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RESEARCH ARTICLE

Artificial intelligence of things -based Fuzzy C-Means Control for energy-efficient greenhouse microclimate management

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Abstract - The aim of modern greenhouses is to keep the optimal environmental conditions for plant growth, but this goal usually involves a high energy consumption, especially for temperature and humidity control. In this paper, an intelligent control strategy is presented based upon the Internet of Things (IoT) and a Fuzzy C-Means (FCM) clustering-based control model. The model is designed for the regulation of the greenhouse microclimate with the observance of temperature and humidity requirements for melon plants, which will increase operational efficiency and reduce energy consumption. To evaluate the performance of the proposed model and to compare the results with traditional control strategies, a simulation environment was created. Both simulation and experimental outcomes indicate that the proposed FCM-based controller has decreased the fan operating time by 28.0% and the cooling system operating time by 33.1%, resulting in an estimated daily energy saving of 29.9% in comparison with the conventional ON/OFF control method while maintaining stable microclimate conditions in the greenhouse. The control system was deployed in a greenhouse with data acquisition, remote monitoring, and real-time control functions, improving energy management and equipment operation in small-scale and family-run greenhouses while supporting smart agriculture applications.

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1. Introduction

Fresh fruits and vegetables have become an increasingly important part of the daily diet of urban residents. This trend is particularly evident among consumers who prefer high-quality products grown using organic farming practices. However, agricultural practices in southern Vietnam are not adequately suited to the climate and weather conditions, particularly for crops that are not naturally adapted to tropical environments. High ambient temperatures and sudden weather changes reduce crop yields. Because of these limitations, many fruits and vegetables consumed in urban areas are imported from foreign markets. Due to long-distance transportation, harvesting must occur before fruits and vegetables reach full ripeness, thereby negatively affecting their nutritional value and quality. In addition, transportation also incurs a certain cost for this item. Post-harvest processing methods for fruits and vegetables, such as using ripening chemicals like ethylene gas to accelerate ripening during storage and distribution, reduce shelf life and freshness of fruits and vegetables [1]. Therefore, after import, they are often more expensive and lower in quality than locally produced products. The above issues have spurred investor interest in food production methods in agricultural areas. Crops are harvested and transported at their freshest and most delicious stages, making them safer than those preserved by other methods. Therefore, greenhouse farming has become an optimal and efficient solution for year-round crop production. By insulating crops from external temperatures and humidity, greenhouses allow growers to adjust conditions to suit crop growth.

Smart greenhouse systems have been widely adopted to manage agricultural production under controlled environments. By leveraging Internet of Things (IoT) technology, greenhouses can use DHT22 sensors to continuously measure air temperature and relative humidity. The collected data are transmitted to control units, which subsequently activate or deactivate devices such as ventilation fans, irrigation systems, and cooling equipment in response to prevailing environmental conditions [2]-[3]. Several prior studies have demonstrated that IoT-based greenhouse systems can enhance crop growth and the quality of agricultural products. Furthermore, such systems can mitigate energy and resource waste, an essential consideration for sustainable agriculture, particularly under increasingly unpredictable climatic conditions [4]-[5]. Despite these advantages, maintaining a stable greenhouse climate while simultaneously curbing energy consumption remains a non-trivial challenge. Numerous recent studies indicate that conventional control methods perform poorly in nonlinear greenhouse environments. To address this limitation, artificial intelligence (AI) and machine learning techniques have progressively been incorporated into greenhouse climate control systems. These data-driven approaches enable the control system to adapt more flexibly to environmental fluctuations and to reduce the need for continual human intervention, especially under rapidly varying external conditions [6]-[8]. Recent studies have further shown that IoT-integrated fuzzy logic systems can enhance the efficiency of greenhouse automation and environmental monitoring [9]-[12]. In addition, fuzzy-based smart farming approaches have been successfully applied to irrigation and hydroponic control systems [13]-[14].

This work develops an automated greenhouse system that combines IoT technology and fuzzy logic control for cantaloupe cultivation in Southern Vietnam. Cantaloupe is a high-value crop with strong market demand in many regions of the country. Its growth is highly sensitive to environmental conditions. Suitable growing conditions require temperatures of about 25–30 °C and relative humidity of about 60–80%. Maintaining these conditions in Vietnam's tropical climate remains a technical challenge. In this study, an experimental greenhouse measuring 6.0 m × 6.0 m × 4.0 m was used, and several basic smart control devices, such as industrial fans, water-based cooling equipment, and an

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automatic irrigation system, were installed. The greenhouse is used mainly for cultivating cantaloupe in Vietnam's tropical climate, where temperature and humidity are decisive factors in plant development. IoT sensors, such as the DHT22, continuously collect environmental data to control temperature and humidity inside the greenhouse. The system maintains the air temperature within 25-30°C and the relative humidity within 60-80% to support cantaloupe growth throughout the entire cultivation cycle. These operating conditions establish the control environment for evaluating the proposed Artificial Intelligence of Things (AIoT)-based system. The research presented in this paper is summarised as follows: The design and development of an intelligent temperature and humidity control system based on Fuzzy C-Means (FCM) clustering, tailored to the biological requirements of melon plants. The integration of the proposed control system with Internet of Things infrastructure for real-time environmental monitoring and control within the greenhouse. The implementation of a distributed, cloud-connected architecture to facilitate remote supervision and reduce system latency. Simulation-based performance evaluation comparing energy efficiency and environmental stability against traditional on/off control methods. The proposal for a scalable, cost-effective automation model suitable for small-scale or household greenhouses under tropical conditions.

2. Materials and Methods

2.1 Fuzzy Controller

Fuzzy control has been used for a long time in nonlinear and uncertain systems. It uses IF–THEN rules, rather than exact mathematical models, and can perform well even with noisy or imprecise input data [15]. This capability has been exploited in such applications as home appliances, furnaces, power systems, traffic management, and motion control [16]. Fuzzy control is often used in greenhouse engineering to stabilise the temperature and humidity when the external environment frequently changes [17].

2.2 Fuzzy C-Means

Fuzzy C-Means is a clustering technique based on fuzzy set theory and is well suited for nonlinear data that cannot be clearly separated into distinct groups. Unlike K-Means, which assigns each sample to a single cluster, FCM allows a data point to belong to multiple clusters with varying degrees of membership. This feature makes FCM more flexible when dealing with overlapping patterns and gradual transitions. By representing data through multiple memberships, the method can better capture uncertainty and reduce the impact of fluctuations commonly found in real-world measurements. As a result, FCM is well suited to control applications in which environmental conditions, such as temperature levels (high, medium, or low), must be inferred from sensor data that are not always accurate or stable [18]. In the present study, FCM is integrated with fuzzy control to enhance the adaptability and accuracy of the microclimate control system in an IoT-based greenhouse.

2.2.1 Principle

FCM partitions a dataset $X = \{x_1, x_2, \ldots, x_n\}$ into C clusters, where each data point x_i is assigned a membership degree with respect to cluster j. The sum of the membership values of a given data point across all clusters equals 1:

$$\sum_{j=1}^{C}\mu_{ij}=1\ \ \forall i \tag{1}$$

The membership value is computed based on the distance between each data point and the corresponding cluster centre, with this distance typically measured using the Euclidean metric.

2.2.2 Objective Function

FCM minimises the following objective function:

$$J_m=\sum_{i=1}^{N}\sum_{j=1}^{C}u_{ij}^{m}.||X_i\text{-}C_j||^2 \tag{2}$$

where N is represents number of data points; C is the number of clusters; u_{ij} is the membership degree of data point X_i to cluster j; m is fuzziness coefficient; $||X_i\text{-}C_j||$ is Euclidean distance between data point X_i and cluster centre C_j

The algorithm minimises J_m by iteratively executing the following two steps:

Update the membership degrees μ_{ij}.

$$\mu_{ij}=\frac{1}{\sum_{k=1}^{C}\left(\frac{||x_i\text{-}c_j||}{||x_i\text{-}c_k||}\right)^{\frac{2}{m\text{-}1}}} \tag{3}$$

Update cluster centers C_j:

$$c_j=\frac{\sum_{i=1}^{n}\mu_{ij}^{m}\,x_i}{\sum_{i=1}^{n}\mu_{ij}^{m}} \tag{4}$$

The iterative procedure continues until the change in the objective function or membership values falls below a predefined threshold, or until the maximum number of iterations is reached.

2.3 Smart Greenhouse System

Modern greenhouses, also known as protected cultivation systems, are widely used to grow vegetables, fruits, and ornamental plants because they mitigate the effects of adverse weather conditions, such as heavy rainfall, strong winds, and extreme temperatures. In most cases, greenhouse structures are constructed using transparent materials—such as plastic films or glass panels for the roof and side walls. Greenhouse covering materials transmit solar radiation while limiting heat loss, creating favourable conditions for crop growth [19]. Environmental control is influenced by solar radiation, seasonal temperature variation, and energy conditions [20]-[21]. Temperature, humidity, and light intensity inside the greenhouse can be managed manually or automatically. The experimental greenhouse (Figure 1) is situated in Phu Dinh Ward, Ho Chi Minh City, Vietnam. The structure is rotated 12 degrees west of north to improve solar distribution and thermal stability. The local climate has a dry season from December to April and a rainy season from May to November. Average rainfall is 1,940 mm, and the average temperature is between 27 and 28 °C, with daily variations of 5–10 °C. Relative humidity averages 71 per cent in the dry season and 86 per cent in the rainy season. During the dry and rainy seasons, the seasonal winds blow predominantly from the south-east and south-west, respectively [22]. The greenhouse is equipped with an IoT-based control system for year-round melon production. Sensors measure temperature, humidity, and light intensity using controller conditions. The data is processed and sent to the cloud by an ESP32 controller. This method can reduce manual work and make better use of water and fertilisation [3],[23]. A web dashboard enables real-time monitoring of environmental conditions and device status [25]. Fans, pumps, and misting units are activated automatically when the temperature or humidity falls outside the target ranges of 25–30 °C and 60–80%, respectively [25].

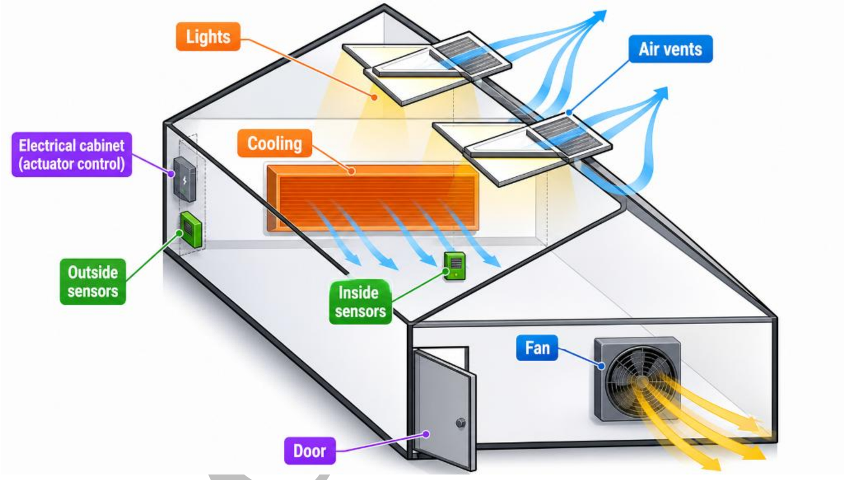


Figure 1. Layout of equipment inside and outside the greenhouse

2.4 System Design and Control Strategy for Smart Greenhouse System

2.4.1 Comparison between Fuzzy logic and PID for greenhouse control

Fuzzy C-Means and Proportional-Integral-Derivative (PID) controllers are both staples in engineering control systems. However, despite sharing the automation spotlight, they rely on completely contrasting operational logic. Because their underlying control principles are so radically different, they yield highly distinct performance characteristics when put to work in real-world scenarios. To further clarify these differences and to highlight the respective strengths and weaknesses of each approach, a comparison between FCM and PID controllers is summarised in Table 1. Rationale for adopting FCM rather than PID in AIoT-based greenhouse systems: AIoT-based greenhouse systems operate under highly variable and interconnected environmental conditions, in which factors such as air temperature, relative humidity, solar radiation, and CO_2 concentration interact continuously. These factors are further influenced by outdoor weather, seasonal variations, and crop growth requirements, making system behaviour difficult to capture using fixed or linear mathematical models. PID controllers rely on fixed gain parameters. They also assume relatively stable operating conditions. As a result, their performance may be limited in greenhouse environments. Fuzzy C-Means uses soft clustering to represent environmental states from sensor data. The method can describe intermediate conditions, including moderate changes in temperature or humidity. Complex nonlinear models are not required. In an AIoT system, the FCM continuously updates control actions based on real-time sensor measurements. Environmental states are modelled by rule-based descriptions based on expert knowledge. The controller then activates ventilation, cooling, or misting devices as required. This control strategy can respond to rapid changes of greenhouse temperature and humidity.

Table 1. Comparison between FCM and PID controller

Criterion	Fuzzy C-Means controller	PID controller
Working Principle	Utilizes fuzzy set theory and clustering concepts to characterize system behaviour through linguistic rules, enabling control decisions to be made under uncertainty and imprecise information.	Employs a classical feedback mechanism in which the control signal is computed as a weighted combination of proportional, integral, and derivative terms derived from the system error.
System Modelling	Does not require an explicit mathematical model of the plant; instead, the system is represented through fuzzy rules and clustering of measured data, which is advantageous for systems that are difficult to model analytically.	Relies on an explicit or approximate mathematical model of the plant to determine appropriate values for the proportional, integral, and derivative gains.
Nonlinear Handling Capability	Exhibits strong adaptability to nonlinear and time-varying systems by virtue of its fuzzy inference mechanism and soft-clustering structure.	Performs effectively in primarily linear or near-linear systems; control performance may degrade in the presence of strong nonlinearities.
Design and Tuning	Control performance is governed by the choice of membership functions and fuzzy rules, which are typically derived from experimental data or expert knowledge.	Control behaviour is adjusted by tuning the K_p, K_i, and K_d parameters, typically using heuristic or analytical tuning methods.
Computation	Requires additional computational effort for evaluating membership functions and clustering-based control logic.	Involves comparatively simple arithmetic operations, which makes it well suited to real-time implementation.
Application	Well suited to intelligent and adaptive systems such as AIoT-based greenhouses, pattern recognition, and data-driven control problems.	Commonly applied in conventional control tasks, including motor drives, basic temperature regulation, and industrial automation.

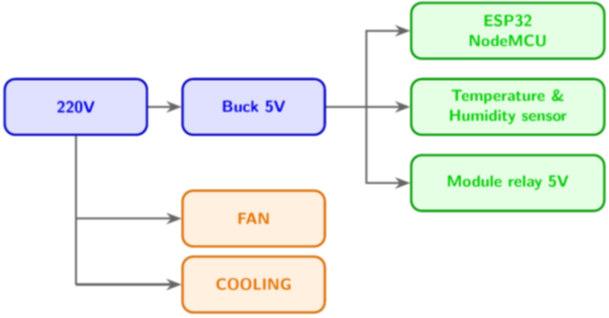


Figure 2. Electrical control system block diagram

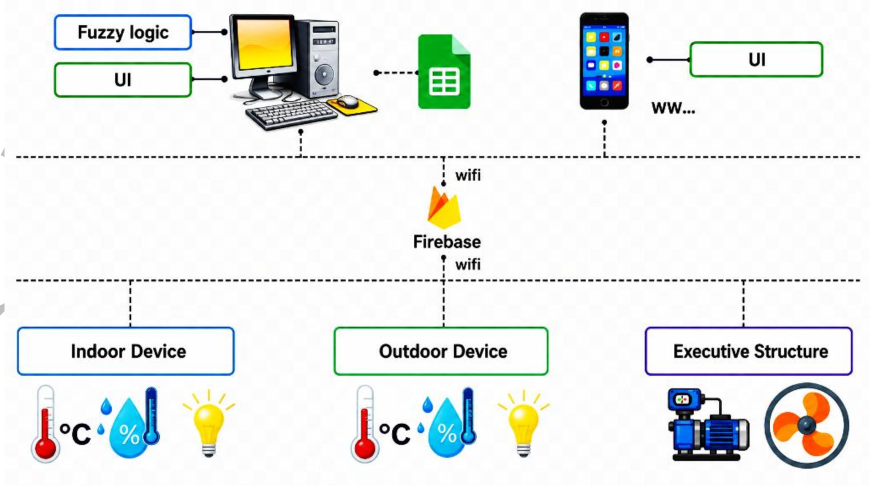


Figure 3. Architecture of the AIoT-based Greenhouse System

2.4.2 System architecture and circuit design of an IoT-based smart greenhouse

Figure 2 presents the greenhouse electrical architecture. The system consists of sensing and actuation subsystems used for automatic control. Fans and water pumps are powered directly from the 220 V mains supply. The microcontroller, sensors, and relay modules receive 5 V from a step-down circuit. This power arrangement protects electronic devices and ensures stable operation. The proposed AIoT architecture for greenhouse climate control is shown in Figure 3. Sensor data is continuously collected and transmitted to the main processor. The FCM algorithm senses the current state of the environment and produces control actions. They control actuators such as fans and water pumps to automatically adjust temperature and humidity. Temperature, humidity, and light intensity sensors inside and outside the greenhouse continuously measure these parameters. The data are uploaded to Firebase for storage and sharing. The local processor receives the measurements, runs the fuzzy control algorithm and updates the control commands. Google Sheets also archives sensor records. The controller will periodically read data from Firebase and run fans and irrigation pumps accordingly. In this architecture, Firebase is used to communicate among the user interface, control system, and devices in the greenhouse

2.4.3 Algorithm flowchart of the proposed control system

The workflow of the proposed IoT-FCM greenhouse control system is shown in Figure 4. The sensors measure temperature and humidity, and the ESP32 uploads those measurements to the cloud for storage and processing. Automatic or manual operation is then selected by the system. In automatic mode, the FCM algorithm detects the actual environmental state, and a Fuzzy Inference System generates the control actions for the fan and cooling devices. In manual mode, the commands are typed in the web interface. The resulting control signals are sent to the ESP32 that drives the respective devices. A closed-loop control scheme is used. Fan operation is monitored continuously. Each time the measured response differs from the expected state, the controller modifies the control signal. This approach improves responsiveness to environmental changes while retaining manual control capability.

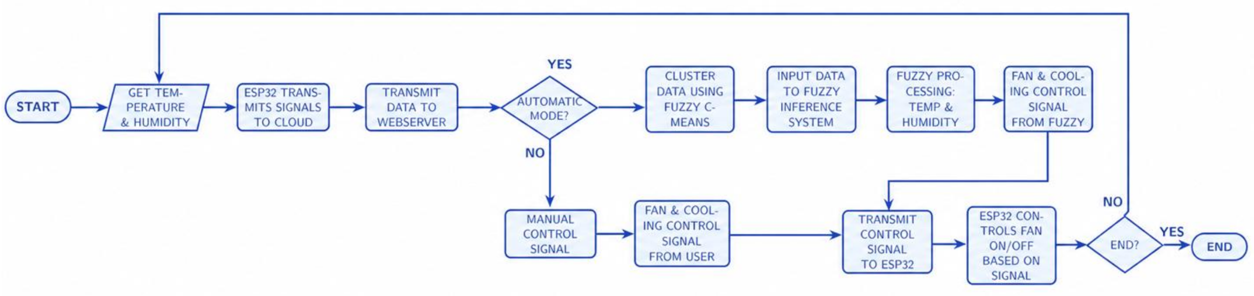


Figure 4. Control flowchart of the AIoT-based greenhouse system

2.4.4 Relationship between Air Temperature and Humidity

This section discusses the relationship between air temperature and relative humidity when the cooling fan and cooling pad operate simultaneously. The analysis is performed based on sensor measurements. The slope and intercept of the regression line, which describe the change in humidity with temperature under cooling conditions, are determined using the linear regression model. The Pearson correlation coefficient was also calculated to assess the relationship between temperature and humidity. Its value indicates the strength and direction of the association while the cooling system is operating. The coefficient of correlation is calculated using the formula:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}} \tag{5}$$

where X_i and Y_i: Individual values in the two data sets, with X_i representing the temperature at time i and Y_i representing the humidity at time i. $\overline{X}$ and $\overline{Y}$: The mean values of the respective data sets.

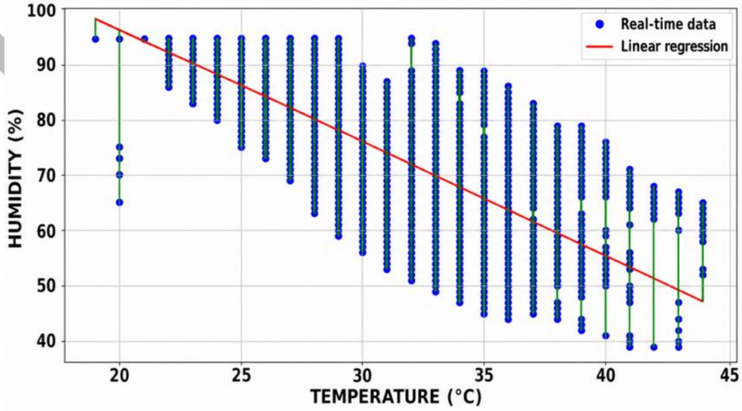
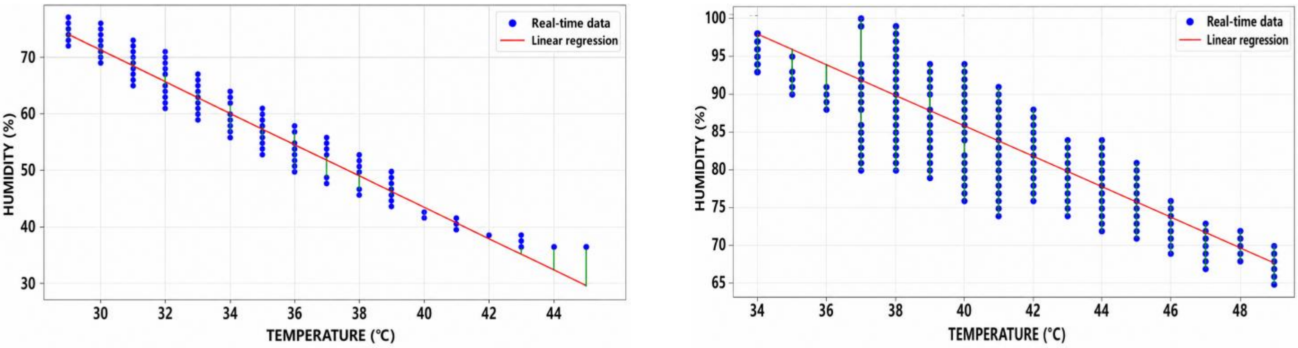


Figure 5. Correlation between air temperature and relative humidity during fan-assisted cooling ($r = -0.7287$)

The resulting Pearson correlation coefficient r reflects the degree of association between temperature and humidity. Strong relationships are shown by values near 1 or -1, whereas weak correlations are suggested by values near 0.The computed coefficient r = -0.7287 (Figure 5) indicates a strong negative correlation between temperature and humidity. This suggests that humidity tends to decrease as temperature rises. Although the relationship is clear, it is not perfectly linear, as r is not exactly -1. Figure 6 shows the temperature–humidity relationship under two operating conditions: fan on with cooling off (Figure 6(a)) and both systems off (Figure 6(b)). An inverse correlation is observed, with humidity generally decreasing as temperature increases. The Pearson coefficient confirms this trend. The scatter plots show considerable variation in humidity at the same temperature level. Temperature alone cannot accurately predict humidity. Linear regression models were therefore developed using outdoor temperature, outdoor humidity, fan status, and cooling pad status as inputs. The resulting equations are given as follows.



(a) (b)

Figure 6. Correlation between temperature and humidity under different operating conditions: (a) fan on and cooling system off (r = 0.9696); (b) both fan and cooling system off (r = 0.8332)

Prediction equation for internal temperature ($Temp_{In}$):

$$Temp_{In} = 0.538Temp_{Out} + 0.5094Temp_{In} - 1.303FAN - 6.276COOLING + 0.2362Hum_{In} + 0.1351 \tag{6}$$

Prediction equation for internal humidity (Hum_{In}):

$$Hum_{In} = 0.835Hum_{In} + 0.144Hum_{Out} - 5.958FAN + 1.911COOLING - 0.5094Temp_{In} - 0.708 \tag{7}$$

where $Temp_{In}$ is the internal temperature of the greenhouse (°C); $Temp_{Out}$ is the external temperature outside the greenhouse (°C); $Hum_{In}$is the internal humidity of the greenhouse (%); Hum_{Out} is and external humidity outside the greenhouse (%); *FAN* is the operating status of the ventilation fan; *COOLING* is the operating status of the cooling system.

Model performance was assessed by root mean square error (RMSE). RMSE was calculated by taking the difference between the measured indoor conditions and the steady-state values. The average temperature and humidity during stable operation were taken as the predicted values, rather than the direct outputs of the regression models.

i) Root mean square error

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{8}$$

where, y_i is the actual value for the i-th observation; $\hat{y}_i$ is the predicted value for the i-th observation; n is the number of observations.

The linear regression models produced RMSE values of 5.63°C for temperature and 11.87% for humidity. These results suggest that the models adequately represent the greenhouse's temperature and humidity behaviour under steady-state operating conditions.

Table 2. Root mean squared error of internal temperature and humidity

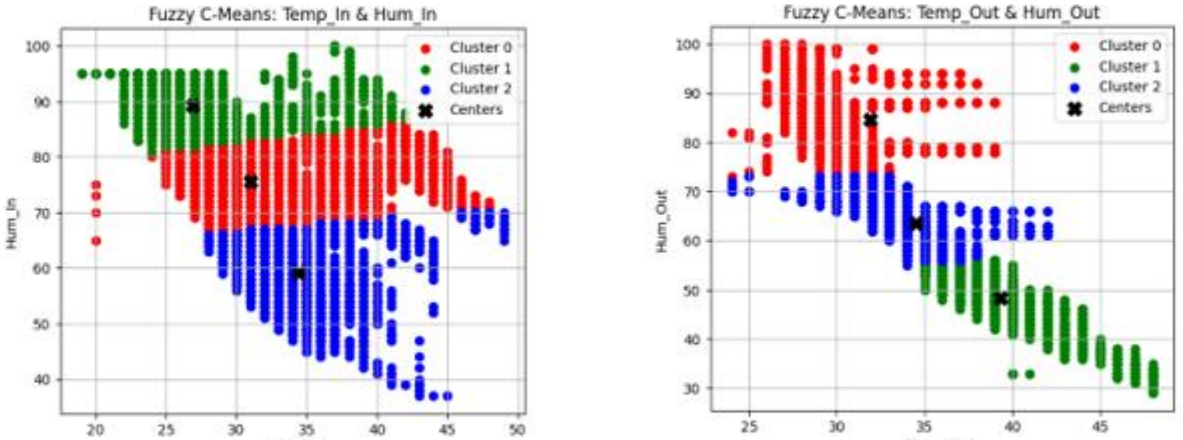
Output variable	Root mean square error
Internal temperature °C)	5.63
Internal humidity (%)	11.87

2.4.5 Application of the Fuzzy Logic C-Means algorithm to the problem

Fuzzy C-Means is a soft clustering algorithm in which each data point is permitted to belong to multiple clusters with varying degrees of membership (ranging from 0 to 1), rather than being assigned exclusively to a single cluster as in K-Means. For each data point, the sum of the membership degrees across all clusters equals 1. The algorithm simultaneously optimises the cluster centres and the membership matrix to minimise an objective function that captures the quality of the clustering:

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m} \cdot ||X_i - C_j||^2 \tag{9}$$

where, N is the number of data points; C is the number of clusters; u_{ij} is the membership degree of data point X_i to cluster j; m is the fuzziness coefficient; $||X_i - C_j||$ is the euclidean distance between data point X_i and cluster center C_j.



(a) (b)

Figure 7. Fuzzy C-Means identification of cluster centres for temperature and humidity: (a) internal environment; (b) external environment

The internal cluster centres, which represent characteristic temperature–humidity zones within the greenhouse, are as follows (see Figure 7(a)). The results of the Fuzzy C-Means clustering indicate that the temperature and humidity inside the greenhouse can be broadly partitioned into three principal states: cool and humid, hot and dry, and an intermediate or transitional condition. With FCM, each measured data point is not forced to belong to a single cluster but can be simultaneously associated with multiple clusters, each with a different degree of membership. This feature is useful for describing the gradual changes and the uncertainty that often occurs in the greenhouse environment. The fuzzy sets for temperature and humidity are defined by using common linguistic terms such as “low”, “medium,”, and “high” based on the clustering results. These fuzzy sets are generally represented by a triangular membership function and used in a fuzzy inference system. Then, control rules are written in IF-THEN statements. The controller decides based on these rules how the fan and cooling equipment must be operated. As a result, the system can react more smoothly to changes in the environment and keep the greenhouse conditions rather constant.

Cluster 0: Temperature = 24.23 °C, Humidity = 89.33%
Cluster 1: Temperature = 26.82 °C, Humidity = 75.60%
Cluster 2: Temperature = 28.84 °C, Humidity = 59.12%
The external cluster centres (Figure 7(b)) are as follows:
Cluster 0: Temperature = 27.03 °C, Humidity = 84.60%
Cluster 1: Temperature = 28.72 °C, Humidity = 63.45%
Cluster 2: Temperature = 31.53 °C, Humidity = 48.33%

Table 3. Classification of internal cluster centres

Cluster	Temperature_In	Humidity_In	Category
Cluster 0	~24	~89	Cool – Humid
Cluster 1	~27	~75	Moderate
Cluster 2	~31	~59	Hot – Dry

3. Results and Discussion

3.1 Simulation and Performance Testing of the Algorithm

Membership function: Each input variable (e.g., temperature and humidity) is mapped to its corresponding membership values using triangular or trapezoidal functions:

$$\mu\_A(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a < x < b \\ \frac{c-x}{c-b}, & b < x < c \\ 0, & x \geq c \end{cases} \tag{10}$$

where, $\mu\_A(x)$ is the membership degree of value x in fuzzy set A; a, b, c are the characteristic points of the triangular function.

Once the fuzzy rules have been applied, the resulting fuzzy outputs are aggregated as follows:

$$\mu_{\text{output}}(y) = \max\left(\min\left(\mu_{A_1}(x), \mu_{B_1}(y)\right), \min\left(\mu_{A_2}(x), \mu_{B_2}(y)\right), \ldots, \min\left(\mu_{A_n}(x), \mu_{B_n}(y)\right)\right) \tag{11}$$

Desired temperature: 28 °C; Desired humidity: 70%

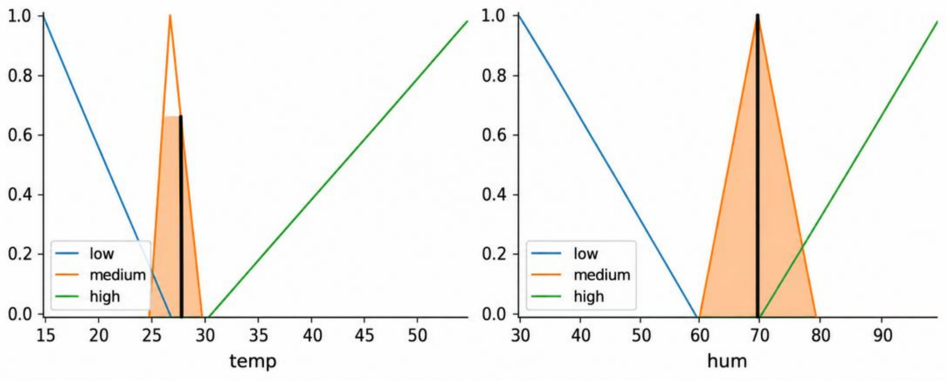


Figure 8. Classification of desired temperature and humidity

The three triangular curves shown in blue, orange, and green represent the fuzzy sets “low,” “medium,” and “high” for temperature (Figure 8). The black line at 28 °C lies within the transition zone between “medium” and “high,” indicating that the current temperature partially belongs to both sets. Similarly, the current humidity (~70%) is also marked by a black line and falls within the “high” region, with the green shaded area indicating a strong contribution to the fuzzy inference process.

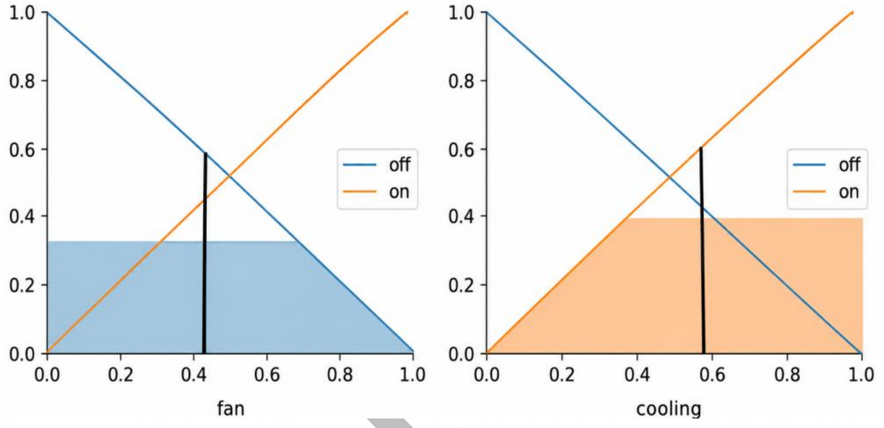


Figure 9. Determination results of the ON/OFF states of the fan and cooling system

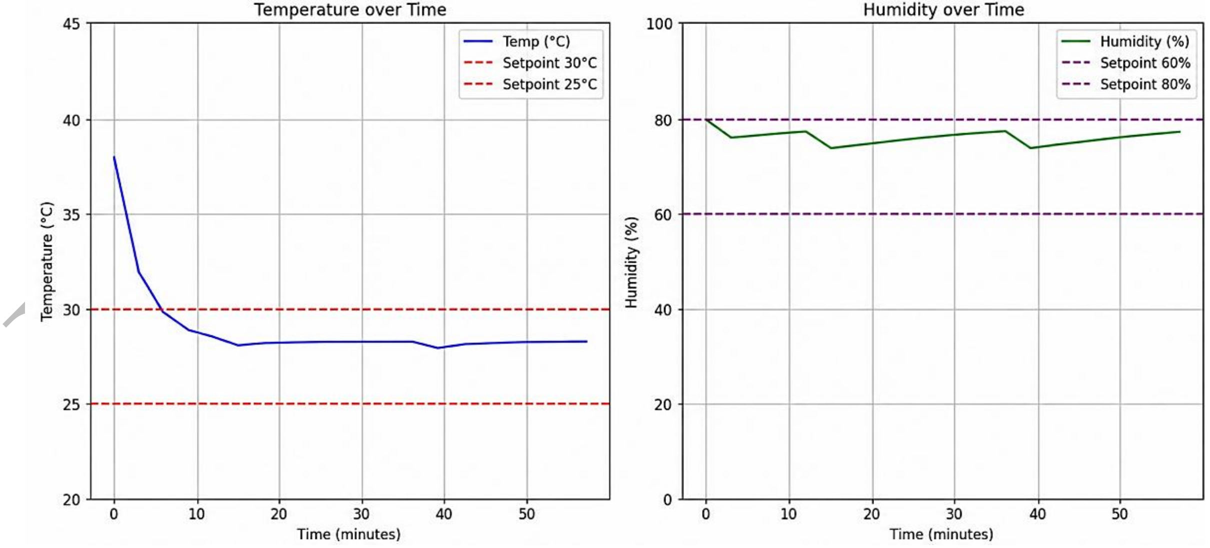


Figure 10. System response of temperature and humidity control in the greenhouse

Two fuzzy output sets are defined—“off” (blue) and “on” (orange)—for the fan and the cooling system (Figure 9). The orange region corresponds to the aggregated output of the fuzzy rules. The vertical black line for the fan is at approximately 0.42, while that for the cooling system is at approximately 0.59; these are the final defuzzified values, representing the activation levels of the fan and the cooling system, respectively. Given an activation threshold of 0.5, the fan remains off (0.42 < 0.5), whereas the cooling system is switched on (0.59 > 0.5). The prediction results indicate that the fan activation level is 0.42 (Off), while the cooling activation level is 0.59 (On). The transfer functions for temperature and humidity are used to simulate the climate control system's response in the greenhouse, as illustrated in Figure 10.

The assessment of the model's accuracy in real-world conditions is depicted in Figure 11. During the implementation phase, from 12:00 PM to 7:00 PM, the AIoT-based control system maintained relatively stable indoor temperature and humidity levels despite continuously fluctuating outdoor conditions. In practical operation, outdoor temperature and humidity are inherently unstable and vary frequently in response to solar radiation, cloud movement, and wind. By processing sensor readings acquired at approximately 2-minute intervals through the fuzzy logic-based controller, the system was able to compensate for most of these variations and to maintain conditions suitable for the growth of the melon plants inside the greenhouse. There were cases in which the indoor environment exceeded the target range when the outdoor temperature increased significantly, or the humidity decreased rapidly. Such deviations point to limitations in the current system. Further optimisation of the control strategy and improvements in cooling or insulation may increase performance in severe weather conditions. The results are shown in Figure 11(a) and Figure 11(b) for the 12:00-19:00 period, when solar radiation and ambient temperature reach their maximum values. This is the worst working condition. Times outside of transition and nighttime are more in the target zone. The FCM-based and ON/OFF controllers both maintain constant temperature and humidity while requiring less actuator activity. Consequently, the performance gap between the two methods is smaller. Comparison of estimated daily energy consumption under different control methods. In this study, the rated power of the fan and the cooling system are 0.55 kW and 0.37 kW, respectively.

$$E = \sum_{i} P_i \times t_i \tag{12}$$

where, E is the total energy consumption in one day (kWh/day); P_i is the rated power of the i-th actuator (kW); t_i is the total operating (ON) time of device i over one day (hours)

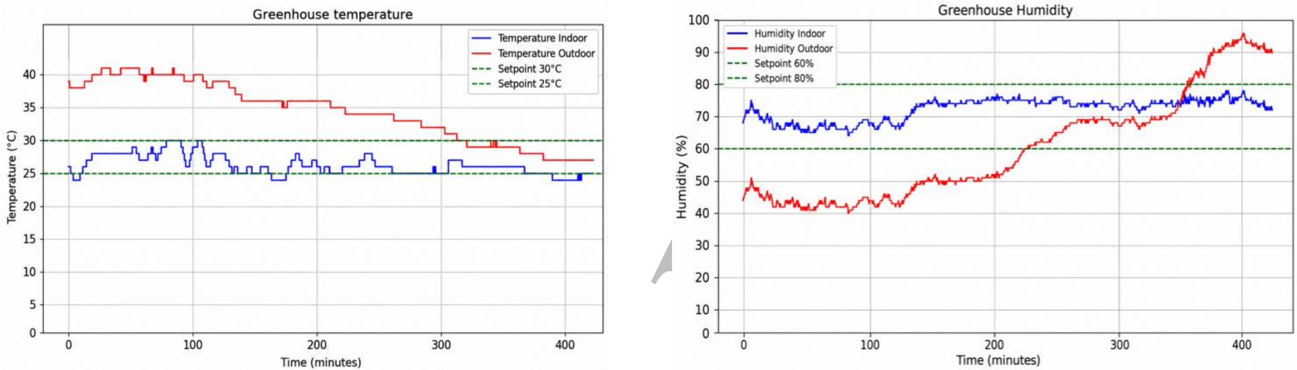


Figure 11. Environmental parameters after applying the Fuzzy C-Means control system under real-world conditions: (a) temperature; (b) humidity

The total daily energy consumption of the fan and the cooling system under ON/OFF control is computed as follows:
i) Daily energy consumption of the fan (ON/OFF control):

$$0.55 \times 18.2 = 10.01 \text{ kWh/day} \tag{13}$$

ii) Daily energy consumption of the cooling system (ON/OFF control):

$$0.37 \times 16.9 = 6.25 \text{ kWh/day} \tag{14}$$

iii) The total daily energy consumption under ON/OFF control is therefore:

$$E_{\text{ON/OFF}} = 10.01 + 6.25 = 16.26 \text{ kWh/day} \tag{15}$$

The total daily energy consumption of the fan and the cooling system under FCM-based control is:
i) Daily energy consumption of the fan (FCM):

$$0.55 \times 13.1 = 7.21 \text{ kWh/day} \tag{16}$$

ii) Daily energy consumption of the cooling system (FCM):

$$0.37 \times 11.3 = 4.18 \text{ kWh/day} \tag{17}$$

The total daily energy consumption under FCM-based control is therefore:

$$E_{\text{FCM}} = 7.21 + 4.18 = 11.39 \text{ kWh/day} \tag{18}$$

Compared with the conventional ON/OFF control strategy, the proposed FCM-based controller (Table 4) reduced fan operating time by 28.0% and cooling system operating time by 33.1%, yielding an estimated daily energy saving of approximately 29.9% while preserving stable microclimate conditions within the greenhouse.

Table 4. Comparison of actuator ON time and energy consumption

Control method	Fan ON time (h/day)	Cooling ON time (h/day)	Energy (kWh/day)
ON/OFF control	18.2	16.9	16.26
FCM-based control	13.1	11.3	11.39
Reduction	–28.0%	–33.1%	–29.9%

3.2 Implementation Results of the AIoT-Based Greenhouse System

Temperature and humidity sensors were mounted inside the greenhouse at heights corresponding to the crop canopy, positioned away from direct airflow to capture representative microclimatic conditions (Figures 12–14). Outdoor environmental sensors were placed in shaded, well-ventilated locations. The measurements were less affected by direct sunlight and rain. The data obtained were more reliable for control purposes. This sensor setup is widely used in a smart greenhouse monitoring system.

Figure 12. Photographs of the Implemented Greenhouse

(a)

(b)

Figure 13. Sensor installation locations for greenhouse environmental monitoring: (a) inside the greenhouse; (b) outside the greenhouse

The temperature and humidity sensors, microcontroller, and relay units are enclosed within protective outdoor enclosures. These enclosures safeguard against rain, dust, and other environmental influences. Such protection ensures the equipment's durability and minimises the risk of failure during ongoing greenhouse operations. The web interface is illustrated in Figure 15. The interface is designed to be straightforward and centred on practical functionality. The principal sections are enumerated. The Control Panel is positioned on the left-hand side and comprises an array of buttons, including “Time Pump” (for setting the cooling duration), “Time Fan” (for configuring the fan operation time), and “Open Google Sheets.” The Fuzzy Result, located above the control panel, exhibits the computed cooling and fan operating times. The Greenhouse Conditions section, situated at the centre of the interface, displays current internal greenhouse parameters such as temperature, humidity, and light intensity. The Outdoor Conditions area presents external temperature, humidity, and light levels. Toggle switches enable direct control over the pump, lighting, and fan.

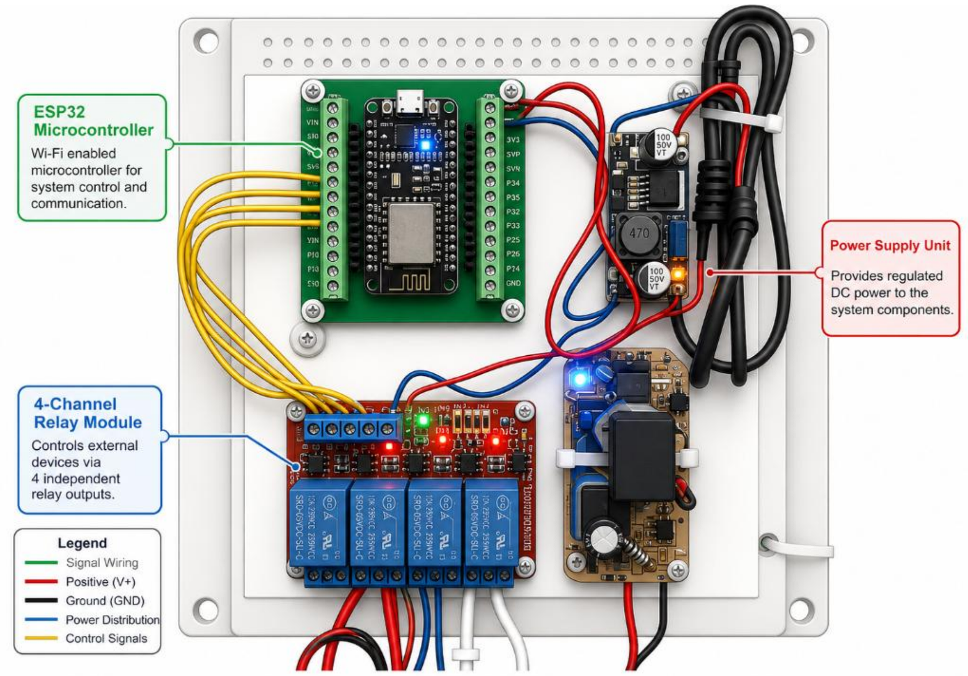
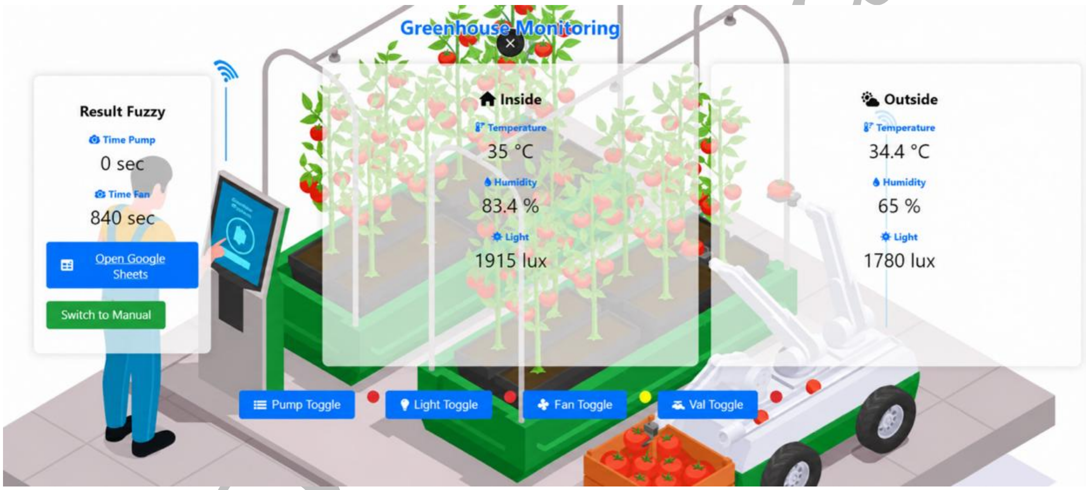


Figure 14. Electrical control system for fan and cooling relays



Result Fuzzy

Time Pump
0 sec

Time Fan
840 sec

Inside

Temperature
35 °C

Humidity
83.4 %

Light
1915 lux

Outside

Temperature
34.4 °C

Humidity
65 %

Light
1780 lux

Figure 15. Web-based monitoring and control interface

(a) (b)

Figure 16. Results of the AIoT-based smart greenhouse system after applying the Fuzzy C-Means controller and IoT integration: (a) greenhouse cantaloupe cultivation under the smart control system; (b) cantaloupe cultivation results after a period of operation

After the temperature and humidity control system was deployed, melon cultivation in the smart greenhouse showed positive initial results (Figures 16 and 17). Automatic operation reduced the need for manual adjustments to fans and cooling equipment, helping lower energy and water use. At the same time, environmental parameters including temperature, humidity, and light intensity were continuously collected both inside and outside the greenhouse and transmitted to the cloud server for monitoring and control. The fuzzy logic controller adjusted system operation in response to changing environmental conditions while maintaining stable performance. The Firebase platform provided reliable data transmission, enabling seamless storage and retrieval of sensor readings and control commands. During the experiment, the system ran continuously with very little communication delay. The web interface was designed to be simple and user-friendly so that it can be used by users with limited technical expertise.

Figure 17. Cantaloupe fruit after harvest is of better quality when grown in a greenhouse

4. Conclusions

An IoT greenhouse controller combining Fuzzy C-Means clustering and fuzzy logic was implemented. Temperature and humidity data from indoor and outdoor environments were used for control. Experimental results showed indoor temperatures near 25–30 °C and relatively stable humidity. Similar patterns were observed in both the greenhouse measurements and simulation results. The FCM controller reduced unnecessary fan and cooling pad operation compared with an ON/OFF strategy. Lower energy and water use were also observed. The system was implemented using an ESP32 controller, Firebase database, and web interface for monitoring, data storage, and remote operation. This configuration is suitable for small greenhouse applications in tropical environments. Short-term deviations in temperature and humidity were still observed during extreme weather events. Future work will focus on improving cooling capacity, greenhouse insulation, and control rules. Additional studies will investigate multivariable control involving light intensity and CO_2, adaptive re-clustering, hybrid control strategies, and long-term field experiments to evaluate energy use, water consumption, and crop productivity across different crops and climatic conditions.

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Declaration of Competing Interests

The authors declare no conflicts of interest

CRediT Author Contribution Statement

Tri Dung Dang: Conceptualization; Methodology; Validation; Visualisation; Writing - original draft; Writing - review & editing; Funding acquisition; Project administration; Supervision
Tri Cuong Do: Methodology; Data curation; Writing - original draft; Resources
Nguyen Minh Trieu: Formal analysis; Resources; Writing - revise & review
Nguyen Truong Thinh: Methodology; Resources; Supervision; Writing - revise & review

Availability of Data and Materials

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

Ethics Statement

This study did not involve human participants or animal subjects. Ethical approval was therefore not required for this research.

Generative Artificial Intelligence Disclosure

This article was written and compiled by the authors themselves without using artificial intelligence tools to complete the content or create the images. All ideas, images, data tables, and image analysis were done by the authors. However, the article used Google Translate to assist with language translation and grammar correction. The authors reviewed and edited the translated content to ensure the accuracy and scientific rigor of the article.

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