ROVIGA: Model-Driven Soil Moisture Sensor for Internet-Connected Plant Pot

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ABSTRACT

The soil moisture sensor provides numerical measurements to detect changes in soil moisture using an analog voltage output. This research aims to develop a capacitive sensor based on a statistical model to detect soil moisture for plant watering, leveraging the Internet of Things (IoT). The analysis was conducted using polynomial and linear regression models. The modeling process was based on primary gravimetric test results from dried soil. The best model coefficients, selected based on the highest adjusted R-squared value, were used for sensor recalibration. A watering system was then developed using an Arduino and a model-driven capacitive soil moisture sensor integrated into an internet-connected smart plant pot, enabling remote control via a mobile phone. The research findings indicate that the 8th-order polynomial model, with the highest adjusted R-squared value of 0.9583, is the most accurate. The smart watering system using the model-driven capacitive sensor achieved soil moisture prediction outcomes ranging from 0.08 to 1.01 for 150 to 418 sensor data points. The internet-connected smart plant pot allows precise and real-time control, delivering notifications and enabling actions when plants require watering.

I. Introduction

Providing the right amount of water is crucial to support plant growth. One of the needed tools is a plant watering device, which has a control system to water plants in smart pots while monitoring it through an application that checks soil moisture and water levels. The advantage of this device can operate automatically that it easier for homeowners to water their plants on time [1], [2]. Using a soil moisture sensor controlled by microcontroller will aid in measuring soil moisture. Thus, it is expected that plants will receive optimal care even if the owner does not directly handle them [3].

Numerous researchers are focused on calibrating sensors specifically soil moisture. Recalibrated low-cost capacitive soil moisture sensors can predict soil water content with high accuracy [4]. The gravimetric technique, which can express soil moisture content considering weight proportion of disparity in weight between wet and dry soil sample. The weight of water was determined by dried the soil to the steady weight. Finally, the weight of the is the difference in weight between the wet and dried soil sample in the oven [5].

Regression models, such as polynomial, are commonly inclined to adjust soil moisture sensor. Polynomial regression is commonly used to model curved relationships, while linear regression is specifically suited for modelling straight-line relationships. Both models utilize R-squared to assess the strength of the relationship. The polynomial order required to explain the dependent variable can be computationally intensive [6].

In our previous research [7], [8], there are many missing values when we calibrated soil moisture sensors based on percentages were calculated in the air and submerged in water. Moreover, research [9] has compared the performance of soil moisture sensors from factory settings to be no better than calibrated sensors. Therefore, this study attempts recalibrated soil moisture sensor from gravimetric tests to find a capacitive sensor based on statistical model that can detect on soil moisture for watering plants. Recalibration caried out using best model with highest adjusted R squared from linear and polynomial regressions [9]. Finally, set up a series of watering systems using an Arduino Uno and a model-driven capacitive soil moisture sensor in an internet connected smart plant pot for watering using a mobile phone.

II. METHOD

This research uses primary data derived from experimental results. The experiment conducted was a gravimetric test, and the results were analyzed using the R package in R stat [10] and shiny [11].

A. *Design of the Smart Plant Pot*

The design of smart pot consists of three parts. The bottom part for storing the con-troller, the middle part as the water tank, and the top part for irrigation. An overall description of the smart pot is shown in Figure 1.

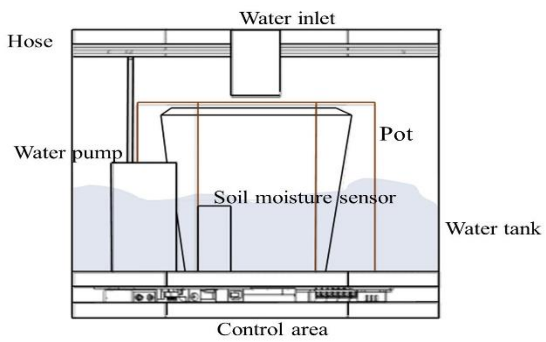

Figure 1 General design of a smart plot

In the water tank, there is a water pump and water level sensor to measure the water level. At the top, there are openings for adding water and hose to channel water from the water tank to the growing medium. The design of the smart pot is shown in Figure 2. On the side of the pot, there are two plugs, namely a USB and an adapter 12V.

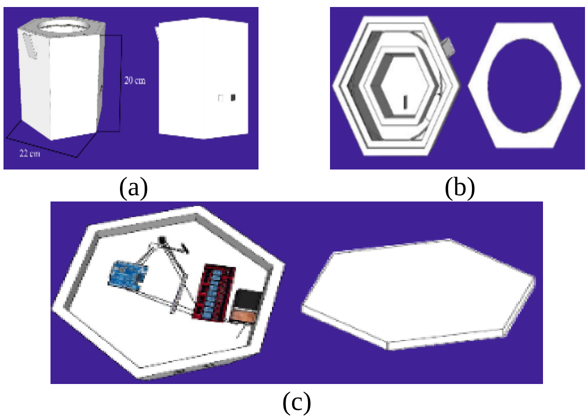

Figure 2 The 3D pot model from (a) flank, (b) upper surface, (c) lower surface

A smart plan pot is equipped with sensors to support plant growth, specifically a soil moisture sensor. This sensor is processed by an ESP-01 to be sent to a smartphone and to control the on/off function of a water pump. The ESP-01 is a WiFi serial transceiver microcontroller that can work with other microcontrollers or operate independently as a System on Chip (SoC) incorporated with Soft Access Point , TCP/IP, and WiFi Direct Peer-to-Peer [12]. The software design for the smart pot is developed using the Blynk application [13], allowing the monitoring of soil moisture on a mobile phone through an internet connection from a remote location. The smart pot needs to be connected to WiFi to access the internet. Sensor data is transmitted in real-time and stored in a cloud-based database.

B. *Design of the Soil Moisture Sensor*

Design of the soil moisture sensor using several components. The components used are Arduino Uno, relay, capacitive soil moisture sensor, jumper, water pump, ESP-01 WIFI module, mini breadboard, relay and battery [8]. The following is circuit for soil moisture system as follows in Figure 3:

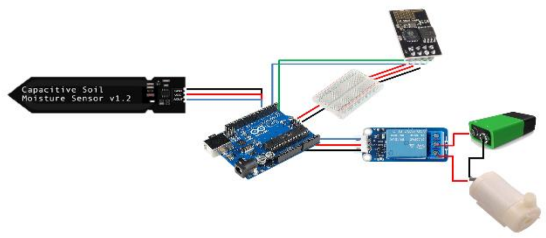

Figure 3 Circuit of soil moisture sensor

The components are assembled according to the Figure 3 diagram and programmed using Arduino IDE [14]

C. *Gravimetric Test*

Gravimetry offers direct measurement of moisture content and allows estimation of available water, particularly soil moisture. Gravimetry is performed by comparing the sensitivity of sensors at various soil moisture levels. Essentially, it involves measuring the loss of water by weighing a soil sample before and after drying it at 105-110°C. The soil moisture content determined by gravimetric analysis was converted into volumetric soil moisture through.

$$\theta_v = \frac{\frac{(m_{wet}-m_{dry})}{m_{dry}} \times 100\% \times \rho_{soil}}{\rho_{water}} \tag{1}$$

Where, m is the mass, m_{wet} is the wet and m_{dry} is dry weight of soil + cup, θ_v is volumetric soil moisture level, and ρ is a density. The gravimetric test was obtained from each soil. In short, soil samples were gathered, weighed, dried in a forced-air oven, reweighed, allowing the water content to be expressed based on mass [5].

D. Regression

Here, it needs to be emphasized again that the output of Gravimetric is a linear model.Common to use Linear regression. In this step, the gravimetric data outputs are the response variable and the predictor variable is a the soil moisture sensor. The analysis utilized both linear and polynomial model regression models. The linear regression equation same as polynomial equation with order 1, as follows:

$$\hat{Y} = \beta_0 + \beta_1 x + \beta_2 x^2 + \ldots + \beta_n x^n + \varepsilon \quad (2)$$

By applying R-squared to the regression analysis, we can evaluate how independent variable explain dependent variable. The coefficient of determination is at $0 \leq R^2 \leq 1$. The closer it is to 1, the stronger the relationship between the independent variable and the dependent variable. Conversely, if the coefficient of determination is 0 or close to 0, it indicates a weak or no relationship. Due to the limited number of gravimetric test samples, the adjusted R-squared is used to address this limitation [15].

$$R^2_{adjusted} = R^2 - \frac{(1-R^2)k}{n-(k+1)} \quad (3)$$

III. Result And Discussion

A. Gravimetric Test

A 1000 ml soil sample was used for the gravimetric test. From this, soil was initially extracted and dried with alcohol, both processes involving 100 ml. The drying procedure involved two separate applications of 50 ml of alcohol each, with durations of 5 minutes and 10 seconds for the first application and 4 minutes and 30 seconds for the second. After cooling, it was weighed to establish a correction factor for soil measurements under air-dry conditions for the entire 1000 ml soil volume, denoted as m_{dry}. Subsequently, measurements were taken at 31 water volume levels, ranging from air dry to 600 ml, including increments of 20 ml up to 580 ml. Each water volume level was assessed usin model-driven soil moisture sensor. The gravimetric test outcomes are provided below:

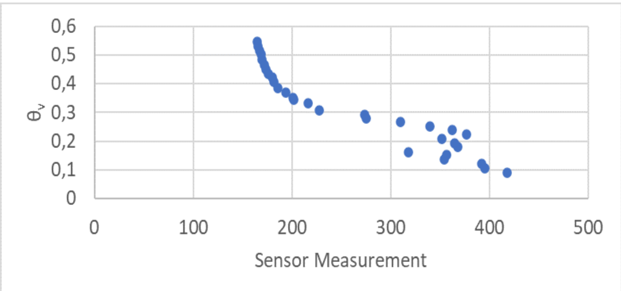

Figure 4 Gravimetric test result

Figure 4 shows that as θ_v increases, the sensor measurement decreases. The θ_v value is derived from ρ_{soil} = 0.600377. The θ_v and the sensor measurements are subsequently fitted into both linear and polynomial regression models to acquire prediction of soil moisture. The θ_v is treated as the response variable, while the raw data of sensor serves as the predictor variable. For each model, $R^2_{adjusted}$ is calculated as follows.:

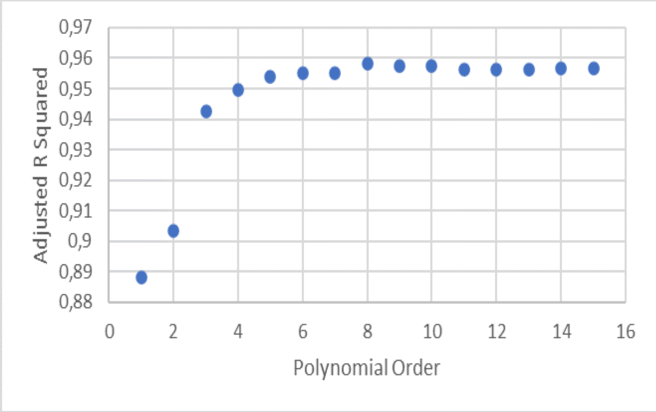

Figure 5 Best order of polynomial regression

Figure 5 shows that the highest Adjusted R-squared ($\bar{R}^2$) was achieved by the eighth-order polynomial regression model. The $\bar{R}^2 = 0.9583$ indicates that the model can explain 95.83% of volumetric soil moisture level variance. The polynomial regression order 8 model as follows.

$$\hat{Y} = 968.6 + 29.3x_1 + 0.3x_1^2 - 0.003x_1^3 + 1.3x10^{-5}x_1^4 - 3.9x10^{-8}x_1^5 + 7.1x10^{-11}x_1^6 - 7.2x10^{-14}x_1^7 + 3.1x10^{-17}x_1^8 + \varepsilon \quad (4)$$

The model coefficients are subsequently applied to estimate soil moisture content. Prediction results were obtained at 0.08 - 1.01 for raw sensor data from 150 to 418. Predicted values are used to set the minimum and maximum values that will be used as status bars for the soil moisture indicator display. Model coefficients then installed to smart plant pot. The program code of the calibration scheme is given as follows

```
double SMv = 0;
double SMp = 0;
double SMv2 =0;
double SMv3 =0;
double SMv4 =0;
double SMv5 =0;
double SMv6 =0;
double SMv7 =0;
double SMv8 =0;

double b0=968.6;
double b1=29.3;
double b2=0.3;
double b3=0.003;
double b4= 0.000013;
double b5= 0.000000039;
double b6= 0.000000000071;
double b7= 0.000000000000072;
```

```
double b8= 0.000000000000000031;

void loop()
{
Blynk.run();
SMv= analogRead(A1);

SMv2= SMv* SMv;
SMv3= SMv* SMv*SMv;
SMv4= SMv* SMv* SMv* SMv;
SMv5= SMv* SMv* SMv* SMv*SMV;
SMv6= SMv* SMv* SMv* SMv* SMv* SMv;
SMv7= SMv* SMv* SMv* SMv* SMv* SMv*SMv;
SMv8= SMv* SMv* SMv* SMv* SMv* SMv* SMv*SMv;

SMp = b0
-b1*SMv+b2*SMv2-+b3*
SMv3+b4*SMv4+b5*SMv5+b6*SMv6+b7*SMv7+b8*SMv8;
}
```

Figure 6 Calibration Code

B. *Soil Moisture Prediction based on IoT*

The soil moisture prediction system is set up using Figure 3. IoT plays a role to control in real time by providing information and alerts on soil moisture and water levels. The algorithm used is as follows

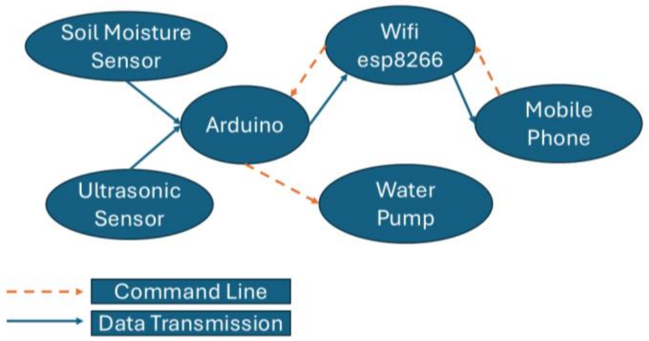

Figure 7 IoT of smart plant pot

Based on Figure 7, soil moisture and water level data are sent by the sensor to the Arduino. The data is processed into various values using equation (4) and forwarded to the mobile phone application via the Wi-Fi module for display. Furthermore, the user can provide instructions related to the operation of the water pump as shown on the command line.

C. *Smart Plant Pot*

Figure 8 shows the results of a smart wooden pot, where the length is 20 cm, width 22 cm and height 20 cm. Planting area can be attached and detached from smart pot. The smart pot can be used with a charger adapter. The Smart watering plants pot is as follows:

Figure 8 Prototype of the smart plant pot

The smart plant pot is equipped with a 600 ml water tank, as illustrated in Figure 8. The main screen of the smartphone application, shown in Figure 9, displays information on soil moisture and the water tank level. Additionally, there is an irrigation control button. When this button is set to "off," irrigation is disabled, whereas setting it to "on" enables the irrigation process.

(a) (b)

Figure 9 The display of (a) the mobile application and (b) Blynk notifications of water

D. *Discussion*

This article is limited to the implementation of smart pots utilizing soil moisture sensor that have been parameterized using machine learning models. It does not discuss whether this system helps to significantly reduce water consumption or improve plant health compared to manual systems.

Another thing that needs to be recognized is that the use of an 8th order polynomial model may produce high adjusted R-squared values, but this model tends to experience overfitting, especially for data that is not too complex in nature. However, our seemingly complex model performed well on the field test data (gravimetric test), successfully predicting new values or real-time data.

IV. Conclusion

Based on experiments, The optimal model is an eighth-order polynomial regression model, which has the largest Adjusted R Squared (0.9583). Furthermore, the internet-connected smart plant pot allows you to take control and provides information on when your plant needs water accurately and in real-time. Smart plant pots using model-driven capacitive sensors have predicted soil moisture values in the range of 0.08 - 1.01 for raw sensor data values from 150 to 418.

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