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INNOVATIVE IOT-BASED STRATEGY FOR WATER QUALITY CONTROL IN HYDROPONIC PLANTS USING MEDIAN FILTER AND LINEAR QUADRATIC ESTIMATION

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ABSTRACT

Controlling water quality in hydroponic farming is essential but challenging. IoT sensors help monitor water conditions, but the data they produce is often inaccurate and water quality control becomes ineffective. This research uses an innovative approach in remote monitoring and controlling water quality in hydroponic systems through the integration of Internet of Things (IoT) technology for real-time data collection and data processing algorithms. The proposed strategy is to use a Median Filter combined with Linear Quadratic Estimation to produce more precise water quality control for hydroponic plants. Median Filter effectively reduces the noise from data obtained from sensors, while Linear Quadratic Estimation is used to predict the state of water quality of hydroponic plans. Experimental results show that the proposed system achieves mean absolute error (MAE), and root mean square error (RMSE) values below 1% for both PPM and pH measurements. This indicates that sensor data can be effectively processed, and the estimation of water quality changes closely reflects the actual conditions of the water. The approach using these two methods can ensure that the water quality of hydroponic plants becomes more stable and controlled, thus having an impact on the fertility and health of the plants and increasing better yields.

Keywords: *Internet of Things, Hydroponics, Water Quality, Median Filter, Linear Quadratic Estimation*

1. INTRODUCTION

Global demand for food continues to increase along with population growth and less agricultural land. In this context, hydroponic farming has emerged as a sustainable and space-saving alternative to traditional farming, with the ability to grow crops in a controlled environment using nutrient-rich water solutions [1]. Water mixed with the nutrients needed by plants is continuously circulated to the plant roots 24 hours a day. It is important to note that the success of a hydroponic system is highly dependent on setting the right water quality parameters such as pH, nutrient concentration, and temperature. Deviations in water quality parameters from the needs of hydroponic plants can result in reduced nutrient absorption, suboptimal plant growth, and reduced yields.

To address these challenges, the integration of the Internet of Things (IoT) in hydroponic systems allows for the collection of data from various sensors such as water pH, nutrient concentration, and water temperature in real-time, and enables remote water quality control [2]. In the practical deployment of IoT in hydroponic systems is often hampered by corrupt sensor data due to unstable voltage, environmental disturbances, and device limitations. This noisy data reduces measurement accuracy and risks causing wrong decisions in water quality management [3], which has an impact on crop health.

This research is driven by the need to enhance the reliability and precision of water quality control in IoT-based hydroponic systems. To overcome the limitations caused by noisy sensor data in hydroponic systems. This research proposes to develop an innovative IoT-based strategy for water quality control in hydroponic plants. It is a two-stage data processing approach that integrates Median Filter and Linear Quadratic Estimation. Median Filter is used as the first-stage noise reduction technique, which is highly effective in removing

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impulsive or spike noise while maintaining the integrity of the original signal. This ensures that outliers do not distort the overall data trend. Linear Quadratic Estimation is applied to further refine the sensor data processing by minimizing between the observed sensor values and the estimated values. The integration of Median Filter and Linear Quadratic Estimation (LQE) is designed to provide robust, real-time estimates of water pH and nutrient levels, allowing for more accurate and enhance the ability to control water quality more optimally to get better end-in result.

This strategy is expected to help maximize the growth of hydroponic plants, contributing to increased food production; and providing solutions to global challenges in terms of food security and sustainable water use [4]. The next step of this research is to build a hydroponic plant management system equipped with Machine Learning technology to increase the efficiency and productivity of modern agriculture. This research roadmap also aims to increase sustainable water use, as well as for food security. This is in line with the objectives of the Sustainable Development Goals (SDGs) to achieve a better and more sustainable life for everyone on this planet [5].

2. OBJECTIVES AND BENEFITS

The rapid advancements of Information and Communication Technology (ICT) and Electronics has led to the use of Internet of Things (IoT) systems in hydroponic farming, marking a significant step towards future agricultural technology. IoT systems allow for real-time remote monitoring and control of water quality, including parameters like pH and nutrient levels [2]. This continuous monitoring enables timely decision-making to optimize water quality for hydroponic plants.

The objectives of this research are to address the primary challenge in hydroponic farming related to water quality control by designing and implementing an Internet of Things (IoT)-based system that can monitor and control the water quality of hydroponic plants in real-time and remotely. To address issues of inaccurate measurements and noise interference, this research applies Median Filter and Linear Quadratic Estimation (LQE) techniques to reduce noise in sensor data, thereby enhancing measurement accuracy and data quality. Additionally, it aims to improve the prediction of hydroponic water quality conditions. By applying these innovative IoT-based strategies, the research seeks to optimize water resource usage, ultimately minimizing the environmental impact of agriculture and contributing to more sustainable farming practices.

The benefits of this research include the enhancement of hydroponic plant growth through real-time data and effective IoT-based water quality control, enabling farmers to make quicker decisions in response to water quality changes. The developed strategies will support optimal and sustainable water use in hydroponic farming. Additionally, this research provides a foundational framework for future studies on improving water quality management using predictive data capabilities from machine learning technology.

3. LITERATURE REVIEW

3.1 Water Quality

Hydroponic systems allow plants to grow without soil by using water mixed with essential mineral nutrients. This nutrient-rich water is stored in a reservoir and pumped to the plant roots. Utilizing gravity, the water flows back to the reservoir through designated pipes. It is crucial to continuously monitor and maintain water quality to ensure that hydroponic plants can absorb the necessary nutrients and grow effectively [6]. Hydroponic farming offers numerous advantages, including faster and larger plant growth compared to soil-based systems, due to efficient water management and optimal sunlight exposure. Additionally, water usage is more efficient with a recirculating system, making hydroponics an environmentally friendly, clean, and healthy approach to enhancing food security [4].

3.2 ESP32 Development Kit

The ESP32 is an open-source development board for a wide range of hardware and software applications. This powerful board is equipped with the capability to interface with both analog and digital sensors, enabling it to read several types of input such as touch switches, button presses, and environmental data. Furthermore, the ESP32 is designed to receive and process information through WiFi networks, leveraging its robust microprocessor to convert these inputs into actionable outputs [7].

There are many ESP32 software libraries that make the process of creating custom applications. These libraries offer pre-built functions and modules, so developers can focus on the core logic of their projects without having to worry about low-level programming details. This combination of hardware flexibility and software support makes the ESP32 an invaluable tool for both novice and experienced embedded systems developers.

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The effect of voltage changes has an impact on the Analog to Digital value, this can cause deviant measurement results from the installed sensor. The application of the Median Filter algorithm is needed as the first step to reduce impulse noise [8]. It will improve data quality from the measurement results of water pH sensors, and water nutrients (PPM).

3.3 Sensor Module

Monitoring water temperature is crucial for calculating electrical conductivity, as temperature variations can significantly affect electrical conductivity (EC) readings. Simultaneously, water temperature measurements help in assessing the overall environmental conditions of the hydroponic system and towards EC measurements as well [9]. The Parts per Million (PPM) concentration of dissolved substances in the water can be derived from the EC sensor measurement results. For this purpose, two waterproof DS18B20 temperature sensors are used. One sensor is used to monitor the water temperature within the reservoir of a hydroponic system, while the other measures the ambient air temperature. These DS18B20 sensors are capable of operating in environments with temperatures up to 125 degrees Celsius and provide digital output with a resolution ranging from 9 to 12 bits [10].

To measure water pH and water electrical conductivity (EC), it is essential to connect each of specific sensors to the analog pins of the ESP32 module. Here is the water pH and PPM sensor specification [11]:

- Water pH probe specification:
  - Detection Range: 0~14
  - Temperature Range: 0~60°C
  - Accuracy: ± 0.1pH (25 °C)
  - Response Time: <1min
- Water pH Signal Conversion Board specification:
  - Supply Voltage: 3.3~5.5V
  - Output Voltage: 0~3.0V
  - Probe Connector: BNC
  - Signal Connector: PH2.0-3P
  - Measurement Accuracy: ±0.1@25℃
  - Dimensions: 42mm x 32mm
- Water Conductivity probe specification:
  - Cell Constant: 1.0
  - Support Detection Range: 0~20ms/cm
  - Temperature Range: 0~40°C
- Water Conductivity Signal Conversion Board specification:
  - Supply Voltage: 3.0~5.0V
  - Output Voltage: 0~3.4V
  - Probe Connector: BNC
  - Signal Connector: PH2.0-3Pin
  - Measurement Accuracy: ±5% F.S.
  - Board size: 42mm x32mm

3.4 Raspberry-Pi

The Raspberry Pi, a credit card-sized minicomputer, was developed by the Raspberry Pi Foundation in the UK under the guidance of Broadcom's Hardware Architect, Eben Upton. The Raspberry Pi functions similarly to a personal computer, enabling tasks such as email management, document creation, web browsing, and multimedia playback [12].

In this study, Raspberry Pi will be utilized as Database and to perform noise reduction by implemented Median Filter and perform predictions using Linear Quadratic Estimation (LQE). This algorithm will be implemented on Node-RED, it is a flow-based development tool for visual programming [13].

Additionally, Raspberry Pi will function as an MQTT broker, facilitating communication between various sensor modules in IoT devices. All measurement data from the water pH, PPM (parts per million), and temperature sensor modules will be transmitted to the Raspberry Pi using the MQTT protocol over a WiFi TCP/IP-based local area network. This setup ensures efficient data collection and processing, enabling real-time monitoring and analysis of the sensor data.

3.5 MQTT Broker

The Message Queuing Telemetry Transport (MQTT) protocol, in accordance with OASIS standards [14], is a technology that has a significant role in the field of the Internet of Things (IoT). Designed as a lightweight publish/subscribe messaging transport protocol, MQTT is optimized for connecting remote devices with minimal bandwidth consumption. The flexibility of MQTT technology has resulted in its widespread use across a variety of industries, including automotive, manufacturing, telecommunications, mining, and gas. The protocol facilitates seamless message transmission between IoT devices. This bidirectional communication capability enables the efficient broadcasting of messages to groups of devices, thus supporting the implementation of IoT on a large scale.

One of the key strengths of MQTT is its ability to connect millions of IoT devices, ensuring reliable and scalable communication. This research is using Eclipse Mosquitto, an open-source message broker that implements MQTT versions 3.1 [15]. Eclipse

Mosquitto is known for its lightweight architecture, making it suitable for use on both simple computing devices and high-performance servers. MQTT's lightweight and robust performance characteristics make it an ideal choice for IoT applications that require efficient and reliable communication. The use of Eclipse Mosquitto further enhances the adoption of this protocol, providing a flexible and scalable solution for diverse IoT applications.

3.6 Node-RED

Node-RED is a powerful programming tool designed to facilitate the integration of various hardware components, APIs, and online services in innovative and engaging ways [13]. It features a user-friendly, browser-based flow editor that simplifies the creation and management of complex workflows by allowing users to combine multiple nodes from an extensive palette.

Node-RED's intuitive flow-based programming interface allows researchers to efficiently design and implement these modules, while ensuring seamless integration and functionality. In this research, Node-RED is used to develop the Median Filter software module and Linear Quadratic Estimation (LQE) software module, as well as several other computational methods and functions. In addition, Node-RED is also used to create comprehensive dashboards that visualize important measurements such as water pH, parts per million (PPM), water temperature, and air temperature. The dashboards provide real-time data visualization, which enhances the monitoring and control capabilities of the system.

Node-RED's flexibility and ease of use make it an ideal choice for developing advanced IoT applications and data-driven solutions. Its ability to integrate multiple technologies and present data in an easily accessible format underscores its value in both research and practical implementation.

3.7 Median Filter

Median filter is a highly effective method for eliminating noise while preserving the quality of the original signal [8]. Impulse noise, characterized by narrow, high-amplitude spikes, can severely distort sensor readings. In this research, Moving Median Filter is applied as a powerful technique to minimize impulse noise in sensor measurements, resulting in more accurate and reliable readings. Here is a brief overview of how a moving median filter works:

1. Sliding Window: The filter uses a sliding window that moves across the sensor data. The window size is usually an odd number to ensure there is a middle value.
2. Median Calculation: For each window position, the filter calculates the median value of the data points in that window. The median is the middle value after the data in the window has been sorted in ascending order.
3. Value Replacement: The middle value in the window is replaced with the median value. This process is repeated as the window moves across the entire dataset.

The output of the Moving Median Filter is a smoother signal with reduced impulse noise, making it more reliable for further analysis and processing. This technique is particularly useful in applications where maintaining signal purity is critical, such as in liquid sensors used to monitor water quality.

3.8 Linear Quadratic Estimation

The Linear Quadratic Estimation (LQE) algorithm, also known as the Kalman filter, is one of widely used estimation methods [16]. This algorithm works by estimating the next position based on the last known position and movement pattern, then adjusting the prediction using new incoming data to produce a more accurate position estimate.

In this research, the system model and measurements model are assumed to be linear. Additionally, both process noise and measurement noise are considered to be zero-mean Gaussian. Initial estimates of the state and error covariance are derived from prior knowledge or empirical data. Furthermore, process noise and measurement noise are assumed to be independent, which simplifies the covariance calculations. Here is a simplified explanation of the key mathematical concepts involved in single dimension of LQE:

1. Initialization Step
   - Set the initial state estimate $\hat{x}_0$
   - Set the initial uncertainty P_0
2. Prediction Step
   The prediction step is about forecasting the state of the system and its uncertainties before introducing new measurements. It involves two key equations:
   - State prediction:
     $$\hat{x}_{k|k-1} = \hat{x}_{k-1|k-1} \quad (1)$$
     This equation predicts the state at the current time step (k) based on the state estimate from the previous time step $(k-1)$. It assumes that the state remains the same unless updated by new measurements.

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- Error covariant prediction:
  $P_{k|k-1} = P_{k-1|k-1} + Q$ (2)
  This equation is the predicted error covariance, representing the uncertainty in the state prediction. (Q) is the process noise covariance, accounting for uncertainties in the process model.

3. Update Step
   The update step refines the state prediction by incorporating new measurements. It consists of three main parts:
   - Calculate the Kalman Gain:
     $K_k = \frac{P_{k|k-1}}{P_{k|k-1}+R}$ (3)
     The Kalman Gain (K_k) determines how much the predictions should be adjusted based on the new measurement. It balances the uncertainty in the prediction $(P_{k|k-1})$ and the measurement noise (R). A higher Kalman Gain means more weight is given to the new measurement.
   - Update the state estimate:
     $\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - \hat{x}_{k|k-1})$ (4)
     This equation updates the state estimate $(\hat{x}_{k|k})$ by incorporating the incoming new measurement (z_k). The difference $(z_k - \hat{x}_{k|k-1})$ is the measurement residual, indicating how much the prediction deviates from the actual measurement.
   - Update the error covariance:
     $P_{k|k} = (1 - K_k)P_{k|k-1}$ (5)
     This updates the error covariance $(P_{k|k})$, reflecting the reduced uncertainty after incorporating the new measurement.

Where:
- $\hat{x}$ is the state estimate
- P is the error covariance
- Q is the process noise covariance
- R is the measurement noise covariance
- K is the Kalman Gain
- z_k is the measurement at time (k)

This cycle repeats for each new measurement, allowing the LQE algorithm to continuously refine its estimates. This iterative process helps in maintaining an accurate estimate of the true state over time. The algorithm is also capable of handling missing or delayed data, thus maintaining stability and regulation in the system.

3.9 Results on Previous Research

Hydroponic farming helps reduce soil erosion, water pollution, and pesticide use, all of which can have a major positive impact on the environment. Plants grown in a hydroponic system are completely dependent on the nutrients provided in the water. Maintaining proper nutrient levels throughout the growing cycle can be a challenge, as plant needs can change over time [1].

Traditional water monitoring systems and devices have several limitations. They require a lot of human effort to monitor water quality, which results in high time and labor costs. In addition, many traditional systems are unable to analyze and process the collected data [2].

Maintaining a stable pH level in a hydroponic system is a challenge. Experimental results indicate that attempts to lower water pH often result in temporary spikes, both upwards and downwards, leading to inaccurate decisions regarding the addition of pH-Down solutions. Even after achieving a homogeneous solution, fluctuations in pH sensor reading persist. These inaccuracies are attributed to unstable power supply voltages to the sensor modules and noise interference, which cause wide deviations and potential oscillations in measurement results [3].

Recent advances in Internet of Things (IoT) technology have significantly improved the monitoring and control of hydroponic farming systems. The iPONICS system is a prime example of an IoT-based hydroponic system capable of monitoring and controlling water quality to ensure optimal plant growth. Further reliability analysis, including fault induction and stress testing, is needed to improve system robustness. Furthermore, predicting nutrient values based on water quality sensor data remains a challenging task, especially in the context of more specific nutrient monitoring [17].

Monitoring and controlling hydroponic systems can be challenging. The Internet of Things (IoT) offers a solution by enabling real-time monitoring and control of these systems from anywhere and at any time. IoT system integration increases crop productivity through real-time monitoring and easy accessibility. In addition, the use of IoT can increase the efficiency of hydroponic systems, with a focus on evaluating IoT sensors and actuators to measure and regulate nutrient supply, thereby encouraging sustainable agricultural productivity [18].

4. RESEACH METHOD

Research methodology is the set of stages that must be established before conducting the research, ensuring that the research is conducted in a directed,

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clear, efficient, and effective manner. The following, Figure 1 is a fishbone diagram of the research describe what will be done in this study.

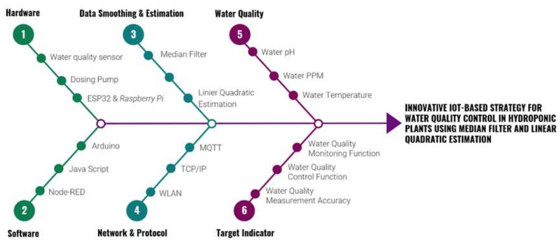

Figure 1: Research flow based on fish bone diagram

Several research has been conducted on the deployment of Internet of Things (IoT) within hydroponic systems [2][17][18]. This study adopts an applied experimental research design, grounded in engineering-based prototyping and empirical validation by presenting an advanced IoT-based strategy for enhancing water quality control in hydroponic systems. It is leveraging the integration of hardware, software, computer network and IoT protocols. The system utilizes water quality sensors, dosing pumps, ESP32 microcontrollers and Raspberry Pi, programmed with Arduino, JavaScript and Node-RED, to collect and process water quality data. The implementation of MQTT and TCP/IP protocols ensures seamless data transmission across the network.

To improve the accuracy of water quality measurements, the research uses the Median Filter data smoothing techniques and Linear Quadratic Estimation (LQE). Data was collected through live trials and performance was evaluated using standard accuracy metrics such as MAE and RMSE. This design emphasizes iterative testing under controlled conditions, reflecting common practices in embedded systems and control engineering research. This type of research design aligns with previous studies in industrial process control and environmental monitoring, where similar filtering and estimation techniques have been used to improve sensor data reliability. For example, Kalman-based filters have been applied in pipeline integrity monitoring technique which is based on Linear Quadratic Estimator (LQE) [19].

This study is guided by the following research questions:

1. How effectively can a Median Filter reduce impulsive noise in pH sensor and EC sensor measurements?
2. Can the integration of Median Filter with Linear Quadratic Estimation (LQE) further improve the accuracy and stability of real-time water quality estimation?
3. What is the impact on the overall performance of an IoT-based hydroponic system in terms of error metrics such as MAE and RMSE?

The primary focus is on monitoring water quality parameters, including pH, PPM, and temperature, to ensure optimal conditions for plant growth. This comprehensive approach not only enhances the precision of water quality measurements but also provides an effective control mechanism, thereby improving the overall efficiency and productivity of hydroponic farming. The relevant data used in this research can be accessed in Mendeley Data (https://doi.org/10.17632/ghhxdnyh6v.1)

4.1 Research Stages

In this study, it will conduct IoT implementation to monitor and control water quality, MQTT integration, and as well as hardware and software development enhancements. The research stages are outlined as follows:

1. Establish Requirements and Collect Data: Begin by gathering detailed information on the Median Filter, Linear Quadratic Estimation, relevant hardware modules, and their supporting software libraries.
2. Construct Hardware:
   Building hardware modules that meet the usability goals, while ensuring compatibility and functionality.
3. Software Development:
   Develop monitoring and control software, along with modular software tailored for each functional hardware modules.
4. Integrate MQTT Broker:
   Set up and configure the MQTT Broker on a Raspberry Pi to facilitate communication between IoT devices.
5. Implement Water Quality Monitoring and Control: Utilize Node-RED to implement IoT solutions for monitoring and controlling water quality parameters effectively.
6. Deployment on Live Trial:
   Deploy the developed hardware and software modules in a Wireless-LAN for live hydroponic trial model.
7. Evaluation:
   Conduct a comprehensive evaluation to assess the performance and effectiveness of the system.

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4.2 Achievement Indicators

Testing is an iterative process to identify errors in a system that may be caused by numerous factors, either related to software, hardware, or errors in the design, implementation, and specification processes. Correction of these errors is continuously carried out until the desired results are achieved. The following are the achievement indicators for this research:

1. Median Filter and Linear Quadratic Estimation development were successfully developed and integrated into a model of hydroponic system with IoT-based sensors for real-time water quality monitoring and control.
2. The accuracy of water quality measurement is increased by reducing sensor data noise by up to 90% through median filtering and increasing the accuracy of water quality measurement with LQE, resulting in a deviation of less than 5% from the true value.
3. Monitoring pH, water PPM, and temperature can be done effectively and in real-time, with data stored locally and water quality reports generated periodically.
4. Successfully integrated IoT-based monitoring and control system with MQTT protocol that enables comprehensive remote and real-time farm management.
5. Designing a user-friendly interface with clear visualization of water quality data and control options for manual adjustment, as well as ensuring that the functions on the dashboard work properly.

5. IMPLEMENTATION

5.1 System Architecture Design

The air temperature, water temperature, water pH, and water EC sensors are connected to an ESP32 microcontroller, which also controls the dosing pump for adjusting water pH and nutrient levels. The ESP32 module includes MQTT client software to connect with the Node-RED MQTT client on the Raspberry Pi via Wireless LAN for sending and message reception.

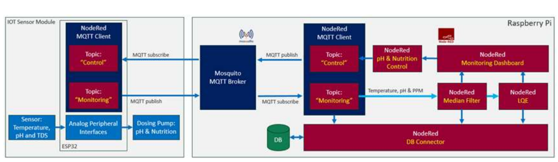

Figure 2: Water Quality Control for Hydroponic Plan System Architecture

The Raspberry Pi module functions as an MQTT broker and water quality controller, equipped with a monitoring dashboard and database. Measurement data from the air temperature, water temperature, water EC sensor, and water pH sensors are sent to the MQTT broker under the topic "Monitoring." The data received by the Node-RED MQTT client is processed by the Median Filter and Linear Quadratic Estimation (LQE) modules within Node-RED, then stored in a database and displayed on the monitoring dashboard. The control of water nutrient levels and pH for hydroponic plants is managed through the Nutrient and pH control module in Node-RED using the topic "Control." These messages are received by the ESP32 module, which activates the dosing pump to add the required solution to the water.

5.2 Water Quality Control and Monitoring Function

Under normal conditions, the system operates periodically every 2 seconds to measure air temperature, water temperature, water PPM, and water pH. The water PPM adjustment function can be performed by entering the amount of AB-Mix plant nutrient solution in milliliters unit, pressing the "AB MIX" button to activate the dosing pumps of nutrient solutions-A and nutrient solutions-B. Similarly, water pH control can be achieved by entering the desired amount of pH solution to be added to the water and pressing the "PH UP" button to increase the water pH or the "PH DN" button to decrease it. All hydroponic plants have specific pH and nutrient targets. For example, Pak-Choi grows optimally in water with a pH of 7 and a nutrient concentration from 1050 to 1400 PPM. An example of water quality monitoring and control over a 2-hour period is shown in Figure 3 and the final result in Figure 4.

Figure 3: Water Quality monitoring

The orange line represents the processed raw sensor data using a Median Filter, while the final values estimated using LQE are shown by the red line. The data displayed on the dashboard can be cleared by pressing the "CLEAR" button. As shown in Figure 4, the LQE estimation results provide a final measurement of water PPM is 1109.08 and final measurement of water pH value is 7.02.

Figure 4: Final result Water Quality monitoring

5.3 pH and PPM Water Sensor Measurement

The results of the solution measurement example at a temperature of 30°C for the pH sensor using a pH 7 buffer solution, and the EC sensor using a conductivity standard of PPM 1084 can be presented in Figure 5 and Figure 6. Visual observations indicate significant impulse noise in the direct measurements from the pH and EC sensors, which can affect measurement accuracy.

As seen in Figure 5, the pH measurement of water varies from 6.95 to 7.70. The average pH value of solution is 7.06, the median is 7, and has a deviation of 0.1. Comparing the average and median values, it is evident that the median-based measurements are same to the true pH solution values, which is 7.

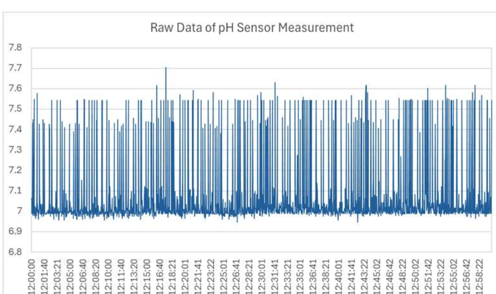

Figure 5: pH Sensor Measurement

The PPM measurements calculation taken from EC sensor result in Figure 6, ranged from 0 to 1133.27. The average PPM value of solution is 1048.85, the median is 1089.83 and has a deviation of 81.41. Comparing the average and median values, it is evident that the median-based measurements are closer to the true values of conductivity standard solution, which is 1084.

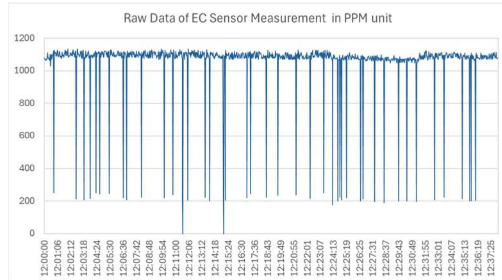

Figure 6: EC Sensor Measurement in PPM unit

5.4 Median Filter Implementation

The application of the Median Filter in measuring PPM and pH values of water can reduce noise that may be caused by electrical fluctuations, environmental disturbances such as residues on the sensor, or variations within the sensor itself. The window size for the data sample observation in the Median Filter needs to be carefully determined. A window size that is too small is ineffective at eliminating noise, while a window size that is too large can remove important measurement details [8]. As a reference for determining the window size, values around the inflection point of the Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE) calculations can be chosen, as shown in Figure 7 for pH water measurement and Figure 8 for PPM water measurement.

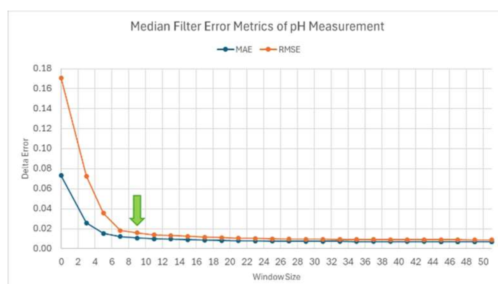

Figure 7: pH Median Filter Windows Size

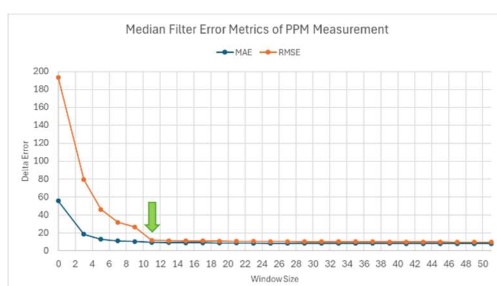

Figure 8: PPM Median Filter Windows Size

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In this research, the window size for the PPM Median Filter is 11, and the window size for the pH Median Filter is 9. As shown in Figure 9 and Figure 10, the significant noise in the sensor measurement results has been greatly reduced after passing through the Median Filter. The PPM measurements varied from 1063.61 to 1116.83, with an average value of 1089.79 and a deviation of 8.01. The pH measurements varied from 6.98 to 7.15, with an average value of 7 and a deviation of 0.01.

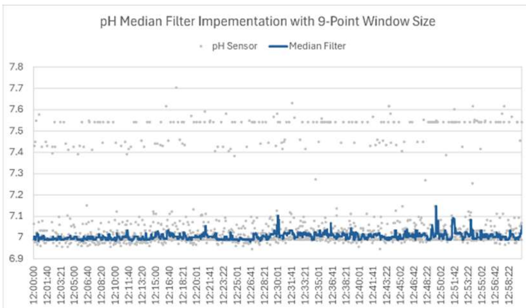

Figure 9: pH Median Filter Implementation

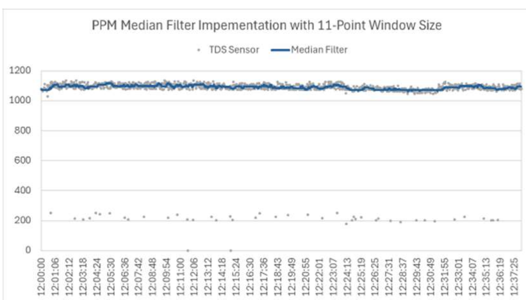

Figure 10: PPM Median Filter Implementation

5.5 Linear Quadratic Estimation Implementation

After passing through the Median Filter, water quality estimation can be done using Linear Quadratic Estimation (LQE). LQE is an estimation method that uses a mathematical model to predict the actual value based on observed data. This method was chosen because of its ability to provide more accurate estimates even though there is uncertainty in the data. The values (R) and (Q) are matrices used in the LQE algorithm to improve the estimation [19].

(R) represents the covariance of measurement noise that reflects the uncertainty in sensor measurements. For a 1-dimensional model, the determination of the value of (R) can be obtained from the calculation of the variance value of the sensor output data. (Q) represents the covariance of process noise that reflects the uncertainty in the process model, where a smaller value (Q) indicates that the process model is more dependable. The determination of the value (Q) is determined based on an understanding of the dynamics of the system obtained from the results of the trial and visual observations of the output produced by considering the expected accuracy and speed of estimation factors. Some of the testing results from all the tests that have been carried out can be seen in Figure 11 to Figure 15. The red line is the outcome LQE calculation result.

Figure 11: LQE Trial with Q Values is (R/1)

Figure 12: LQE Trial with Q Values is (R/50)

Figure 13: LQE Trial with Q Values is (R/500)

Figure 14: LQE Trial with Q Values is (R/5000)

Figure 15: LQE Trial with Q Values is (R/100000)

It can be seen that the application of estimation using LEQ on the outcome of Median Filter output has a significant impact as shown in Figure 16 and Figure 17. Based on the variance calculation of the data sample, the values (R) for water pH is 0.0002, and PPM is 97.12. From the results of the trial application of several values (Q) for measuring water pH and PPM, it was found that the optimal value (Q) is (R/5000). By adding the LQE module, the results of water PPM measurements have a variation in value from 1074.23 to 1101.23. The average value is 1090.10 and the deviation is 4.46. While the measurement of water pH has a variation in value from 6.98 to 7.02, with an average value of 7 and a deviation value of 0.005.

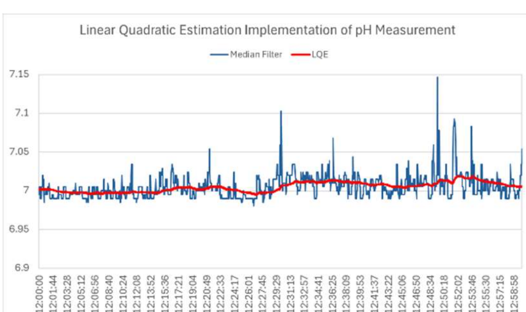

Figure 16: LQE Implementation for pH Measurement

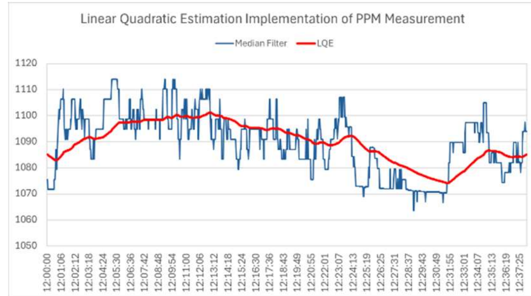

Figure 17: LQE Implementation for PPM Measurement

6. RESULT

The main objective of this research was to develop and evaluate an IoT-based water quality control system for hydroponic farming that enhances the accuracy of sensor data through the integration of Median Filtering and Linear Quadratic Estimation (LQE). The system aimed to reduce noise in sensor measurements, improve estimation accuracy, and enable real-time monitoring and control of water parameters such as pH and PPM.

The following describes the results in controlling water quality in hydroponic systems through the integration of Internet of Things (IoT) technology for real-time data collection, and the implementation of strategies using Median Filters combined with Linier Quadratic Estimation.

6.1 Median Filter and LQE Result Analysis

This study was to evaluate the accuracy of pH and PPM measurements for hydroponic plants using effective data processing techniques, namely the combination of Median Filter and LQE. Measurements were carried out on a pH 7 buffer solution, and a conductivity standard with a PPM value of 1084 at a temperature of 30 Celsius. The results of MAE and RSME calculations can be seen in Table 1 and Table 2.

Table 1: MAE Relative Error of pH

PPM Measurement	MAE	RMSE	Relative Error (MAE)
Sensor	0.073	0.171	1.044%
Median Filter	0.011	0.016	0.153%
LQE	0.006	0.008	0.092%

Table 2: MAE Relative Error of PPM

PPM Measurement	MAE	RMSE	Relative Error (MAE)
Sensor	55.792	193.535	5.147%
Median Filter	9.297	11.426	0.858%
LQE	7.009	8.393	0.64%

The results show that the application of the Median Filter significantly reduced impulsive noise in both pH and PPM measurements. The raw sensor data for PPM showed a mean absolute error (MAE) of 55.792 with a relative error of 5.147%, which was reduced to an MAE of 9.297 and relative error of 0.858% after Median Filtering. This confirms that the first-stage noise reduction method achieved its objective of enhancing sensor reliability.

The addition of LQE further refined the sensor data. PPM measurement errors decreased to an MAE of 7.009 and relative error of 0.64%, indicating an 87.44% improvement from the original sensor readings. Similarly, for water pH measurements, the relative error decreased from 1.044% to 0.092%, showing an overall improvement of 91.21%. These results validate the effectiveness of LQE in generating stable and accurate estimates for real-time applications.

From the results of the application of the Median Filter and LQE, it was found that this method is effective for use in controlling water quality for hydroponic plants. The measurement results from the sensor that has been processed using the Median Filter and LQE showed values very close to the actual data. It was found that the average error value was less than 1% for water PPM measurements and the average error value was less than 0.1% for water pH measurements. Further analysis showed that this method is able to respond to changes in water quality accurately, so it can be used to maintain optimal conditions for the growth of hydroponic plants. The measurement results showed that the MAE and RMSE values for water PPM and pH measurements provide a good picture of accuracy.

7. DISCUSSION

Several studies have explored the integration of IoT in hydroponic systems for real-time monitoring [2][17][18]. While earlier systems acknowledged the issue of sensor inaccuracy due to environmental noise or unstable voltage sources [3]. The majority rely on simple averaging techniques, which require a deeper investigation into the root cause of signal limitations by noisy sensor data. This research proposes a hybrid signal processing method that integrates a Median Filter for impulse noise suppression and Linear Quadratic Estimation (LQE) for predictive refinement.

The results of this study indicate that the use of Median Filter and LQE can significantly improve the accuracy of water quality control for hydroponic plants. The system architecture, which integrates pH and EC sensor to ESP32 as IoT device, a Raspberry Pi functioning as an MQTT broker, and a Node-RED dashboard, facilitated real-time data collection, analysis, and control. It allowed users to remotely track water quality metrics and operate dosing pumps via an intuitive interface.

While the proposed system performs effectively in terms of sensor, there are several limitations such as the need for periodic sensor calibration, requiring longer measurement times and dependence on WLAN connectivity. The experiments were conducted using a limited set of calibration conditions, including a single pH buffer solution (pH 7) and one standard nutrient concentration (PPM 1084). Further studies with more variations of buffer solutions and measurements are needed to strengthen these findings and explore the influence of other factors on the accuracy of PPM and pH measurements of water.

In addition, the implementation of this system on a larger scale may require additional adjustments to ensure optimal performance. The system currently relies on fixed parameters for the Median Filter window size and LQE covariance values. While effective in the current setup, these parameters may not be optimal under different sensor vendor. An adaptive mechanism or learning-based optimization for tuning these parameters dynamically was outside the scope of this research but represents a promising area for future exploration. Further research is needed to overcome these limitations and evaluate this method under different environmental conditions.

8. CONCLUSION

This research presents an innovative two-stage data enhancement approach that integrates Median Filtering and Linear Quadratic Estimation (LQE) to address a persistent challenge in IoT-based hydroponic systems related to inaccurate sensor readings [3]. Although IoT has been widely adopted for hydroponic monitoring, many existing approaches lack effective noise mitigation techniques, resulting in inconsistent and unreliable data [17].

Overall, an innovative IoT-based strategy utilizing Median Filter and Linear Quadratic Estimator (LQE) has demonstrated its effectiveness in managing water quality in hydroponic systems. This approach not only improves measurement accuracy but also provides reliable estimates despite significant sensor interference. As a result, this study provides a systematic and experimentally validated solution that significantly enhances measurement accuracy, with relative error reductions exceeding 85% for both pH and PPM readings.

By validating the approach through MAE and RMSE analysis, this study advances the state of the art in precision agriculture and smart farming. It offers a low-cost, high-accuracy methodology for water quality control. it can help hydroponic farmers maintain optimal water conditions for plant growth, thereby increasing yields and resource efficiency.

The integration of technology in hydroponic farming is expected to increase further, with advances such as smart sensors and artificial intelligence enabling more precise control over plant growth and nutrient management [1]. It is certain that artificial intelligence can overcome issues such as faulty sensors and abnormal measurements due to environmental factors by making informed decisions based on the state of the system. In addition, machine learning methods offer accurate water quality assessments [2]. Future developments can focus on improving the lag experienced in eliminating impulse interference and the estimation process using machine learning techniques.

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AUTHOR'S CONTRIBUTION

Cahya Lukito: Conducted experiments, performed data analysis, and contributed to the written report. Rony Baskoro Lukito: Conducted experiments, performed data analysis, and prepared the manuscript draft. Endang Ernawati: Contributed to manuscript writing and performed proofreading.

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