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Water Quality Monitoring with Regression Based PPM Sensor for Controlling Hydroponic Dissolved Nutrient

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ABSTRACT

Hydroponic cultivation requires rigorous monitoring and control of several parameters, such as turbidity, electric conductivity, acidity (pH), dissolved oxygen and nutrient, which usually be measured once a day manually. Therefore, automation in hydroponic cultivation requires those water quality information as the controlled variable. The dissolved nutrient is especially important because it significantly affects the hydroponic plant growth. Acquiring the dissolved nutrient can be done by using a PPM (parts per million) sensor, but most of the time the sensor needs further processing to obtain the desired measurement. This study presents a reading correction of a PPM sensor based on a regression method so the desired measurement can be done. Sample water with different PPM, such 309 PPM, 290 PPM, 762 PPM, 1910 PPM and 2420 PPM are measured first using a standard PPM meter. Then, the sample PPM is measured by using the PPM sensor. The study also investigates the best regression method to map the PPM sensor measurement to the standard PPM meter measurement by comparing several line equations, such as linear, exponential, polynomial and logarithmic. The function coefficient and bias is chosen by using least square methods. After comparing, the result shows that the polynomial function provides the best reading correction with average error of 76 PPM. The error is especially few when measuring the higher PPM (more than 500 PPM), which is suitable with hydroponic cultivation. Therefore, the PPM sensor with the polynomial function shown in this study can be used to measure the dissolve nutrient accurately in the automation of hydroponic activity compare to other line equations. This study is limited to small sample sizes to prove the concept. The generalization can also be considered in the future study.

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1. INTRODUCTION

Food scarcity becoming concern nowadays as stated in the Sustainable Development Goals (SDG) number 2 zero hunger [1]. It became global issue because of the climate change [2] and growing population, but less field to grow the crops [3]. One of the solution is to do urban farming either using pot method or hydroponic method [4]–[6]. The hydroponic is especially conservative because it is soilless and water efficient, but produce more than soil-based method [7]. Although it is relatively easy to do the hydroponic cultivation compare to the conventional agriculture practice [8], [9], doing the maintenance routinely is a burden for the urban citizen who mainly works every Monday to Friday [10]. Especially, when the work life balance become an issue for the next generation, the additional activity of hydroponic treatment is hard to be done [11].

Automation is the alternative so the hydroponic can be maintained regularly. The daily maintenance requires the water quality control, such as the turbidity, electric conductivity, acidity (pH), dissolved oxygen and nutrient that can be automated [12], [13].

The dissolved nutrient is especially important because it significantly affects the hydroponic plant growth [14]. So, it is necessary to have information about the nutritional needs of plants [15]. Too many nutrients does not guarantee higher nutrient absorption [16]. But too few nutrients might not enough to optimizes the crops growth. Different plant requires different dissolved nutrients [17]. For instance, study by [18] shows hydroponic cultivation of Kale with AB mix nutrients of 1877 PPM while study by [19] shows hydroponic cultivation of lettuce with AB mix nutrients of 200 PPM. Maintaining the dissolved nutrients can be done by adding it regularly whenever the nutrients is not enough. Therefore, the owner of the hydroponic have to measures the dissolved nutrient regularly, which can be done through automation with Internet of Things technology [20].

Acquiring the dissolved nutrient can be done by using a PPM (parts per million) sensor and sometimes can be estimated based on pH [21]. However, most of the time the sensor needs further signal processing to obtain the desired measurement. If the sensor reading is inappropriate, then predictions on the hydroponic water quality cannot be made. Hardware signal processing using capacitor as a filter reduces the signal ripple [NO_PRINTED_FORM]. In case of noisy signal, the bandpass filter is the way to go for discarding the noise. Software based signal processing also can be done, such as using regression method to map the sensor reading correctly or using moving average for smoothing the signal [22]. The software approach is very cost effective because it does not require additional component [23]. Instead, suitable algorithm embedded in the microcontroller is necessary to do the software based signal processing [24]–[26].

Another advantage of using the software approach is the flexibility. For instance, the farmer already proved that the plant can grow optimally when the parameter is 100 for example, measured by his own instrument. If the sensor of the monitoring device measures the 100 as 80, then it will produces inappropriate hydroponic water quality control. The plant cannot grow optimally when the cultivation is automated with the developed monitoring device. Here, adjustment can be made by using software approaches easily so the developed monitoring device can immitate the measurement of the farmer instrument. The 100 will be measured as 100 also by the monitoring device and mediocre plant growth due to the automation can be avoided.

Therefore, this study presents a reading correction of a PPM sensor based on a regression method so the desired measurement can be done[NO_PRINTED_FORM]. Several regression equation, such as linear, polynomial, exponential and logarithmic are compared to get the best equation for correcting the PPM sensor readings. In most of the cases, the linear regression is enough to obtain the representative data, but it can be improved using other functions depends on the data characteristics [27], [28]. The regression method has been commonly uses in hydroponic monitoring as shown by previous researches to predict the nutrient needs [29] or the nutrient content [30].The most accurate reading is the reading with the less error among others. Achieving an accurate reading of the sensor will enable the automation of hydroponic cultivation to run smoothly [31], [32].

2. METHODS

The overall automatic hydroponic system is shown in Fig. 1. The hydroponic water is contained in the main tank. There are also two other tanks that contains tap water and nutrient, which will be mixed to fill the main tank [30], [33]. Three pumps available to control the hydroponic water quality in the main tank. The first pump is to increase tap water while the second pump is to increase the nutrient. The third pump is used to decrease the water level. The tap water pump (increase and decrease) are 60 Watt 220VAC pump with capacity of 3000 L/h. The nutrient pump is 3.5 Watt 5V DC pump with capacity of 150 L/h. The pump has different specification due to the tap water pump has a higher volume than the nutrient. There are also ultrasonic sensors (HC-SR04, 5V, up to 300 cm distance) measures the water level in each tank. Lastly, the PPM sensor measures the water quality. The water quality control generally goes like this [34]:

- If the water level in the main tank is not enough, then the tap water is increased.
- If the PPM in the main tank is not enough, then the nutrient is increased.
- If the water level or the PPM is too much, then the hydroponic water is decreased.

Fig. 1. The automatic hydroponic system with water quality control.

As the key of good dissolved nutrient control lies in the accurate reading of the PPM, the reading correction of the PPM sensor is necessary. In this research, the reading correction methods are divided into three steps, which are data collection, regression, and error calculation, as shown in Fig. 2. The collected data comes from a several samples of salt water with different PPM, which come from solution of tap water and kitchen salt There are five samples, such as 309 PPM (1 table spoon of salt), 290 PPM (2 table spoon of salt), 762 PPM (4 table spoon of salt), 1910 PPM (8 table spoon of salt) and 2420 PPM (15 table spoon of salt). First, a standard PPM meter (TDS meter 0-9999 PPM) measures the samples and the reading serves as the standard reading. The amount of the diluted salt depends on the PPM meter reading. If the reading increment is not significant compared to the previous, then the salt is still added. The samples are normally distributed between 375.35 PPM to 1901.05 PPM with confidence level of 95%, which includes the optimal PPM value for growing Lettuce and Bok Choy using hydroponic method [35]. Table 1 shows the samples statistical analysis.

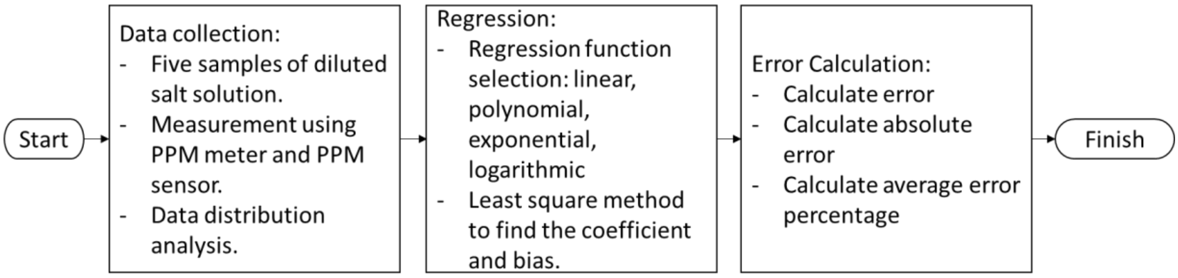

Fig. 2. Research methodology flowchart.

Table 1. The statistical analysis of the samples.

Statistical Parameter	Value
Mean	1138.2
Standard Deviation	870.314
Alpha value	0.05
Confidence Value	±762.85
Confidence Interval	375.35 – 1901.05
Sample Size	5

After that, the measurement is repeated by using the PPM sensor. The sensor returns a voltage value, V (0 to 5V), which can be converted to do measurement of dissolved nutrient, dN, from 0 to 2000 PPM as in (1).

$$dN = V \times \frac{2000}{1023} \tag{1}$$

The study uses arduino UNO, which the ADC reads the maximum 5V as a maximum numerical value of 1023. Therefore, the measured voltage should be divided by 1023 before be multiplied with 2000 PPM. The next step is to make the regression function, which mapping the PPM sensor reading to the standard sensor reading. The regression functions are linear, polynomial, exponential, and logarithmic. The Table 2 shows the regression functions, where y is the dependent variable or the corrected reading, x is the independent variable or the PPM sensor reading, a is the coefficient of x and b is the bias.

Table 2. The regression equations

Regression line	Function
Linear	$y = ax + b$
Polynomial	$y = a_1x^2 + a_2x + b$
Exponential	$y = be^{ax}$
Logarithmic	$y = a\ln(x) + b$

The least squares method

$$\sum_{i=0}^{n} e_i{}^2 = \sum_{i=0}^{n} (yt_i - yr_i)^2 \tag{2}$$

calculates the sum of squared error (e_i) [36], which in this research is the difference between the PPM sensor reading (yr) and the standard PPM meter reading (yt). Here, the n is the number of the data sample. The value of a and b is optimal whenever the sum of squared error on that function is the least throughout all the data. Finally the research compare the average error of each regression functions. The lowest the error, the more accurate the PPM sensor reading. Average error percentage, $\overline{e_\iota\%}$

$$\overline{e_\iota\%} = \frac{\sum_{i=0}^{n} \frac{e_i}{yt_i}}{n} \tag{3}$$

is calculated by averaging the division of the absolute error (e_i) reading with the standard measurement (yt). At the end, the research concludes a regression function that should be used for correcting the PPM sensor readings.

Although, previous study shows several parameters to be considered in hydroponic cultivation [24], [25], this study is limited only to PPM representing the dissolved nutrients only. The reason is to match the cultivation practices of hydroponic farmer in Surabaya that usually only monitor the PPM everyday. Introducing the proposed method to the farmer can open up future research with other parameters, such as pH, temperature, and so on.

3. RESULTS AND DISCUSSION

The data has been sampling for five samples of salt solution that has been explained in the methods section. The regression functions are shown in Table 3, which is the result from the least square method optimization. There is a solid correlation between the PPM sensor reading and the standard PPM meter. As shown in Fig. 3. The target (black circle) shapes like a straight line, but that is not the case when the linear regression is being applied. Some regression lines are more fitted at the beginning, but the others are more fitted at the half end. For instance, the polynomial (grey square) and logarithmic (blue triangle) functions estimate significantly higher PPM for lower PPM measurement (less than 1000 PPM) although the linear (orange cross) function estimates the target PPM nicely. As for higher PPM measurement (more than 1000 PPM), the polynomial and logarithmic functions estimate better. Meanwhile, the exponential seems off to estimate the target across all the measurement.

Table 3. The regression functions

Regression line	Function
Linear	$y = 1.29x + 184$
Polynomial	$y = -0.0006x^2 + 2.5x - 120.32$
Exponential	$y = 315.6e^{0.0012x}$
Logarithmic	$y = 851.18\ln(x) - 4097.1$

Since comparing the regression visually is not enough, the errors are compared. Fig. 4 shows the error on each sample for each regression function. It can be seen that the initial error (red cross square) is very high especially on the 4th sample (1910 PPM). When applying the regression function, the absolute error became few at the low PPM measurement (first sample 309 PPM and second sample 290 PPM) for all the functions.

However, started from third sample (762 PPM), the absolure error becomes higher especially the exponential (green square) and logarithmic (blue circle) function. The linear absolute error (red diamond) gradually increases, but stay at the middle value with maximum error of 400 PPM. Only the polynomial absolute error (yellow triangle) that stays under 200 PPM. The averages also show that the polynomial function resulted in the least absolute error, which is stable across the sample measurement. Respectively the averages absolute error of linear, polynomial, exponential, and logarithmic are 160 PPM ($\overline{e_\iota\%}$ = 18%), 76 PPM ($\overline{e_\iota\%}$ = 11%), 364 PPM ($\overline{e_\iota\%}$ = 30%), and 154 PPM ($\overline{e_\iota\%}$ = 24%).

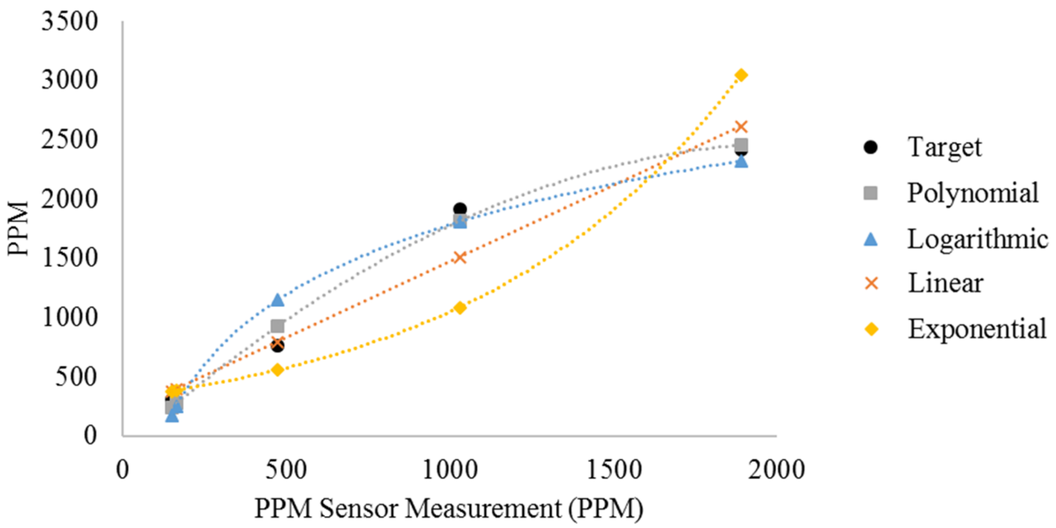

Fig. 3. The regression line compares to the actual data.

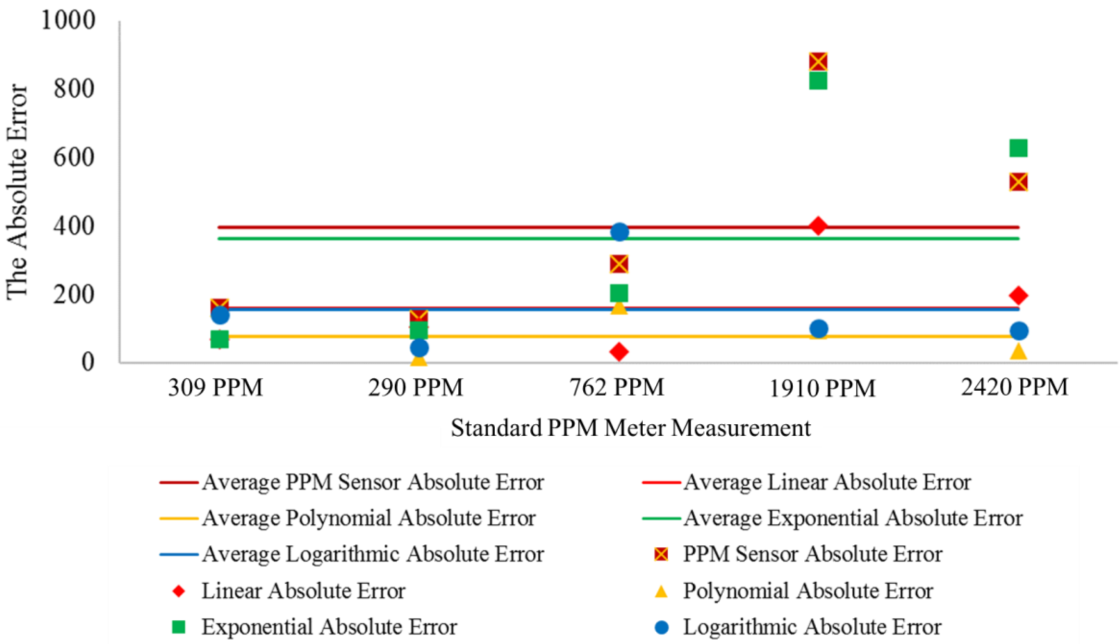

Fig. 4. The errors of each regression line to the actual data.

The absolute error of the PPM sensor is very high (396 PPM), but it has been successfully decreased by implementing regression method. Overall, the result shows that the polynomial function ($y = -0.0006x^2 + 2.5x - 120.32$) provides the best reading correction with average error of 76 PPM. The polynomial performs better because the actual data shaped like a closed curve, where the gradient decreases over the x-axis unit. The logarithmic functions has closed result because the shape is also a closed curve, but the gradient changes differently. The logarithmic function has higher gradient at the beginning compare to the polynomial functions, which made the error at the low PPM measurement bigger. The linear function also has rather small error since it crossed the actual measurement on second sample measurements, as shown in Fig. 3. The exponential will never produced good estimation for the presented actual data since the curve gradient is too low at the low PPM measurement but increases to much on the high PPM measurement.

Despite the polynomial regression can estimates the actual data well it cannot produces zero value because of the bias, which should be considered during implementation. However, the polynomial functions does necessarily to start from zero [37]. Also, the zero PPM is rarely considered in automation of hydroponic cultivation. As shown by [38], the critical measurement for optimal lettuce growth the critical measurement is between 560 PPM and 840 PPM. Other research by [35] also demonstrated similar thing where ideally the Bok Choy should have hydroponic water with PPM ranges from the 750 PPM to 1250 PPM. The important thing is to measure the PPM value that contributes to the optimal growth of the hydroponic plant. Therefore, the research concludes that PPM sensor with the polynomial function shown in this study can be used to measure the dissolve nutrient accurately in the automation of hydroponic activity.

This study shows a premliminary study before doing a water quality prediction based on the PPM reading, as shown in Table 4. Practically, if the measured PPM is below the reference value, then additional nutrient should be added. Meanwhile, the previous studies as shown in [24], [25] focuses more on water quality prediction methods, which in a way is the continuation of this study. Table 3 shows the comparison of this study with the previouses. The reported water quality predictions are already accurate, which proves the advatanges of using the machine learning method. However, if the input data from the sensors are wrong, then it will produces inappropriate predictions. This study complements the previous studies by focusing more on the sensor approaches. The better measurement can be provided to the system using the proposed method so it can make the water quality prediction better. Although, the proposed method only shows treatment on PPM sensor, it can also be duplicated for other measurement.

Table 4. Result comparison with previous studies.

Researches	Water quality parameters	Approaches	Methods	Result
[24]	Dissolved oxygen, pH, Conductivity, Biological oxygen demand, Nitrate, Fecal coliform, Total coliform.	Water quality predictions based on standardized measurement	nonlinear autoregressive neural network (NARNET) and long short-term memory (LSTM) deep learning algorithm	Predictions error percentage of <5%
[25]	pH, Electrical, Conductivity, Mineralization, Magnesium, Calcium, Potassium, Sodium, Chlorides, Sulphates, Nitrates, Bicarbonates.	Water quality predictions based on standardized measurement	Support Vector Machine (SVM)	Predictions error percentage of 11.1%
This study	PPM.	Sensor for water quality predictions	Linear regression using polynomial line equation.	Measurement can be made by implementing polynomial regression with error percentage of 11%

Outside combining the proposed method with the previous studies, the future study can also implement the proposed methods to predict hydroponic water quality control solely from the dissolved nutrients only. When the dissolved nutrient is controlled to be ideal, it is expected that the growth can be maximized [14], [18], [39]. Other methods of hydroponic also involves fish pond to form aquaponics [33]. The water quality in the fish pond should also be controlled before it reaches the plant, which can be done by implementing the presented methods in this study. Controlled variable such as pH [40], turbidity [41], dissolved oxygen [42] and so on is also an object for implementing the methods of correcting the sensors reading.

4. CONCLUSION

This study have presented a regression function comparison to be implemented in an automatic hydroponic system. The controlled variable is the dissolved nutrient measured using a PPM sensor. Initially, the absolute error is apparent when measuring the data using PPM sensor. Then several regression functions are applied to correct the reading, such as linear, polynpomial, exponential and logarithmic functions. Applying the polynomial functions to map the PPM sensor reading to the target data has improved the measurement significantly by decreasing the averages absolute error from 396 PPM to 76 PPM (average error % = 11%). Previously, the hydroponic farmer should monitor the plant water regularly using their instrument. The hydroponic water quality control can be automated, but sometimes the sensor measurement might be different with the usual farmer's instrument measurement. For instance, the farmer instrument measure the optimal water quality as 1000 PPM, but the sensor measures it as 800 PPM. By implementing the proposed method, the sensor measurement can match the farmer instrument to control the hydroponic water quality.

Although, previous study shows several parameters to be considered in hydroponic cultivation [24], [25], this study is limited only to PPM representing the dissolved nutrients only. The reason is to match the cultivation practices of hydroponic farmer in Surabaya that usually only monitor the PPM everyday. Introducing the proposed method to the farmer can open up future research with other parameters, such as pH, temperature, and so on. The sample sizes presented in the study is also small. However, the concept has been proved and generalization by adding more sample can be considered in the future study.

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