Development of a fuzzy logic-based greenhouse system for optimizing bio-fertigation

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ABSTRACT

Modern agriculture faces growing challenges in meeting food and resource demands, particularly with increasing pressure on water and fertilizer usage. This study proposes a fuzzy logic-based algorithm to optimize bio-fertigation by managing key greenhouse parameters: temperature, humidity, soil pH, and soil moisture. Implemented in MATLAB, the system automates the control of actuators (fan, heater, irrigation, fertilization and fertigation pumps) based on sensor data and fuzzy rules. Results show a 27.58% reduction in water use, 58.82% decrease in fertilizer consumption, and a 47.5% increase in tomato yield. Additionally, statistical error metrics mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE) were reduced to zero, confirming the system's high precision and effectiveness in promoting sustainable agricultural practices.

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1. INTRODUCTION

Rising global population, industrialization, and climate change are reducing arable land [1] and increasing food production demands. The Food and Agriculture Organization of the United Nations (FAO) estimates significant increases in cropland and water will be needed by 2050 [2], [3]. Challenges such as labor shortages and water scarcity make traditional greenhouse methods insufficient [4]. Greenhouse farming—originating in the 19th century—now offers a sustainable solution by enabling year-round cultivation through controlled environments [5], [6]. However, conventional greenhouses rely heavily on manual labor [7]. Smart greenhouse technologies can improve efficiency by automating the monitoring and control of growing conditions [8]. Tomatoes, a nutritious and widely consumed crop, require careful water and nutrient management [9], [10]. Overuse of water and fertilizers has caused environmental harm, emphasizing the need for sustainable regulation of inputs in controlled agriculture.

Organic fertilizers provide a balanced and gradual release of nutrients, enhancing soil fertility and microbial health while reducing reliance on synthetic fertilizers. However, improper use can lead to nutrient imbalances [11]. Controlled-release formulations and compost further improve soil properties [12]. Drip irrigation conserves water and improves crop quality by delivering precise amounts at the right time [13]. Fertigation—applying fertilizers through irrigation—boosts nutrient efficiency, reduces labor, and can lower fertilizer use by 15%–25% without affecting yield, especially when tailored to crop growth stages through drip systems [14].

Diverse studies and research have been carried out in the area of monitoring internal climatic parameters and plant fertigation in greenhouses. Deepak *et al.* [15] investigates the application of fertigation—a combined irrigation and fertilization technique—in open-field agriculture with a focus on aquaponic systems. Amudha *et al.* [16] focus on optimizing fertilizer application in agriculture using bio-inspired algorithms, specifically the fruit fly optimization (FFO) algorithm and social spider algorithm (SSA). These algorithms, inspired by biological species, aim to balance chemical fertilizer use with manure to enhance soil fertility, conserve resources, and minimize environmental impacts. Dahlila *et al.* [17] propose an IoT-based smart fertigation management system designed for agricultural areas prone to power outages. The system integrates sensors for real-time monitoring of irrigation and power outages, with features such as automated irrigation scheduling, pesticide management, and polybag cleaning. Dwiratna *et al.* [18] introduce a modified hydroponic kit featuring a self-fertigation system, specifically designed for remote areas with unreliable electricity supply. Bao *et al.* [19] investigate the impact of intelligent drip fertigation (IF) on watermelon production in a greenhouse environment over three growing seasons (2019–2021). IF integrates real-time soil moisture sensors with IoT-based automated irrigation and fertilization to optimize water and nutrient application. Imbernón-mulero *et al.* [20] evaluate an advanced autonomous fertigation system designed to optimize the use of variable-quality irrigation water. Bonelli *et al.* [21] evaluated the performance of timer-based (TB) versus smart sensor-based (SB) irrigation strategies. Wang *et al.* [22] conducted a field experiment in Shouguang, Shandong Province, to assess the effects of various irrigation scheduling treatments—farmer drip irrigation (FI), intelligent irrigation (II1), and intelligent irrigation (II2)—on tomato growth, irrigation water usage, and nutrient efficiency across two growing seasons. Idris *et al.* [23] developed an internet of things (IoT)-based fertigation system to automatically deliver a fertilizer mixture with a consistent electrical conductivity (EC) value to plants. Vojnovic *et al.* [24] aimed to explore new methods for fertigation and grafting to optimize cucumber yield and quality in the greenhouse.

Traditional greenhouse control systems struggle with complexity and uncertainty, often leading to inefficient resource use and poor plant growth. Fuzzy logic provides a more adaptive and intelligent approach by mimicking human reasoning and handling nonlinear, uncertain conditions through expert-defined rules. This results in more efficient, scalable, and sustainable greenhouse management, ultimately improving crop yields.

This study presents a fuzzy logic-based algorithm for optimizing bio-fertigation in a tomato greenhouse in southern Algeria. Unlike traditional systems that manage only one or two environmental parameters, our approach integrates four key variables (temperature, humidity, soil pH, and soil moisture) and controls five actuators simultaneously (fan, heater, irrigation pump, fertilization pump, and fertigation pump). The novelty lies in the combination of real-time sensor data, expert-derived fuzzy rules, and the use of biofertilizers instead of chemical fertilizers—an environmentally sustainable practice. This multi-variable control system provides an adaptive, intelligent, and energy-efficient solution for optimizing tomato production in arid regions like southern Algeria. The article details the algorithm design, membership functions, fuzzy rule base, experimental validation, and results, concluding with future research directions.

2. METHOD

In this section, we present the proposed algorithms developed to optimize the greenhouse microclimate using fuzzy logic. The system integrates various sensors, actuators, and a microcontroller to monitor and control multiple key environmental parameters, including internal air temperature, internal air humidity, soil pH, and soil moisture. By employing fuzzy inference techniques, the algorithms dynamically adjust control actions to enhance the efficiency of bio-fertigation and promote optimal plant growth conditions.

2.1. Proposed algorithm

In this section, we present the proposed algorithm that employs fuzzy logic to monitor and control four critical parameters in the greenhouse: internal air temperature, internal air humidity, soil pH, and soil moisture. These parameters are essential for maintaining a stable microclimate and supporting healthy plant growth. By applying fuzzy logic techniques, the system ensures adaptive decision-making that improves microclimate regulation and enhances the efficiency of bio-fertigation.

The fuzzy system uses membership function graphs to illustrate how input parameters relate, where each x-axis value corresponds to two y-axis values [25]. Fuzzy logic, widely used in many fields including networking, helps convert multiple inputs into a single output [26], [27]. This study adopts the Mamdani model [28]—one of the most widely used fuzzy inference methods—following a four-step fuzzy process [27] in Figure 1. Algorithm 1 provides the pseudocode for controlling the greenhouse's microclimate.

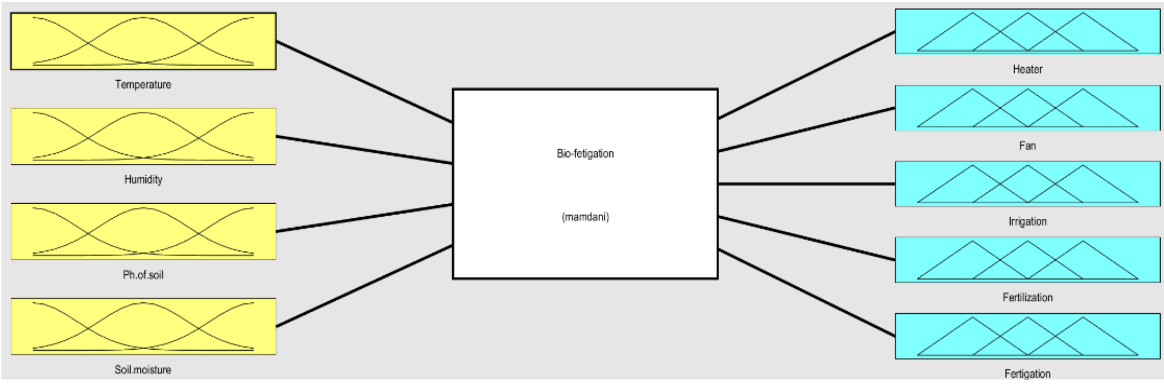

Figure 1. Our approach's fuzzy process model

Algorithm 1. Monitoring of the internal microclimate
Fuzzy inputs: Internal air temperature (Ti), internal air humidity (Hi), internal soil pH (Pi), internal soil moisture (Si), temperature threshold (Tt), humidity threshold (Ht), pH threshold (Pt), soil moisture threshold (St).
Fuzzy outputs: optimal temperature, optimal humidity, optimal soil pH, optimal soil moisture.
1. Initialize input parameters.
2. Define fuzzy sets and membership functions for each parameter.
3. Capture the real-time values of the input parameters.
4. Fuzzify the input parameters: Calculate the degree of membership for each input variable.
5. Perform fuzzy inference: Apply fuzzy rules based on input parameters to generate fuzzy output.
6. Aggregate the results from all fuzzy rules.
7. Defuzzify the output: Convert the fuzzy output into a precise control value.
8. Adjust the greenhouse systems (heating, ventilation, irrigation, fertigation) based on the defuzzified output.
9. Repeat the process in real-time to maintain the optimal microclimate.

Fuzzy logic uses linguistic variables—ranging between true and false—to represent the strength of relationships among metrics and to determine the resulting output [26], [27]. Table 1 defines how the fuzzy logic system interprets real-world sensor values (like temperature and humidity) and decides what to do with output devices (like a fan or heater) using fuzzy sets. The membership function shapes were chosen for their simplicity and suitability to the input data. Their boundaries were defined through expert input from farmers and agronomists and by analyzing real environmental data, ensuring accurate representation of linguistic terms and real-world conditions.

Table 1. Linguistic variables and Membership functions

Variable type	Variable	Linguistic terms (MFs)	Type of MF	Range
Input	Internal air temperature (°C)	Low, Average, High	Triangular	[0-50]
	Internal air humidity (%)	Low, Moderate, High	Triangular	[0-100]
	Soil pH	Acidic, Neutral, Basic	Triangular	[3-9]
	Soil moisture (%)	Dry, moderately wet, Saturated	Triangular	[0-100]
Output	Fan (Speed %)	Off, Low, High	Triangular	[0-100]
	Heater (Power %)	Off, Low, High	Triangular	[0-100]
	Water pump 1 for irrigation (%)	Off, Low, High	Triangular	[0-100]
	Water pump 2 for fertilization (%)	Off, Low, High	Triangular	[0-100]
	Water pump 3 for fertigation (%)	Off, Low, High	Triangular	[0-100]

The fuzzy graph for the air temperature parameter, with low, average, and high membership functions, is shown in Figure 2. 50 °C is the highest recorded temperature in this investigation. The air humidity fuzzy graph, which ranges from 0% to 100%, is shown in Figure 3. There are three types of air humidity: low, moderate, and high.

The fuzzy soil pH chart, which is divided into three categories: acidic, neutral, and basic, is shown in Figure 4. The fuzzy chart for soil moisture, which is divided into three categories: dry, moderately wet, and saturated, is shown in Figure 5. Figure 6 shows the fuzzy membership function for the heater, with power levels categorized as low, off, or high based on temperature deviations from the threshold. Figure 7 displays the fuzzy membership function for the fan, with power levels determined by temperature and humidity levels relative to their optimal thresholds.

Figures 8, 9, and 10 illustrate the fuzzy membership functions for irrigation, fertilization, and fertigation. Irrigation control depends on soil moisture and humidity levels, with power levels set to low, off, or high accordingly. Fertilization is regulated based on soil pH, adjusting power levels based on deviations from the optimal range. Fertigation considers both soil pH and moisture, combining conditions to determine the appropriate control power level.

The fuzzy rule base used to connect the input-output membership functions is shown in Figure 11. In our study, we have 81 rules. The fuzzy rules were primarily formulated based on expert knowledge from local farmers, agronomists, and greenhouse technicians, combined with observations from previous studies and real-world behavior of the crop under varying climatic and soil conditions [28]–[30]. The IF-THEN guidelines listed in Table 2 govern how the fuzzy inference system functions. To connect different language variables, these rules use certain fuzzy logic operators like “AND” or “OR.”

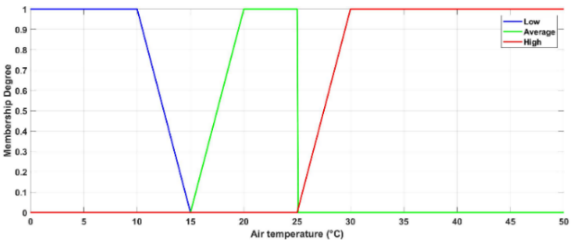

Figure 2. The membership function of air temperature

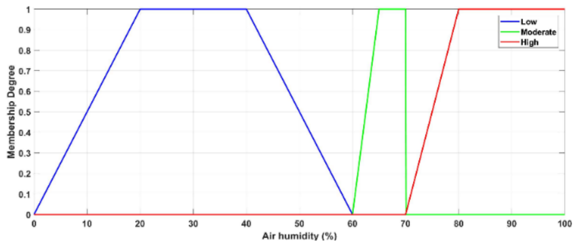

Figure 3. The membership function of air humidity

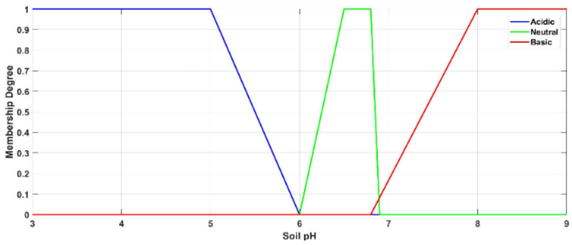

Figure 4. The membership function of soil pH

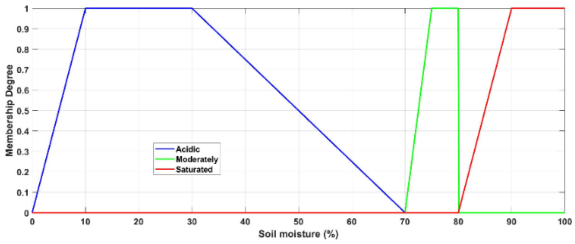

Figure 5. The membership function of soil moisture

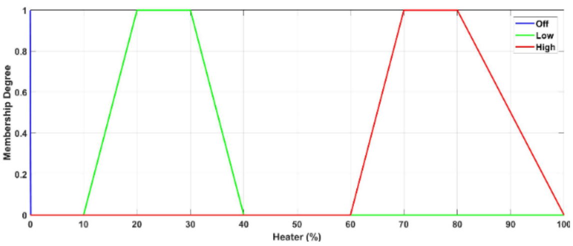

Figure 6. The membership function of the heater

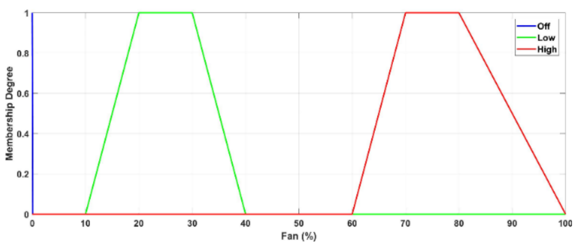

Figure 7. The membership function of the fan

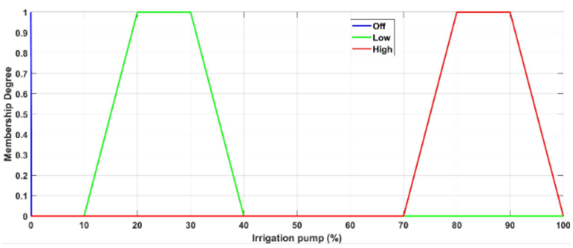

Figure 8. The membership function of irrigation pump

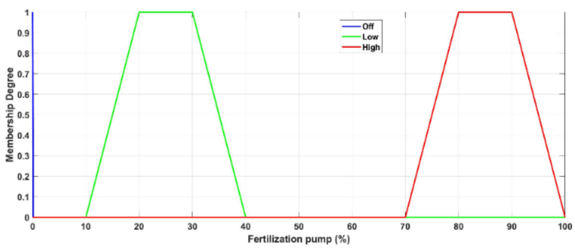

Figure 9. The membership function of fertilization pump

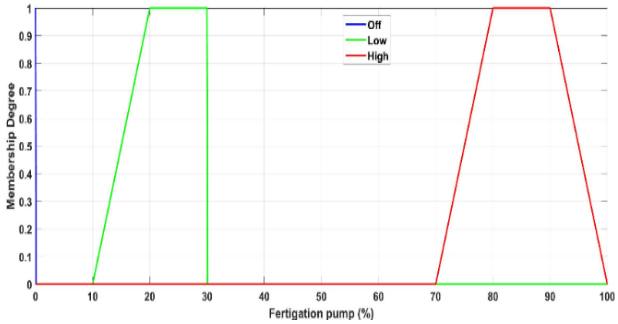

Figure 10. The membership function of fertigation pump

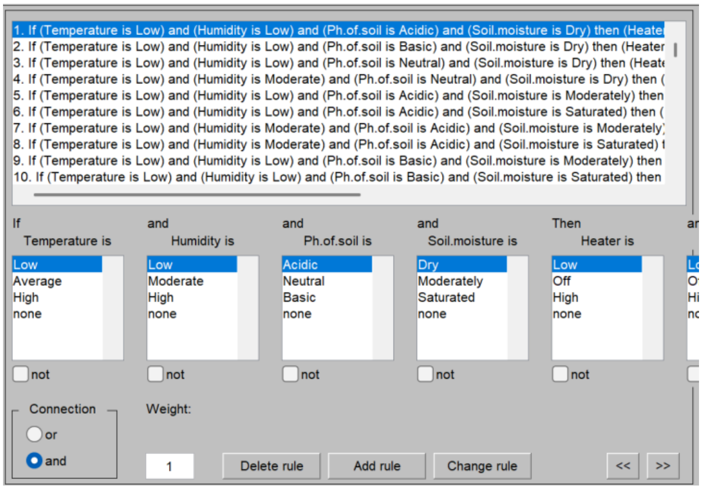

Figure 11. Fuzzy rule base

Table 2. Some fuzzy rules

Temperature	Humidity	Soil pH	Soil moisture	Actuators decision	
Low	Low	Acidic	Dry	Fan=Off Water pump 1=High Water pump 3=High	Heater=High Water pump 2=High
Low	Moderate	Neutral	Moderately wet	Fan=Low Water pump 1=Low Water pump 3=Off	Heater=High Water pump 2=Off
Average	High	Neutral	Saturated	Fan=Low Water pump 1=Off Water pump 3=Off	Heater=Low Water pump 2=Off
Average	Low	Basic	Dry	Fan=Low Water pump 1=Low Water pump 3=Low	Heater=Low Water pump 2=Low
High	High	Basic	Saturated	Fan=High Water pump 1=Off Water pump 3=Off	Heater=Off Water pump 2=Low

2.2. Block diagram of the fuzzy control system

The overall structure of the fuzzy logic-based greenhouse control system is represented in the block diagram in Figure 12. The process consists of five main stages:

a. Environmental sensors (inputs): the system starts by collecting real-time data from four key sensors that measure: internal air temperature, internal air humidity, soil pH, and soil moisture.
b. Fuzzification module: the sensor readings (crisp input values) are passed to the fuzzification module. Here, each input is mapped to corresponding linguistic variables (*e.g.*, off, low, high) using membership functions.
c. Fuzzy inference engine: based on the fuzzified inputs, a set of expert-defined fuzzy rules (IF–THEN statements) is applied. These rules model the decision-making process and determine the appropriate control actions under varying environmental conditions.

d. Defuzzification module: The fuzzy outputs produced by the inference engine are converted into precise (crisp) values using the centroid defuzzification method. This ensures that the system provides continuous, smooth control actions.
e. Actuator outputs: The final crisp control signals are sent to the corresponding actuators: fan, heater, water pump (for irrigation), fertilization pump, and fertigation pump (for combined watering and fertilization).

This entire process runs continuously in real-time, ensuring optimal growing conditions inside the greenhouse by responding adaptively to environmental changes.

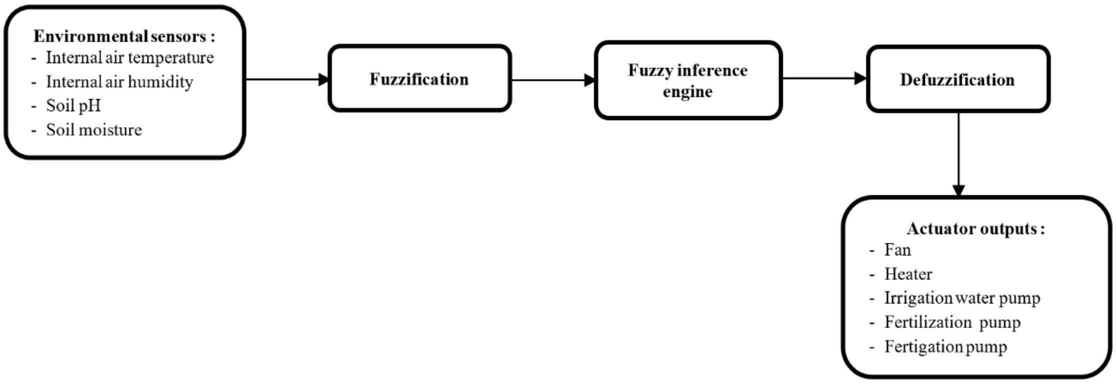

Figure 12. Block diagram

3. RESULTS AND DISCUSSION

The section begins by describing the experimental setup, and then presents a detailed analysis of the results achieved.

3.1. Experimental setting

This study, conducted in 2023/2024 at Tahri Mohammed University, Béchar, Algeria, aimed to enhance the fertigation process for farmers. The experimental setup used a glass greenhouse model in Figure 13 measuring 80 × 40 × 40 cm, divided into two sections: one for the plant, sensors, and actuators, and the other for housing three tanks (water, organic fertilizer, and mixing) and the microcontrollers. Moreover, our greenhouse includes:

- An Arduino Uno board, based on the ATMega328 microcontroller.
- An ESP8266 integrated circuit.
- A DHT11 temperature and humidity sensor.
- A soil moisture sensor.
- An HY-SRF05 ultrasonic sensor.
- A PH sensor (PH-4502C).
- Two 12V fans.
- A heater.
- Three 12V water pumps, one for each tank.

Figure 13. Our experimental greenhouse

3.2. Experimental study for the optimization of fertilization measures

In Laboratory No. 04 at Tahri Mohamed University – Béchar, Algeria, two 500 ml solutions were prepared: tap water with a pH of 6.97 and a liquid organic fertilizer (made by soaking sheep manure in water) with a pH of 4.25. Both measurements were taken at 25 °C, as shown in Figure 14.

Figure 14. Measured the mixture with a pH meter

3.2.1. Steps of the experiment

The experimental steps included:

a. After measuring the pH values, 10 ml of the liquid fertilizer was added to the tap water using a pipette and mixed thoroughly to prepare the fertigation solution.
b. The pH electrode is placed into the mixture, and the pH value is read directly from the connected electronic meter's display.
c. After each measurement, the pH electrode is rinsed with distilled water, left for ten seconds, and then wiped with Joseph paper to prepare it for the next measurement after additional fertilizer is added.
d. We measure the pH of the mixture and repeat the process until we obtain the following results in Table 3.

Table 3. pH results and the volume of the mixture using a pH meter

	Volume of the sample before adding the fertilizer	pH of the sample before adding the fertilizer	Volume of fertilizer added	Volume of the sample after adding the fertilizer	pH of the sample after adding the fertilizer
The 1st case	500 ml	6.97	10 ml	510 ml	6.84
The 2nd case	510 ml	6.84	10 ml	520 ml	6.18
The 3rd case	520 ml	6.17	10 ml	530 ml	5.96

3.2.2. Analysis of results

The experiment showed that adding 20 ml of organic fertilizer to 500 ml of water with an initial pH of 6.94–6.97 adjusts the mixture's pH to fall within the optimal range (6–6.84) for tomato plants. Adding more than 20 ml caused the pH to fall below the suitable range. This result was confirmed through repeated testing in Figure 15.

Figure 15. Results using a pH meter

3.2.3. Proof

Assuming we have 500 ml of water that we wish to use for fertilization, this is equivalent to 100%, so 20 ml of liquid fertilizer is equivalent to 4% (1) and (2): Total volume of water=500 ml and volume of fertilizer added=20 ml.

Now, to find the percentage of fertilizer in the solution:

$$Precentage\ of\ fertilizer = \left(\frac{Volume\ of\ fertilizer}{Total\ volume\ of\ solution}\right) \times 100 \quad (1)$$

Substitute the values:

$$Precentage\ of\ fertilizer = \left(\frac{20\ ml}{500\ ml}\right) \times 100{=}4\% \quad (2)$$

We know that 20 ml of fertilizer is needed for 500 ml of water, which is equivalent to 4%. So, the amount of fertilizer required for any volume of water V can be calculated based on this ratio (3).

$$Percentage\ of\ fertilizer = \left(\frac{V \times 4}{500}\right) \quad (3)$$

And, the volume of fertilizer added is:

$$Volume\ of\ fertilizer = \left(\frac{V \times 20}{500}\right) \quad (4)$$

3.3. Results

This study applied a real benchmark over a spring season (May 14–22), using captured data on internal air temperature, humidity, soil pH, and soil moisture. The objective was to maintain these parameters within thresholds defined in consultation with local farmers as shown in Table 4 and to optimize tomato plant fertigation using a bio-fertigation approach. Results plotted in MATLAB show that all four parameters were effectively controlled, ensuring efficient fertigation.

Table 4. Thresholds of the four climatic parameters for the tomato greenhouse

	Minimum threshold	Maximum threshold
Temperature	15 °C	25 °C
Humidity	60%	70%
Soil pH	6	6.8
Soil moisture	70%	80%

In our work, we used six actuators in the:
a. First fan to regulate the temperature.
b. Second fan to regulate the humidity.
c. Heater to regulate the temperature.
d. Water pump 1 to distribute water.
e. Water pump 2 to distribute bio-fertilizer.
f. Water pump 3 to distribute liquid bio-fertilizer (water + bio-fertilizer).

Figures 16, 17, 18 and 19 present monitoring of the air temperature, air humidity, soil pH, and soil moisture over a sequence of hours, respectively. These figures illustrate the indoor air temperature, indoor air humidity, indoor soil pH, and indoor soil moisture. After applying our fuzzy logic algorithm, we observed that the four internal microclimatic parameters of our greenhouse were well adjusted within the specified thresholds. Specifically, the measured parameters, over the sequence of hours, remained between the minimum and maximum thresholds.

Additionally, the actuators, including the heater, fans, and three water pumps, functioned effectively to regulate the internal microclimate and fertigate the tomato plants. In our study, we have 81 cases. For instance:

Case 1. If ((temperature<15 °C) AND (humidity<60%) AND (soil moisture<70%) AND (pH<6)) OR ((temperature<15 °C) AND (humidity<60%) AND (soil moisture<70%) AND (pH>6.8)), then the actuators for the heater, water pump 1, and water pump 3 are activated. After a few seconds, the actuators stop working, and the captured parameters stabilize between the minimum and maximum thresholds.

Case 2. If ((temperature is optimal) AND (humidity<60%) AND (soil moisture<70%) AND (pH<6)) OR ((temperature is optimal) AND (humidity is optimal) AND (soil moisture<70%) AND (pH>6.8)), then the actuators for water pump 1, water pump 2, and water pump 3 are activated. After a few seconds, the actuators stop working, and the captured parameters stabilize between the minimum and maximum thresholds.

Case 3. If ((temperature>25 °C) AND (humidity<60%) AND (soil moisture is optimal) AND (pH<6)) OR ((temperature>25 °C) AND (humidity<60%) AND (soil moisture is optimal) AND (pH>6.8)), then the actuators for the fan, water pump 1, and water pump 2 are activated. After a few seconds, the actuators stop working, and the captured parameters stabilize between the minimum and maximum thresholds.

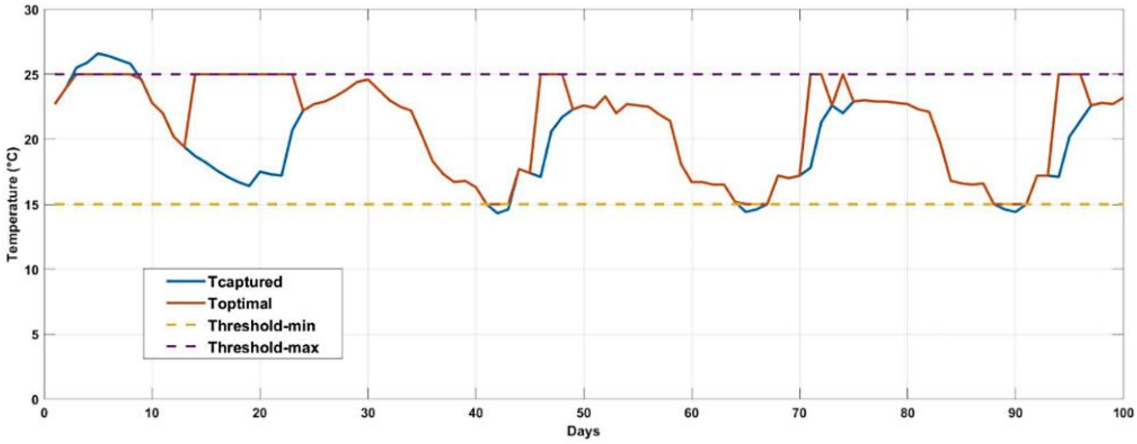

Figure 16. Monitoring the air temperature of our greenhouse

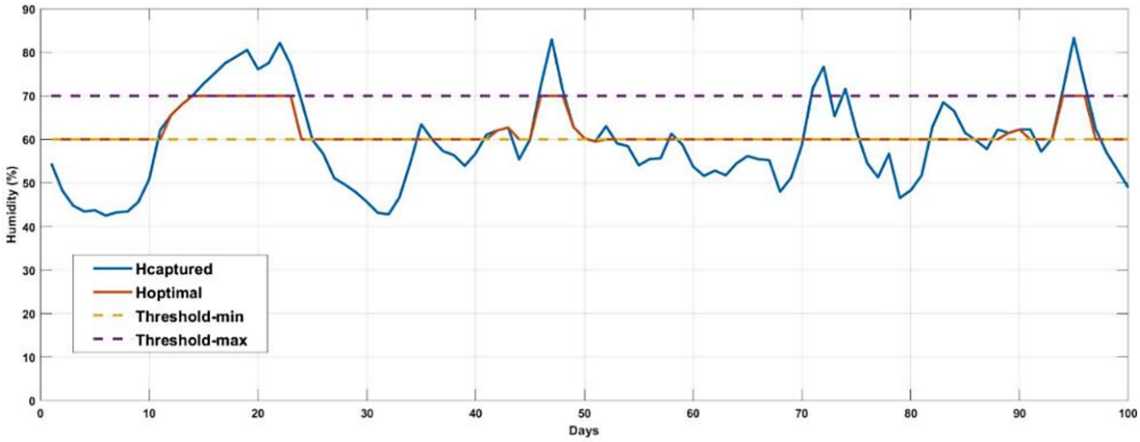

Figure 17. Monitoring the air humidity of our greenhouse

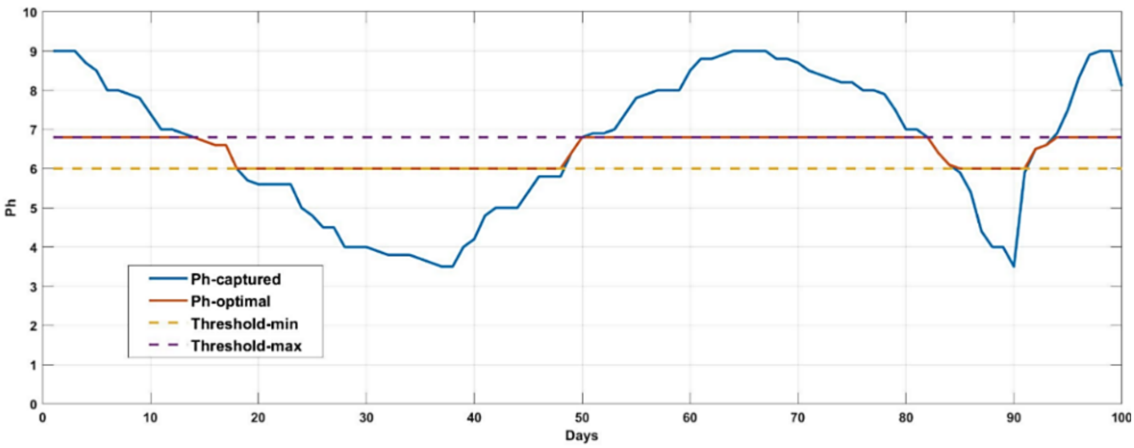

Figure 18. Monitoring the soil pH of our greenhouse

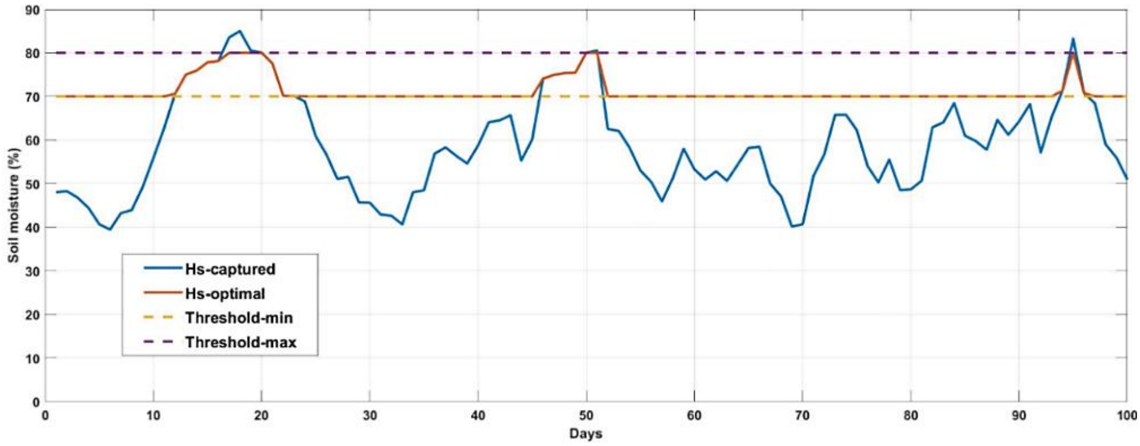

Figure 19. Monitoring the soil moisture of our greenhouse

Table 5 summarizes the output responses of the fuzzy inference system based on four different environmental conditions measured by sensors. Each test case includes values for internal air temperature, air humidity, soil pH, and soil moisture, which are processed using fuzzy logic rules to control five actuators: fan, heater, irrigation pump, fertilization pump, and fertigation pump. For example, in test case 1, low temperature and highly acidic soil activate the heater, fertilization, and fertigation systems, while the fan remains off. In contrast, test case 5 shows a hot and humid environment with alkaline soil, triggering a high-speed fan and fertilization, but no irrigation or fertigation due to sufficient moisture. The system demonstrates adaptive control based on combined climate and soil conditions.

To demonstrate how the optimization of our fuzzy logic-based system enhances the efficiency of bio-fertigation, we calculated the percentage improvements in water efficiency, fertilizer usage, and crop yields using (5)-(7) respectively [31].

$$Water\ saving\ (\%) = \left(\frac{Water_{traditional} - Water_{fuzzy}}{Water_{traditional}}\right) \times 100 \quad (5)$$

$$Fertilizer\ saving\ (\%) = \left(\frac{Fertilizer_{traditional} - Fertilizer_{fuzzy}}{Fertilizer_{traditional}}\right) \times 100 \quad (6)$$

$$Yield\ increase\ (\%) = \left(\frac{Fertilizer_{fuzzy} - Fertilizer_{traditionnal}}{Fertilizer_{traditional}}\right) \times 100 \quad (7)$$

The implementation of the fuzzy logic-based bio-fertigation system led to measurable improvements in key agricultural performance metrics. As shown in Table 6, water usage was reduced by approximately 27.58%, fertilizer usage decreased by over 58.82%, and crop yield increased by more than 47.5% compared to the traditional method. These results confirm the system's ability to optimize resource use and improve productivity.

Table 5. Input data and output results of the fuzzy inference system

Test case	Temperature (°C)	Humidity (%)	Soil pH	Soil moisture (%)	Fan (%)	Heater (%)	Irrigation (%)	Fertilization (%)	Fertigation (%)
1	10	35	3.5	50	0	80	50	70	50
2	13	65	6.3	72	10	60	20	0	0
3	17.3	95	6.5	90	20	30	0	0	0
4	20	40	7.8	60	30	20	10	40	10
5	35	85	7.5	85	90	0	0	30	0

Table 6. Percentage improvements results

Parameter	Traditional method	Fuzzy logic system	Improvement (%)
Water usage (L/ha)	5800	4200	27.58 %
Fertilizer usage (kg/ha)	255	105	58.82%
Crop yields (tons/ha)	4	5.9	47.5 %

3.4. Statistical estimators

The performance of our contribution can be assessed using four criteria: mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE). Equations are used to calculate these metrics from the obtained data set in order to compare the ideal values with the measured ones. Equations (8)–(11), in that order [10], [32]–[34].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Pm_i - Po_i| \tag{8}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Pm_i - Po_i)^2 \tag{9}$$

$$RMSE = \sqrt{MSE} \tag{10}$$

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{Pm_i - Po_i}{Pm_i}\right| \tag{11}$$

Where P_m and P_o are, respectively, the measured parameter and the optimized parameter. The results are summarized in Table 7, which presents a comparison between the conditions before and after applying control to our greenhouse using the proposed fuzzy logic algorithm.

Table 7. Statistical estimators results

	Before				After			
	T	H	P	S	T	H	P	S
MAE	0.032	3.0980987	0.164	11.3269	0	0	0	0
MSE	0.0912	58.108464	2.044	219.589188	0	0	0	0
RMSE	0.301993	7.62289079	1.42968528	14.818542	0	0	0	0
MAPE (%)	0.455167	10.2652472	19.948195	23.111186	0	0	0	0

Where T, H, P and S are, respectively, air temperature, air humidity, soil pH, and soil moisture. We observe that the values of MAE, MSE, RMSE, and MAPE after implementing our algorithm are reduced to zero, indicating that the system meets acceptable thresholds for accuracy and precision.

4. CONCLUSION

The results of this study demonstrate the effectiveness of the fuzzy logic-based control system in optimizing the greenhouse microclimate, particularly by maintaining balanced internal air temperature, humidity, soil pH, and soil moisture. The system successfully automated actuator responses—including fan, heater, and irrigation/fertilization/fertigation pumps—based on real-time sensor inputs. Statistical evaluations using MAE, MSE, RMSE, and MAPE confirmed the model's accuracy and reliability. Moreover, the implementation of this algorithm led to measurable improvements in resource efficiency, with significant reductions in water and fertilizer usage. Most importantly, the optimized environmental conditions resulted in a noticeable increase in tomato yield, confirming the practical benefit of the system in precision agriculture. These findings highlight the potential of fuzzy logic as a robust and intelligent solution for sustainable crop production.

Looking ahead, in our future work, we plan to include additional parameters, add other crops, combine our fuzzy logic system with machine learning or optimization algorithms and integrate cloud computing, and AI to further optimize crop growth through real-time data analytics. Finally, we aim to explore hydroponic greenhouses, vertical farming, and urban farming as part of our ongoing research.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

There are no conflicts of interest, according to the authors.

DATA AVAILABILITY

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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