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MULTIPLE LINEAR REGRESSION METHOD USED TO CONTROL NUTRIENT SOLUTION ON HYDROPONIC CULTIVATION

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Abstract

Hydroponic has been receiving much attention in soilless agriculture technique for its many advantages. Preparation of nutrients becomes the most essential part of hydroponic. Thus, controlling the nutrient is indispensable. This paper proposes a hydroponic system using NFT (Nutrient Film Technique) with an IoT-based control system in Bok Choy (Chinese cabbage) plant with nutrients A and B and evaluates the performance. The control system was implemented using multiple linear regression to obtain the pump time value for Arduino nano to activate the pump. Accuracy metrics on multiple linear regression were performed using MAE and MAPE. The amount of nutrition needed was calculated based on the threshold values set by the hydroponic farmers. The results show the value of MAE in nutrients A and B are in good results and MAPE in the highly accurate category in 7.7% and 7.6% respectively. The experimental results indicate that the IoT-based hydroponic nutrient control system can work well to reach the threshold value with an accuracy of 92.42%. This study makes a significant contribution to understanding the control system on nutrient concentration in hydroponic with formula generated by multiple linear regression because, in conclusion, the system can work well at under and over 1,000 ppm TDS (Total Dissolved Solids) in several volume reservoirs from 20 – 40 litres.

Keywords: Control, EC Sensor, Hydroponics, NFT, TDS.

1. Introduction

Food needs in Indonesia, especially vegetables, are always increasing every year along with the population, economic growth rate, and the people's purchasing power. Based on RENSTRA (Strategic Plan of Indonesia Ministry of Agriculture) released by the Ministry of Agriculture, 2019's production target of 11,782,187 tons becomes an urge for farmers to produce crop yields that meet the quality and quantity requirements [1].

Increasing population and industrialization have been the reasons to upgrade agricultural techniques to meet the needs of people. Soilless agriculture offers a way to overcome the shortage of land-based agriculture. Hydroponic is one of the soilless agriculture systems that simply growing plants without soil [2, 3]. This is possible because plants do not need soil, but they need the vitamins and minerals, water, carbon dioxide and oxygen at the root zone that soil can provide them. Hydroponics as an urban farming method is able to become the solution to the need for fresh vegetables in Indonesia, as almost any kind of plant can grow hydroponically including vegetables.

Hydroponics serves advantages over the soil for several reasons, such as the plant can be grown year-round, since controlling plant in a greenhouse is way easier than providing the roots with available nutrients and not having to waste time growing extensive root system to provide exposure to nutrients and water in the soil. This is what makes the yields bigger. Besides, the nutrient solutions maintain the same amount of nutrients available all the time, meanwhile, soil tends to weary when the nutrients in the soil are taken up. Besides, hydroponics is pesticide-free, plants turn more sterile and resistant to diseases. The urgency of meeting food supply for the people and considering the benefits of hydroponic make hydroponic practice has become the burning need [4].

One of the techniques in hydroponic is called NFT (Nutrient Film Technique). In this technique, the fertilization is done in a reservoir by adding nutrient solution, which then will be circulated to every plant. The nutrient solution contains every nutrient needed by the plants. The amount of nutrients dissolved is represented by TDS (Total Dissolved Solid). TDS can be used as a parameter to find out about the nutrient solution concentration level in ppm (part per million) [5-7].

The preparation of nutrient solution has been identified as the most sensitive part of hydroponics because nutrient solution varies randomly in the growth cycle of crops due to ion absorption and plant need different nutrition in their growth [8, 9]. Thus, ensuring an optimum level of nutrient and very little error tolerance nutrient quality in order to maintain a high yield is very crucial. Automation in hydroponics is one concept that can solve the challenge [10]. The Internet of Things (IoT) helps the automation to keep human intervention at a minimum and is used in hydroponic to improve reliability as well as allow remote monitoring and control [11-14]. Even farmers use drones to monitor plant growth [15].

Principal parameters in hydroponic such as electric conductivity (EC), pH and water temperature are hence necessary to control. Those parameters should be kept at an optimum level to ensure the absorption of nutrients from the solution so that the plants received the right amount of nutrition [16-19]. Moreover, this control system is also necessary to prevent the plants from harvest failure. Traditional hydroponic farming is conducted manually by monitoring the nutrition as well as in giving the nutrient. However, it will be hard to achieve the exact value that the system needs [20].

Some preliminary works were carried out in the control system of hydroponic nutrients. The forward chaining method was used to calculate and produce conclusions from input parameters. The system's conclusion will give commands to the actuator, i.e., pump and cooling fan to lower the temperature so that the nutrient is normal [21]. Another research used the fuzzy logic method. This research result said that increasing pH value as much as 0.01 can be reached by adding 1mL pH up solution, decreasing pH value as much 0.015 can be reached by adding 0.015 mL pH down solution, and increasing EC value as much as 0.034 mS/cm can be obtained by adding 1mL A and B nutrient solution [22]. However, the systems don't control the concentration of the solution and because of unset nutrition, as consequence, the TDS value tends to overshoot from the threshold. Though the concentration of the solution can reach 1,000 pm, however, it is implemented only in a 10-liter reservoir.

The concentration of macronutrients (NO_3, Ca, PO_4, Mg) can be controlled by the dosing algorithm, by adding the stock solution to increase the initial concentration. This research used lettuce in an ebb-flow system with a 70-liter reservoir and employed a cobalt rod-based electrode for phosphate sensing. Nevertheless, PO_4 is still lacking at 19% less providing the desired concentration. Meanwhile, this condition can lead to phosphorus deficiency resulting in small and chlorotic leaves [23, 24]. The WinCE-based embedded system combined with a robust fertilizer dosing algorithm was used to overcome decoupled replenishment nutrients. The use of embedded systems as part of IoT has successfully improved the control performance of nutrients compared to PC-based systems in maintaining target concentration [25]. A key problem with much of the literature in relation to hydroponic is that the system should be able to maintain the optimum concentration of nutrients.

We undertook this study by NFT hydroponic system with the purpose to make an IoT-based control system to the nutrient concentration threshold value in 500; 700; 1,000 and 1,400 pm and implemented in 20, 25, 30, 35 and 40 litres reservoir volume. We used Bok Choy (Chinese cabbage) as the hydroponics plant. Bok choy should range in 750 – 1,250 ppm [26], thus we build control to be able to maintain ppm level at under or over 1,000 ppm. Accuracy of the control system is also provided. Multiple linear regression was applied to obtain the pump time value. The regression accuracy metrics were analysed using MAE and MAPE. The objective of our work is to create a control system that can control nutrient solutions under and over 1,000 ppm according to the need of the hydroponic plants and evaluate the control system performance.

Our technique shows a clear advantage over the control system in hydroponic in terms of solution concentration with IoT. IoT enables the control of the system so that the accuracy of the control system can reach 92.42% on average. It is according to the condition of the reservoir volume value and the threshold value which shows that the average percentage of control system accuracy, i.e., 92.42% tends to be directly proportional to the volume increase and the threshold increase. In conditions of higher volume and threshold, the percentage value of the average accuracy of the control system is also higher. This shows that the system performance works well either in a high volume of the reservoir (20 – 40 litres) or threshold (under and over 1000 ppm) with no overshoot in TDS value to retain the threshold. Multiple linear regression is used to model the relationship between two or more variables by fitting a linear equation to observed data.

Multiple linear regression determines any relationship between dependent and independent variables and how much the power of the relationship is [27]. The regression estimates the dependent variables changes as the independent variable changes. In relation to this research, multiple linear regression generates a formula in which the value of pump time as a dependent variable changes according to the change of delta TDS as an independent variable that is controlled. So, the exact amount of nutrients is given precisely based on the formula. Besides, the formula generated in our research shows accuracy using MAE in good results and MAPE in the highly accurate category with a value of error less than 10%, i.e., 7.7% and 7.6% for nutrients A and B respectively. Not to mention, multiple linear regression is considered a more effective and accurate way in prediction accuracy as well as providing information about the relationship of two or more variables especially for control systems than simple linear regression [28, 29]. Nutrient availability must be controlled in hydroponic as it is one main factor determining the growth and weight of the hydroponically grown plants [30].

This paper consists of 4 Sections: Section 1 is an introduction, Section 2 explains system design, Section 3 explains results and discussion, and Section 4 is the research conclusion.

2. Design

2.1. System model design

This system was designed to control nutrient solution concentration parameters on hydroponic plants. Figure 1 shows the system architecture of Nutrient Solution Concentration Control. The control system works as the feedback from the EC sensor's nutrient solution concentration parameter monitoring results.

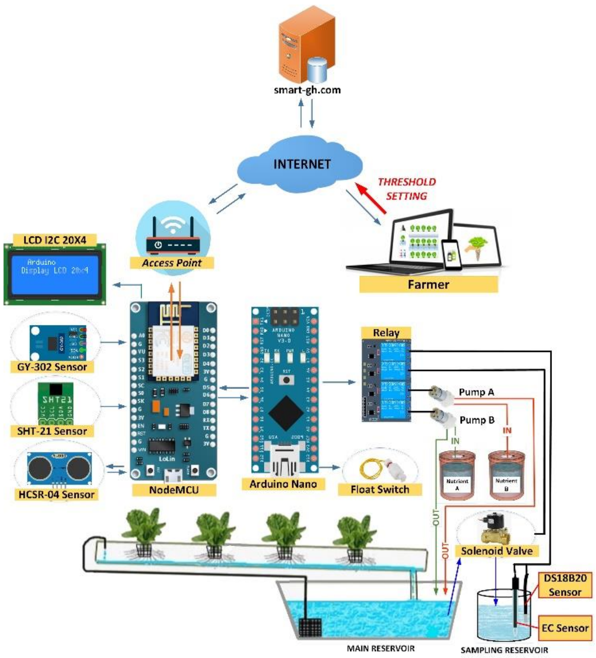

Fig. 1. Nutrient solution concentration control system architecture.

NodeMCU will give commands to Arduino Nano to measure nutrient solution concentration value. The measurements were performed by EC sensor and DS18B20 temperature sensor. Both sensors were placed in the sampling reservoir. The measurement result of the EC sensor and temperature sensor will be sent from Arduino nano to NodeMCU. Then, it will be forwarded to the database server. So, the farmer can monitor the data through the website.

In the EC controlling process, farmers can adjust the concentration level of nutrient solution needed for plants through the website. The concentration level of the nutrient solution was set by farmers at one time before the control system is activated to minimalize the possibility of internet failure during data uploading. NodeMCU will read this data from the server every 60 seconds. Then, Arduino nano will compare the measurement of the EC sensor and threshold data. If the EC sensor measurement is lower than the threshold value, then the control system will work by activating the relay that was connected to the DC pump actuator. The pump will distribute the nutrient to the main reservoir by using the hose. The pump's active time is determined by the X_2 variable from the multiple linear regression equation applied in Arduino Nano's program.

2.2. Software design

The software design on this system involved multiple linear regression modelling in Minitab version 18 and program design for NodeMCU and Arduino Nano in Arduino IDE. Minitab will process the sample data from the tests. The output that was used for analysis is the multiple linear regression equation. On the other hand, Arduino IDE was used to program the microcontrollers. Before making the program, we need to figure out how NodeMCU and Arduino Nano work here. The program's flowchart can be seen in *Appendix A*.

On initialization, NodeMCU has to be connected to the access point to send sensor data and grab threshold data from the *sn.php* file on the smart-gh.com server. Next, the threshold data will be sent to Arduino Nano. After that, NodeMCU will wait for TDS measurement results from Arduino Nano, which will then be sent to the server database. When Arduino Nano received the threshold data, it will parse the data. If the parsing is successful, the EC sensor will become active and perform TDS measurements inside the sampling reservoir. Then, if the TDS measurements are lower than the threshold, Arduino Nano will activate the relay that was connected to the pump to add nutrients to the main reservoir.

2.3. Multiple linear regression method

The regression model is a statistical technique presented to estimate the relationship among variables that have cause-effect relations, to make predictions as well as for the case of the control system [31]. When the variables are one dependent and more than one independent variable, it is called multiple linear regression. Multiple linear regression is made in an attempt to account for the variation of independent variables in the dependent variable. In its implementation, the multiple linear regression equation can be described as Eq. (1):

$$Y = a + b_1X_1 + b_2X_2 \quad (1)$$

Regression analysis was chosen in this research to control a case of the concentration parameter of hydroponic plant nutrient solution through the implementation of the obtained regression equation and since we have one dependent variable and two independent variables, the multiple linear regression method was presented. There are two steps in multiple linear regression. First, data sample test to obtain the equation of multiple linear regression. Second, the accuracy metric test was performed to the equation obtained.

Based on Eq. (1), the Y variable or the independent variable is the delta TDS value, while the X_1 variable (dependent variable) is reservoir volume, and the X_2 variable (also dependent variable) is pump time. The value needed by Arduino Nano to perform any controlling is the pump time or the X_2 variable. So, in its application, the X_2 is described as Eq. (2):

$$X_2 = \frac{(Y - a - b1 * X1)}{b2} \tag{2}$$

In this research, the X_2 is represented in seconds. Arduino Nano will give commands to the relay to activate the pump according to the value produced from the equation.

2.3.1. Data sampling

Data sampling is the first step to perform multiple linear regression. Data samples are used to find the multiple linear regression equation by determining the dependent variables (X_1 and X_2) to get the independent variable (Y). In this research, we applied nutrients A and B. The sampling used nutrient A for equation A and nutrient B for equation B. The data sample was done to each nutrition A and B separately in reservoir volume 20 litres, 25 litres, 35 litres, and 40 litres with pump time variation 1 second, 1.5 seconds, 2 seconds, 2.5 seconds and 3 seconds. Data sampling was done five times on each pump time variation. Figure 2 shows the results of the average value of data sampling nutrition A.

Figure 2 indicates that with the addition of nutrient A, the reservoir volume variable and the pump time variable play a significant role in delta TDS change. In the same conditions, the higher the pump time, the higher the delta TDS value will be. The same relation goes for the other way around.

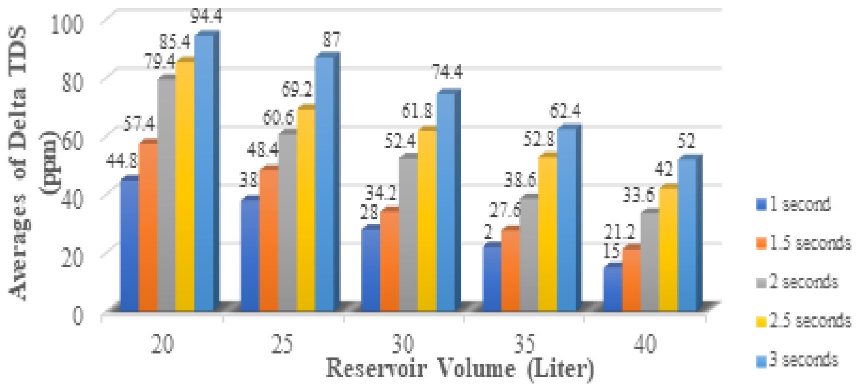

Fig. 2. Diagram of sample data using Nutrient A.

Subsequently, the normality test was performed to understand whether the data sample is normally distributed so that the regression results will be valid. The normal distribution is shown when the plots spread out and following the diagonal line. Minitab application was used in performing normality tests.

Figure 3 shows the result of the normality test for nutrient A. It presents the conclusion that nutrient A data sampling is normally distributed shown by the plots following the diagonal line. Thus, the data sampling of nutrient A is valid and can be processed using multiple linear regression.

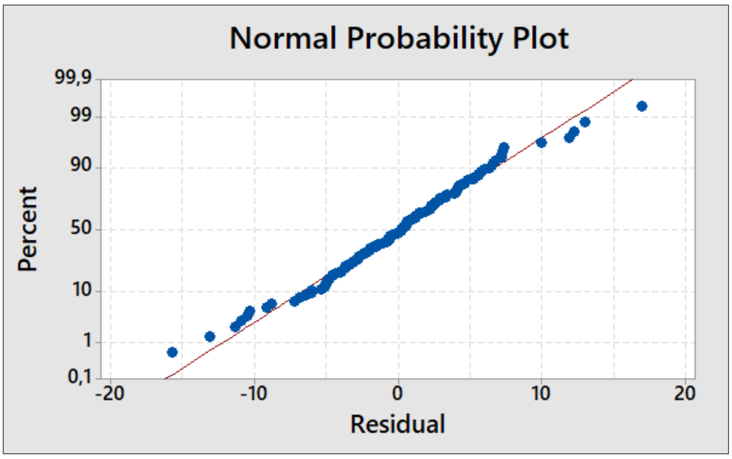

Fig. 3. Nutrient A normality data.

Figure 4 shows the data sampling with the addition of nutrient B, the reservoir volume variable and the pump time variable also play a significant role in delta TDS change.

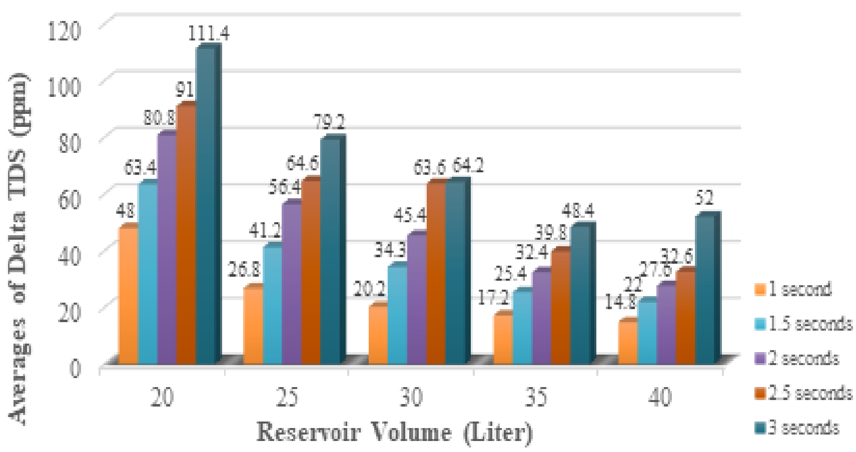

Fig. 4. Diagram of sample data using Nutrient B.

Figure 5 shows the normal probability plot of nutrient B which indicates that the data sampling of nutrient B is normally distributed and hence, are valid to use with multiple linear regression analysis.

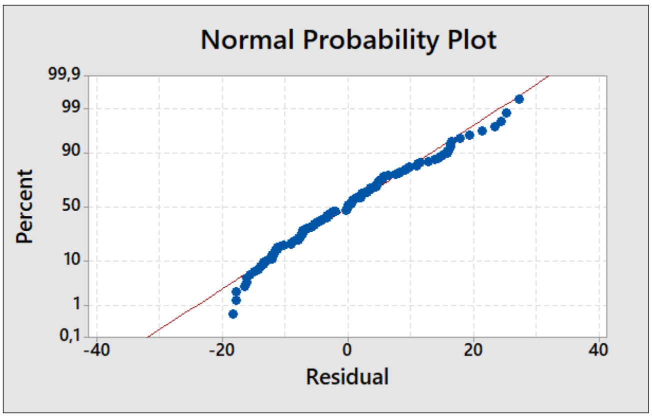

Fig. 5. Nutrient B normality data.

2.3.2. Multiple linear regression equation

The data sampling was processed in a regression equation using Minitab. All the data sampling of nutrient A were inputted to the Minitab table following the independent variable which is delta TDS and dependent variables of X_1 reservoir volume and X_2 pump time. In Minitab, click Stat – Regression – Regression – Fit Regression Model. Afterwards, the regression equation appears as in Eq. (3).

$$Y = 65.33 - 1.9800\, X_1 + 22.68\, X_2 \tag{3}$$

The same step was also done using the data sampling of nutrient B as shown in Fig. 4. The regression equation for nutrient B is shown in Eq. (4).

$$Y = 65.33 - 1.9800\, X_1 + 22.68\, X_2 \tag{4}$$

Then, Eq. (3) was changed to Eq. (5) according to the formula in Eq. (2).

$$X_2 Nutrient\ A = \frac{(Y - 65.33 + (1.98 * X_1))}{22.688} \tag{5}$$

The same step was also done for nutrient B. The Eq. (4) is changed to Eq. (6).

$$X_2 Nutrient\ B = \frac{(Y - 100.29 + (3.16 * X_1))}{22.9} \tag{6}$$

The X_2 on Eqs. (5) and (6) is the pump time, the amount of time elapsed to activate the nutrient of pump A and B respectively (represented in seconds/s). These multiple linear regression equations are put in Arduino Nano's program for the nutrient pump delay. So, the nutrient pump will become active based on the value of each variable (Y and X_1).

3. Results and Discussions

3.1. TDS accuracy

This test was done to measure TDS sensor accuracy in both systems (control and monitoring) by comparing the results to a digital measurement tool (EC meter).

Equation (7) is used to perform an accuracy test on the EC sensor. At first, the calibration was done to the EC sensor to get the accuracy value. The difference of sensor EC and TDS meter values are used for the input of error percentage. Equation (7) shows the accuracy formula for the EC sensor.

$$Accuracy = 100\% - \left\{\left(\frac{EC\ sensor\ value - TDS\ meter\ value}{TDS\ meter\ value}\right) x\ 100\%\right\} \quad (7)$$

Figure 6 shows the comparison of TDS measurements using an EC sensor and an EC meter. We can see that on the EC sensor, the higher the measured value is, the higher the error will be. According to the results of the EC sensor and EC meter, the average error percentage is 8.57%. This is still within the tolerance error of the EC sensor in as much as ±10% **[32]**. Based on the calculation using Eq. (7), the accuracy of this TDS measurement is 91.43%. In conclusion, the EC sensor can work well and is feasible to use.

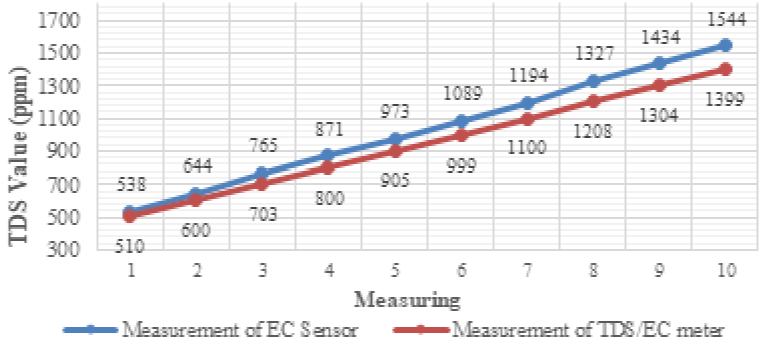

Fig. 6. Measurement result of EC sensor with TDS/EC meter.

3.2. Accuracy of linear regression

An accuracy metric test was performed to evaluate the linear regression. The accuracy was evaluated using MAE (Mean Absolute Error) and MAPE (Mean Percentage Absolute Error) separately. MAE and MAPE are two reliable accuracy metrics and the most commonly used measures for assessing forecasts [33]. Equation (8) shows the MAE formula and Eq. (9) is for MAPE.

$$MAE = \sum \frac{|Y' - Y|}{n} \quad (8)$$

$$MAPE = \sum_{t=1}^{n} \frac{|Y_t - Y'_t|}{Y_t} x100\% \quad (9)$$

where *Y'* is the expected or prediction value and *Y* is the actual value. According to this research, *Y'* is the value of the delta set point and Y is the delta TDS. The delta set point was adjusted to 50, 100, 200 and 300 ppm for each volume of the reservoir (20, 25, 30, 35, 40 litres). While delta TDS is based on the difference value of set point and end TDS measurement. The calculation of accuracy metrics using MAE and MAPE in nutrients A and B is shown in Table 1.

Table 1 presents the value of accuracy metric results in nutrients A and B. The table informs that nutrient A has MAE in 12.3 and MAPE 7.7%. While nutrient B obtain MAE 11.4 and MAPE 7.6%.

Table 1. Accuracy metric results.

Nutrient	MAE	MAPE
Nutrient A	12.3	7.7%
Nutrient B	11.4	7.6%

MAE is classified into good when the value is 6, 7, 8-16, 21 and 22 [34]. Based on table 1, therefore, the value of MAE in both nutrients A and B are classified into good categories. MAPE is categorized as highly accurate when the result of the error is less than 10%, good when the result is 10 – 20%, reasonable with 21 – 50% and inaccurate when the result is more than 51% [35]. As seen in Table 1, the value of MAPE in nutrient A and B are less than 10%. Meaning that the value of accuracy of nutrient A and B are highly accurate. From these accuracy values, it is concluded that multiple linear regression either using nutrition A or B is feasible to be applied in the control system in terms of its pump time (X_2) value in seconds.

3.3. Control system test result

After the values of pump time were inputted into the system, the results of the control system were analysed. This is the final test to ensure that the overall system can work well on the threshold value and on several reservoir volumes. The test was done 10 times consecutively in volume 20 – 40 litres with the threshold of 500 ppm, 700 ppm, 1,000 ppm and 1,400 ppm to see whether it would be able to retain the threshold value or cause overshoot. Figure 7 shows the control system performance graph in volume 20 – 40 litres when the control is turning on to retain the threshold values.

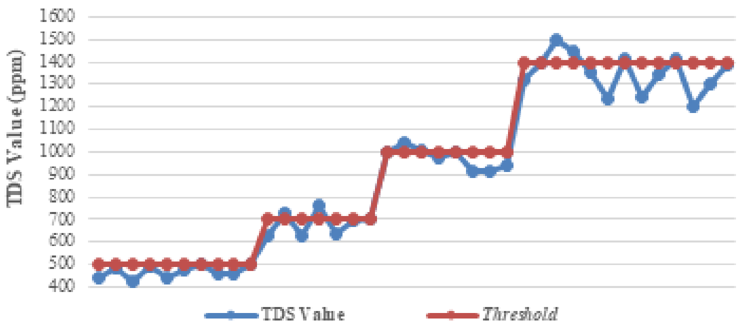

Fig. 7. Control system performance.

According to Fig. 7 where the TDS end value is compared to the threshold value (500; 700; 1,000; and 1,400 ppm) the control system indicates working really well on reaching and maintaining 500 ppm, 700 ppm, 1,000 ppm, and 1,400 ppm threshold values. This means that the control system can be implemented in reservoir volume of 20 – 40 litres and is able to control the concentration of nutrient solution under and over 1,000 according to the threshold values determined.

On the other hand, the control system accuracy on different volumes and thresholds was performed according to the measurements of TDS set point and TDS end values as shown by Fig. 7, then calculated using Eq. (10). The results can be seen in Table 2.

$$Accuracy = 100 - \left\{\left(\frac{TDS\ end\ value - TDS\ set\ point}{TDS\ set\ point}\right) x\ 100\%\right\} \tag{10}$$

Table 2. Accuracy results of the system.

Volume (liter)	Threshold (ppm)				Average accuracy (%)
	500	700	1000	1400	
20	87.26	85.12	91.58	92.59	**89.13**
25	92.58	90.92	94.98	90.40	**92.22**
30	86.32	93.07	94.69	96.53	**92.65**
35	95.30	93.39	94.61	95.51	**94.70**
40	89.70	94.37	94.36	95.27	**93.43**
Average accuracy (%)	**90.23**	**91.37**	**94.04**	**94.06**	**92.42**

Table 2 shows the overall conclusion of the average percentage of control system accuracy in each volume and threshold. The test results in Table 2 present for example, with a threshold of 500 ppm, it shows that the control system has an average percentage of accuracy of 90.23% in achieving and maintaining a threshold value of 500 ppm. Meanwhile, the control system has an average percentage of 91.37% to achieve 700 ppm, 94.04% to achieve 1,000 ppm and 94.06% to achieve 1,400 ppm. Over these percentages, in conclusion, the average accuracy of the control system shows 92.42%.

Based on the condition of the reservoir volume value and the threshold value, it shows that the average percentage of control system accuracy tends to be directly proportional to the volume increase and the threshold increase. In conditions of higher volume and threshold, the percentage value of the average accuracy of the control system is also higher. This shows that the performance of the control system can work well at high volume and threshold conditions.

4. Conclusion

We have presented a cutting-edge solution of an NFT hydroponic IoT-based control system applying multiple linear regression method in the topic of concentration of the nutrient solution.

Our findings underline the importance of controlling nutrient solution in hydroponic by exact calculation. We have found that multiple regression linear applied in the IoT-based control system successfully achieve overall accuracy of 92.42%.

Besides, the control system is applicable to the reservoir of 20 – 40 litres and can control the concentration of nutrient solution under 1,000 ppm and over 1,000 ppm. This is within the required ppm needed in this research.

Future studies should address the control of environmental conditions such as temperature and relative humidity of hydroponic systems by using machine learning such as fuzzy logic to achieve tractability and robustness. Fuzzy logic is a powerful soft computing tool to control the environmental condition and nutrient solution in hydroponic systems specially to deal with energy efficiency. Since this control system depends on the internet connection on the threshold set by the farmers, to cope with the internet failure, Raspberry Pi is used to store the threshold information for its small and powerful micro-computer with low consumption, low cost and reconfigurability.

Nomenclatures

b_1	X_1 variable coefficient
b_2	X_2 variable coefficient
X_1	Reservoir volume variable, litre
X_2	Pump time variable, second
Y	Body diameter, m

Abbreviations

EC	Electrical Conductivity
NFT	Nutrient Film Technique
ppm	Part per million
RENSTRA	Rencana Strategis (Strategic Plan)
TDS	Total Dissolved Solids

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Appendix A

Control System Program Flowchart