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IoT-based smart agriculture system using fuzzy logic: case study in Vietnam

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ABSTRACT

This paper presents an internet of things (IoT)-based smart agriculture system using fuzzy logic. This system automatically supervise and regulate pivotal parameters like temperature, humidity, pH, nutrients (NPK), and electrical conductivity (Ec) for vegetables. Data from the cultivation environment is gathered by sensors system and processed by fuzzy logic algorithms to make appropriate control decisions, ensuring optimal crop growth conditions. Additionally, a web application was developed to monitor temperature, humidity, Ec, pH, and NPK content. Moreover, when any of the NPK, Ec, pH, temperature or humidity indices fall outside allowed ranges, the system send warning notifications through the web application. Furthermore, an IP camera was installed to take images of the garden and send them to users via this web app. Experimental results demonstrate the system's reliability with a pH root mean square error (RMSE) of 0.22 and temperature RMSE of 0.93, corresponding to low errors of 0.034% and 0.056% respectively. Concurrently, this system optimizes resource utilization including water and electricity to assist in reducing production costs.

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1. INTRODUCTION

Digital agriculture in Vietnam is experiencing rapid advancements, driven by collaborative efforts among government bodies, the private sector, and academic institutions. These advancements are essential in addressing the complex challenges faced by the agricultural sector, such as low productivity, sustainability concerns, and inefficiencies in the supply chain. The integration of technologies like internet of things (IoT), artificial intelligence (AI), big data analytics, sensors, and robotics is increasingly prevalent, aiming to enhance agricultural outcomes. These technologies are specifically designed to provide farmers with timely, localized recommendations, thereby improving crop yields, ensuring environmental sustainability, and building resilience against climate change [1]–[3].

Despite these significant advancements, the agriculture sector continues to face challenges related to the optimal utilization of resources and environmental management factors critical to improving crop yields and achieving long-term sustainability. Applications are being developed to offer Vietnamese farmers localized advice on seeds, nutrients, irrigation, pest management, harvest timing, and marketing channels tailored to their specific soil health, terrain, and microclimate conditions. Furthermore, these applications aim to strengthen climate resilience within agriculture and address environmental issues such as soil erosion, biodiversity loss, water contamination, and greenhouse gas emissions associated with the sector [4].

However, gaps in technological experience, confidence in using smart systems, and cybersecurity readiness may hinder the adoption of these technologies, particularly among smallholder farms and ethnic minority communities [5]. Further assessments are required to identify upskilling needs and develop inclusive policies to support these groups [6].

Several studies have contributed to the development of smart agriculture systems by integrating IoT, machine learning (ML), and fuzzy logic, as shown in Table 1 [7]–[16]. For example, Pravallika *et al.* [7] developed an IoT and ML-based system for crop yield prediction with 78% accuracy, while Ikram *et al.* [8] focused on maximizing yield using smart IoT, achieving an 18% increase in yield and a 15% reduction in costs. Other notable contributions include Bakthavatchalam *et al.* [9], who used IoT and ML for high-accuracy crop prediction, and Fatima *et al.* [13], who constructed a smart greenhouse utilizing deep learning for disease prediction. Despite these advancements, most studies remain limited in scope, focusing on specific applications such as irrigation control, yield prediction, or disease management, without integrating multiple environmental parameters into a cohesive monitoring and control system. While existing studies have demonstrated the potential of IoT and fuzzy logic in enhancing agricultural efficiency, they often lack comprehensive integration of various environmental factors necessary for optimal crop growth. Current systems typically address only one or two parameters, such as irrigation or nutrient management, but do not offer a holistic approach that includes temperature, humidity, pH, and nutrient levels. Additionally, there is a gap in providing flexible, cost-effective solutions that can be easily adopted by smallholder farmers, especially in regions like Vietnam, where technological experience and cybersecurity readiness are limited.

Table 1. The comparison of methods for the smart agriculture based IoT platform

Reference	Objective	Methods	Results
Pravallika *et al.* [7]	Crop yield prediction based on smart soil	IoT, ML	78% accuracy, cost-effective, increase their productivity and profit
Ikram *et al.* [8]	Maximize yield using smart IoT	IoT, ML	18% yield increase, 15% cost reduction
Bakthavatchalam *et al.* [9]	Crop prediction based on IoT and ML	IoT, ML	Predict crop yield with high accuracy
Nigam *et al.* [10]	Crop yield prediction using machine learning	ML	Crop yield prediction compared on the basis of mean absolute error
Jain and Ramesh [11]	Weather-based crop selection	ML	Combined weather data with machine learning to select appropriate crop varieties
Chlingaryan *et al.* [12]	Crop prediction based on IoT and ML	IoT, ML	Predict crop yield with high accuracy
Fatima *et al.* [13]	Crop disease prediction	IoT, deep learning	Constructed a smart greenhouse based on IoT and used deep learning to predict plant diseases
Dumitrescu *et al.* [14]	Intelligent control using fuzzy logic	Fuzzy logic	High control efficiency
Rajagiri *et al.* [15]	DC motor control using fuzzy logic	Fuzzy logic	Precise speed control
Liu *et al.* [16]	Accurate estimation of crop yield and optimal nitrogen management	IoT	Cost-effective and comprehensive solutions
This study	Monitoring and intelligent control using fuzzy logic	IoT, fuzzy logic	Cost-effective, flexible monitoring, reliable accuracy, mobility

Previous studies primarily used fuzzy logic or machine learning for irrigation control, prediction, and crop care to reduce costs and increase efficiency. In Vietnam's transition to digital agriculture, applying smart monitoring technology is a crucial step forward.

Several studies have developed smart agriculture systems using IoT, employing data transmission technologies like Zigbee, WiFi, and LoRa, combined with sensors and microcontrollers such as Arduino, Raspberry Pi, and ESP32. These systems achieved significant results in water conservation, yield increase, and resource waste reduction [17]–[22] as shown in Table 2.

Common hardware includes environmental sensors and microcontrollers. Software utilizes conventional programming platforms and web/mobile applications. Wireless communication protocols like WiFi, Bluetooth, and low power wide area network (LPWAN) are widely used.

The current challenge in smart agriculture is the creation of monitoring and control systems that are both flexible and cost-effective. This study addresses these challenges by proposing a novel IoT-based smart agriculture system that utilizes fuzzy logic to optimize multiple parameters critical for crop growth, including temperature, humidity, pH, and nutrient levels. Unlike previous studies, which primarily focused on specific applications like irrigation control or yield prediction, this study aims to bridge these gaps by integrating these parameters into a single, cohesive monitoring and control platform. The proposed system not only provides a comprehensive solution for optimizing crop growth conditions but also offers a cost-effective and flexible approach that can be remotely managed through a web-based application. This platform enables real-time insights and automated management of agricultural operations, representing a significant advancement over existing systems. The rest of this paper is organized as follows: section 2 presents the system description, section 3 details the methodology, section 4 discusses the experimental results, and section 5 concludes the study.

Table 2. The comparison of hardware and software components of the agriculturally based IoT platform

Reference	Objective	Data transmission method	Hardware	Monitoring platform	Results
Awawda and Ishaq [17]	Smart irrigation system	Zigbee	Moisture, rain, temperature sensor. Arduino/Raspberry Pi MCU	Flask framework	Water saving; reducing the need for manpower
Zhao *et al.* [18]	Precision agriculture system	WiFi	Rasberry Pi/Arduino, DHT 11 sensor	Thinkspeak	Reduction of resource wastage
Phasinam *et al.* [19]	Monitoring and smart crop tracking	WiFi	Various sensors; Arduino Uno	Mobile application	Monitoring and reduce agricultural waste
Kumar *et al.* [20]	Smart drip irrigation	WiFi	DHT 11, DS18B20; ESP32; ESP8266	Thingspeak	High yield about 12.05% and water saving 11%
Benzaouia *et al.* [21]	Smart precision irrigation system	LoRa protocol	Soil moisture, ambient temperature, solar irradiance, and rainfall sensors; ATmega2560	Mobile app	Remote data monitoring, saving water, and energy consumption
Rahman *et al.* [22]	Remote monitoring and management based IoT	WiFi	ESP32, Raspberry Pi; camera; temperature and humidity sensor	Web app	Real-time farm
This study	Smart precision irrigation system and monitoring based IoT	WiFi	All in one sensor, camera IP, ESP32 sensor	Webserver	Water saving, intelligent control, monitoring and warning via web app

2. SYSTEM DESCRIPTION

As shown in Figure 1, the hardware of the vegetable care system based on the IoT platform and fuzzy control system consists of three main parts. The first part is the input sensor block, which is integrated into an IoT data collection system using the ES-SOIL-7-IN-1 sensor, designed to help farmers cultivate plants under optimal conditions. This block includes a temperature sensor for measuring temperature, a soil moisture sensor for monitoring moisture levels, a pH sensor for assessing soil pH, and soil nitrogen, phosphorus, potassium (NPK) nutrient sensors to determine the levels of these essential nutrients.

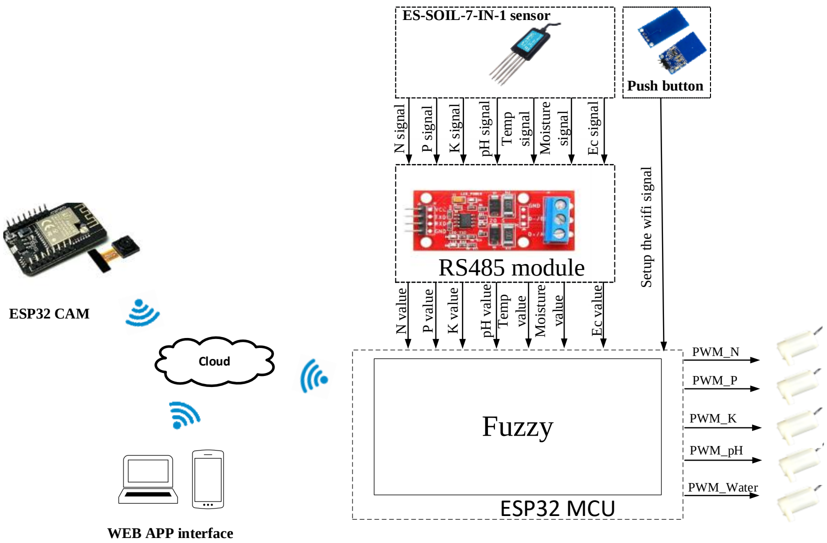

Figure 1. Vegetable care system based on IoT platform and fuzzy control

The second part is the ESP32 microcontroller, which receives signals from the sensor block and implements a fuzzy logic model to control the pumping of NPK, pH, and water. The final part is the output voltage controller, which sends signals to manage the pumping of NPK, pH, and water based on the rules established by the fuzzy logic system. Additionally, all data is transferred to a server for monitoring and control via a smartphone and/or computer web application.

The crop data used in this study was collected at the Environmental Technology Laboratory at Lac Hong University, focusing on Vietnamese mustard greens (*Cải bẹ xanh*). The mustard greens were planted in pots and placed outdoors in natural conditions to ensure that the experimental conditions closely resemble real-world scenarios. Using outdoor mustard greens helps evaluate the system's feasibility and effectiveness in practical agricultural applications.

3. METHOD

This study addresses the need for a comprehensive and cost-effective monitoring system for smart agriculture. The system employs a fuzzy logic controller to regulate key environmental parameters such as temperature, humidity, pH, and nutrient levels. The selection of fuzzy logic is justified by its ability to handle the inherent uncertainties and variations in agricultural environments, which are often difficult to model using traditional control methods.

The experimental setup involves an all-in-one sensor system integrated with an ESP32 microcontroller, which collects real-time data on the aforementioned parameters. The fuzzy logic model processes this data to make control decisions, which are then executed by the system to maintain optimal growing conditions. The use of the Mamdani method for fuzzy inference is particularly suitable for this application, as it allows for intuitive rule-based decision-making, which is crucial for managing the complex interactions between different environmental factors.

The web-based platform developed as part of this study provides a user-friendly interface for monitoring and controlling the system. This platform not only allows for real-time data visualization but also enables users to set thresholds for automated warnings and interventions. The use of a cloud-based server ensures that data is securely stored and can be accessed remotely, offering flexibility, and scalability for future applications.

3.1. Fuzzy logic controller

In this study, a fuzzy logic model was built to control the irrigation system, NPK fertilizer amount and pH value. The inputs of the fuzzy logic controller are the measured values from the sensors. The sensor system includes temperature, pressure, humidity, Ec, NPK, and pH value. The measured values from the sensors will be transferred to the fuzzy logic controller for processing.

In the first stages, the process of transforming input data related to soil moisture, temperature, pH, NPK, and electrical conductivity (Ec) from crisp values to linguistic values has been executed. Specifically, linguistic values have been mapped into fuzzy membership functions (MF), encompassing factors such as moisture, temperature, pH, NPK, and Ec (min, nor, and max), as well as irrigation pump states (off, min, nor, and max). This process characterizes the transition from specific and explicit data to a more flexible and fuzzy representation. To determine the parameters of the fuzzy MF, we rely on the lower and upper bounds provided by sensors. This aids in constructing fuzzy functions that describe the relationships between moisture, temperature, pH, NPK, Ec, and irrigation pump states. Detailed information regarding the fuzzy MF of these factors is presented in Table 3.

Through this process, a fuzzy representation of the input data is established, enhancing the system's ability to process information and improve decision-making in soil and water management. In a fuzzy logic controller, the sensor input values are converted into fuzzy sets using MF. These functions define the degree to which an input value belongs to a particular fuzzy set. The control rules, which are predetermined based on expert knowledge and experience, then use these fuzzy sets to generate control responses. Each rule corresponds to a specific control action depending on the input fuzzy sets.

The fuzzy logic controller processes the control decisions from these rules to produce an output, which can either be a numerical value or another fuzzy set, depending on the system’s requirements. This output is then used to regulate devices or processes within the system to meet the desired control objectives, as illustrated in Tables 4 and 5. This mechanism ensures that the system can continuously adjust and optimize its performance to manage soil and water efficiently.

Table 3. The fuzzy MF

Input/output	Name of MF	Range	MF parameters
Soil moisture	Min	[0 100]	[0 50 70]
	Nor	[0 100]	[50 70 90]
	Max	[0 100]	[70 90 100]
Temperature	Min	[0 100]	[0 15 25]
	Nor	[0 100]	[15 25 35]
	Max	[0 100]	[25 35 100]
pH	Min	[5 7]	[5 5 6]
	Nor	[5 7]	[5.5 6 6.5]
	Max	[5 7]	[6 6.5 7]
Nitrogen	Min	[0 250]	[0 80 120]
	Nor	[0 250]	[80 120 160]
	Max	[0 250]	[120 160 250]
Phosphorus	Min	[0 250]	[0 80 120]
	Nor	[0 250]	[80 120 160]
	Max	[0 250]	[120 160 250]
Potassium	Min	[0 120]	[0 40 70]
	Nor	[0 120]	[40 70 90]
	Max	[0 120]	[70 90 120]
Ec	Min	[0 3000]	[0 1000 1750]
	Nor	[0 3000]	[1000 1750 2500]
	Max	[0 3000]	[1750 2500 3000]
Pump 6	OFF	[0 150]	[0 0 30 60]
	Min	[0 150]	[30 60 75]
	Nor	[0 150]	[70 75 90]
	Max	[0 150]	[75 90 100 150]

Table 4. Fuzzy rule for water pH and Ec pump

Hum	Temp	Motor 1	Motor 2,3,4,5	Ph	Ec	Motor 2	Motor 1,3,4,5
Min	Min	Max	OFF	Min	Min	Max	OFF
Nor	Min	Max	OFF	Nor	Min	Max	OFF
Max	Min	Min	OFF	Max	Min	Min	OFF
Min	Nor	Max	OFF	Min	Nor	Max	OFF
Nor	Nor	Med	OFF	Nor	Nor	Med	OFF
Max	Nor	Off	OFF	Max	Nor	OFF	OFF
Min	Max	Max	OFF	Min	Max	Max	OFF
Nor	Max	Max	OFF	Nor	Max	Max	OFF
Max	Max	OFF	OFF	Max	Max	OFF	OFF

Table 5. Fuzzy rule for NPK

N	Motor 3	Motor 1,2,4,5
Min	Max	OFF
Nor	Med	OFF
Max	OFF	OFF
P	Motor 4	Motor 1,2,3,5
Min	Max	OFF
Nor	Med	OFF
Max	OFF	OFF
K	Motor 5	Motor 1,2,3,4
Min	Max	OFF
Nor	Med	OFF
Max	OFF	OFF

Furthermore, defuzzification is the process of converting fuzzy outputs into crisp outputs. Defuzzification is calculated as in (1) [23]:

$$\mathrm{COA} == \frac{\int_{x_{min}}^{x_{max}} f(x).x\,dx}{\int_{x_{min}}^{x_{max}} f(x)dx} \tag{1}$$

where COA is the center of area x is the value of the linguistic variable, and $xmin$ and $xmax$ represent the range of the linguistic variable.

3.2. Algorithm flowchart of the system

The system algorithm flowchart as shown in Figure 2 includes 3 functions: MCU data transfer block to server, fuzzy logic block, and web app interface block. The MCU to server data transfer block is the bridge between the microcontroller and the server, helping to convert information from sensors and device status into a suitable format to send to the server. This provides the necessary data for the fuzzy logic control system. The fuzzy logic control system is where data processing from the conversion block is concentrated. Using fuzzy algorithms, this block makes decisions on how to control the system based on the collected information. This decision is then sent back to the microcontroller to perform control actions. The web app interface block creates a user interface via an Android platform application. Users can monitor status and control the irrigation system through this app. Data and control decisions from the fuzzy logic system are displayed directly on the app interface, providing convenience and flexibility in system management.

3.3. Simulation setup

In addition, as Figure 3, the algorithm flowchart of the ESP32MCU security camera system describes the operating process of the camera. The system starts by connecting WiFi and Firebase to transfer image data to the server. The recording process begins, and after successfully capturing images, they are stored and displayed on the web app interface. In case of unsuccessful image capture or corrupted data, the system will automatically reboot to retry or capture new images. The automated behavior and error handling help the system maintain stability and provide accurate information to the server and user interface.

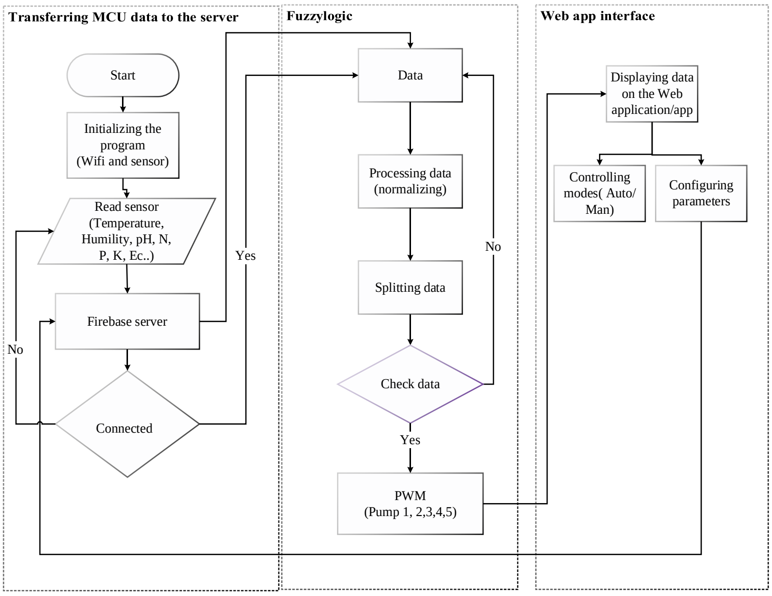

Figure 2. Algorithm flowchart of the system

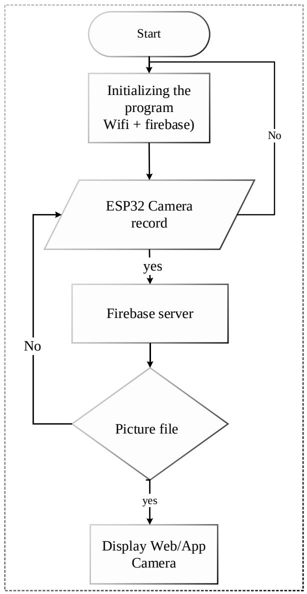

Figure 3. Algorithm flowchart of the camera

To test the fuzzy algorithm, a fuzzy logic model was carried out on MATLAB. Its shows a total of 7 inputs including pH, temperature, humidity, N, P, K, and Ec being fed into the control model of pump pulse width modulation (PWM) according to the Mamdani method. From these inputs, the model will generate 5 outputs corresponding to the PWM of the pumps: T-H PWM for pump 1, pH-Ec PWM for pump 2, N PWM for pump 3, P PWM for pump 4 and K PWM for pump 5. This helps manage and adjust the operation of irrigation and drainage pumps based on specific parameters such as pH, temperature, humidity, and nutrient concentrations in the growing environment to best meet the specific needs of the vegetable.

The fuzzification process illustrated in Table 5 transforms precise numerical input values into fuzzy linguistic values, each associated with a degree of membership. To achieve this, predefined MF are employed, mapping each input value to a membership degree ranging from 0 to 1 within the relevant fuzzy sets. In the case of soil moisture input, it is correlated with "Min," "Nor," and "Max" fuzzy sets based on the provided range and MF parameters. The MF for “min” is [0 50 70], “Nor” [50 70 90], and “Max” [70, 90, 100].

This process essentially translates an exact soil moisture content into a representation indicating a reasonably normal condition in qualitative terms. Similarly, temperature, pH, and nutrient levels undergo fuzzification into linguistic descriptors such as "Min," "Nor," and "Max" using analogous MF. The output variable, pump, is also fuzzified into various operation levels spanning from "OFF" to "Max".

3.4. Development the web app interface

The web application interface is devised for monitoring, displaying, storing, and configuring the crop care system. It encompasses the following pages:

- Home page: this serves as an overview page providing system information, highlighting key features, and furnishing control buttons to enable/disable the system. Users can observe and control the automatic or manual operation of the pump based on parameters such as pH, soil moisture, temperature, NPK, and Ec. The page displays the system connectivity status and general alerts for enhanced management. Additionally, it affords the capability to view and download data from sensors and system operations, along with the option to view images from cameras for real-time assessment of the vegetable garden's status.
- Settings page: this page enables users to configure specific alert parameters according to their requirements.
- Charts page: it presents real-time charts tracking soil moisture, pH, N, P, K, and Ec over time from sensors. Users can select specific time intervals to view the charts.
- Data page: users can view sensor readings, controls, pump status, and charts. The page also allows for updating and configuring the software for the system.

This interface provides a comprehensive approach, facilitating users in seamlessly and flexibly controlling and monitoring critical parameters of the crop garden through a web browser.

4. RESULTS AND DISCUSSION

4.1. Simulation results

This fuzzy logic control system is simulated using MATLAB Simulink, with the results representing the output of the simulated algorithm, as illustrated in Figure 4. In this simulation, environmental parameters such as pH, temperature, humidity, nutrient concentrations (N, P, K), and Ec are input into the fuzzy logic controller. The controller employs MF to convert the input values into fuzzy linguistic categories such as "low," "medium," and "high." Based on these fuzzy inputs and pre-programmed rules, the algorithm calculates the output as a PWM signal, which simulates the operation level of the irrigation pump.

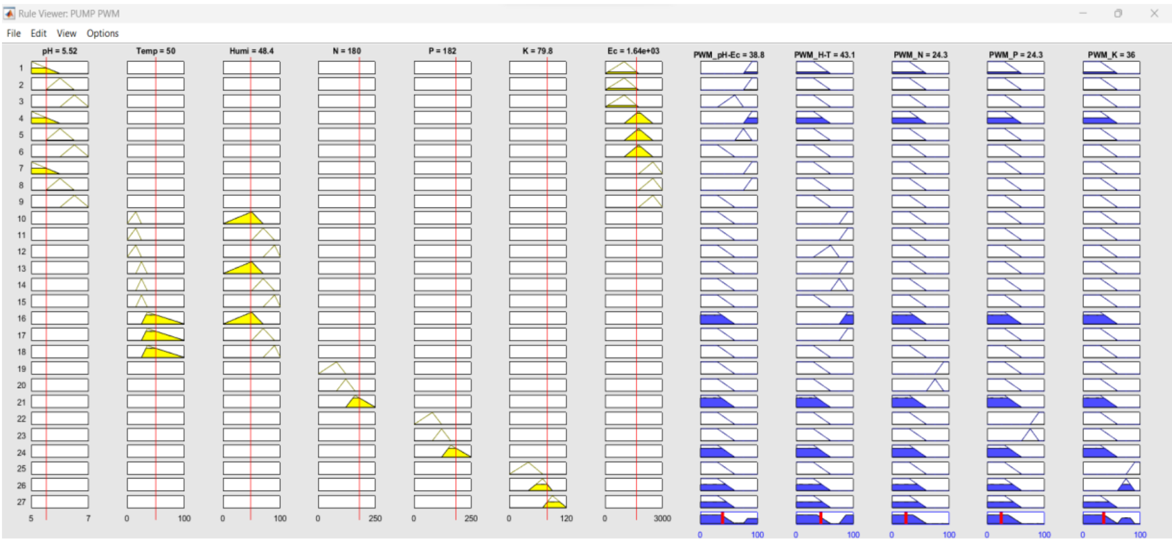

Figure 4. The simulation result of vegetable based fuzzy control

The results, shown in Figure 4, demonstrate that when environmental conditions change — for instance, a decrease in humidity or an increase in temperature — the algorithm responds by increasing the

PWM value, simulating a higher water supply. Conversely, when humidity reaches the desired level, the PWM value decreases to reduce the water supply. This simulation models a closed-loop feedback mechanism, optimizing irrigation based on real-time environmental conditions, and thus evaluating the effectiveness of the algorithm in controlling irrigation.

4.2. Experimental results

To implement the vegetable care system presented in Figure 5, a sensor system was inserted into the soil to collect data such as temperature, humidity, pH, Ec, and NPK nutrient levels. Additionally, to test the control algorithm and system settings for vegetable care, temperature, humidity, and pH were fluctuated over 30 minutes on December 25th, 2023 by taking readings every minute. To increase and decrease temperature, diluted hot water followed by cold ice water was used. For humidity, mist spray with water vapor and drying methods were utilized. To adjust the Ec and pH indices in the sample, limewater was increased and decreased to vary the pH and Ec according to system specifications. Furthermore, the concentration of essential nutrients like NPK was adjusted by using mist spraying and modulating NPK levels in the soil for 24 hours on December 27^{th}, 2023. The testing results are presented in Figure 6. According to the proposed system, the monitoring and regulation of critical parameters such as temperature, humidity, pH, nutrients (NPK), and Ec are performed automatically. Specifically, when the Ec drops below 1750 and the pH value falls below 6.5, the system automatically pumps limewater to adjust these parameters. The limewater pumping will stop when Ec reaches 2500 and the pH exceeds 6.5. As shown in Figure 6(a), the pump operates within the time frame of 0-10 minutes when the pH is below 6.5 and Ec is above 1750. However, more specifically, under the control of the fuzzy algorithm, the pump’s operation is adjusted according to the pH and Ec variables through the MF of this algorithm to ensure optimal vegetable care conditions. For instance, in the 21st minute of Figure 6(a), when the pH drops below 6 and Ec exceeds 2400, the pump will operate at maximum capacity. Similarly, the irrigation system is adjusted based on the soil’s humidity and temperature, as illustrated in Figure 6(b). Additionally, the NPK levels in the soil are automatically regulated through NPK MF, with appropriate indices set for each type of vegetable and their growth cycle, as shown in Figures 6(c) and (d).

These details are essential to understand how the system maintains optimal conditions for crop development. In addition, a web application was developed to monitor and configure the warning parameters of the vegetable care system, as shown in Figure 7. Specifically, Figure 7(a) shows the real-time system status, (b) illustrates the warning setup interface, and (c) presents the online chart for historical data visualization. All sensor data is stored on the server in real-time. Users can easily track the key indices of the system such as pH, Ec, NPK, temperature, and humidity. Moreover, an IP camera is installed to monitor abnormalities in the vegetable's physical appearance, such as irregularities in leaves and stems, so users can make appropriate decisions for each growth stage of the vegetables.

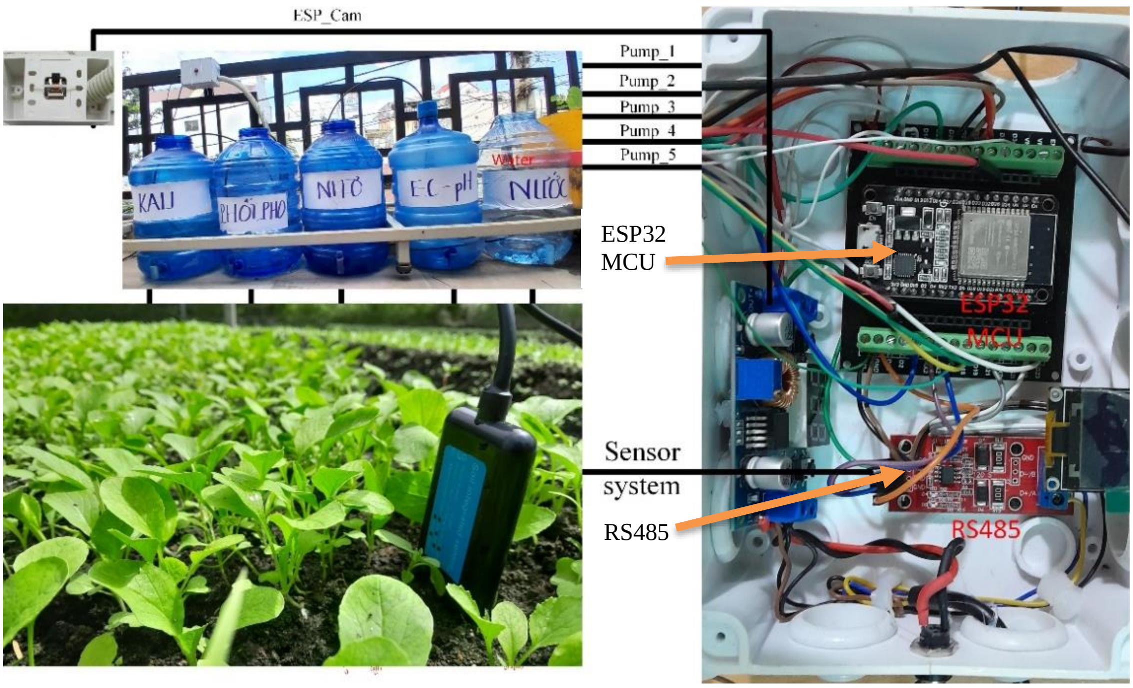

Figure 5. The vegetable care system base IoT and fuzzy logic control

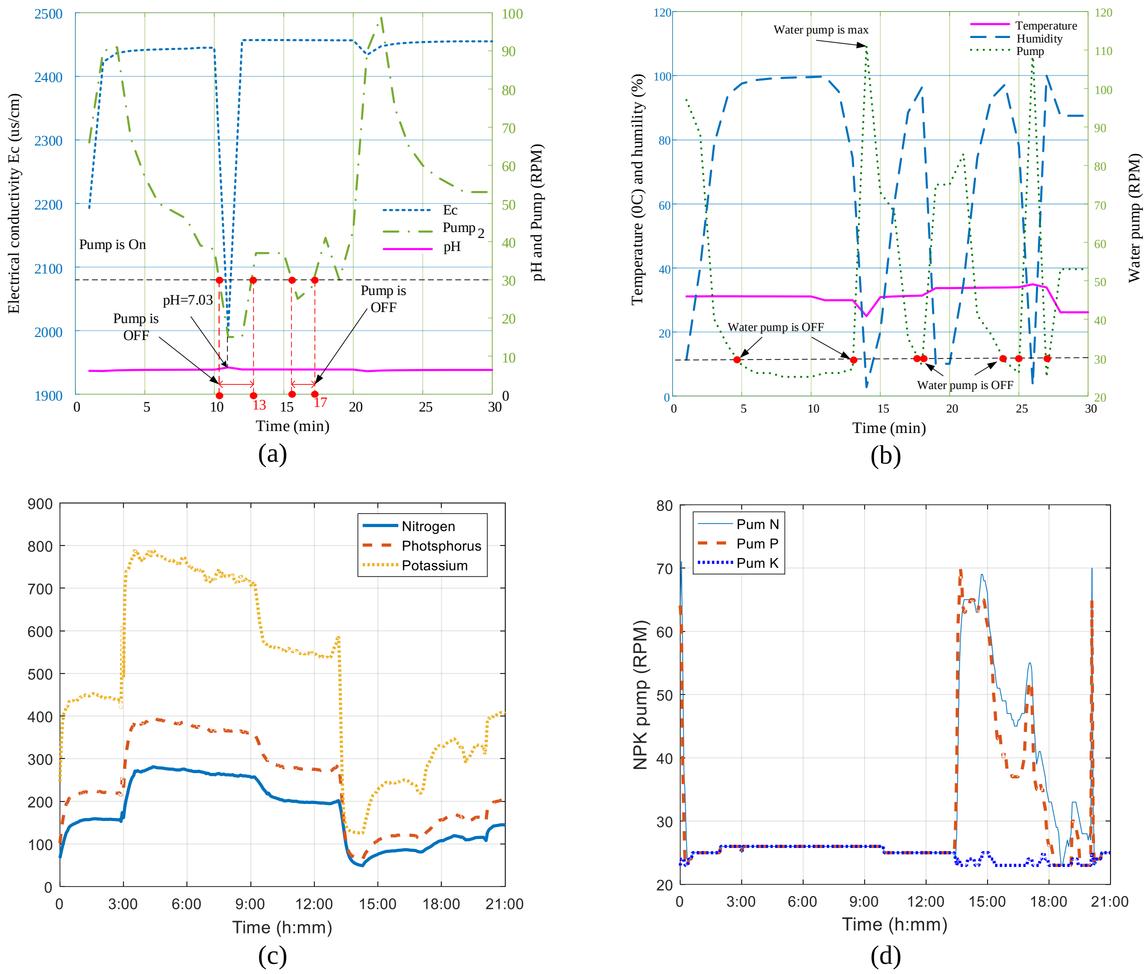

Figure 6. Testing fuzzy logic algorithm and system settings for vegetable care based IoT for (a) pumping limewater, (b) pumping water, (c) NPK levels, and (d) pumping NPK

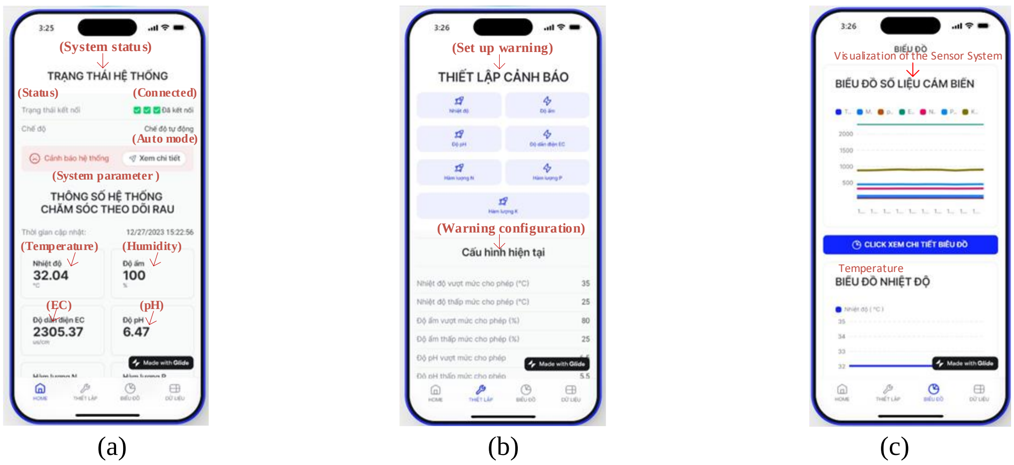

Figure 7. Mobile phone interface web app for (a) status of system, (b) set up warning, and (c) online chart of system

4.3. Analysis of the accuracy of the system

The temperature and pH measurement experiment took place at the Environmental Technology Laboratory, specifically in Room 403 at Campus 6 of Lac Hong University, on December 6, 2023, from

15:00 to 16:10. The objective of the experiment was to test and evaluate the performance of the temperature and pH measurement system in a laboratory environment. The primary measurement system employed was the ESP32 microcontroller, utilized for recording temperature and pH data. For reference values, we used the HANNA GroTine HI9814 meter. The collected data was directly displayed on the ESP32 microcontroller's serial monitor every minute.

To assess the accuracy of the system, the author computed the difference between the measured value and the reference result. Performance indices included the average absolute error (e), average absolute percentage error (e%), and root mean square error (RMSE) as per (2) to (4) [24]–[26]:

$$\mathrm{e} = y_i - \hat{y}_i \tag{2}$$

$$\mathrm{e}\% = \frac{|y_i - \hat{y}_i|}{\hat{y}_i} \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{4}$$

where y_i and $\hat{y}_i$ are the ith measurement result and reference result respectively, and n is the total number of measurements.

The difference between the measured values and reference values of pH and temperature are -0.11–0.22 and -0.9–0.8 °C. The average difference between the measured and reference values of pH and temperature are 0.034 and 0.056 and the mean squared errors are 0.22 and 0.93 °C respectively as shown in Table 6.

Table 6. The RMSE of pH and temperature

	e	e%	RMSE
pH	−0.11–0.22	0.034	0.22
Temperature	−0.9–0.8	0.056	0.93

4.4. Warning system

The warning system was triggered by the divergence of the measured temperature, humidity, pH, NPK output from the ranges of set values. In this study, the ranges of set values for the pH, temperature, Humidity, and NPK of the testing system were respectively 5.5-6.5, 15-35°C, 50%-90%, N and P 80-160, K 40-90, and Ec 1000-2500. If a measured value diverges from the corresponding range, the system will send a warning via web app.

4.5. Discussion

The results obtained from the simulation of the fuzzy logic control demonstrate the system's ability to autonomously regulate essential parameters like water and nutrient levels, which are critical for optimizing crop growth. The simulation outcomes align with the objectives set forth in the introduction, particularly in achieving a flexible and cost-effective solution for smart agriculture. When compared to existing studies, our system offers improvements in terms of multi-parameter integration and real-time monitoring capabilities. For instance, while Pravallika *et al.* [7] focused on crop yield prediction using an IoT-based smart soil system, our approach extends beyond yield prediction to include comprehensive monitoring and control of various environmental factors. Similarly, Ikram *et al.* [8] demonstrated an IoT-based system for yield maximization, but their focus was limited to yield alone. In contrast, our system offers a holistic approach by adjusting multiple factors such as pH, temperature, and nutrient levels. The outcomes of the physical model testing align with the findings of Bakthavatchalam *et al.* [9] in their study on an IoT framework for precision agriculture. Notably, our system, in comparison to the one developed by Nigam *et al.* [10], predicts crop yield by applying various machine learning techniques. The early warning system, as evidenced by the research conducted by Fatima *et al.* [13], proves effective in facilitating timely interventions, thereby enhancing farming efficiency. Specifically, our fuzzy logic controller emulates expert knowledge by correlating inputs such as temperature, humidity, pH, and nutrient levels with appropriate irrigation and fertilization amounts using MF and if-then rules. This ensures automated, optimal control that accurately reflects real-time crop requirements.

The physical prototype, which utilizes ESP32 MCU-based sensors, demonstrated stable control over water, nutrients, and environmental factors. The accuracy of the system was validated through rigorous testing, with the pH sensor showing a minimal RMSE of 0.22 and the temperature sensor showing an RMSE of 0.93 °C. These results instill confidence in the reliability of the measurements and the overall system performance. The broader implications of these findings suggest that the system can significantly enhance agricultural productivity by providing timely and accurate control over critical parameters. Moreover, the integration of a web-based monitoring platform enables users to make data-driven decisions, thereby reducing the risk of crop failure and optimizing resource utilization.

5. CONCLUSION

This study presents an IoT-based smart agriculture system that leverages fuzzy logic to optimize key environmental parameters for crop growth. The system's ability to monitor and control temperature, humidity, pH, and nutrient levels in real-time offers a significant advancement over existing solutions. The experimental results confirm the system's accuracy and reliability, with minimal errors observed in pH and temperature measurements. From a practical perspective, the system's key advantages include cost-effectiveness, flexibility, reliable accuracy, and mobility. The integration of a web-based platform further enhances its usability, providing users with real-time insights and automated control capabilities. Overall, this system has the potential to revolutionize agricultural practices by enabling more precise and efficient resource management, ultimately contributing to increased productivity and sustainability in the sector.

REFERENCES

[1] V. D. Nguyen, T. C. Pham, T. T. Pham, and A. N. Phan, "Digital and circular technologies for climate-smart and sustainable agriculture: the case of Vietnamese coffee," *IOP Conference Series: Earth and Environmental Science*, vol. 1278, no. 1, p. 12003, Dec. 2023, doi: 10.1088/1755-1315/1278/1/012003.

[2] C. N. Phan, T. H. Vuong, T. L. Ton, and T. V. Pham, "Potential land for agriculture development in three coastal districts of Ben Tre province in the Mekong delta, Vietnam," *Ministry of Science and Technology, Vietnam*, vol. 64, no. 3, pp. 76–81, Sep. 2022, doi: 10.31276/vjste.64(3).76-81.

[3] V. K. Quy, B. T. Thanh, A. Chehri, D. M. Linh, and D. A. Tuan, "AI and digital transformation in higher education: vision and approach of a specific University in Vietnam," *Sustainability*, vol. 15, no. 14, p. 11093, Jul. 2023, doi: 10.3390/su151411093.

[4] N. H. Nhuan, N. T. T. Huyen, and N. T. K. Ly, "Overview of gender mainstreaming in agriculture and rural development in Vietnam," *Ministry of Science and Technology, Vietnam*, vol. 65, no. 1, pp. 100–109, Apr. 2023, doi: 10.31276/vmostjossh.65(1).100-109.

[5] T. C. Uy *et al.*, "Mobile phone use for farm-related activities by ethnic minority farmers during the Covid-19 pandemic in Quang Tri Province, Central Vietnam," *Information Services and Use*, vol. 43, no. 1, pp. 27–37, Mar. 2023, doi: 10.3233/isu-230179.

[6] H. T. Toan, T. T. Hai, and D. T. Kien, "Requirements for information technology application competence for Vietnam agro-forestry students in the time of the 4th technology revolution," *Asian Journal of Education and Training*, vol. 10, no. 1, pp. 33–39, Feb. 2024, doi: 10.20448/edu.v10i1.5361.

[7] G. S. Pravallika, L. Kundana, K. S. Thanvi, G. Sirisha, and C. Rupa, "Proficient smart soil based IoT System for crop prediction," in *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*, Jul. 2020, pp. 752–757, doi: 10.1109/icirca48905.2020.9183054.

[8] A. Ikram *et al.*, "Crop yield maximization using an IoT-based smart decision," *Journal of Sensors*, vol. 2022, pp. 1–15, May 2022, doi: 10.1155/2022/2022923.

[9] K. Bakthavatchalam *et al.*, "IoT framework for measurement and precision agriculture: predicting the crop using machine learning algorithms," *Technologies*, vol. 10, no. 1, p. 13, Jan. 2022, doi: 10.3390/technologies10010013.

[10] A. Nigam, S. Garg, A. Agrawal, and P. Agrawal, "Crop yield prediction using machine learning algorithms," in *2019 Fifth International Conference on Image Information Processing (ICIIP)*, Nov. 2019, pp. 125–130, doi: 10.1109/iciip47207.2019.8985951.

[11] S. Jain and D. Ramesh, "Machine Learning convergence for weather based crop selection," in *2020 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS)*, Feb. 2020, pp. 1–6, doi: 10.1109/sceecs48394.2020.75.

[12] A. Chlingaryan, S. Sukkarieh, and B. Whelan, "Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review," *Computers and Electronics in Agriculture*, vol. 151, pp. 61–69, Aug. 2018, doi: 10.1016/j.compag.2018.05.012.

[13] N. Fatima, S. A. Siddiqui, and A. Ahmad, "IoT-based smart greenhouse with disease prediction using deep learning," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 7, 2021, doi: 10.14569/ijacsa.2021.0120713.

[14] C. Dumitrescu, P. Ciotirnae, and C. Vizitiu, "Fuzzy logic for intelligent control system using soft computing applications," *Sensors*, vol. 21, no. 8, p. 2617, Apr. 2021, doi: 10.3390/s21082617.

[15] A. K. Rajagiri, S. R. MN, S. S. Nawaz, and S. K. T, "Speed control of DC motor using fuzzy logic controller by PCI 6221 with MATLAB," in *E3S Web of Conferences*, vol. 87, p. 1004, 2019, doi: 10.1051/e3sconf/20198701004.

[16] S. Liu, L. Guo, H. Webb, X. Ya, and X. Chang, "Internet of things monitoring system of modern eco-agriculture based on cloud computing," *IEEE Access*, vol. 7, pp. 37050–37058, 2019, doi: 10.1109/access.2019.2903720.

[17] J. Awawda and I. Ishaq, "IoT Smart irrigation system for precision agriculture," in *Intelligent Sustainable Systems*, Springer Nature Singapore, 2023, pp. 335–346, doi: 10.1007/978-981-19-7663-6_32.

[18] L. Zhao, M. Gao, N. Lei, H. Duan, W. Qiu, and Z. Chen, "3D forward modeling and response characteristics of low-resistivity overburden of the CFS-PML absorbing boundary for ground-well transient electromagnetic method," *International Journal of Mining Science and Technology*, vol. 33, no. 12, pp. 1541–1550, Dec. 2023, doi: 10.1016/j.ijmst.2023.10.005.

[19] K. Phasinam, T. Kassanuk, and M. Shabaz, "Applicability of internet of things in smart farming," *Journal of Food Quality*, vol. 2022, pp. 1–7, Feb. 2022, doi: 10.1155/2022/7692922.

[20] V. K. S *et al.*, "Evaluation of IoT based smart drip irrigation and ETc based system for sweet corn," *Smart Agricultural Technology*, vol. 5, p. 100248, Oct. 2023, doi: 10.1016/j.atech.2023.100248.

[21] M. Benzaouia, B. Hajji, A. Mellit, and A. Rabhi, "Fuzzy-IoT smart irrigation system for precision scheduling and monitoring,"

Computers and Electronics in Agriculture, vol. 215, p. 108407, Dec. 2023, doi: 10.1016/j.compag.2023.108407.
[22] H. Rahman *et al.*, "IoT enabled mushroom farm automation with machine learning to classify toxic mushrooms in Bangladesh," *Journal of Agriculture and Food Research*, vol. 7, p. 100267, Mar. 2022, doi: 10.1016/j.jafr.2021.100267.
[23] D. K. Widyawati and A. Ambarwari, "Fuzzy logic design to control the duration of irrigation time in the greenhouse," in *IOP Conference Series: Earth and Environmental Science*, vol. 1012, no. 1, p. 12086, Apr. 2022, doi: 10.1088/1755-1315/1012/1/012086.
[24] M. S. M. Mendes, M. E. Rosa, J. A. P. Coutinho, M. G. Freire, and F. A. e Silva, "Improved accuracy in pentraxin-3 quantification assisted by aqueous biphasic systems as serum pretreatment strategies," *International Journal of Biological Macromolecules*, vol. 253, p. 127540, Dec. 2023, doi: 10.1016/j.ijbiomac.2023.127540.
[25] Z. Peng, J. Li, and H. Hao, "Development and experimental verification of an IoT sensing system for drive-by bridge health monitoring," *Engineering Structures*, vol. 293, p. 116705, Oct. 2023, doi: 10.1016/j.engstruct.2023.116705.
[26] S. Liu and A. Papanikolaou, "Regression analysis of experimental data for added resistance in waves of arbitrary heading and development of a semi-empirical formula," *Ocean Engineering*, vol. 206, p. 107357, Jun. 2020, doi: 10.1016/j.oceaneng.2020.107357.

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