Re-Calibration of Model-Based Capacitive Sensor for IoT Soil Moisture Measurements

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ABSTRACT

Low-cost automatic irrigation systems require quality calibrated soil moisture sensors. The sensor is an indirect method of soil moisture measurement. The sensor works based on the change in the dielectric constant. So, it requires to be calibrated in terms of the soil water content. Polynomial and linear models are frequently used to calibrate soil moisture sensor data in the gravimetric test method. However, computational effort is required. This study aims to obtain a sensor calibration application that can provide the best model of the available models for model-based capacitive soil moisture sensor. This research was conducted using primary data from gravimetric test experiment on Internet of things (IoT) based soil moisture sensor. Web-based re-calibration application produced best model based on adjusted R Squared. Finally, model-based capacitive soil moisture sensor set up using best model coefficient. The results show that the web-based re-calibration application can provide the best model for model-based capacitive soil moisture sensor. Based on gravimetric test experiments and web applications, the best model is a polynomial regression model order 3 with 0.945 adjusted R Squared. The model predicted value for soil moisture is in the range 0 – 1.2 for raw sensor data values of 100 – 530. When the model coefficient configured in capacitive soil moisture sensor and Blynk application, soil moisture measurement can be done via mobile phone in real time.

I. Introduction

Many researchers are interested in calibrating sensors to measure soil moisture content. Soil moisture sensor calibration is required to be able to develop a low-cost automatic irrigation system. Considering that the performance of soil moisture sensors is highly dependent on the physical and chemical properties of the soil, the development of a durable low-cost soil moisture monitoring automation system depend on the quality of the calibrated sensor [1].

A thermo-gravimetric, which technique by drying the soil sample in an oven, have been developed to measure soil moisture content. So, dry soil is given a certain volume of water and then the moisture sensor value is measured. Because the moisture sensor is a qualitative measurement, the soil moisture sensor value is expected to change as the water volume increases. This technique commonly as the regular reference because it can provide more accurate measurements. Extended technique of thermos gravimetric be carried out based on data-driven [2].

Polynomial and linear regression models are frequently used to calibrate soil moisture sensors data. Ordinary polynomial regression analysis is often used for curve fitting while the linear regression model is used for linear fitting. Both models express R Squared as a relationship measurement. The order of the polynomial necessary to explain the dependent variable. But, computational effort required [3].

This research aims to provide an application, which interactively allows retrieving a calibration equation, based on user defined requirements. This application makes gravimetric tests easier and accommodates the use of non-linear models to determine the best model. Interactive web-based calibration application as has been done previously by

[4] but not using capacitive soil moisture sensor. Our previous research [5], [6], we calibrated a percentage-based soil moisture sensor. The percentage is calculated using observation data when the sensor is in the air and immersed in water. There are many missing values found in the stored data. This indicates that the sensor calibration process is not adaptive, especially if used for a long period of time. So that, this research aims to visualise data points and the estimated linear and non-linear model in a web-based application. Additional features are an interactive web application handles small sample sizes problem for model selection by using adjusted R squared. The coefficients model obtained is then programmed into an Arduino Uno which is connected to a mobile phone so that an IoT model-based soil moisture sensor is formed.

II. METHOD

This research is quantitative research. Analysis was conducted using primary data from gravimetric test experiment on soil moisture sensors. Interactive web dashboard system compiled using R Software. The steps of this research are as follows:

1) Build an Internet of things (IoT) based soil moisture sensor. The process of measurement of soil moisture can be seen via mobile phone through the Bynk application which is connected to the internet.

2) Perform a gravimetric test experiment. Instead of using an oven, the soil is dried using 100 ml of 95% alcohol for 100 ml of sun-dried soil samples. The number of data used in this research is five, which comes from the level of increase in water volume. The gravimetric test steps as follows:

- Prepare 1000 ml of dry soil sample in a container
- 100 ml of soil sample was taken and then dried using 100 ml of 95% alcohol. The burning process was carried out twice with 50 ml of 95% alcohol each. After that, the soil sample was cooled and then its weight was measured for Gravimetric Water Content
- The next step is to measure the dry weight of the soil.
- Measure and record soil moisture using an IoT-based soil moisture sensor
- Repeat steps c) & d) at increasing levels of water volume, namely 100 ml, 200 ml, 300 ml and 400 ml.
- Perform volumetric soil moisture content calculations using equations (1) and (2)

3) Modelling the gravimetric test results. Modelling process performance evaluation using adjusted R Squares. Modelling was carried out using linear and polynomial regression model in R stat package [7].

4) *Set up Re-calibration Application.* The re-calibration application uses the R shiny package in the R application [8].

5) Assemble a model-based capacitive soil moisture sensor system. The model coefficients resulting from the re-calibration are then programmed into the Arduino.

A. Gravimetric Test

Gravimetry is a method of determining soil moisture. The soil moisture sensor is calibrated based on gravimetric results on soil samples before being installed in the field. After weighing the fresh weight, the samples were dried at 105 ºC. Soil water content is determined using the equation

$$\theta_g = \frac{(m_{wet} - m_{dry})}{m_{dry}} \tag{1}$$

Where, θ_g is the gravimetric soil moisture content, m_{wet} and m_{dry} is the fresh and dry weight of soil (g). The gravimetric soil moisture content was converted to volumetric soil moisture content using

$$\theta_v = \frac{\theta_g \; x \; \rho_{soil}}{\rho_{water}} \tag{2}$$

Where, θ_v is the volumetric soil moisture content, ρ_{soil} and ρ_{water} are soil and water density. $\rho_{water} = 1\ gcm^{-3}$. The digital value that the sensor observes varies by sensor type. Linear, quadratic and exponential relationship patterns can be found between the volumetric soil water content and the sensor digital value. The greater the coefficient of determination, the better the relationship pattern obtained. [9]

Gravimetric test is one of the most frequently used tests in soil moisture sensor calibration. The concept of the gravimetric test is that the moisture sensor is able to follow changes for the increasing of water volume in previously dried soil. Some of the studies using the Gravimetric test are as follows.

TABLE 1.
PREVIOUS RESEARCH ON THE GRAVIMETRIC TEST

No	Authors	Input Variables
1	Shukla et al., 2014 [10]	Moisture content in dry weight (g), water content in volumetric (ml), volume of water (ml), volume of soil (cm³), bulk density (g/cm³), Sensor data (v)
2	Hrisko, 2020 [11]	container mass (g), sensor data(v), Density of Water ($k.gm^{-3}$), Mass of Dried Soil from 200ml (g), Bulk Density of Soil ($g.ml^{-1}$), Soil Volume (ml)
3	Ogwo et al., 2020 [12]	Weight of wet soil (g), Weight of oven dry soil (g), Weight of water (ml), Gravimetric percentage moisture content (g), Sensor Capacitance Reading (v)
4	Setyowati et al., 2020 [13]	Weight of wet soil (g), Weight of oven dry soil (g), Soil Moisture Sensor (v)
5	Campbell et al., 2023 [14]	Volumetric water content (cm³/cm³), volume of water (cm³), mass of the dry soil (g), density of water (1 g/cm³), density of dry soil (g/cm³), soil volume(cm³), raw sensor data (v)

Table 1 shows that although using different types of soil and sensors, in general gravimetric tests are carried out by calculating soil volume (cm^3), container weight, mass of the dry soil (g), bulk density (g/cm^3), mass of the wet soil (g) and raw sensor data (v). The difference in the gravimetric test is whether the gravimetric soil moisture content (θ_g) is done iteratively [10], [12] or without iteration [11], [13], [14] . If it's done iteratively, the bulk density (ρ_{soil}) will be recalculated for each increase in the volume of water in the soil. Conversely, without iteration, bulk density (ρ_{soil}) is only calculated once using a soil sample and then used for each increase in the volume of water in the soil. In this research, we use gravimetric test without iterations because it provides efficiency in the measurement process without sacrificing the quality of the test results.

B. *Regression Model*

Data from the gravimetric test results were then analysed using a soil moisture sensor as the independent variable and volumetric soil moisture content as the dependent variable. The model to be used is based on following a linear or quadratic pattern.

Lot of time and cost required make it impossible to calibrate the soil moisture sensor at all levels of increasing water volume. The output value of the soil moisture sensor, for all levels of increasing water volume, is obtained based on the predicted value of the linear or non-linear models. The linear model (linear regression) will provide a prediction of the maximum voltage generated by the soil moisture sensor so that soil moisture can be calibrated using a percentage ratio. Linear regression models are very often used for modelling soil moisture as has been done by [15]. The linear model to be used is as follows:

$$\hat{y} = \beta_0 + \beta_1 x_1 + \varepsilon \tag{3}$$

The non-linear model will provide predictions of soil moisture by assuming the soil moisture sensor voltage varies during time the sensor is used. The non-linear model that will be used in this study is a polynomial model with order 2 and 3. The polynomial model is as follows

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_1^2 + \beta_3 x_1^3 + \varepsilon \tag{4}$$

The model results will then be evaluated using R squared (R^2). Considering that the number of observed samples in the gravimetric test is small, the adjusted R squared is used. The adjusted R squared equation is as follows [16].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \tag{5}$$

$$R^2_{adjusted} = R^2 - \frac{(1-R^2)k}{n-(k+1)} \tag{6}$$

III. RESULT AND DISCUSSION

A. *IoT-Based Soil Moisture Sensor*

The Internet of Things (IoT) makes it easy for users to measure soil moisture using various electronic devices. The IoT soil moisture sensor uses Arduino Uno as a controller and the ESP-01 Wifi module as a wireless transceiver. The IoT Based Soil Moisture Sensor circuit is as follows:

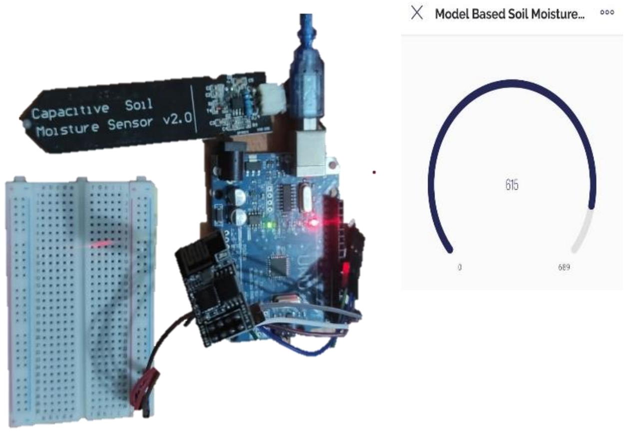

Figure 1. IoT-Based Soil Moisture Sensor

Figure 1 shows that the appearance of the IoT-based soil moisture sensor circuit. IoT-based soil moisture sensor using capacitive sensor with 5.5v power supply. The output value of IoT-based soil moisture before calibration is in the form of voltage (v). This circuit gets a voltage of 615 (v) in air conditions and 240 (v) when in water. The changes in voltage values indicates that IoT-based soil moisture sensor able to describe soil moisture under various condition.

B. *Gravimetric Test*

Soil moisture can be determined by carrying out a gravimetric test. The experiment was carried out on 1000 ml of soil. Next, 100 ml of soil sample was taken and then dried using 100 ml of 95% alcohol. The burning process was carried out twice with 50 ml of 95% alcohol each time. The drying process lasts for 5 minutes 10 seconds and 4 minutes 30 seconds. After that, the sample soil was cooled and then its weight was measured. The measurement results are as follows:

TABLE 2.
GRAVIMETRIC WATER CONTENT

Item	Values	Units
Wet Soil + Tin	86	g
Dry Soil + Tin	78	g
Tin Weight	17	g
Gravimetric Water Content	0,131147541	$g\ g^{-1}$

Gravimetric water content as shown in Table 2 was only carried out once on a 100 ml soil sample. This value is then used as a correction factor for dry soil measurements under air dry conditions for 1000 ml of soil. The dry soil measurement is then used as m_{dry}.

The next step is that measurements are carried out at five levels of increase in water volume, namely air dry, 100 ml, 200 ml, 300 ml and 400 ml. For each increase in water volume, measurements are also carried out using an IoT-based soil moisture sensor. The results of the gravimetric test experiment are as follows.

TABLE 3.
GRAVIMETRIC TEST

Volume of Water	**Soil + Container Weights (g)**	m_{wet} **(g)**	$m_{wet} - m_{dry}$ **(g)**	θ_g	θ_v	**Sensor Measurement**
Air dry	676	656	86,03	0,150	0,086	530
100 ml	770	750	180,03	0,315	0,180	360
200 ml	836	816	246,03	0,431	0,246	270
300 ml	931	911	341,03	0,598	0,341	246
400 ml	1002	982	412,03	0,722	0,412	214

Table 3 shows that the greater the soil + container weights, the smaller the sensor measurement. The same pattern was also obtained for volumetric soil moisture content (θ_v). The θ_v value is obtained using ρ_{soil}=0.57. To obtain predictions of soil moisture, the θ_v and sensor measurement values are then modelled into the linear and polynomial regression models.

C. Model

Volumetric soil moisture content and raw sensor data were analyzed using linear regression and polynomial regression models. The volumetric soil moisture content becomes the response variable (y) and raw soil moisture sensor data becomes the predictor variable (x). Adjusted R Squared is then carried out for each model as follows:

TABLE 4
MODEL SELECTION

Model	**Adjusted R Squared**
Linear Regression	0.821
Polynomial Regression Order 2	0.927
Polynomial Regression Order 3	0.945

Table 4 shows that polynomial regression order 3 has the highest Adjusted R Squared value. Adjusted R Squared of 0.945 means that 94.5% of the variation in volumetric soil moisture content can be explained by the model. The polynomial regression order 3 equation is then used to predict soil moisture.

D. Re-calibration Application

Based on the results of the analysis that has been carried out, an interactive web application is assemble using the shiny package in R. An interactive web application uses an event observation system, namely specific actions that must be taken from the user before calculating an expression, on the analyze button. The web application can be accessed and used on pages that have links:
https://statisticsontraining1.shinyapps.io/soilmoisture/.
The re-calibration application algorithm to produce the best model is as follows.

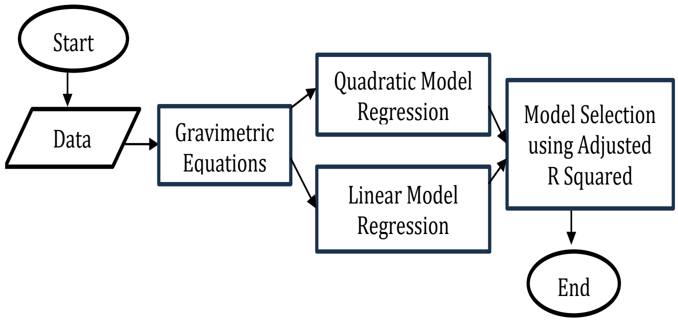

Figure 2. Algorithm for recalibration application

Figure 2 shows the stages of the gravimetric test results modelling process. Recalibration will use gravimetric test input to produce the best model coefficients that will be used for capacitive sensor recalibration. The input panel display is as follows:

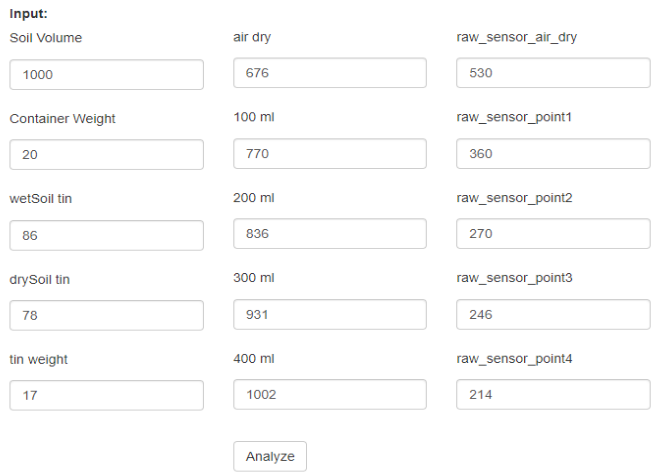

Figure 3. Input Panel of Re-calibration Application

Figure 3 shows that the input panel on the web dashboard application divided into three columns. The first column is to calculate the gravimetric water content in dry soil sample. The second column is the mass of the soil (g) to the increase in water volume. The third column is the raw data of the soil moisture sensor (v). At the bottom, there is an analyze button which will trigger the modelling process. The output panel display is as follows:

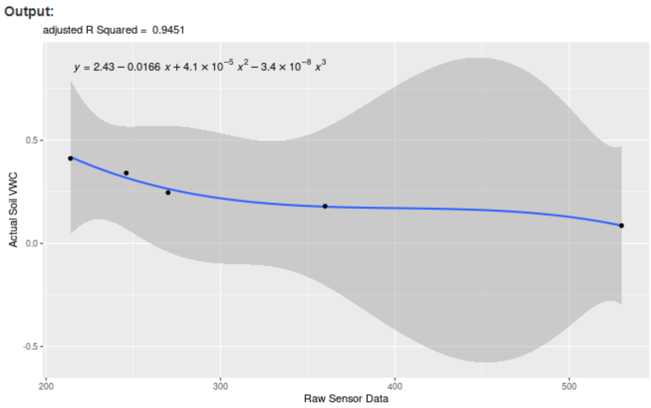

Figure 4. Output Panel of Re-calibration Application

Figure *4* shows that polynomial regression order 3 is the best model with coefficients b_0=2.43, b_1=-0.0166, b_2=4.1 x 10^{-5} dan b_3=3.4 x 10^{-8}. The results of the Re-Calibration application are the same as the previous manual *modelling* process. In the scatter plot there is also a gray background color which is the 95% confidence interval in the actual soil volumetric water content (VWC) estimation results. Coefficient model configuration on IoT application.

```
double soilMoistureValue = 0;
double soilMoisturePredict = 0;
double b0=2.43;
double b1=0.0166;
double b2=0.000041;
double b3=0.000000034;

void loop()
{
  Blynk.run();

soilMoistureValue = analogRead(A0);  //put Sensor
insert into soil
soilMoisturePredict = b0-
b1*soilMoistureValue+b2*soilMoistureValue*soilMoistur
eValue-
b3*soilMoistureValue*soilMoistureValue*soilMoistureVa
lue;
}
```

The calibration results are then programmed into a Capacitive Soil Moisture Sensor as in Figure 5 so that a model-based capacitive soil moisture sensor is obtained. After that, the prediction results are displayed on the Blynk application so that soil moisture can be monitored on a mobile phone. The results of the soil moisture prediction simulation and monitoring display on the mobile phone are as follows:

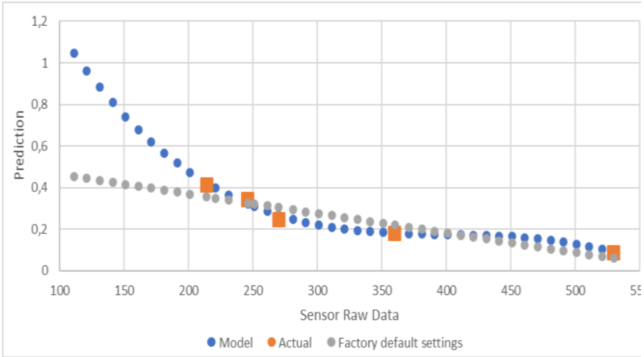

Figure 5. Model-based capacitive soil moisture prediction

Figure 6 shows that the model-based capacitive sensor that has been recalibrated can follow the pattern of gravimetric test results (actual) better than the capacitive soil moisture sensor with factory settings. Figure 6 shows the relationship pattern between predictions and raw sensor data following an exponential pattern. The predicted value of soil moisture is in the range 0 – 1.2 for raw sensor data values of 100 – 530. This range is then used to configure value limits on the mobile phone display.

The model selection process for re-calibration capacitive soil moisture sensors becomes easier with a web-based application. The application will automatically carry out calculations related to the gravimetric test. The results of the modelling can be used to make predictions of soil moisture so that soil moisture measurement can be done via mobile phone in real time.

This application can be used on any soil types and sensors other than capacitive sensors. It's just that there are a few things to consider. First, the re-calibration application was set up based on gravimetric experiments at 4 levels of increasing water volume with 100 ml intervals. Second, because of this, the polynomial order that can best be used is 3. Lastly, measurements are made using grams unit.

IV. CONCLUSION

The web-based recalibration application can provide the best model for model-based capacitive soil moisture sensor. Based on gravimetric test experiments and web applications, the best model is a polynomial regression model order 3. It has Adjusted R Squared of 0.945 which means that 94.5% of the variation in volumetric soil moisture content can be explained by the model. Based on model, the predicted value for soil moisture is in the range 0 – 1.2 for raw sensor data values of 100 – 530. When the model coefficient configured in capacitive soil moisture sensor and Blynk application, soil moisture measurement can be done via mobile phone in real time.

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