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Analysis comparison, calibration, and application of low-cost soil moisture in smart agriculture based on internet of things

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ABSTRACT

The gravimetric method is one of the most accurate for determining soil water content (SWC). Several low-cost sensors have been developed to simplify measuring water content in soil by measuring soil moisture. However, the sensor must be calibrated to determine soil moisture parameters accurately. In this research, comparative analysis, and calibration of resistive and capacitive low-cost sensors were carried out. The calibration method for each sensor uses the gravimetric water content (GWC) and volumetric water content (VWC) methods. Measuring changes in SWC using sensors is performed in real time based on internet of things (IoT). Based on the measurements of the capacitive, resistive type 1, and resistive type 2 sensors with three repetitions, the linear regression R^2 values were obtained at 0.980, 0.827, and 0.942, respectively. Furthermore, a stability test is carried out to see how stable the sensor is when making measurements over a long period. The result is that the capacitive, resistive type 1, and resistive type 2 sensors have errors 1.971×10^{-4}, 7.001×10^{-4}, and 6.270×10^{-4}. Based on the results obtained, capacitive sensors have the highest level of accuracy and stability. Furthermore, capacitive sensors are applied to IoT-based agriculture with long range (LoRa) as communication data.

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1. INTRODUCTION

Soil moisture is crucial in assessing several environmental and agricultural processes, including climate change, drought prediction, and irrigation scheduling. It is essential for evaluating water stress on agricultural land. For optimal plant growth in agriculture, providing water in the appropriate quantity, at the correct timing, and with high quality is crucial [1]–[9]. Controlling the water supply in agriculture is crucial for promoting optimal plant growth and conserving water resources for other purposes.

The main factor governing the interchange of water and heat energy between the soil surface and the atmosphere through evaporation and plant transpiration is soil moisture, which establishes the amount of water in the soil. Soil moisture can affect plant health, growth, and production. Generally, soil moisture requirements are met through irrigation or rainfall processes. Controlled irrigation functions manage good water to maintain soil moisture in the plant root zone [10]–[16]. Soil moisture information on agricultural land must be obtained accurately and precisely to make appropriate predictions and estimates as one of the variables influencing agricultural crop yields. Hence, the surveillance of soil moisture levels is a crucial factor in agriculture since it directly impacts crop yield outcomes.

Plants necessitate varying quantities of water throughout their growth cycle, which fluctuates in response to shifting climatic circumstances [17], [18]. Precise irrigation scheduling can be achieved by monitoring the soil moisture content in real-time [19]–[21]. Soil moisture can be measured in two ways: directly and indirectly. The gravimetric method is very accurate and straightforward for quantifying soil moisture. Nevertheless, this approach requires a significant amount of manual labor and consumes considerable time despite its ability to yield precise measurements of the current soil moisture levels. The method of indirectly assessing soil moisture using sensors involves monitoring alterations in the internal characteristics of the sensor system as a proxy for soil water content (SWC). Soil contact-type sensors can directly measure soil moisture content in addition to the gravimetric approach. Several precise sensor-based measurements include the team-domain reflectometry method, time-domain transmission, frequency domain reflectometry, neutron probes, electrical resistance, electromagnetic sensors, and widely utilized tensiometers. Nevertheless, the higher installation costs and the substantial dimensions make these approaches less favored for soil moisture monitoring [22]–[24].

This research was conducted to compare the capabilities of cheap commercial soil moisture sensors for applying soil moisture monitoring in smart agriculture. The measurement results of each sensor will be compared with the calculation results using the gravimetric water content (GWC) and volumetric water content (VWC) methods as has been done by [25]–[28]. The sensors used in this research are three different sensors with resistive and capacitive-based measurements. Capacitive-based soil moisture measurements are carried out by measuring changes in the media's dielectric constant due to changes in water content, while resistive-based measurements work by measuring the resistance between sensor electrodes [29].

In this research, measurements are carried out in real-time using internet of things (IoT) technology to monitor soil moisture anytime and anywhere. Determining the best sensor results can be seen from the level of sensor precision in several repeated measurements; then, linear regression is carried out, as well as determining the error of each sensor in several measurements using samples with the same water content in the soil. Detectors with the best accuracy and precision will be used for direct monitoring of agricultural land and as essential parameters for carrying out irrigation processes based on the water needs of each plant.

2. THE COMPREHENSIVE THEORETICAL BASIS

2.1. Soil moisture measurements

Both direct and indirect measurement techniques typically assess soil moisture. The direct method is a conventional measurement approach that determines the water content in soil by either the gravimetric method (also known as the oven drying method) or the volumetric method, which involves primary measurements of the mass or volume of water and soil, respectively. The gravimetric oven drying method involves drying the soil in an oven at a specific temperature range of 105 °C to 110 °C for 24 hours. The resulting dry soil mass is then measured and recorded. Subsequently, the soil is saturated with water, and the mass of the saturated soil is measured to ascertain the mass of water present in the soil, allowing for the calculation of the GWC, expressed as a percentage, which serves as an indicator of soil moisture. The GWC is determined by dividing the mass of water in a particular amount of dry soil by the mass of the dry soil itself. This ratio is expressed in units such as grams of water per gram of soil. The calculation for GWC is represented by (1):

$$\theta_g = \frac{M_w}{M_s} = \frac{M_{wet} - M_d}{M_d} \tag{1}$$

M_w, M_s, M_{wet}, and M_d are the mass of water, soil mass, wet soil mass, and dry soil mass in the soil.

Volumetric techniques directly measure soil moisture by quantifying the proportion of VWC. VWC is determined by dividing the water volume by the dry soil volume. The link between ground (GND) water content (GWC) and vadose zone water content (VWC) is described as:

$$\theta_v = \frac{V_w}{V_s} = \frac{\frac{M_w}{\rho_w}}{\frac{M_s}{\rho_s}} \tag{2}$$

$$\theta_v = \frac{M_w}{M_s} \cdot \frac{\rho_s}{\rho_w} \tag{3}$$

$$\theta_v = \theta_g \cdot \rho_s \tag{4}$$

ρ_w is the density of water, assumed to be 1 g/cm³. Therefore, (4) shows the relationship between GWC and VWC, where ρs is the combined density of the soil. The integrated density of soil is determined by dividing the weight of dry soil by the soil volume, as expressed in the (5).

$$\rho_s = \rho_{bulk} = \frac{Weight\ of\ dry\ soil}{Volume\ of\ soil} \tag{5}$$

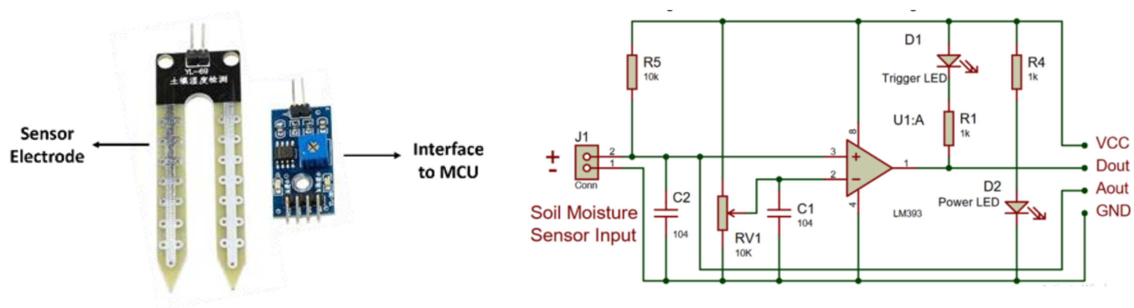
The indirect approach involves utilizing a soil moisture sensor to detect changes in electrical parameters that are influenced by the moisture content of the soil, hence generating an output. The sensor output is analyzed and adjusted to measure soil moisture accurately. These measurement methods are distinguished by many physical concepts, such as the soil's dielectric characteristics or the soil matrix's potential, which vary depending on the amount of water in the soil [30]. The indirect method uses several soil parameters, such as soil resistance and capacitance, to gauge water content. Standard soil moisture sensors that utilize indirect techniques include tensiometers, electrical resistance blocks, capacitive sensors, and time-frequency domain reflectometer sensors [26], [31].

2.2. Low-cost soil moisture sensor

This study examines the performance of two widely used soil moisture sensors, specifically the resistive soil moisture sensor (groove resistive soil moisture sensor type) and the capacitive soil moisture sensor (capacitive soil moisture sensor V2.0). The sensors were tested, calibrated, and modeled to improve the precision of GWC measurements. Moreover, a comparison is conducted between the two types of sensors to assess their accuracy and precision performance. This analysis establishes criteria for selecting sensors for use in agricultural land applications [24], [31]. These sensors have generally been widely used in projects related to irrigation management in IoT because they are cheap, relatively small in size, and easy to use [31]–[34]. These sensors offer a readily available processed, amplified, and scaled voltage output in response to changes in soil moisture. Furthermore, these sensors operate with minimal direct current (DC) excitation (EXC), have low power consumption, and may be directly connected to low-power microcontrollers, data-gathering devices, and IoT platforms using three-pin connectors [35].

The resistive soil moisture sensor, depicted in Figure 1(a), is specifically intended to measure the moisture content in soil for plants. Resistive soil moisture sensors measure soil moisture levels by monitoring soil resistance. The basic principle of this sensor is that the resistance value of a material, in this case soil, can change based on the surrounding humidity level. Resistive soil moisture sensors consist of two electrodes plugged into the soil. When the soil is dry, the resistance between the two electrodes is high because dry soil has low electrical conductivity. Conversely, electrical conductivity increases, and resistance decreases when the soil is moist or wet.

Figure 1(b) displays the circuit interfacing with the resistive sensor. When the signal is on the circuit board, the resistance change is transformed into a higher voltage adjusted to a range between 0 and 3.3 volts. This sensor necessitates a 5V DC excitation and utilizes 75 milliwatts (mW) of electricity. The interface of this sensor is uncomplicated, consisting of three pins for EXC, GND, and output (V).



(a) (b)

Figure 1. Resistive soil moisture sensor type 1: (a) electrode sensor and (b) circuit sensor

The resistive soil moisture sensor type 2 has the same measurement procedure and interface as the resistive sensor type 1 used in this study. The primary difference between the two sensors is the shape of the electrodes. The general characteristics of resistive soil moisture sensors involve the measurement of resistance and its conversion into moisture values. Figure 2 shows the electrodes of the resistive sensor type 2 [14], [36], [37].

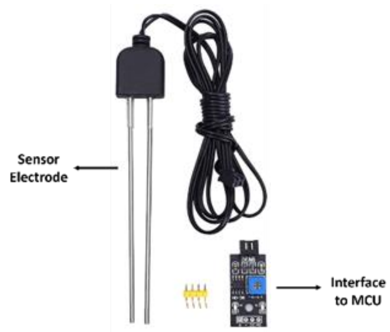
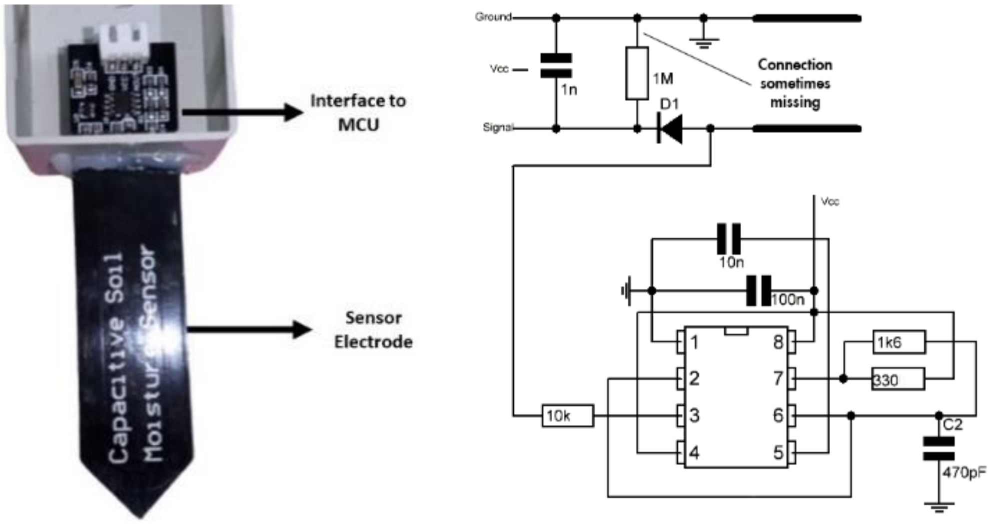


Figure 2. Resistive soil moisture sensor type 2

The capacitive soil moisture sensor, seen in Figure 3(a), operates by detecting variations in capacitance resulting from alterations in dielectric properties produced by fluctuations in soil moisture levels. This sensor does not directly quantify humidity; it quantifies water-soluble ions (moisture). Various variables can affect ion concentrations, with soil moisture being a prominent factor. Figure 3(b) is used to measure changes in sensor capacitance. It is conducted by employing a 555-timer circuit that generates a voltage directly proportional to the capacitance created by the capacitive sensor when placed in the GND. The sensor is inherently embedded into this circuit. The soil moisture sensor provides a voltage output ranging from 0 V to 3 V, corresponding to a soil moisture level between 0% and 100% [38], [39].



(a) (b)

Figure 3. Capacitive soil moisture: (a) electrode sensor and (b) circuit sensor

3. METHOD

Figure 4 illustrates the sequence of steps in the calibration experiment. The experimental results provide the GWC value, which is then used to determine the VWC by using the GWC value obtained and the bulk density of each soil volume. The primary prerequisite for the experiment is that the soil must be entirely moisture-free. Multiple measurements of the soil are optimal to ascertain this, supposing it has remained devoid of moisture for a considerable duration. If there is a substantial change in mass, water will remain trapped in the soil and continue to evaporate. Once the mass remains constant throughout multiple measurements, it can be regarded as the mass of dry soil (MD).

The density is commonly recognized and approximated to be approximately 1000 kg/m^3. Soil bulk density can be determined by measuring the volume of a specific soil sample, drying the material, weighing it, and then dividing the weight of the soil by the initial volume. Figure 5 illustrates the standard process for calibrating a soil moisture sensor using the gravimetric approach.

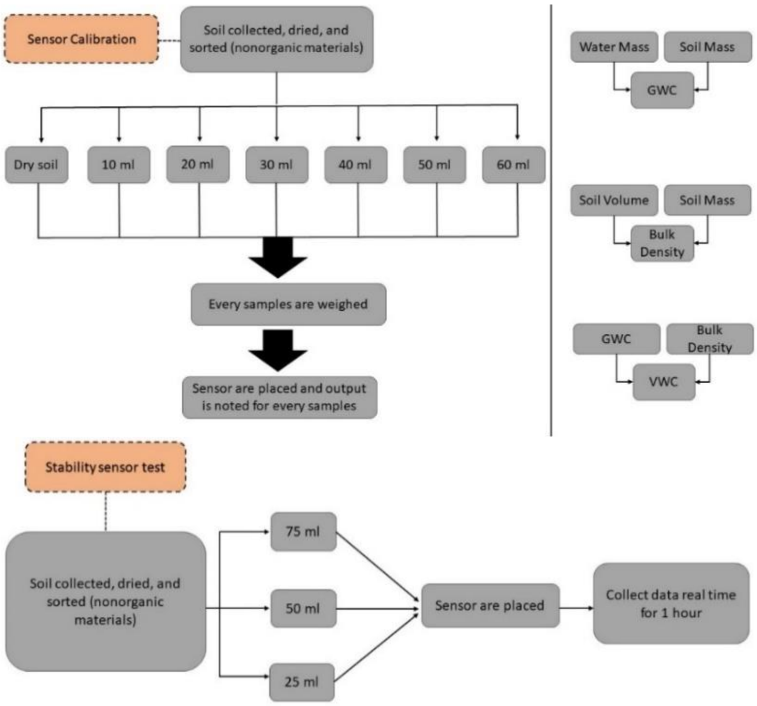


Figure 4. Experiment flow

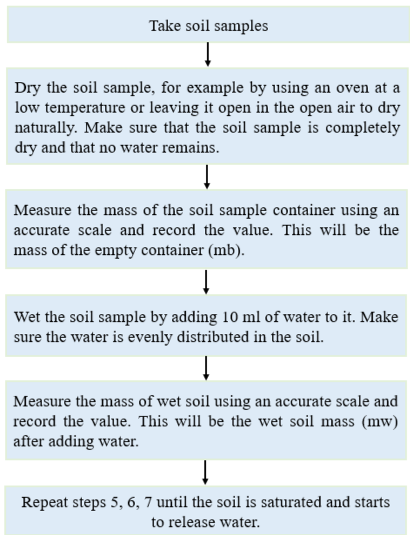


Figure 5. General procedure for calibrating a soil moisture sensor via the gravimetric method

Research has been conducted on resistive and capacitive soil moisture sensors to analyze how changes in the quantity of water added to a fixed amount of soil affect their performance. The experiment was designed to ensure that the sensor response is unaffected by other environmental factors, such as fluctuations in ambient temperature and humidity. This experiment is conducted in a laboratory, and the experimental data is sent to a cloud server. Then, the data is collected and processed to get the best sensor for soil moisture. After laboratory measurements, the sensor was applied directly to the Cilembu sweet potato farm.

IoT system measurements and schematics are shown in Figure 6. The data delivery system uses long range (LoRa) to the gateway connected to the local server, and then the data is sent to the cloud server using a Wi-Fi connection. The gateway system has a Raspberry Pi consisting of Node-RED, InfluxDB, and user interface. Node-RED is used as the basis of the entire system where analytical data can be carried out, InfluxDB is used as a database, and the user interface is used as a data display medium.

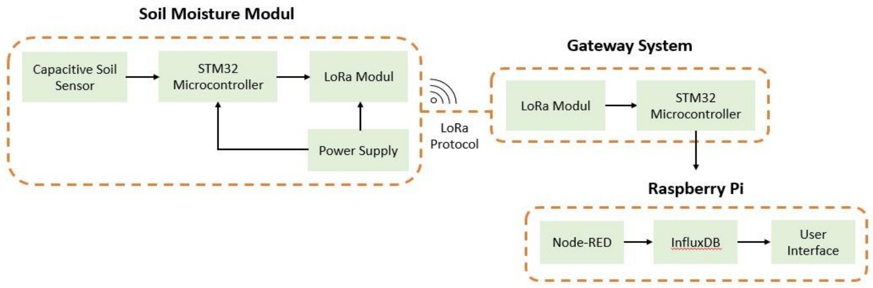


Figure 6. IoT system measurements and schematics

4. RESULTS AND DISCUSSION

This study compares three types of inexpensive commercial soil moisture sensors to determine the advantages and disadvantages of each type of sensor. The calibration process in this study was carried out by looking at the relationship of SWC to changes in the voltage value read from each sensor. The water content in the soil is calculated using the GWC and VWC methods based on (1) and (4). The calibration results of each sensor are shown in Figures 7(a), 7(b), and 7(c).

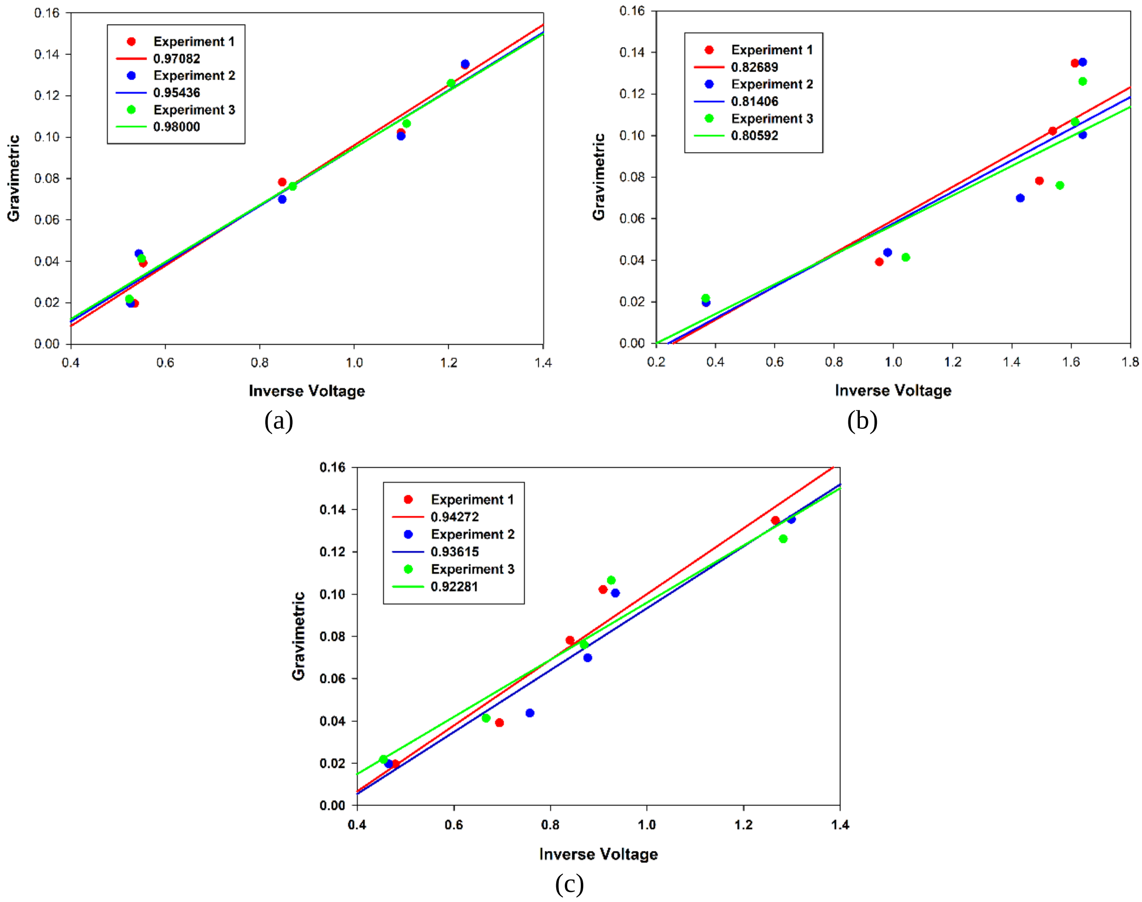


Figure 7. Calibrate three types of sensors against GWC values: (a) capacitive sensor, (b) resistive sensor type 1, and (c) resistive sensor type 2

Figure 7 shows measurements of three types of soil moisture sensors repeated three times. The measurement results show that the inverse sensor voltage is proportional to the increase in water content in the SWC soil. The relationship between SWC and the inverse output voltage of each sensor can be determined by linear regression between the points obtained. The results of linear regression (R^2) for capacitive sensors for each measurement are 0.97082, 0.95436, and 0.9800, for resistive sensor type 1, the results obtained are 0.82689, 0.81406, and 0.80592, while on the resistive sensor type 2, it is 0.92472, 0.93615, and 0.92281. Next, a comparison of the sensor response against time is carried out to see the stability of the sensor during the measurement. The measurement results are shown in Figures 8(a), 8(b), and 8(c).

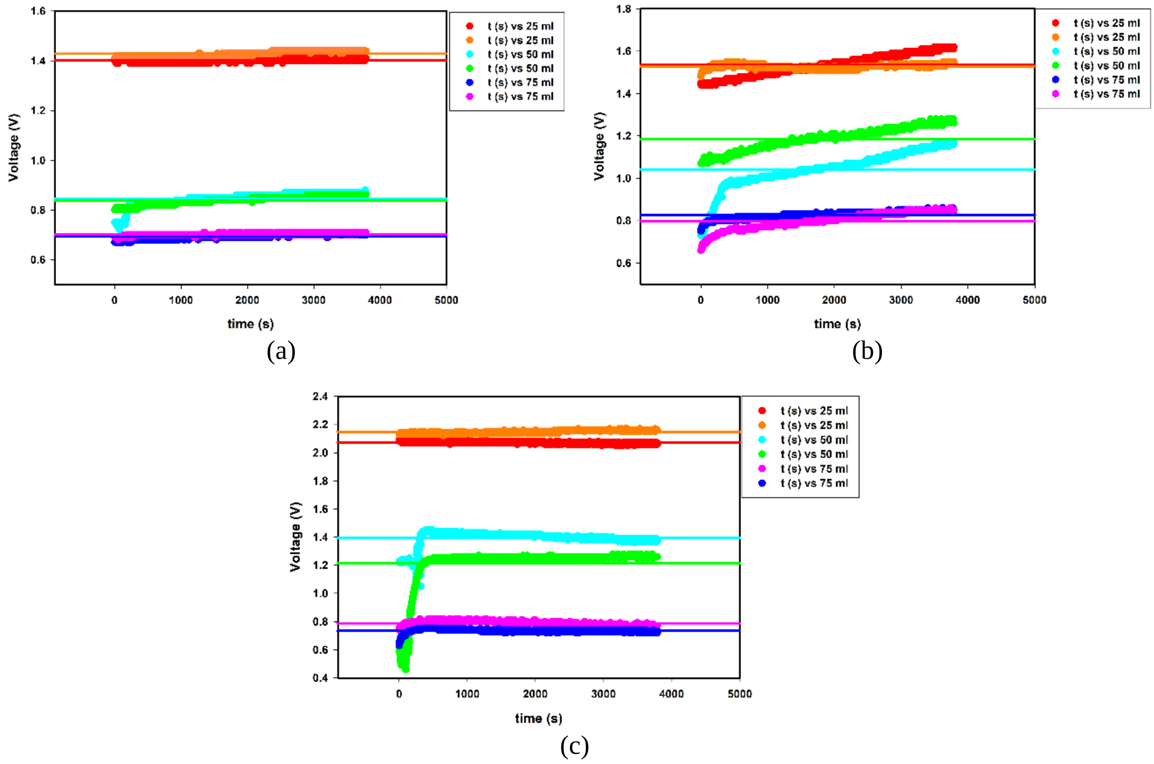


Figure 8. Stable level measurement of three types of sensors to time: (a) capacitive sensor, (b) resistive sensor type 1, and (c) resistive sensor type 2

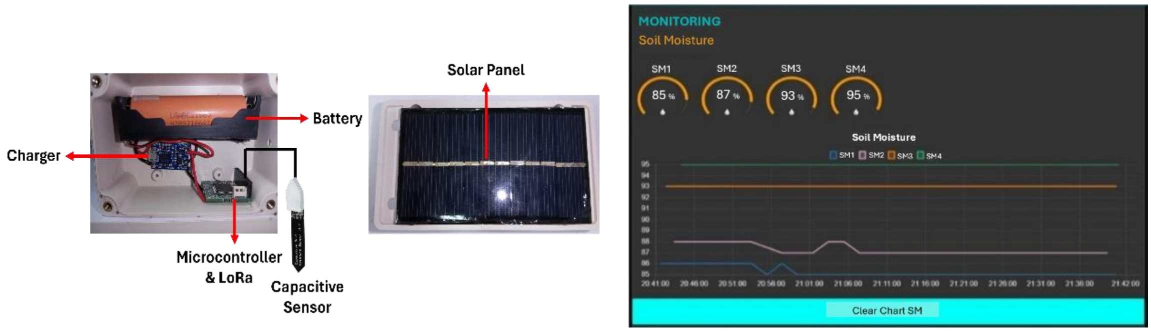
The stability level of the sensor is calculated by finding the average value and the standard deviation resulting from each type of sensor for one hour of measurement. The results of calculating each sensor's average value and standard deviation with two repetitions are shown in Table 1. Capacitive sensors have a better level of stability than resistive sensors type 1 and type 2. They are validated by the standard deviation range obtained from each measurement. Table 1 shows that the largest standard deviation is the resistive sensor type 1, and the smallest is the capacitive sensor. The higher the standard deviation value, the greater the measurement deviation, indicating that the sensor is increasingly unstable.

Table 1. Comparison of standard deviation and error calculations for each sensor

Sensor type	Soil+water (ml)	Experiment 1			Experiment 2		
		Average (V)	Deviation standard	Error	Average (V)	Deviation standard	Error
Capacitive	25	1.4022	5.382×10^{-3}	8.742×10^{-5}	1.4285	9.676×10^{-3}	1.571×10^{-4}
	50	0.8448	0,0275	4.463×10^{-4}	0.8388	0.0169	2.745×10^{-4}
	75	0.6924	8.513×10^{-3}	1.382×10^{-4}	0.7014	4.883×10^{-3}	7.933×10^{-5}
Resistive 1	25	1.5347	0.0520	8.442×10^{-4}	1.5273	9.812×10^{-3}	1.496×10^{-4}
	50	1.0422	0.0883	1.434×10^{-3}	1.1841	0.0533	8.651×10^{-4}
	75	0.8260	0.0165	2.679×10^{-4}	0.7987	0.0394	6.399×10^{-4}
Resistive 2	25	2.0726	7.421×10^{-3}	1.205×10^{-4}	2.1486	9.778×10^{-3}	1.588×10^{-4}
	50	1.3935	0.0516	8.387×10^{-4}	1.2155	0.1385	2.249×10^{-3}
	75	0.7878	0.0131	2.126×10^{-4}	0.7333	0.0110	1.788×10^{-4}

Table 1 also shows that the highest error in the first experiment occurred in measurements using a resistive sensor type 1, and the lowest was on a capacitive sensor. In the second experiment, the highest error was the resistive sensor type 2, and the lowest was the capacitive sensor. The average error of each sensor is capacitive 1.971×10^{-4}, resistive type 1 is 7.001×10^{-4}, and resistive type 2 is 6.270×10^{-4}. Based on the results above, capacitive sensors have the highest level of stability with the lowest error results and standard deviation.

Furthermore, the measurement field test examined the sensor's response when the soil experienced increased water. The faster the sensor response, the faster and more accurate the information sent for water control. Therefore, testing the sensor response speed displayed in real-time based on IoT is necessary. Monitoring changes in measured values from the soil moisture sensor are shown in Figures 9(a) and 9(b).



(a) (b)

Figure 9. LoRa and IoT-based monitoring system: (a) system configuration and (b) user interface display of the soil moisture monitoring system

The sensor response is displayed via the user interface from data stored on the cloud and local servers. Based on this, comparing three types of commercial sensors (resistive type 1, resistive type 2, and capacitive) shows that capacitive sensors have advantages in accuracy, precision, linearity, and high response time. In addition, resistive sensor type 1 is more susceptible to corrosion, whereas capacitive and resistive sensor type 2 are more resistant to decay. When used in the GND and open spaces, capacitive sensors must be protected because the circuit is integrated with the sensor electrode, so the sensor will be damaged if it comes into contact with water. In contrast, resistive type 1 and type 2 sensors have a separate interface with the electrode, making them safer. Applying sensors into the soil is more straightforward using resistive sensors type 1 and type 2. In contrast, using capacitive sensors is more difficult to insert in soil with a high density.

5. CONCLUSION

Each sensor type used in smart agricultural applications was compared by calibrating measurements of capacitive, resistive type 1, and resistive type 2 sensors. According to the investigation, capacitive sensors present better accuracy and stability than two resistive sensors when measuring soil moisture. In addition, the capacitive sensor has corrosion resistance so that the sensor electrode is safe from external influences. However, capacitive sensors have an interface circuit integrated with the electrode. Hence, they are vulnerable to damage if exposed to water, while resistive type sensors have a separate circuit from the electrode to be placed in a safe place and out of reach of water. Based on the results of calibration and comparison, the soil moisture sensor chosen for monitoring soil moisture on agricultural land is a capacitive sensor. Measurements are carried out in real-time based on IoT to store data on local and cloud servers. Sending data from several sensor nodes to the local server uses radio frequency-based LoRa communication while sending data from the gateway to the cloud server uses Wi-Fi.

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