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Research Article

IoT-Based Light Intensity Control System for Melon Photoperiodism Optimization Using the Fuzzy Sugeno Method

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Abstract. Melon cultivation requires appropriate light intensity and photoperiod management because light directly affects photosynthesis, vegetative growth, and plant productivity. In conventional cultivation, additional lighting is often controlled manually, making it less adaptive to changes in sunlight intensity, temperature, and daily photoperiod. This study develops an Internet of Things (IoT)-based automatic light intensity control system using the Fuzzy Sugeno method to optimize photoperiodism in melon plants during the vegetative phase. The system integrates an ESP32 microcontroller, BH1750 light intensity sensor, DHT21 temperature sensor, real-time clock, AC light dimmer, LED grow light, LCD I2C, and Blynk application. The Fuzzy Sugeno method was implemented to determine the percentage of LED grow light output based on light intensity, temperature, and daily time period. Experimental results showed that the BH1750 sensor calibration reduced the average measurement error from 10.13% to 2.753%, while the DHT21 temperature sensor calibration reduced the average error from 3.95% to 0.31%. The AC light dimmer responded proportionally to PWM input, producing lamp outputs from 0 lux to approximately 28,000 lux. Data transmission to Blynk was successful with an average delay of about 1.01 seconds. Plant testing for 14 days showed that the IoT-based automatic lighting system produced better vegetative growth than the conventional method, with plant height reaching 19 cm and five leaves. These findings indicate that the developed system can support adaptive lighting control for melon photoperiodism optimization.

Keywords: Fuzzy Sugeno; Internet of Things; Light Intensity Control; Photoperiodism; Smart Agriculture.

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1. Introduction

Agriculture plays a strategic role in Indonesia because it supports food security, provides raw materials for various industries, creates employment opportunities, and contributes to rural economic development. As an agrarian country, Indonesia depends on agricultural productivity to maintain national food supply and improve community welfare. Previous studies have emphasized that the agricultural sector remains an important contributor to the Indonesian economy and has a significant role in poverty reduction, labor absorption, and regional development (Delanova, 2016; Kusumaningrum, 2019; Nurhanifa & Budiasih, 2023; Septindo et al., 2016). Therefore, modernization of agricultural practices through digital technology is needed to increase efficiency, productivity, and sustainability.

One horticultural commodity with high economic value is melon (*Cucumis melo* L.). Melon cultivation is considered promising because market demand continues to increase, the fruit has good commercial value, and melon can be processed into various value-added products. Several studies have reported that melon farming is financially feasible and can support agribusiness development, agrotourism, and local community empowerment (Daryono et al., 2016; Megawati et al., 2018; Nofrida et al., 2019; Padapi et al., 2024). From an agronomic perspective, melon has distinctive morphological and physiological characteristics, including leaf structure, branching pattern, flowering behavior, and fruit morphology, which are closely related to cultivation practices and environmental management (Al-Mughni & Daryono, 2020; Fitriani et al., 2022; Huda et al., 2017).

Melon plants require suitable environmental conditions to support optimal growth and productivity. One of the most important environmental factors is light. Light functions as the main energy source for photosynthesis and affects physiological processes, including vegetative growth, flowering, and fruit development (Rosadi & Hakim, 2023; Triadiati et al., 2019). In melon cultivation, photoperiodism refers to the response of plants to the duration of light exposure within a daily cycle. Proper photoperiod management is important because insufficient light can inhibit photosynthesis, reduce vegetative growth, and potentially lower fruit quality (Siadari et al., 2023; Sutoyo, 2011). In addition, light spectrum and exposure duration influence plant development because red and blue light are closely associated with photosynthetic activity and biomass formation (Nugraha, 2020; Nurwahyudin & Rintyarna, 2023).

In practical cultivation, natural light availability may fluctuate due to weather, season, shading, greenhouse conditions, and time of day. During cloudy weather or rainy seasons, melon plants may receive insufficient light, especially during the vegetative phase. Conversely, excessive artificial lighting may increase energy consumption and may not always be required by the plant. The ideal growth environment for melon also involves temperature, humidity, and adequate light intensity, where melon generally requires sufficient light exposure for 10–12 hours per day and stable environmental conditions (Sari et al., 2013; Setiadi & Parimin, 2006). Therefore, lighting control should not only consider whether the environment is dark or bright, but also the time period and temperature condition around the plant.

Conventional lighting management is usually performed manually by farmers. Although manual control is simple, it has several weaknesses. Farmers must observe environmental conditions directly, determine whether additional lighting is needed, and manually adjust the light output. This approach is not always responsive to dynamic environmental changes. Light intensity may change rapidly due to weather, time of day, and shading conditions. If lighting control is delayed or inaccurate, melon plants may receive insufficient or excessive light. Insufficient light may reduce photosynthetic activity, while excessive light may waste energy and potentially cause plant stress. Therefore, an automatic lighting control system is needed to regulate light intensity more precisely and adaptively.

The Internet of Things (IoT) has become an important technology in smart agriculture because it enables real-time monitoring, remote access, and automatic control of environmental parameters. IoT-based agricultural systems can integrate sensors, microcontrollers, cloud platforms, mobile applications, and actuators to monitor and control parameters such as light intensity, temperature, humidity, soil moisture, and irrigation status (Ahen et al., 2022; Arifin & Rizal, 2023; Caniago, 2023; Lazim & Hidayat, 2022; Wijaya & Rivai, 2018). In plant cultivation, IoT allows environmental data to be collected continuously and used as a basis for automated decision-making. The use of mobile platforms also allows users to monitor system performance remotely and receive real-time information about plant growing conditions (Nasution et al., 2023; Prihatmoko, 2016).

Several sensor and actuator technologies have been used in IoT-based agricultural systems. The BH1750 sensor is widely used for light intensity measurement because it directly provides lux-based digital readings and is suitable for environmental light monitoring. The DHT21 sensor can be used to monitor temperature and humidity conditions around the plant. Meanwhile, ESP32 is suitable as the main controller because it provides Wi-Fi connectivity, sufficient processing capability, and multiple input-output interfaces for sensors and actuators. In lighting systems, LED grow light and AC light dimmer modules can be used to regulate artificial light intensity according to plant requirements. Accurate measurement and reliable instrumentation are important because control decisions depend on sensor readings and actuator response (Malaric, 2011).

Previous studies have developed IoT-based lighting and greenhouse control systems for agricultural applications. Utami et al. (2023) implemented a greenhouse monitoring and control system for melon using the BH1750 sensor, three-color LEDs, NodeMCU ESP8266, and Fuzzy Mamdani. Al-Gadri (2023) developed an auto light dimmer for hydroponic pakcoy using the BH1750 sensor, LED grow light, ESP32, and fuzzy controller. Ittaqullah et al. (2022) developed a greenhouse monitoring and control system using BH1750, DHT11, lamp, fan, NodeMCU ESP8266, and fuzzy logic. These studies indicate that IoT and fuzzy-based control are relevant for plant light management. However, most previous works have not specifically focused on melon photoperiodism optimization using Fuzzy Sugeno, and not all systems integrate light intensity, temperature, daily time period, dimmer control, local display, and mobile monitoring in a single prototype.

Fuzzy logic is relevant for automatic lighting control because environmental conditions are gradual and uncertain rather than strictly binary. In control systems, fuzzy logic can represent linguistic conditions such as dark, dim, normal, bright, cold, hot, daytime, and nighttime (Chaudhari & Patil, 2014; Lee, 1990). The Fuzzy Sugeno method is particularly suitable for embedded control because it produces numerical outputs that can be directly converted into control signals, such as PWM values or light intensity percentages (Rifai & Fitriyadi, 2023; Telleng et al., 2020). Several studies also show that Fuzzy Sugeno and related fuzzy inference methods can be effective in decision-making and control applications because of their computational efficiency and structured defuzzification process (Andryadi & Nugraha, 2021; Mizumoto, 2020; Nizar et al., 2021; Pamungkas et al., 2019; Rumfot et al., 2024).

Based on these problems and research gaps, this study develops an IoT-based automatic light intensity control system for melon plants using the Fuzzy Sugeno method. The system integrates a BH1750 light intensity sensor, DHT21 temperature sensor, ESP32 microcontroller, real-time clock, AC light dimmer, LED grow light, LCD I2C, and Blynk application. The system is designed to monitor light intensity and temperature, determine the required lighting percentage using Fuzzy Sugeno, control the LED grow light automatically, display data locally through LCD I2C, and transmit data to Blynk for remote monitoring.

The novelty of this study lies in the integration of IoT-based monitoring, Fuzzy Sugeno-based light intensity control, and melon photoperiodism optimization in a single low-cost prototype. Unlike monitoring-only systems, the developed system does not only display environmental data but also determines the lighting percentage needed by the plant based on fuzzy inference. Unlike threshold-based systems, the Fuzzy Sugeno approach allows the system to generate gradual lighting outputs according to the combination of natural light intensity, temperature, and daily time period.

The main contributions of this study are as follows. First, this study designs and implements an IoT-based automatic light intensity control system for melon plants. Second, this study applies Fuzzy Sugeno to determine LED grow light output based on light intensity, temperature, and daily time period. Third, this study evaluates the system through sensor calibration, dimmer testing, Blynk communication testing, fuzzy validation, and plant growth comparison. Fourth, this study analyzes the effect of automatic lighting control on early vegetative growth of melon plants compared with conventional lighting.

The rest of this paper is organized as follows. Section 2 describes the research method, including system architecture, hardware and software design, Fuzzy Sugeno model, control rules, algorithm, and evaluation scenario. Section 3 presents the results and discussion, including sensor calibration, actuator testing, IoT data transmission, fuzzy validation, and plant growth evaluation. Section 4 compares the developed system with previous studies. Section 5 concludes the paper and provides suggestions for future research.

2. Research Method

This section describes the research method used to develop the IoT-based automatic light intensity control system for melon photoperiodism optimization. The method includes research design, system architecture, hardware design, software and IoT data flow, Fuzzy Sugeno design, actuator control, algorithm, and evaluation scenario.

Research Design

This study used a system development approach. The research stages consisted of literature study, system requirement analysis, system design, tool development, system testing, and evaluation. The literature study was conducted to identify the characteristics of melon plants, the role of photoperiodism, IoT implementation in agriculture, sensor and actuator specifications, and the application of Fuzzy Sugeno in lighting control. Requirement analysis was used to determine input variables, output variables, hardware components, software components, and performance indicators.

The system design stage included the development of hardware architecture, fuzzy control design, electrical design, software workflow, and user interface design. The tool development stage involved assembling the hardware, programming the ESP32 using Arduino IDE, configuring the Blynk application, implementing the fuzzy inference rules, and integrating the LED grow light control system. The evaluation stage included testing the BH1750 sensor, DHT21 sensor, LCD I2C display, AC light dimmer, Blynk data transmission, Fuzzy Sugeno output, and plant growth comparison.

System Architecture

The developed system consists of input, processing, output, and interface units. The input unit includes the BH1750 sensor, DHT21 sensor, and real-time clock. The BH1750 sensor measures light intensity in lux. The DHT21 sensor measures environmental temperature. The real-time clock provides daily time information to support photoperiod-based decision-making. The processing unit uses an ESP32 microcontroller that reads sensor data, processes the fuzzy logic algorithm, controls the AC light dimmer, displays data on LCD I2C, and sends data to the Blynk application through Wi-Fi.

The output unit consists of an AC light dimmer and LED grow light. The AC light dimmer regulates the power delivered to the LED grow light based on the output percentage generated by the Fuzzy Sugeno model. The interface unit consists of LCD I2C and Blynk. LCD I2C displays real-time data locally, while Blynk allows users to monitor system data remotely through a mobile device.

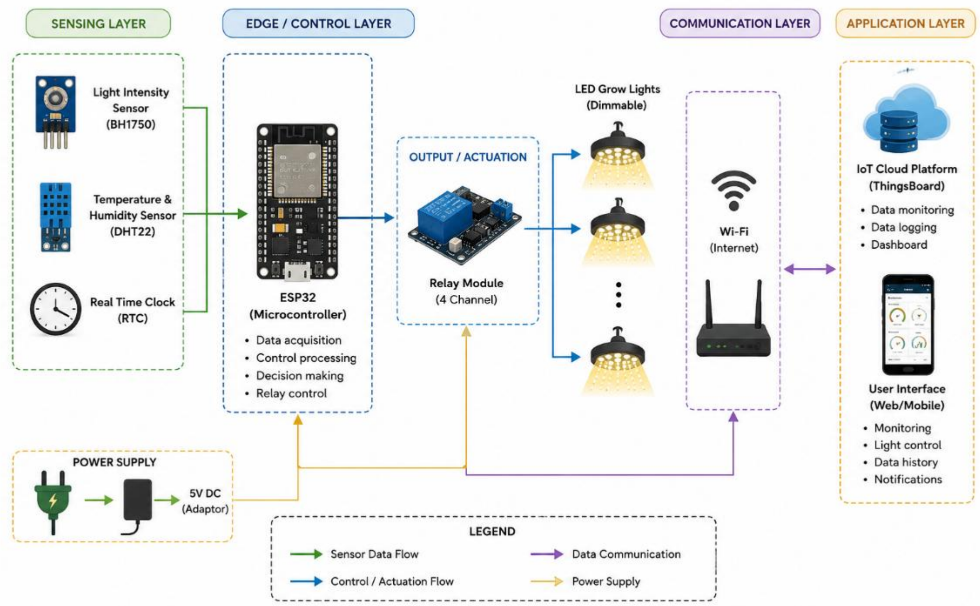

Figure 1. Iot-Based Light Intensity Control System Architecture for Melon Photoperiodism Optimization.

Hardware Design

The hardware design was developed to support automatic light control for melon cultivation. The main hardware components are presented in Table 1.

Table 1. Hardware Components Used in The Developed System.

Component	Quantity	Function
ESP32 microcontroller	1	Main controller, Wi-Fi communication, fuzzy processing, and actuator control
BH1750 sensor	1	Measuring light intensity in lux
DHT21 sensor	1	Measuring environmental temperature
Real-time clock module	1	Providing daily time information for photoperiod control
AC light dimmer	1	Controlling output power to the LED grow light
LED grow light	1	Providing artificial light for melon plants
LCD I2C 20x4	1	Displaying sensor and system output data
Blynk application	1	Remote monitoring and data visualization
Jumper cables and project board	Several	Connecting electronic components

The BH1750 sensor was connected to the ESP32 through the I2C communication pins. The DHT21 sensor was connected to a digital input pin of the ESP32. The LCD I2C shared the I2C communication line with the system. The AC light dimmer was connected to the ESP32 through zero-crossing and PWM control pins. The LED grow light was connected as the controlled lighting actuator

Software and IoT Data Flow

The software design consists of ESP32 firmware, Fuzzy Sugeno control logic, LCD display routine, and Blynk communication. The ESP32 firmware was developed using Arduino IDE. The program initializes sensors, connects to Wi-Fi, reads light intensity, temperature, and time data, performs fuzzy inference, determines the lighting output percentage, sends PWM control to the AC light dimmer, displays data on LCD I2C, and transmits data to Blynk.

The data flow begins when the ESP32 checks the Wi-Fi connection. After the connection is established, the system initializes the BH1750 sensor, DHT21 sensor, real-time clock, LCD I2C, and AC light dimmer. The system then reads light intensity, temperature, and time data. These inputs are processed through the Fuzzy Sugeno model. The fuzzy output is converted into a PWM value used to regulate the LED grow light intensity. At the same time, the data are displayed on LCD I2C and sent to the Blynk application. The system workflow is shown in Fig. 2.

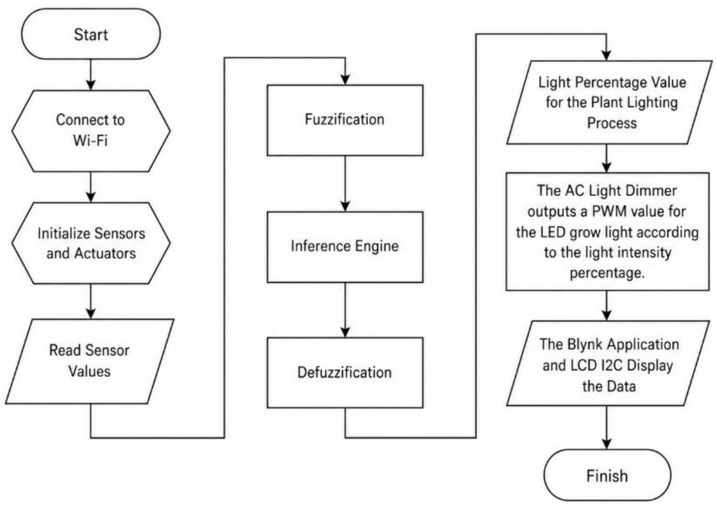

Figure 2. Workflow of the IoT-Based Light Intensity Control System.

Fuzzy Sugeno Input and Output Variables

The Fuzzy Sugeno model used three input variables and one output variable. The input variables were natural light intensity, environmental temperature, and daily time period. The output variable was the percentage of LED grow light intensity.

The light intensity variable was divided into four linguistic categories: dark, dim, normal, and bright. The daily time period variable was divided into three categories: daytime, early night, and late night. The temperature variable was divided into three categories: cold, normal, and hot. The output variable was expressed as singleton values consisting of off, dim, normal, and bright, corresponding to 0%, 30%, 80%, and 100% lamp intensity.

Table 2. Fuzzy Input and Output Variables.

Variable	Linguistic categories	Domain / output representation
Natural light intensity	Dark, Dim, Normal, Bright	Lux-based membership functions
Daily time period	Daytime, Early Night, Late Night	Hour-based membership functions
Temperature	Cold, Normal, Hot	Temperature-based membership functions
LED grow light output	Off, Dim, Normal, Bright	0%, 30%, 80%, 100%

The Sugeno fuzzy rule format used in this study is shown in Eq. (1).

$$\text{If } (\boldsymbol{x} \text{ is } \boldsymbol{A}) \text{ and } (\boldsymbol{y} \text{ is } \boldsymbol{B}) \text{ and } (\boldsymbol{t} \text{ is } \boldsymbol{C}) \text{ then } \boldsymbol{z} = \boldsymbol{k} \tag{1}$$

where ($\boldsymbol{x}$) is natural light intensity, ($\boldsymbol{y}$) is temperature, ($\boldsymbol{t}$) is daily time period, and ($\boldsymbol{z}$) is the output percentage of LED grow light intensity. The output ($\boldsymbol{k}$) is a singleton value representing off, dim, normal, or bright lighting output.

Fuzzy Rule Base and Defuzzification

The fuzzy rule base consisted of 36 rules derived from the combination of four light intensity categories, three temperature categories, and three daily time period categories. The rule base determined whether the LED grow light should be off, dim, normal, or bright. For example, when natural light intensity is bright, the system tends to reduce or turn off artificial lighting to avoid unnecessary energy use. When natural light intensity is low during the active daily period and temperature is within a suitable range, the system increases the LED grow light output.

The final output of the Fuzzy Sugeno model was calculated using the weighted average defuzzification method, as shown in Eq. (2).

$$\boldsymbol{z}^* = \frac{\sum_{i=1}^{n} \mu_i z_i}{\sum_{i=1}^{n} \mu_i} \tag{2}$$

where ($\boldsymbol{z}^*$) is the crisp output value, ($\boldsymbol{\mu_i}$) is the firing strength of the (i)-th rule, and ($\boldsymbol{z_i}$) is the singleton output value of the corresponding rule. The resulting crisp value represents the percentage of LED grow light intensity.

2.8. Algorithm/Pseudocode

The IoT-based light intensity control process using Fuzzy Sugeno is presented in Algorithm 1.

Table 3. IoT-Based Light Intensity Control Using Fuzzy Sugeno.

Algorithm 1. IoT-Based Light Intensity Control Using Fuzzy Sugeno

INPUT: Light intensity (L), temperature (T), daily time (H), fuzzy membership functions, fuzzy rules
OUTPUT: LED grow light intensity percentage, PWM output, monitoring data
1: Initialize ESP32, BH1750 sensor, DHT21 sensor, RTC, LCD I2C, AC light dimmer, and Blynk connection
2: Connect ESP32 to Wi-Fi network
3: If Wi-Fi is connected, initialize all sensors and actuators
4: Read light intensity (L) from BH1750 sensor
5: Read temperature (T) from DHT21 sensor
6: Read daily time (H) from RTC
7: Convert crisp input values into fuzzy membership degrees
8: Apply the Fuzzy Sugeno rule base
9: Calculate rule firing strength using the minimum operator

```
Compute crisp output (z^) using weighted average defuzzification
Convert (z^) into PWM control value
Send PWM signal to AC light dimmer
Adjust LED grow light intensity according to PWM output
Display light intensity, temperature, time, and output percentage on LCD I2C
Send monitoring data to Blynk
Repeat the process continuously
```

Evaluation Scenario

The system evaluation was designed to measure sensor accuracy, actuator performance, IoT communication performance, fuzzy output validity, and plant growth response. First, the BH1750 sensor was compared with a lux meter before and after calibration. Second, the DHT21 sensor was compared with a thermo hygrometer before and after calibration. Third, the AC light dimmer was tested using several PWM values to observe voltage output, lamp response, light intensity, and temperature output. Fourth, Blynk communication was evaluated by measuring data transmission status and delay. Fifth, the Fuzzy Sugeno implementation on ESP32 was validated against MATLAB simulation and manual calculation. Sixth, the system was tested on melon plants by comparing two groups: Plant A with automatic IoT-based lighting and Plant B with conventional lighting.

Sensor error was calculated using Eq. (3).

$$\text{Error}(\%) = \frac{|X_i - X_p|}{X_p} \times \mathbf{100}\% \tag{3}$$

where ($\boldsymbol{X_i}$) is the sensor reading and ($\boldsymbol{X_p}$) is the reference measurement. The improvement in sensor accuracy was analyzed by comparing average error before and after calibration. The plant growth comparison was evaluated based on plant height, number of leaves, and leaf color during the observation period.

3. Results and Discussion

This section presents the results and discussion of the developed IoT-based light intensity control system. The discussion includes hardware and software implementation, sensor calibration, AC light dimmer performance, data transmission to Blynk, Fuzzy Sugeno validation, plant growth evaluation, and visual evidence from the experimental setup and monitoring interface.

System Implementation and Experimental Setup

The developed system was implemented using ESP32 as the main controller, BH1750 as the light intensity sensor, DHT21 as the temperature sensor, AC light dimmer as the lamp power controller, LED grow light as the lighting actuator, LCD I2C as the local display, and Blynk as the remote monitoring platform. The system was designed to operate automatically by reading environmental data, calculating lighting needs using Fuzzy Sugeno, and controlling the LED grow light output.

Fig. 3 shows the experimental setup used to test the integrated system on melon plants. In the experiment, Plant A was placed under the IoT-based automatic lighting system controlled by Fuzzy Sugeno, while Plant B was used as the conventional comparison treatment. This setup was used to evaluate whether the automatic lighting system could support early vegetative growth more effectively than conventional lighting.

Figure 3. Experimental Setup of the Iot-Based Automatic Lighting System on Melon Plants.

The implementation result shows that the system could integrate sensing, fuzzy processing, dimmer-based lighting control, local display, and IoT communication. The ESP32 successfully handled sensor reading, fuzzy processing, PWM control, LCD display, and Blynk data transmission. This confirms that a low-cost IoT platform can be used to support adaptive lighting control for melon cultivation.

BH1750 Light Intensity Sensor Calibration

The BH1750 sensor was tested by comparing its readings with a lux meter. The test was conducted under three lighting conditions: indoor lighting, dim outdoor lighting, and bright outdoor lighting. Ten measurements were collected before and after calibration. The summary of the calibration result is presented in Table 3, and the visual calibration result is shown in Fig. 4.

Table 4. BH1750 Sensor Calibration Result.

Condition	Measurement Range	Average Error Before Calibration	Average error after calibration
Indoor, dim outdoor, bright outdoor	77–66,590 lux	10.13%	2.753%

Figure 4. BH1750 Calibration Result.

Before calibration, the BH1750 sensor produced an average error of 10.13%. The highest error occurred under high-intensity lighting, indicating that the sensor reading tended to deviate more when the light intensity was high. After calibration, the average error decreased to 2.753%, with the lowest error of 1.27% and the highest error of 3.74%. This result shows that calibration significantly improved sensor accuracy and made the BH1750 readings more consistent with the reference lux meter.

The improved accuracy is important because light intensity is the primary input variable in the Fuzzy Sugeno control system. If the sensor reading is inaccurate, the fuzzy system may produce an inappropriate lighting output. Therefore, BH1750 calibration is a critical step in ensuring that the LED grow light output reflects the actual light condition received by the plant.

DHT21 Temperature Sensor Calibration

The DHT21 sensor was tested by comparing its temperature readings with a thermo hygrometer. Ten measurements were collected during daytime and nighttime conditions. The summary of the calibration result is shown in Table 4, while the visual calibration result is shown in Fig. 5.

Table 5. DHT21 Temperature Sensor Calibration Result.

Condition	Average absolute error before calibration	Average percentage error before calibration	Average absolute error after calibration	Average percentage error after calibration
Daytime and nighttime temperature testing	1.16°C	3.95%	0.1°C	0.31%

Figure 5. DHT21 Calibration Result.

Before calibration, the DHT21 reading was consistently higher than the thermo hygrometer, with an average absolute error of 1.16°C and an average percentage error of 3.95%. A simple correction equation was applied by subtracting 1.16°C from the DHT21 reading. After calibration, the average absolute error decreased to 0.1°C and the average percentage error decreased to 0.31%.

This result indicates that the calibration process successfully improved DHT21 temperature measurement accuracy. Although temperature is not the only factor determining lighting needs, it is important in the fuzzy system because temperature helps determine whether the plant environment is suitable for receiving additional light. Accurate temperature measurement helps the fuzzy system avoid inappropriate lighting output under unsuitable temperature conditions.

LCD I2C Display Testing

The LCD I2C was tested to verify its ability to display characters and sensor readings. The test showed that LCD I2C could display information clearly, including initial text, sensor data, date, and time. This indicates that the display unit functioned properly as a local monitoring interface. The LCD display is important because it allows users to observe system conditions directly without relying only on the Blynk application.

AC Light Dimmer Testing

The AC light dimmer was tested by applying several PWM values representing different dimming levels. The lamp response, voltage output, light intensity, and temperature output were observed. The result is presented in Table 5, and the visual testing condition is shown in Fig. 6.

Table 5. AC Light Dimmer Testing With PWM Variation.

PWM Value	Duty Cycle	Voltage Output	Lamp Response	Light Intensity Output	Temperature Output

0	0%	~12–18 V AC	Off	0 lux	0
77	30%	~150–162 V AC	Dim	~1,900 lux	~24°C
128	50%	~185–190 V AC	Normal	~11,000 lux	~26°C
204	80%	~210–214 V AC	Bright	~19,000 lux	~27°C
255	100%	~215–222 V AC	Bright	~28,000 lux	~28°C

Figure 6. AC Light Dimmer Testing on LED Grow Light.

The test result shows that the AC light dimmer could regulate lamp intensity proportionally according to PWM input. When PWM was 0, the lamp was off. At 30% duty cycle, the lamp produced dim light. At 50%, the lamp produced normal lighting. At 80% and 100%, the lamp produced bright lighting. The light intensity increased from 0 lux to approximately 28,000 lux as PWM increased.

This result confirms that the dimmer can function as an effective actuator for controlling LED grow light intensity. The proportional response between PWM value and lighting output is important because the Fuzzy Sugeno system generates output in the form of lighting percentage. Therefore, the dimmer must be able to convert the fuzzy output into physical light intensity changes.

Data Transmission to Blynk and Data Logging

The IoT communication test was conducted to evaluate whether sensor data and system output could be transmitted to the Blynk application in real time. The test was performed at four different times with different light intensity, temperature, and lamp output values. The result is shown in Table 6. The Blynk transmission display and historical graph are shown in Fig. 7.

Table 6. Data Transmission Testing to Blynk.

Time	Natural light intensity	Temperature	Lamp output	Data status in Blynk	Delay
07:00	18,736 lux	25.30°C	0%	Sent, matched	1.06 s
10:43	30,990 lux	31.30°C	0%	Sent, matched	0.96 s
16:03	1,447 lux	23.40°C	82%	Sent, matched	0.88 s
19:07	0 lux	24.70°C	3%	Sent, matched	1.13 s

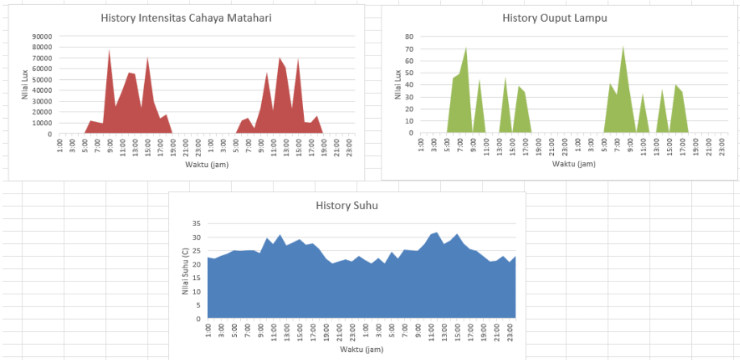

Figure 7. IoT Monitoring and Historical Graph of the Automatic Lighting System.

The result shows that all data were successfully sent and matched the values displayed on the device. The delay ranged from 0.88 to 1.13 seconds, with an average of approximately 1.01 seconds. This indicates that the system can support near real-time monitoring through Blynk.

The test also demonstrates that the system output changed according to environmental conditions. At 07:00 and 10:43, the lamp output was 0% because natural light intensity was already sufficient. At 16:03, natural light intensity was low, and the system produced 82% lamp output. At 19:07, natural light intensity was 0 lux, but the lamp output was only 3%, indicating that the fuzzy system considered not only light intensity but also the daily time period and temperature. This shows that the system does not simply turn on the lamp whenever it is dark, but evaluates the lighting need based on multiple inputs.

The data logger and historical graph in Fig. 5 also provide visual evidence that the system was able to record and display operational data over time. This feature is useful for evaluating lighting patterns, checking system stability, and supporting future analysis of plant growth responses.

Fuzzy Sugeno Implementation and Validation

The Fuzzy Sugeno method was implemented on ESP32 using Arduino IDE. The program translated the membership functions and fuzzy rule base into conditional logic. The output of the ESP32 fuzzy program was validated by comparing it with MATLAB simulation. Five test scenarios were used, as shown in Table 7.

Table 7. Evaluation of Fuzzy Sugeno Output Against MATLAB Simulation.

No.	Light intensity	Time	Temperature	Arduino / Proteus Output	MATLAB output	Difference
1	13,000 lux	06:00	23°C	53.09%	53.1%	0.09
2	23,000 lux	17:00	24°C	16.46%	16.3%	0.16
3	10,000 lux	12:00	25°C	80%	80%	0
4	30,000 lux	10:00	30°C	0%	0%	0
5	0 lux	21:00	25°C	0%	0%	0

The comparison shows that the ESP32 fuzzy program produced outputs very close to the MATLAB model. The largest difference was 0.16 percentage points, while three scenarios showed identical results. This indicates that the Fuzzy Sugeno implementation in the microcontroller was consistent with the simulation model.

Manual validation was also conducted for the first scenario using light intensity of 13,000 lux, temperature of 23°C, and time at 06:00. The manual calculation produced an output of approximately 52.82%, while the Arduino and MATLAB outputs were approximately 53.09% and 53.10%, respectively. The difference was very small and acceptable for a microcontroller-based control system. This confirms that the fuzzification, rule inference, and weighted average defuzzification processes were implemented correctly.

Plant Growth Evaluation

The integrated system was tested on melon plants by comparing two treatments. Plant A was placed under the IoT-based automatic lighting system controlled by Fuzzy Sugeno. Plant B was cultivated using conventional lighting without automatic control. Growth observations were conducted every seven days for 14 days. The observed parameters included plant height, number of leaves, and leaf color. The comparison result is presented in Table 8.

Table 8. Growth Comparison Between Automatic Lighting and Conventional Lighting.

Day	Date	Plant A Height	Plant A Leaves	Plant A Leaf Color	Plant B Height	Plant B Leaves	Plant B Leaf Color
1	16 April 2025	3cm	2 leaves	Dark green	3cm	2 leaves	Dark green
7	23 April 2025	8cm	4 leaves	Bright green	6cm	2 leaves	Bright green
14	30 April 2025	19cm	5 leaves	Bright green	16cm	4 leaves	Pale green

The results show that Plant A had better vegetative growth than Plant B. Both plants started with the same height of 3 cm and two leaves. On day 7, Plant A reached 8 cm with four leaves, while Plant B reached 6 cm with two leaves. On day 14, Plant A reached 19 cm with five leaves and bright green leaf color, while Plant B reached 16 cm with four leaves and pale green leaf color.

The difference indicates that the automatic lighting system had a positive effect on early melon growth. Plant A showed faster height growth, more leaf development, and better leaf color. Bright green leaves may indicate more suitable light exposure for photosynthesis. The Blynk data logger and historical graph also showed that the system recorded environmental data and adjusted lighting output according to fuzzy logic. This supports the conclusion that adaptive lighting control can improve the stability of light exposure during vegetative growth.

However, the plant growth test was limited to the early vegetative phase and involved a small number of plant samples. Therefore, the results should be interpreted as preliminary evidence. Further testing with more plants, longer observation periods, and additional parameters such as leaf area, chlorophyll content, flowering time, fruit weight, and fruit quality is needed to determine the broader impact of the system on melon productivity.

Discussion of Main Findings

The experimental results show four main findings. First, the developed IoT system successfully integrated environmental sensing, fuzzy processing, dimmer-based lighting control, local display, mobile monitoring, and data logging. This integration is important because lighting control for plants requires real-time data acquisition, responsive actuator control, and traceable historical data.

Second, sensor calibration significantly improved measurement accuracy. The BH1750 average error decreased from 10.13% to 2.753%, and the DHT21 average error decreased from 3.95% to 0.31%. These improvements are important because the quality of fuzzy control output depends on the accuracy of input data.

Third, the Fuzzy Sugeno method provided adaptive lighting control. The system did not only respond to light intensity but also considered temperature and daily time period. This allowed the system to avoid unnecessary lighting during periods when plants did not require additional light. Therefore, the system has potential to improve energy efficiency while supporting plant growth.

Fourth, the initial plant test showed that automatic lighting control could support better vegetative growth than conventional lighting. Plant A showed higher growth, more leaves, and better leaf color than Plant B after 14 days. These findings suggest that IoT and Fuzzy Sugeno-based lighting control can support photoperiodism optimization in melon cultivation.

Limitations

This study has several limitations. First, the plant growth evaluation was conducted only during the vegetative phase and for a short observation period of 14 days. Second, the number of plant samples was limited, so statistical analysis could not be performed robustly. Third, the system focused mainly on light intensity control, while humidity was used only as supporting monitoring data and was not integrated into fuzzy decision-making. Fourth, the system did not yet evaluate long-term outcomes such as flowering, fruit formation, fruit weight, sweetness, or harvest quality. Fifth, energy consumption analysis was not yet performed, although the system has potential for energy-efficient lighting control.

Future development should include longer field testing, more plant samples, energy consumption analysis, integration of humidity and ventilation control, and evaluation of fruit productivity and quality.

4. Comparison

Comparison with state-of-the-art studies is important to show the measurable contribution of the system developed in this study. Table 9 compares the developed system with previous studies based on object, sensor, controller, method, monitoring platform, and main contribution.

Table 9. Comparison Between the Developed System and Previous Studies.

Study	Object	Sensor / Actuator	Controller	Method	Platform	Main contribution
Utami et al. (2023)	Melon greenhouse	BH1750, three-color LED	NodeMCU ESP8266	Fuzzy Mamdani	IoT greenhouse monitoring	Monitoring and control system for melon greenhouse growth optimization
Al-Gadri (2023)	Hydroponic pakcoy	BH1750, LED grow light	ESP32	Fuzzy controller	Indoor hydroponic system	Auto light dimmer for indoor hydroponic lighting control
Ittaqullah et al. (2022)	Greenhouse	BH1750, DHT11, lamp, fan	NodeMCU ESP8266	Fuzzy logic	IoT greenhouse system	Monitoring and control of air quality and light intensity
This study	Melon plant photoperiod ism	BH1750, DHT21, LED grow light, AC dimmer, LCD I2C	ESP32	Fuzzy Sugeno	Blynk	Adaptive IoT-based light intensity control for melon vegetative growth

The comparison shows that previous studies have applied IoT and fuzzy logic for plant lighting control. Utami et al. (2023) focused on melon greenhouse monitoring using Fuzzy Mamdani, while Al-Gadri (2023) focused on hydroponic pakcoy using fuzzy-based dimming. Ittaqullah et al. (2022) developed a greenhouse system that combined light intensity monitoring with air quality monitoring.

Compared with these studies, the system developed in this study has several distinguishing features. First, it specifically focuses on melon photoperiodism optimization during the vegetative phase. Second, it uses Fuzzy Sugeno to produce numerical lighting output percentages, making it suitable for dimmer-based light intensity regulation. Third, it integrates BH1750, DHT21, daily time period, ESP32, AC light dimmer, LED grow light, LCD I2C, and Blynk into one system. Fourth, it evaluates not only component performance but also early plant growth comparison between automatic and conventional lighting.

From the performance perspective, the developed system demonstrated improved sensor accuracy after calibration, stable AC dimmer response, successful real-time Blynk communication, data logging capability, and strong agreement between ESP32 fuzzy output and MATLAB simulation. In plant testing, the automatic lighting system produced better vegetative growth than the conventional method after 14 days. These findings show that the system provides a measurable contribution to smart agriculture, particularly in adaptive lighting control for melon cultivation.

5. Conclusions

This study developed an IoT-based automatic light intensity control system for melon photoperiodism optimization using the Fuzzy Sugeno method. The system integrated an ESP32 microcontroller, BH1750 light intensity sensor, DHT21 temperature sensor, real-time clock, AC light dimmer, LED grow light, LCD I2C, and Blynk application. The system was able to read environmental data, process Fuzzy Sugeno rules, generate LED grow light output percentages, control light intensity automatically, display data locally, transmit monitoring data in real time, and record operational history through data logging.

The experimental results showed that the developed system performed well. The BH1750 sensor calibration reduced the average light measurement error from 10.13% to 2.753%. The DHT21 calibration reduced the average temperature error from 3.95% to 0.31%. The AC light dimmer responded proportionally to PWM input, producing light intensity from 0 lux to approximately 28,000 lux. The Blynk communication test showed successful data transmission with an average delay of approximately 1.01 seconds. The Fuzzy Sugeno implementation produced results consistent with MATLAB simulation, with the largest difference of 0.16 percentage points in the tested scenarios.

The plant growth evaluation showed that the automatic lighting system supported better vegetative growth than the conventional method. After 14 days, the plant using the IoT-based automatic lighting system reached 19 cm with five leaves and bright green leaf color, while the conventional plant reached 16 cm with four leaves and pale green leaf color. These findings indicate that the integration of IoT and Fuzzy Sugeno can support adaptive lighting control for melon photoperiodism optimization.

The contribution of this study lies in the development of a low-cost smart agriculture system that integrates real-time sensing, fuzzy decision-making, dimmer-based actuator control, local display, mobile monitoring, data logging, and preliminary plant growth evaluation. However, this study still has limitations, including short observation duration, limited plant samples, and evaluation only in the vegetative phase. Future studies should conduct long-term testing with more plant samples, evaluate flowering and fruit production, analyze energy consumption, add humidity and ventilation control, and compare Fuzzy Sugeno with other control methods.

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