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IoT-Based Fertiliser Mixing for Precision Farming

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Abstract

This paper describes the development and evaluation of a prototype fertiliser-mixing system for hydroponic systems based on precision farming, using the Internet of Things (IoT). The system improves nutrient management by controlling fertiliser volume and monitoring real-time concentrations in parts per million (ppm). Multiple sensors were used to provide precise data for nutrient delivery optimisation, including flow, water-level, and total dissolved solids (TDS) measurements. The Blynk IoT platform allows users to input crop-specific fertiliser ratios via a mobile application. While flow sensors maintained accuracy over 94% across 250–1,000 ml target volumes, experimental evaluations revealed that the TDS sensor reached up to 99.6% accuracy within the 100–1,000 ppm range. The average response time from user command to system action was 22.17 seconds, and the system adjusted fertiliser concentrations to within 92.8–98.8% of target ppm levels. According to these findings, the prototype consistently maintains appropriate nutrient levels, with slight variation, enabling prompt adjustments and ensuring optimal growing conditions in hydroponic farming.

1. Introduction

Precision farming is a modern farming management concept that applies advanced technology, utilising sensors and analytical tools, to increase agricultural yields and support informed management decisions [1]. Precision farming utilises advanced technologies, including global positioning systems (GPS), sensors, and drones, to enhance agricultural management [2]. This approach enhances output, reduces labour costs, and ensures efficient management of irrigation and fertilisation systems. By leveraging extensive data, precision farming optimises resource use, increases yields, and contributes to sustainable crop production.

The evolution of precision farming has integrated it into the Internet of Things (IoT), a network of interconnected devices that exchange data among themselves and with the cloud [3]. IoT applications in agriculture include monitoring livestock, soil conditions, weather patterns, and pest infestations, enabling maximised yields and reduced costs [4]. Maintaining optimal nutrient concentrations, measured as total dissolved solids (TDS), is crucial for successful cultivation in hydroponic farming. This method is typically achieved by manually adding fertiliser AB to regulate TDS and adjust the pH accordingly [5]. Human intervention remains necessary for this process [6]. This is because farmers must constantly monitor the nutritional status of the plan, which may result in time loss and introduce a significant margin of error [6 – 9]. Thus, the traditional approach overuses resources, risking damage to the hydro environment and compromising sustainable agriculture [10].

Recent developments in IoT technology have significantly impacted agriculture, particularly by enabling precision-farming instruments [11, 12], such as IoT-based fertiliser-mixing devices. TDS values are reliable indicators of the nutrient levels in fertiliser solutions, making accurate assessment of nutrient concentration an essential part of these systems. In real time, the importance of using sensors to monitor key water quality indicators, including pH, turbidity, and conductivity, has been highlighted by previous research [9, 13, 14]. Because the precision and reliability of these sensors are critical for efficient fertiliser management in hydroponic systems, Adjovu *et al.* [9] emphasised the need for calibration. IoT-driven solutions have demonstrated efficacy in automating fertiliser management procedures, augmenting accuracy and productivity. For example, Chaikhamwang *et al.* [14] and Aguilando *et al.* [15] have demonstrated the optimisation of IoT fertiliser application and mixing, resulting in more consistent nutrient delivery and increased crop yields. However, sensor calibration stability issues, integration difficulties, or the absence of real-time mobile-based control interfaces remain barriers to many of these implementations.

This paper builds on prior research by presenting the development and evaluation of an IoT-based fertiliser-mixing prototype for precision hydroponic farming. While many existing IoT systems incorporate TDS, flow, and water-level sensors, this prototype integrates these sensors with the Blynk IoT platform. Unlike traditional methods, the prototype allows users to input fertiliser requirements via a mobile application, supporting dynamic adjustments to maintain optimal growing conditions. Functional analysis and experimental evaluations were conducted to verify performance, including fertiliser concentration adjustment, flow-rate measurements, sensor calibration stability, TDS sensor accuracy testing within its operational range of up to 1,000 ppm, and system response-time analysis.

The remainder of the paper is structured as follows: Section 2 summarises previous research on sensor applications in precision agriculture, nutrient optimisation, and IoT-based fertiliser management. The methodology explores system architecture, encompassing hardware and software development, and experimental techniques, which are covered in Section 3. The evaluation results are presented and discussed in Section 4, and the main conclusions and potential future research areas are given in Section 5.

2. Insights from Previous Research

Agriculture has experienced a surge in the adoption of IoT technologies to improve productivity, efficiency, and sustainability. Previous research demonstrates that sensors, microcontrollers, and cloud platforms can control nutrient delivery and irrigation, thereby laying the groundwork for IoT-based fertigation and fertiliser mixing systems. Most implementations, however, handle sensing, mixing, and dosage optimisation independently, indicating the need for an integrated, calibrated IoT fertiliser-mixing system designed explicitly for hydroponic precision farming.

2.1 IoT Technologies in Precision Agriculture

IoT in agriculture commonly combines environmental and nutrient sensors with low-cost microcontrollers and cloud connectivity to enable real-time monitoring and control. A real-time water monitoring study by Ushire and Jaiswal [16] emphasise the significance of using sensors to assess various water quality characteristics such as pH, turbidity, and conductivity. These sensors communicate with a NodeMCU ESP8266 microcontroller unit, which collects data, processes it, and transfers it to cloud storage for continuous assessment. TDS and associated conductivity measurements provide a valuable proxy for nutrient concentration in hydroponics and fertigation, but accurate readings require proper calibration. Therefore, Adjovu *et al.* [17] recommend calibrating TDS sensors against standard solutions of known concentration to ensure reliability in nutrient management procedures. These studies emphasise that, to enable accurate nutrient control, IoT-based fertiliser systems must prioritise sensor selection and calibration.

2.2 IoT-based Fertigation and Fertiliser Mixers

IoT has also been applied directly to fertiliser mixing and fertigation systems. Chaikhamwang *et al.* [14] presented a case study on a fertiliser mixer prototype that typically adjusts ratios based on user input. The A and B tanks will transfer the liquid into the mixer tank, which will be mixed by a basic stirrer powered by a servo motor. The hardware typically comprises actuators to regulate water and fertiliser flow, sensors to monitor soil moisture and nutrient levels, and control devices, such as ESP32S microcontrollers. The results of the automatic fertiliser mixer indicated that it could perform the task within the specified capacity, with a weight error of 7% relative to the total weight of the required fertiliser [14]. Similarly, the case study by Nordin *et al.* [18] investigated the performance of an automatic fertiliser mixer for fertigation farming systems, employing microcontrollers to mix raw fertiliser materials into either set A or set B fertilisers. Moreover, Aguilando *et al.* [19] developed an IoT-based autonomous irrigation and fertiliser application system for Capsicum Frutescens, demonstrating the potential of IoT to optimise water and fertiliser use. Together, these studies demonstrate the need for more precise, closely coupled sensing–mixing architectures and confirm the potential of IoT for automated fertiliser management.

2.3 Nutrient Formulation and Optimisation Strategies

Fertiliser optimisation is a crucial component of precision farming because nutrient formulation and application rate significantly affect plant growth. Using a completely randomised design, Dewi *et al.* [20] assessed various nutrient combinations, such as AB MIX and multiple organic supplements, and demonstrated that different nutrient formulations significantly affected the height of Caisim plants. Giannoccaro *et al.* [21] proposed a modelling-based approach to optimise fertiliser dosing in smart fertigation pipelines, integrating system modelling, control, and testing to translate estimated crop requirements into precise applied doses. To improve sustainability without sacrificing yield, Tabaglio *et al.* [22] modified a nutrient film technique (NFT) system to lower nitrate accumulation and fertiliser usage in lettuce. These results reaffirm that any IoT-based fertiliser mixing system must support adjustable nutrient strategies to match crop needs and environmental conditions over time, in addition to delivering the proper concentration.

2.4 Sensor Platforms for Smart Hydroponics and Aquaponics

Smart farming has been supported by several IoT-based sensor platforms, such as specialised hydroponic/aquaponic monitors and weather station-style devices. Krishnan and Abd. Kadir [23] have proposed novel smart IoT devices for use in agriculture as weather stations, integrating various smart farming sensors with Arduino technology. It aims to collect environmental data and transmit it to the cloud to provide real-time data for efficient environmental monitoring, enabling smart farming and improving overall yield and product quality. Ishak *et al*. [24] demonstrated how mechanical design directly affects sensor accuracy and system reliability by presenting an autonomous fertiliser mixer utilising IoT, and reported difficulties in detecting weight on a revolving drum due to vibration. As a result, they used a static storage drum. Their cost analysis demonstrated the financial advantages of IoT-enabled automation, showing that automated organic fertiliser production could reduce operating costs by nearly twofold compared with manual methods. In hydroponic and aquaponic systems, where plant health is directly impacted by nutrient balance and water quality, real-time monitoring is vital. Gómez-Chabla *et al.* [25] developed a monitoring system for lettuce growing in an NFT hydroponic system, which included a mobile application for monitoring control variables and taking remedial actions to manage environmental parameters. Khaoula *et al.* [26] proposed an architecture for monitoring and controlling an IoT-based solar-powered aquaponics system, emphasising the integration of renewable energy sources and smart agricultural methods.

Together, these studies show significant advancements in IoT-based sensing, fertigation control, and nutrient optimisation. However, there remains a need for an affordable, precisely calibrated TDS-driven fertiliser mixing system that integrates sensing, mixing, and control specifically for hydroponic precision agriculture.

3. Methodology

This section outlines the software implementation, system architecture, and experimental techniques utilised in the development and assessment of the IoT-based fertiliser mixing prototype for precision agriculture.

3.1 System Architecture

The prototype is centred on a NodeMCU ESP32 microcontroller, selected for its wireless fidelity (Wi-Fi) capabilities and compatibility with various analogue and digital sensors. The hardware components work together to create a closed-loop fertiliser mixing and dispensing system. The ESP32 collects sensor data, processes it to determine dosage requirements, and uses it to control solenoid valves and pumps in real time. The system comprises three main processes: real-time monitoring, fertiliser mixing, and the user interface.

Nutrient concentration, dispensed volume, and fertiliser AB levels in the reservoir are tracked in real time using TDS, flow, and water-level sensors. In accordance with the control logic implemented on the ESP32, pumps and solenoid valves are used in the fertiliser mixing process to transfer water and fertiliser from dedicated tanks into a mixing reservoir. The Blynk IoT platform provides a user interface that enables users to view sensor readings in real time and specify target nutrient concentrations and fertiliser volumes via a mobile application. The physical prototype layout and its sensors/actuators, the corresponding circuit design, and the overall system processes are all depicted in Figs. 1–3.

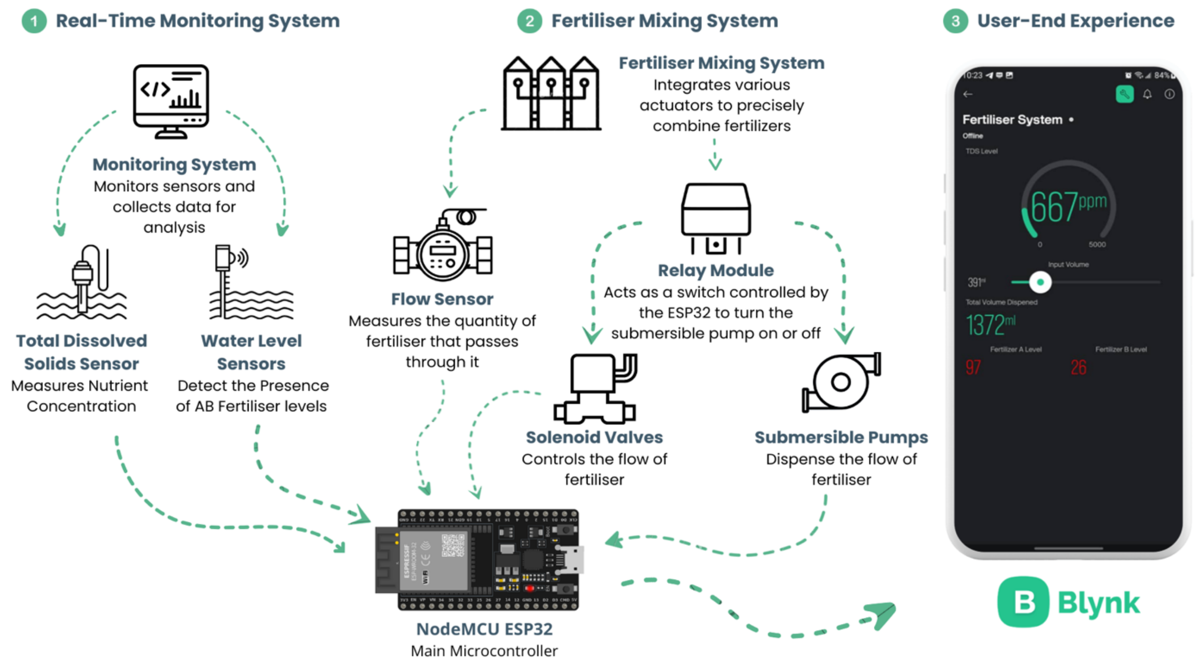
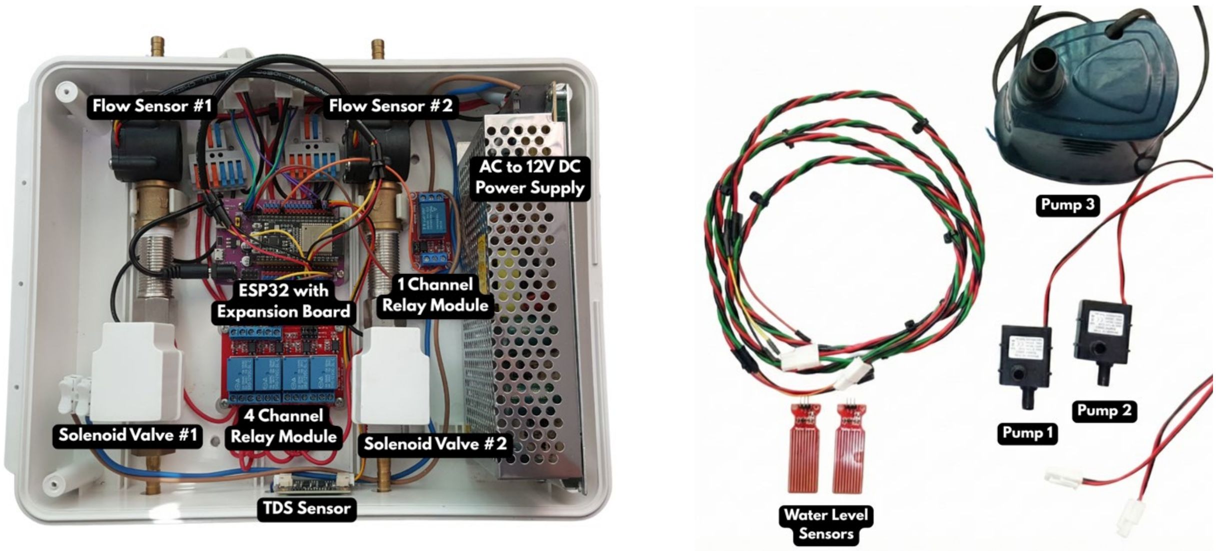


Fig. 1 *Overall IoT-based fertiliser mixing system processes, including TDS sensor, flow sensor, solenoid valves, pumps, NodeMCU ESP32 microcontroller, and Blynk IoT interface*



(a) **(b)**

Fig. 2 *IoT-based fertiliser mixing system prototype (a) Layout of the prototype; (b) Sensors and actuators*

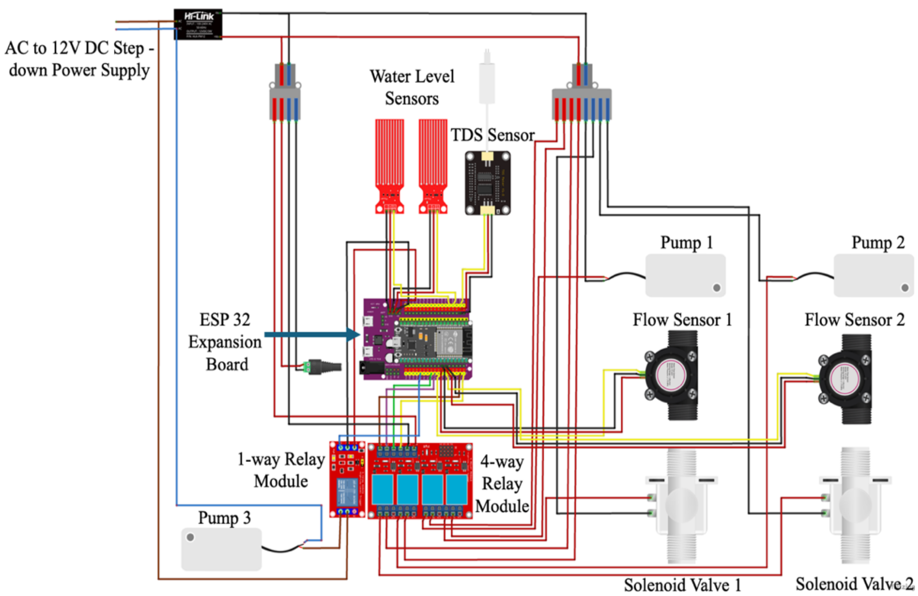


Fig. 3 *Circuit design*

3.2 Software Development

The Arduino IDE was used to develop the system software for the NodeMCU ESP32, and it was integrated with the Blynk IoT platform to enable remote control and monitoring. After collecting data from the TDS, flow, and water-level sensors and applying calibration and filtering, the ESP32 uses relay modules to drive the pumps and solenoid valves in accordance with user-specified goals specified in the Blynk application. The prototype's Wi-Fi connectivity enables real-time command execution and feedback, allowing users to modify fertiliser dosing parameters and observe sensor responses in real time. Fig. 4 summarises the algorithm's workflow, detailing the decision-making and system operations.

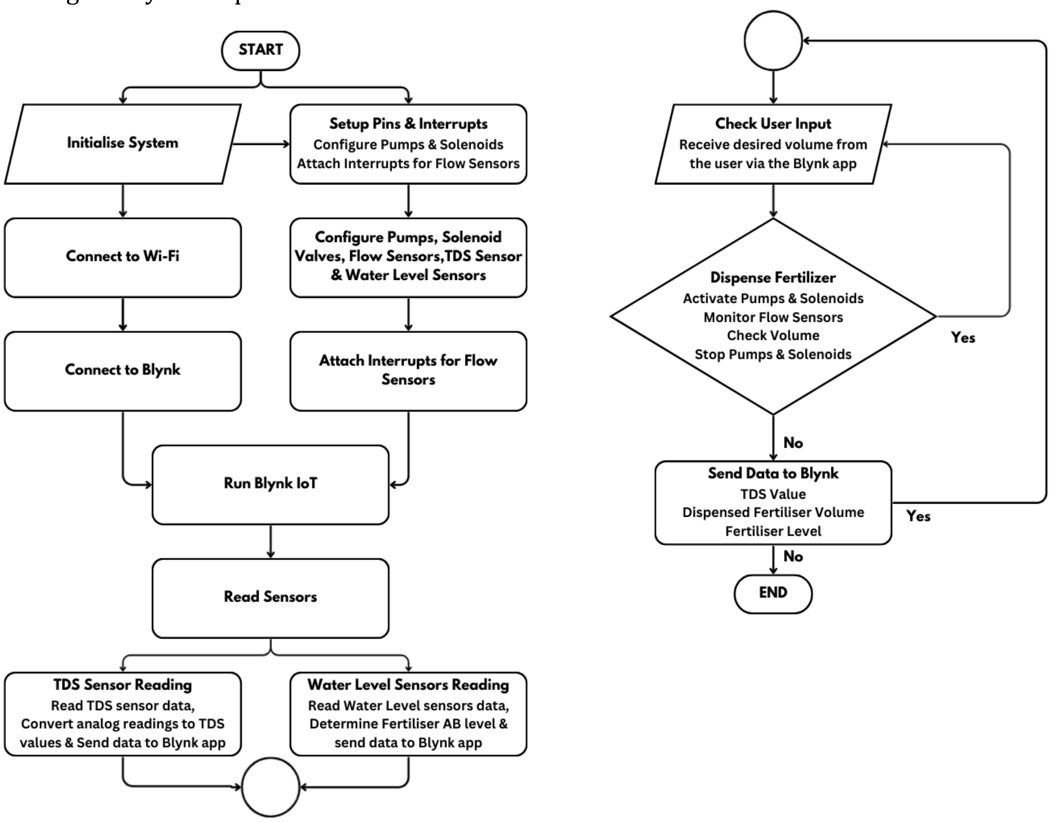


Fig. 4 *Process flow of the prototype's code implementation*

The system software employs a formula to calculate TDS and precisely determine the amount of dissolved solids in the fertiliser solution. The formula is based on empirical relationships derived from the behaviour of water conductivity. It specifically uses the following formula [27].

$$TDS = \frac{133.42 \times V^3 - 255.86 \times V^2 + 857.39 \times V}{2} \times F \tag{1}$$

The compensated voltage from the TDS sensor is denoted V, and the calibration factor is represented as F. TDS levels in aqueous solutions are frequently calculated using this formula, which is based on the conductivity behaviour in water. The code accurately depicts the nutrient concentration in the fertiliser solution by applying a conversion formula to the TDS sensor's voltage readings. To apply median filtering, a digital signal processing method for reducing noise and outliers in data, the *'getMedianNum'* function is used. This function reduces noise and fluctuations in sensor readings by determining the median of a set of measurements. This helps to obtain a more stable and reliable representation of the data.

3.3 Evaluation Configuration and Validation

Key parameters were observed during prototype deployment in a hydroponic environment and during a simulated evaluation of the data collection procedure. The accuracy of the TDS sensor was evaluated by comparing its readings with those of a calibrated TDS meter across a range of prepared standard solution concentrations from 100 to 1,000 ppm. The TDS concentration was measured with a TDS sensor and compared with the expected value. The fertiliser volume was monitored and verified using flow sensor readings, and the results were compared with input volume targets. Furthermore, the water-level sensors were calibrated to determine the reservoir's fertiliser level. The sensors exhibit multiple indication levels for fertiliser AB levels, ranging from 0-700, 701-1,200, and over 1,201, to differentiate between low, medium, and high levels. Thus, the highest fertiliser AB levels were maintained to prevent disruption during the evaluations.

The prototype was connected to a Wi-Fi network and monitored via the Blynk IoT application during each evaluation, enabling adjustments based on real-time sensor feedback in the Arduino IDE's serial monitor. Calibration factors are essential for TDS and flow sensors to achieve the highest accuracy in sensor readings. The dispensed volumes were then measured using a measuring cup, and the readings were compared with the input volume. At the same time, the TDS sensor is calibrated with a standard solution at a fixed ppm to ensure that the sensor readings are close to the actual value before evaluating them with other solutions. Furthermore, real-time data from the Blynk IoT application was analysed to assess the system's performance in response to user inputs.

4. Results and Discussion

The performance of the IoT-based fertiliser mixing prototype was assessed using five metrics: TDS sensor accuracy, TDS calibration stability, flow sensor accuracy, fertiliser concentration adjustment, and system response time. The primary quantitative results and their implications for the control of hydroponic precision fertiliser are presented in this section.

4.1 Accuracy of TDS Sensor

This evaluation validates the accuracy of the TDS sensor within its operational range. The procedure begins by preparing a concentrated nutrient solution by combining 1 L of water with 50 mL of fertiliser AB in a 1:1 ratio. The TDS of this solution was measured and used as the highest reference point, at approximately 900 ppm. The dilution process began by setting aside 300 mL of the concentrated solution as the highest-ppm solution. Subsequently, 200 mL of water was added to the remaining concentrated solution to prepare a second solution with a lower TDS. An additional 300 mL of the diluted solution was then collected for measurement.

This process was repeated twice to prepare the third and fourth dilutions. The TDS for the fourth solution was measured using a TDS sensor and a calibrated TDS meter. The readings from the two devices were recorded for comparison of accuracy. The measurements were recorded three times for each solution to ensure the consistency and reliability of the TDS sensor's results. Fig. 5 depicts an overview of the TDS sensor accuracy test with different ppm solutions.

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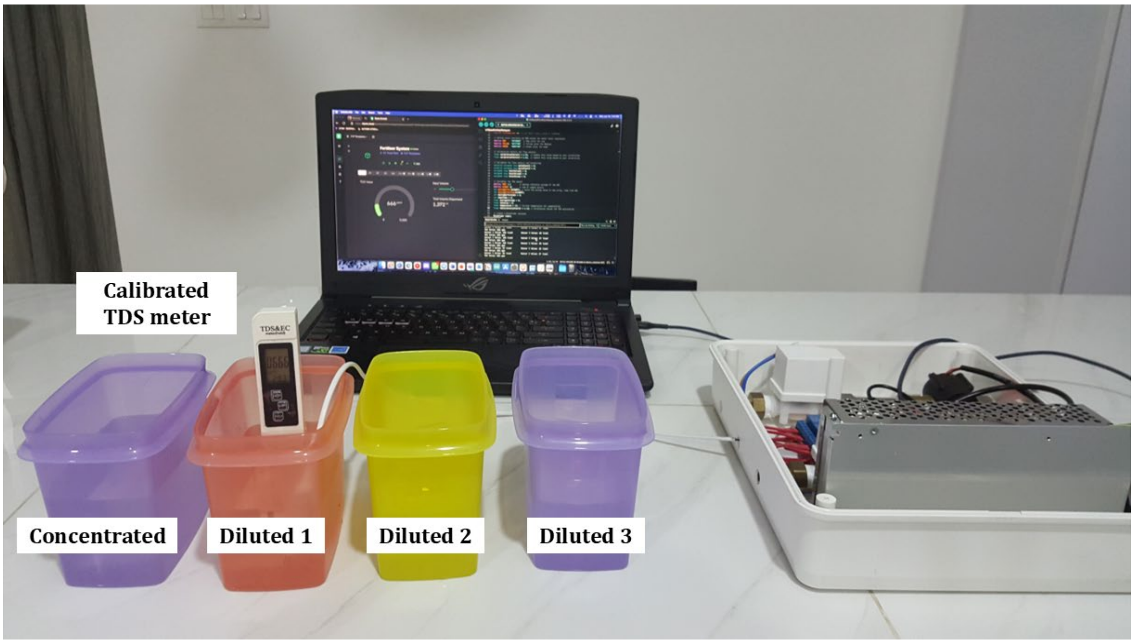


Fig. 5 *Accuracy test of the TDS sensor using different ppm solutions*

Table 1 *Accuracy test results of the TDS sensor across different solution concentrations*

Solution	TDS sensor reading 1 (ppm)	TDS sensor reading 2 (ppm)	TDS sensor reading 3 (ppm)	Average reading (ppm)	Calibrated TDS meter (ppm)	Deviation (ppm)	Percentage accuracy (%)
Concentrated (900 ppm)	893	898	897	896.00	898	4.00	99.56
Diluted 1	667	666	667	666.67	666	0.67	99.90
Diluted 2	458	460	457	458.33	458	0.33	99.93
Diluted 3	233	230	235	232.67	235	2.37	99.01

The TDS sensor readings averaged 896 ppm for the concentrated solution (900 ppm), with a 4-ppm deviation from the calibrated TDS metre reading, yielding an accuracy of 99.56%. These results suggest consistent performance even at elevated concentrations. With an expected TDS of 666 ppm for the first diluted solution, the sensor readings averaged 666.67 ppm, indicating a 99.90% accuracy rate with a minimal deviation of 0.67 ppm. The sensor averaged 458.33 ppm, deviating by only 0.33 ppm, and achieved an accuracy of 99.93% with the second diluted solution (458 ppm), demonstrating continued consistency. With a 2.37 ppm deviation, the sensor averaged 232.67 ppm in the third diluted solution (235 ppm), retaining a high accuracy of 99.01%. Table 1 presents the overall TDS sensor accuracy test results. Fig. 6 illustrates the close agreement between the TDS sensor and calibrated meter readings across the tested concentrations, further confirming that the sensor provides sufficiently precise measurements for feedback-based nutrient adjustment in hydroponic systems.

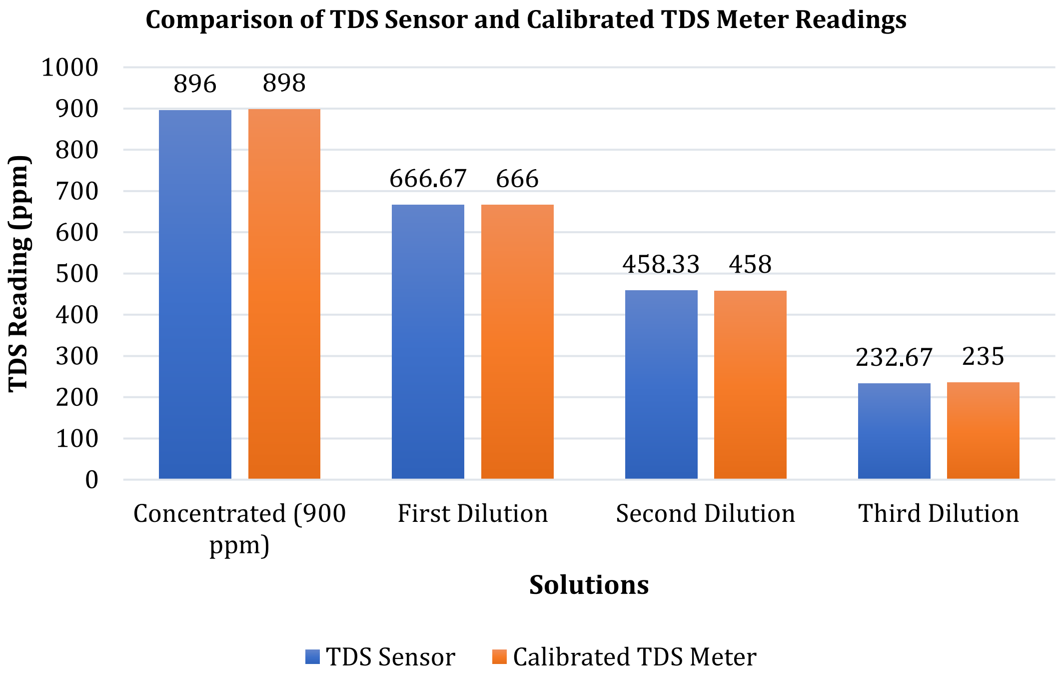


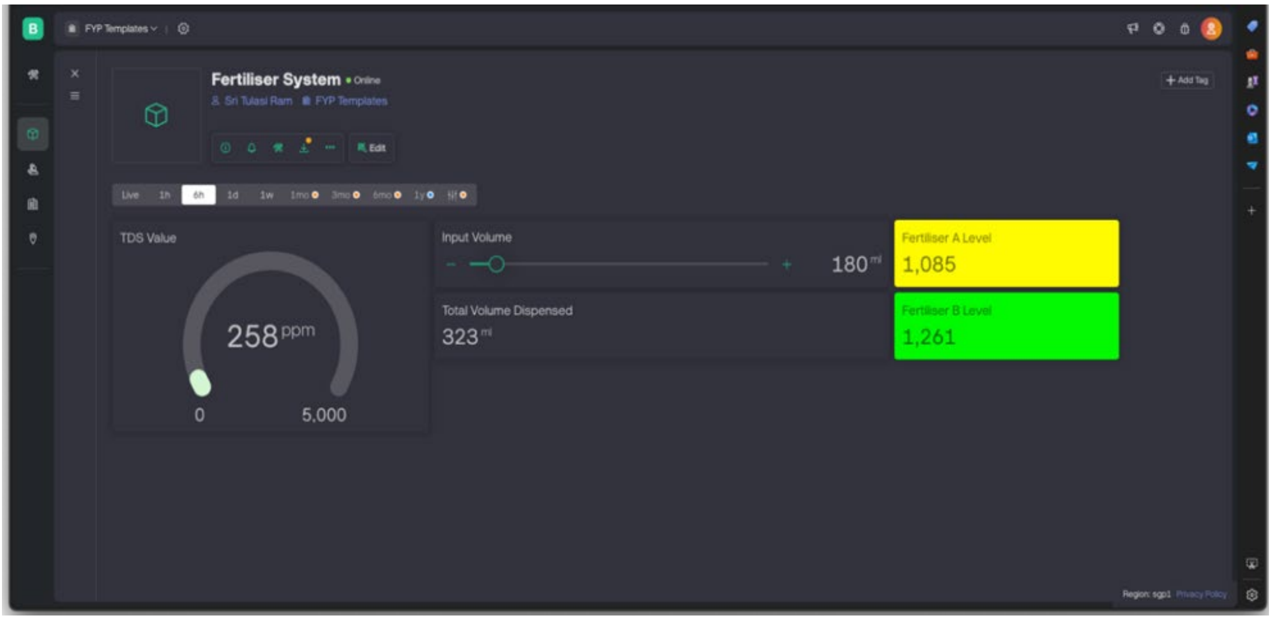
Fig. 6 *Graph of TDS sensor accuracy*

Based on these findings, the TDS sensor accurately measures up to 1,000 ppm within its working range. The results confirm the sensor's ability to deliver accurate data, which is necessary for adjusting nutrient solutions based on reliable TDS measurements.

4.2 Stability of TDS Sensor Calibration

This evaluation assesses the long-term stability and consistency of the TDS sensor readings. Fig. 7 shows the experimental setup, which includes the reference solution, bench arrangement, and Blynk monitoring interface. The mineral water has a labelled TDS value of 258 ppm, as shown on the bottle label in Fig. 7(a). Table 2 and the graph in Fig. 8 present the daily TDS readings and deviations from the initial calibration value.

(a) **(b)**



(c)

Fig. 7 *(a) Reference solution with a TDS value of 258 ppm (mineral water); (b) daily test-bench configuration; and (c) TDS readings obtained from the Blynk IoT*

Subsequently, the TDS of the same standard solution is measured daily at the same time for seven consecutive days, with each day's reading recorded. As presented, these daily readings are then compared to the initial calibration value to document any variations in the sensor's accuracy. Over the week, there was minimal variation in TDS sensor readings relative to the initial calibration value of 258 ppm.

Table 2 *Daily deviation of TDS sensor readings from the initial calibration value*

Day	TDS reading (ppm)	Deviation from initial calibration (%)
1	257	0.39
2	253	1.94
3	255	1.16
4	260	0.78
5	256	0.78
6	258	0.00
7	256	0.78

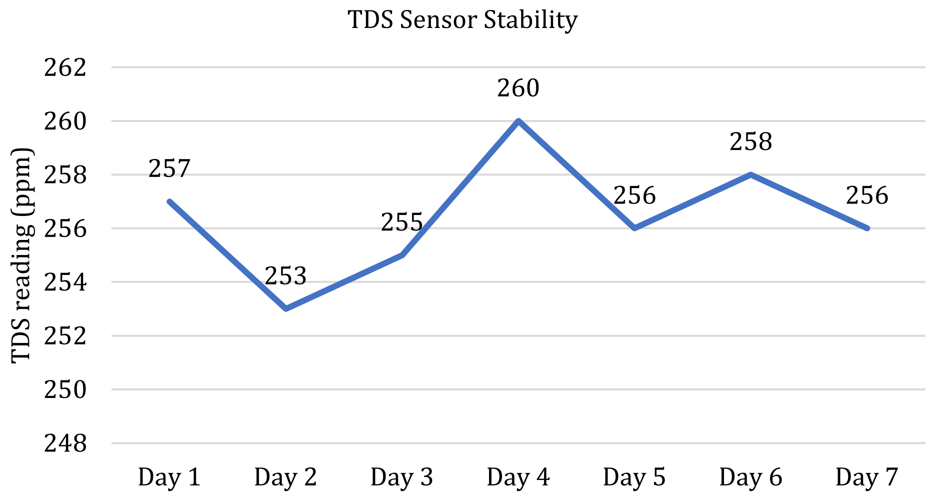


Fig. 8 *Graph of TDS sensor stability*

The maximum deviation observed was 1.94%, which is within allowable bounds. These results suggest that the TDS sensor maintains its accuracy and reliability over time, ensuring consistent performance in nutrient concentration monitoring. The TDS sensor is insignificantly impacted by external factors, such as variations in temperature or humidity within the typical range of the testing environment, as evidenced by the consistent readings over the week. The reliability of the TDS sensor can be further ensured by adhering to a regular calibration and monitoring schedule, thereby enhancing the overall effectiveness of the IoT-based fertiliser mixing system.

4.3 Accuracy of Flow Rate Sensors

The evaluation determines the precision of two flow sensors in measuring liquid volumes in a prototype that simulates fertiliser liquid using tap water. The evaluation involves comparing sensor readings with volumes measured in a calibrated container.

The process commences with the setup phase, during which the flow sensors are calibrated. In the system configuration shown in Fig. 9, the direct output pipes are routed to different containers to enable simultaneous testing of both sensors. The evaluation involves input volumes of 250, 500, 750, and 1,000 mL. During the volume measurement phase, the input quantity is doubled to reach target volumes of 250, 500, 750, and 1,000 mL. For instance, if the target volume is 200 mL, the system requires an input of 400 mL in the Blynk IoT application. The system operates on a 1:1 dispensing ratio, meaning one input unit is dispensed for every fertiliser unit. Each measurement is performed three times during this phase to obtain a consistent average reading. The dispensed liquids were transferred to a measuring cup to determine the volume.

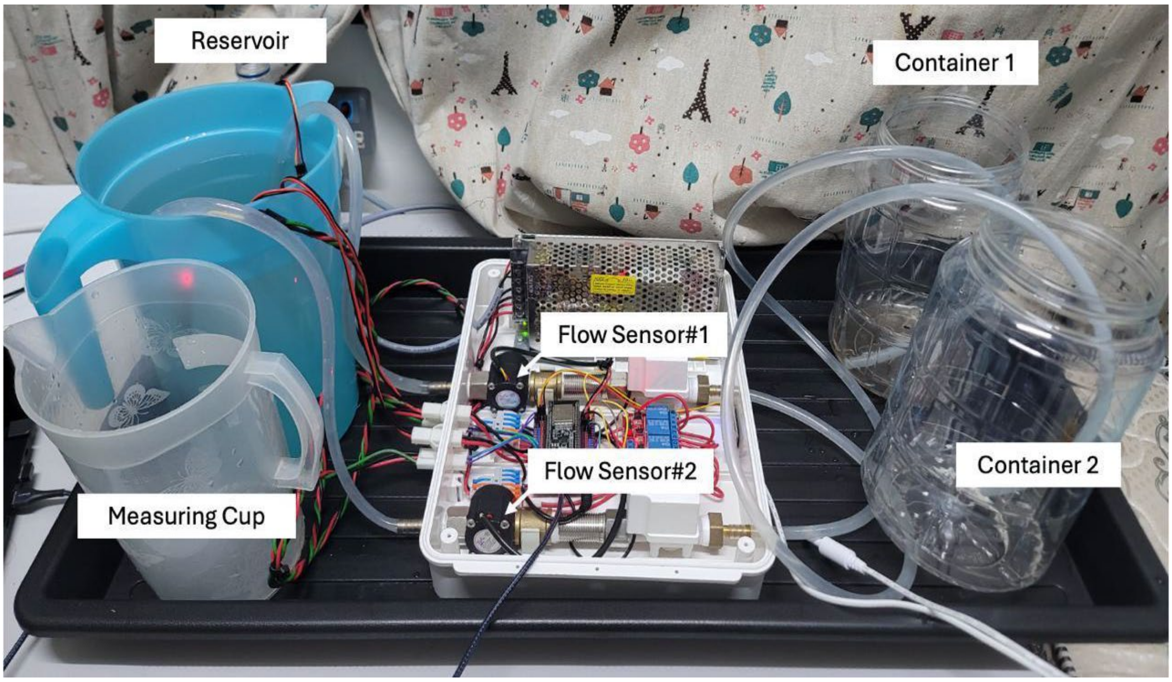


Fig. 9 *Test-bench configuration for flow rate evaluation of the sensors*

During the data analysis phase, the variance between the actual volume and the sensor reading is computed and expressed as a percentage of the exact volume to quantify the deviation. After data collection, the percentage accuracy for each sensor is calculated. The performance of Flow Sensor #1 is presented in Table 3, and the results for Flow Sensor #2 are listed in Table 4.

Table 3 *Volume measurement results of Flow Sensor #1 at different target volumes*

Target volume (ml)	Reading 1 (ml)	Reading 2 (ml)	Reading 3 (ml)	Average reading (ml)	Deviation (ml)	Percentage accuracy (%)
250	230	240	235	235.0	15.0	94.00
500	470	485	480	478.3	21.7	95.66
750	745	750	745	746.6	3.4	99.54
1,000	990	1,000	995	995.0	5.0	99.50

Table 4 *Volume measurement results of Flow Sensor #2 at different target volumes*

Target volume (ml)	Reading 1 (ml)	Reading 2 (ml)	Reading 3 (ml)	Average reading (ml)	Deviation (ml)	Percentage accuracy (%)
250	235	240	235	236.7	13.3	94.68
500	500	505	500	501.7	1.7	99.66
750	760	755	755	756.7	6.7	99.10
1,000	1,025	1,020	1,010	1,018.3	18.3	98.17

The findings reveal that Flow Sensors #1 and #2 exhibit high accuracy, with minor deviations and percentage accuracy remaining within acceptable limits. Differences in volume can be addressed by adjusting the calibration factors of individual sensors. Meanwhile, the excess volume dispensed is likely due to residual liquids in the dispensing pipes. Despite minor discrepancies, possibly due to flow dynamics, sensor calibration, or measurement errors, both flow sensors are suitable for the overall system design.

4.4 Fertiliser Concentration Adjustment

This evaluation determines the volume of AB fertiliser solution required to achieve target ppm values within the operational range of the TDS sensor, up to 1,000 ppm. As shown in Fig. 10, this evaluation setup assesses the system's ability to adjust fertiliser concentrations and ensure that the nutrient solution meets the required ppm levels for optimal plant growth.

The process begins by establishing a baseline TDS level for nutrients in the hydroponic farm's water storage system. Nutrient content was measured using a TDS sensor and a calibrated TDS meter. The water storage system is then gradually added with measured quantities of concentrated AB fertiliser solution, specifically 200, 300, 400, and 500 mL. Each addition is thoroughly mixed to ensure even distribution. After each addition, ppm values are recorded using a calibrated TDS meter to track changes in the solution's nutrient concentration. All the readings are compiled in Table 5.

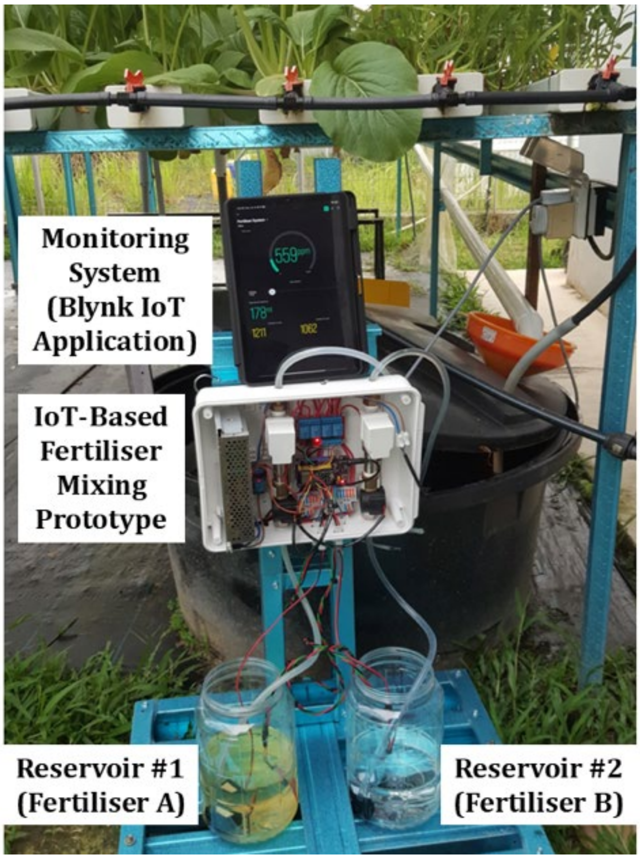


Fig. 10 *Fertiliser dispensing process into the hydroponic water storage system*

Table 5 *TDS sensor and calibrated meter readings after incremental additions of fertiliser AB solution*

Initial TDS (ppm)	Target TDS (ppm)	Volume of Fertiliser AB Added (ml)	TDS Sensor Reading (ppm)	Calibrated TDS Meter (ppm)	Deviation of TDS sensor (ppm)	Percentage achieving target (%)
103	200	200	187	192	13	96.00
192	400	300	392	395	8	98.75
395	600	400	559	557	1	92.83
557	800	500	769	764	31	95.50

Based on the results, the calibrated TDS meter and TDS sensor readings were closely aligned regarding baseline accuracy, with only slight deviations noted in the initial TDS readings and subsequent measurements. The incremental additions of the AB fertiliser solution resulted in a near-linear increase in TDS, indicating precise mixing and dispensing of the fertiliser. The TDS sensor consistently deviated by no more than 31 ppm from the calibrated TDS meter readings, which is within an acceptable range. This can be rectified by adding fertiliser to meet the target ppm values. Thus, the results confirm that the sensor is suitable for this use. The system dispenses fertilisers AB with target achievement ranging from 92.83% to 98.75%. The slight variations are acceptable, given the system's functionality, as they fall within allowable limits.

4.5 System Response Time Analysis

This evaluation assesses the response time of the IoT-based fertiliser mixing system prototype. Fig. 11 shows that the assessment begins with the system setup, which involves verifying that all system components are functional to ensure accurate results.

The evaluation begins with the Blynk IoT app, which receives a user input that triggers three commands sequentially: first, dispensing fertiliser, which activates the pump, and then opening the solenoid valve. Each command and its corresponding action are timed using a stopwatch. Each action is repeated three times to assess the system's operational consistency. During each dispensing process, the duration is recorded. The mean response time for each action is calculated by averaging the recorded times across consecutive trials.

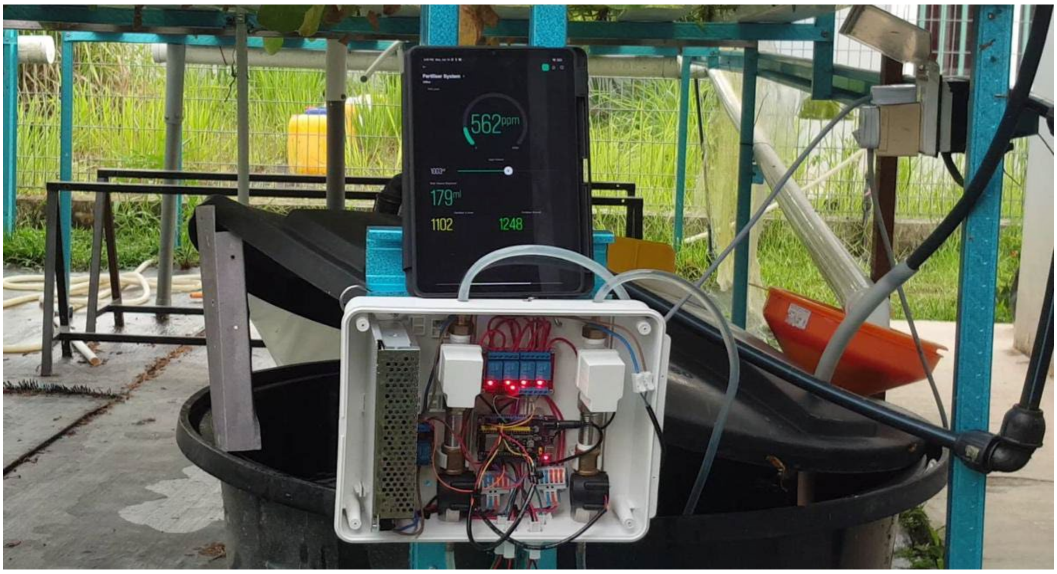


Fig. 11 *Dispensing fertiliser AB while recording the response time of the system*

The solenoid valves had an average response time of 10.85 seconds, the pumps 1.07 seconds, and the fertiliser dispensing process 10.79 seconds. Overall, 22.17 seconds were required to complete the response, measured from the time the command was issued. These findings show a slight delay during the fertiliser dispensing phase, but the system reacts quickly to user commands. The results, as presented in Tables 6 and 7, validate the system's real-time efficiency, demonstrating the speed and reliability required for precision farming applications.

Table 6 *Response times for solenoid valve activation, pump activation, and fertiliser dispensing*

Trial	Solenoid valve activation (seconds)	Pumps activation (seconds)	Fertiliser dispensing (seconds)
1	12.43	12.43	0.79
2	10.45	10.45	0.86
3	9.66	9.66	1.56
Average	**10.85**	10.85	1.07

Table 7 *Overall average system response time for key operations*

Action	Average Response Time (seconds)
Solenoid Valves Open	10.85
Pumps Activation	1.07
Fertiliser Dispense	10.79
Total Response Time	**22.17**

5. Conclusion

In summary, the prototype effectively achieved its goals and established a solid basis for further developments in hydroponic farming technology. By combining high-precision TDS and flow sensing with real-time monitoring and control via the Blynk IoT platform, the created IoT-based fertiliser mixing system enhances the sustainability, accuracy, and efficiency of hydroponic nutrient management. The evaluation findings demonstrate that the system can maintain reaction times appropriate for realistic hydroponic operation while adjusting fertiliser concentrations to the specified ppm range with high TDS measurement accuracy and tolerable flow sensor errors.

These results demonstrate how IoT and data-driven decision-making can enhance modern farming practices, particularly in NFT hydroponics. Scaling the system and incorporating it into larger precision farming infrastructures, such as multi-zone monitoring and centralised data analytics, can be facilitated by insights gained from the design, testing, and evaluation stages. Building on this research, fully automated and versatile hydroponic systems can be developed to enhance resource efficiency and promote more environmentally friendly agricultural practices that benefit farmers, consumers, and the environment.

Future research will focus on extending nutrient monitoring beyond TDS by incorporating more specialised nutrient sensors, using higher-range TDS probes for more concentrated fertiliser solutions, and improving reservoir and mixing design to accommodate a broader range of AB fertiliser volumes and formulations. Additionally, AI-based control algorithms, such as machine-learning or model-predictive controllers, can be developed using real-time data from TDS, flow, and level sensors to optimise fertiliser dosing across crop stages and climatic conditions automatically. Further priorities include conducting long-term field experiments on operational hydroponic farms to evaluate reliability, user engagement, and integration with larger precision farming platforms, as well as enhancing electrical isolation and enclosure design to improve safety in humid conditions.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Sri Tulasi Ram Rajalingam, Muhammad Muzakkir Mohd Nadzri, and Afandi Ahmad;* ***data collection:*** *Sri Tulasi Ram Rajalingam and Muhammad Muzakkir Mohd Nadzri;* ***analysis and interpretation of results:*** *Sri Tulasi Ram Rajalingam;* ***draft manuscript preparation and revision:*** *Sri Tulasi Ram Rajalingam, Muhammad Muzakkir Mohd Nadzri, Afandi Ahmad and Mohamad Khairi Ishak. All authors reviewed the results and approved the final version of the manuscript.*

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