with a paired sample t-test because the normality test results for both datasets passed the minimum p-value (0.05). To know if there is a difference between the mean of the data, the sig (2-tailed) value must be less than 0.05. The value of sig (2-tailed) was 0.000 after the data were tested for both EC and TDS properties as in Table 4 and Table 5, respectively. This indicates that the population mean can be discriminated against each other. The IoT WQM device was tested using samples from the Pasar Jerami's River, Sabak Bernam, which was located near the experiment site. The TDS and EC output results from the river were sent to the ThingSpeak server field as shown in Figure 10.

Table 4. Paired sample T-test for clean river water and polluted river water based on EC properties

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of Difference				
				Lower	Upper			
Pair 1 Drain_EC - Tap_EC	.56868	.01125	.00113	.56645	.57091	505.331	99	.000

Table 5. Paired sample T-test for clean river water and polluted river water based on TDS properties

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of Difference				
				Lower	Upper			
Pair 1 Drain_TDS - Tap_TDS	284.330	5.62831	.56283	283.21322	285.44678	505.178	99	.000

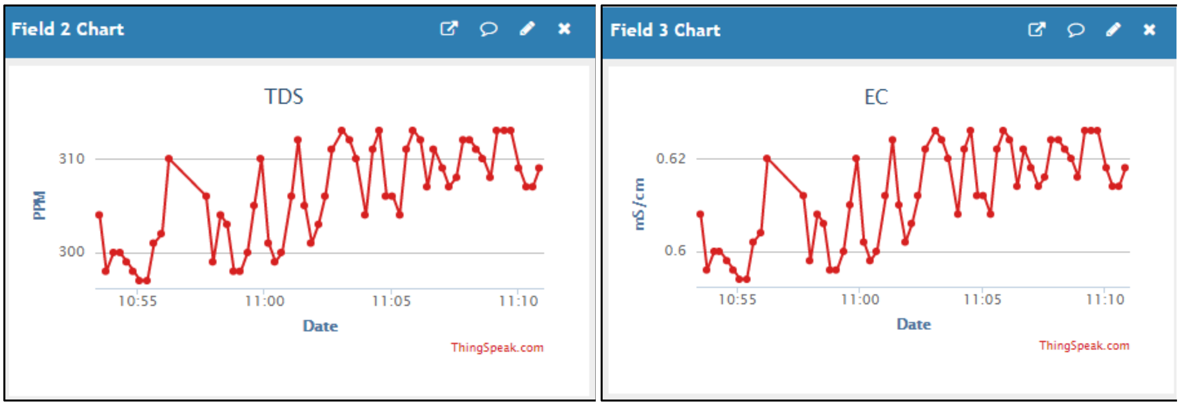

Figure 10. TDS and EC output from ThingSpeak server for river water

Only TDS data from the river (Pasar Jerami's River, Sabak Bernam), polluted river water (drain water from Sungai Besar, Sabak Bernam) and clean river water (tap water from households near Sabak Bernam) were analyzed using the IBM SPSS statistical tool to discriminate between the sample populations and classify the river as either clean or polluted. By looking at Table 6, it can be seen that the river near Pasar Jerami, Sabak Bernam, Selangor can be categorized as a clean river based on its TDS properties.

Table 6. Descriptive statistics for TDS value between drain, tap and river water samples

Descriptive								
TDS Value	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Drain	100	517.3600	6.04949	.60495	516.1596	518.5604	506.00	528.00
Tap	100	233.0300	5.86456	.58646	231.8663	234.1937	222.00	244.00
River	100	301.5900	7.06120	.70612	300.1889	302.9911	290.00	313.00
Total	300	350.6600	121.51939	7.01592	336.8532	364.4668	222.00	528.00

According to Ramadhan [15], the maximum permissible TDS standard is 500 mg/liter or 500 ppm. However, the river water is still not suitable to be consumed directly since the value of the TDS exceeded the TDS limit that has been stated by the World Health Organization (WHO) [27]. Based on the collected data, the TDS values for river water were between 290 ppm and 313 ppm, respectively. The low level of TDS value at Pasar Jerami's River may be due to having no activity carried out in the area as it was during the lockdown.

4. CONCLUSION

In conclusion, the device that has been developed is able to distinguish between clean and polluted water by comparing the values of TDS and EC. The developed device can provide a better alternative for measuring water quality, and it gives an advantage by having the function to read and store real-time data. After testing the device at Pasar Jerami's River, it can be concluded that the IoT WQM device is reliable to test the condition of the river by looking at the values of TDS and EC. In statistical analysis, it shows that the value of the normality test for both samples is greater than 0.05. Meanwhile, the p-value for the paired sample t-test is less than 0.05. This strengthens the point that the device can distinguish between clean and polluted water.

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