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Adaptive-Historical Energy-Efficient Temperature Control Model for Tropical Greenhouses

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Abstract

Maintaining an optimal microclimate is essential for efficient operation of tropical greenhouses, particularly under fluctuating weather conditions. This study proposes an adaptive energy-efficient model for regulating air temperature in tropical greenhouses using historical climate data. The model optimizes the fan rotation speeds via an inverter to meet the temperature targets while minimizing energy consumption. Key methodologies include climate data analysis, development of a predictive model for indoor air temperature using Artificial Neural Networks, and optimization of fan speed control. The model achieved high predictive accuracy, with an RMSE of 0,02 and an R^2 of 0,96. The practical implementation demonstrated effective temperature control, with fan speeds ranging between 30 and 40 Hz during cloudy periods and 50 Hz in sunny conditions. Notably, the system reduced electricity consumption by 33,93% during cloudy weather and 18,54% in sunny weather, showing its potential for significant energy savings. This data-driven adaptive model approach is highly suited for tropical greenhouses experiencing dynamic climatic variations and offers a sustainable and efficient solution for greenhouse microclimate management.

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1. Introduction

The use of greenhouses as an alternative to cultivation is growing in line with the increasing human population and need for horticultural food crops. However, the growth of open agricultural land has become more challenging. This encourages the development of various types and characteristics of greenhouses for cultivation (Suhardiyanto, 2009), employing technological devices to control the environment to match the needs of plants. Cooling pads and fans are evaporative cooling technologies that use water vapor to reduce the air temperature inside greenhouses (Cuce & Riffat, 2016) because high air temperatures impact the environment and plant growth and development (Mahmood & Al-Ansari, 2021). The Performance of the evaporation system is

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maximized through water-cooling technology to cool the air (Misra & Ghosh, 2018) and temperature of root plants (Niam & Suhardiyanto, 2019).

A large amount of energy is required to maintain an optimal air temperature during the operation of a greenhouse system (Iddio et al., 2020), as this has an impact on the quality of plant growth and crop productivity (Ploeg & Heuvelink, 2005) (Mahmood et al., 2021; Zhu et al., 2021). This high energy consumption is primarily derived from large-capacity technological devices that are used continuously. By contrast, limited-use technologies consume only a small amount of electrical energy.

The microclimate of a greenhouse is a linear and dynamic system that is affected by various interconnected factors (Gani, 2021). The high and low air temperatures inside a greenhouse are influenced by the intensity of the sun, wind speed, air humidity, and plant type (Jung et al., 2020). In addition to the microclimate, the structure of the greenhouse (Lin et al., 2020), cost, and energy consumption (Badji et al., 2022) affect the changes in air temperature inside the greenhouse. Moreover, electrical energy efficiency has become a potential sector for greenhouse gas research.

Micro-data models of the air temperature inside greenhouses have been developed in various scenarios. The Prediction of air temperature inside a greenhouse using historical data covering four input parameters, namely air temperature, solar radiation, wind speed, and outside temperature, yielded a reasonably good model performance with an RMSE value of 3,7 °C (Francik & Kurpaska, 2020). A model for predicting the air temperature inside a greenhouse was successfully developed using the Gradient Boost Decision Tree (GBDT) based on the Light Gradient Boosting Machine (LGBM) algorithm (Cai et al., 2022). The adaptive cross-validation method successfully boosted the Performance of the LGBM model and adaptive capability with an RMSE value of 0,65 and has the potential to be developed in an adaptive control system. Furthermore, a Support Vector Regression model based on the PSO algorithm was developed to predict the air temperature inside a greenhouse with accuracy and error rates of 0,00019 and R^2 0,99 (Fan et al., 2021).

Several approaches to controlling the air temperature inside greenhouses have also been developed using artificial neural networks (ANN) as a model for predicting the air temperature with climate parameters and the number of occupants in school buildings as input parameters (Reynolds et al., 2018). The validation results for one week have shown a reduction in energy use of 25 %. An ANN-based adaptive control model of cold room providence in residential areas was developed to provide cooling systems (Coccia et al., 2021). The control model reduces the energy used for cooling by 71 %. A temperature control strategy for a Venlo-type greenhouse in South Africa has also been proposed to improve energy efficiency (Lin et al., 2020). The proposed model strategy can reduce the energy consumption by maintaining the temperature, relative humidity, and concentration within the required range. An artificial neural model was developed to implement the dynamic prediction element of the Model Predictive Control (MPC) system and was compared with Support Vector Regression, Nearest Neighbor, and Decision Tree (Elnour et al., 2022). Comparative simulations

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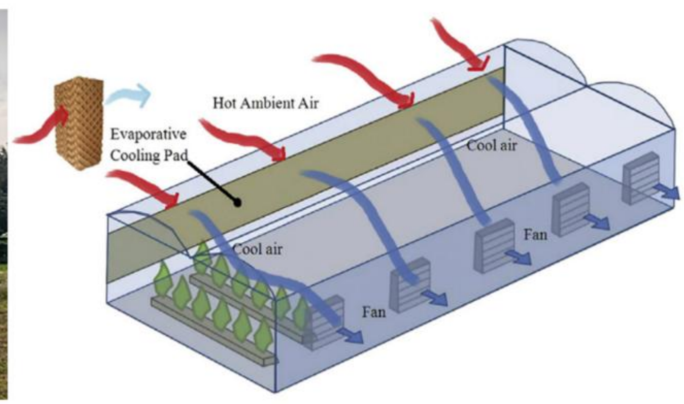
showed that the neural-network-based model can reduce energy use by up to 46 % while optimizing thermal comfort and indoor air quality.

The primary aim of this research is to develop an innovative, adaptive control model that significantly enhances energy efficiency while maintaining optimal air temperatures within tropical greenhouses. Traditional cooling systems in such greenhouses often require high energy consumption, primarily because of their continuous operation, regardless of external climatic variations. This study proposed a novel approach by integrating historical climate data with a predictive model to dynamically adjust fan rotation speeds, thereby optimizing energy usage. The uniqueness of this study lies in its ability to tailor fan operations based on real-time environmental data, offering a customized and responsive solution for temperature regulation. By reducing electricity consumption and improving the precision of temperature control, this adaptive model addresses both the economic and environmental challenges associated with greenhouse management. This research not only contributes to the existing body of knowledge on greenhouse climate control but also provides a practical and scalable solution for tropical regions facing increasingly variable weather patterns.

2. Methods

The study was conducted in an 8 × 24 m^2 arch-type greenhouse (Figure 1a) equipped with evaporative cooling systems and a chiller designed to regulate air temperature and humidity. The system consisted of a fan installed on one wall of the greenhouse and a cooling pad on the opposite wall. Evaporative cooling is achieved by spraying or sprinkling water over the pads, with air drawn through the pads by a fan (Figure 1b). These systems convert sensible heat into latent heat through water evaporation facilitated by the cooling pads (Ghoulem et al., 2019).



(a) (b)

Figure 1. (**a**) 8x24 m2 arch smart greenhouse; (**b**) fan-pad evaporative cooling inside arch-type smart greenhouse (Ghoulem et al., 2019).

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When operating without evaporative cooling, the air temperature inside the greenhouse can exceed 40 °C (Gani, 2021) because there is no air exchange. In contrast, air circulation occurs with evaporative cooling, which can reduce the air temperature from 4 ° to 6 °. Using a chiller to cool the water and circulate it to the cooling pad lowers the air temperature in the greenhouse between 30 and 32 °C.

2.1 Collecting Data

A In this study, a low-energy adaptive model based on historical data was developed to determine the air temperature inside a greenhouse. Data were obtained from eight microparameters in the greenhouse, which were measured using sensors placed around the greenhouse (internal and external) and the chiller tank. The parameters inside the greenhouse included the indoor temperature (T_{in}), indoor humidity (RH_{in}), and indoor solar radiation (SR_{in}). The parameters outside the greenhouse included the outdoor temperature T_{out}, outdoor humidity (RH_{out}), and outdoor sun intensity (SR_{out}). The chiller parameter is the chiller water temperature ($T_{chiller}$). The inverter frequency (F_{inv}) was set on four scales, namely 20 Hz, 30 Hz, 40 Hz, and 50 Hz, according to the specifications of the electric motor on the installed fan. The data were grouped into three variables, namely environmental variables (T_{in}, T_{out}, RH_{in}, RH_{out}, SR_{in}, SR_{out}), a supporting variable ($T_{chiller}$), and a control variable (F_{inv}). Measurements were taken every 10 s between 06:00 and 18:00. The data from all the variables were then organized into a dataset with identified inputs and outputs to build predictive models.

2.2 Pre-data Analysis

Pre-analysis was carried out on the collected data to determine the parameters that most significantly influenced changes in greenhouse air temperature and their impact on the use of electrical energy. The dataset was grouped into four inverter frequency scales, namely 20 Hz, 30 Hz, 40 Hz, and 50 Hz, to analyze the average air temperature and electricity usage. The variability and coefficient of the relationship between environmental parameters were determined using Equation 1 (Mudholkar et al., 1982).

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \tag{1}$$

where r = correlation coefficient, x_i is the input, $\bar{x}$ is the average input value, y_i is the output value, and $\bar{y}$ is the average output value of the considered parameters.

The correlation coefficient is a statistical measure of the covariance between two variables and indicates the strength of the linear relationship and the direction of the relationship between two random variables. If the correlation coefficient is positive, the two variables have a unidirectional relationship, meaning that when the value of variable x increases, the value of variable y also increases. Conversely, if the correlation coefficient is negative, the two variables have an inverse

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relationship, indicating that when the value of variable x increases, the value of variable y decreases. (Sarwono, 2006).

2.3 Adaptive Model Development

Energy consumption can be minimized through optimal environmental control to maintain the desired target values (Yang et al., 2020). Achieving this requires a model capable of accurately capturing the dynamic behavior of the greenhouse microclimate, particularly when controlling air temperature. To this end, an adaptive model was developed to optimize environmental conditions while minimizing electricity consumption. This model integrates predictive and optimization approaches, as illustrated in Figure 2.

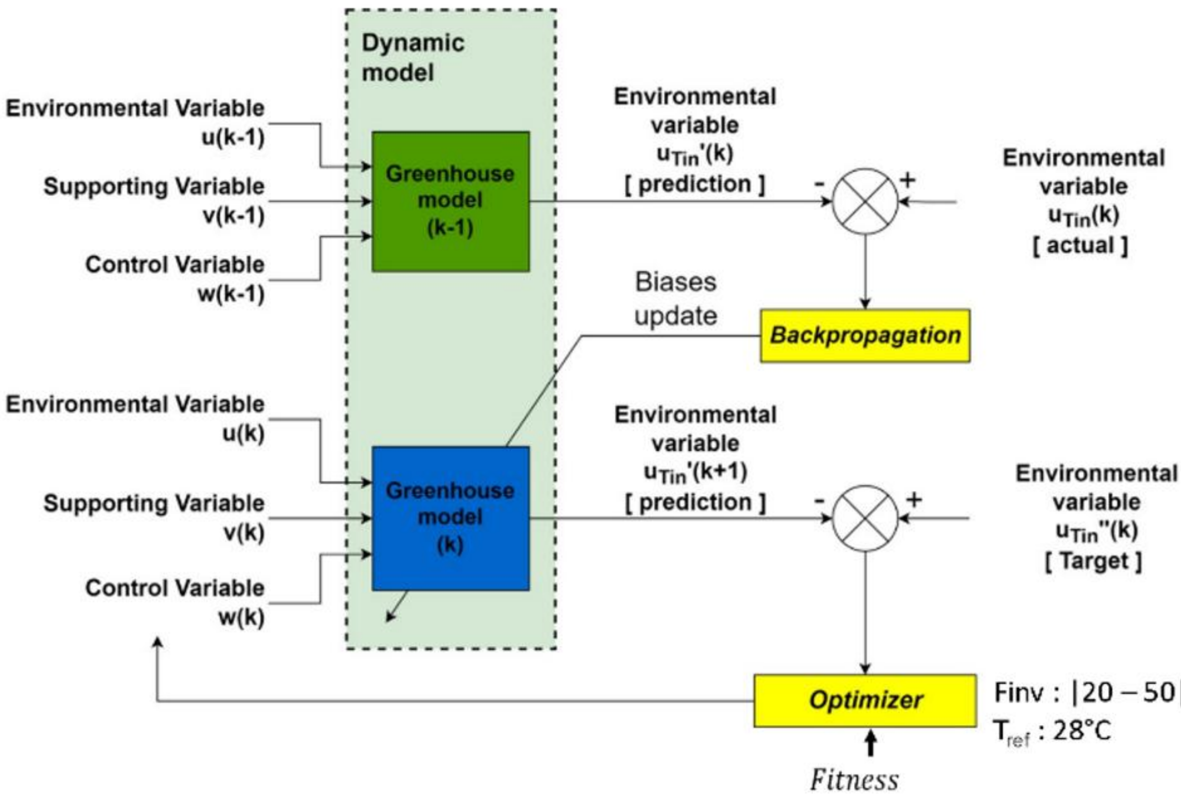

Figure 2. Adaptive model that combines prediction models and optimization.

a. Predicvite Model

The predictive approach employs an Artificial Neural Network (ANN) with a backpropagation method to predict the air temperature inside a greenhouse. Data-driven adaptive models address unmeasured phenomena, such as water absorption by greenhouse structures, by analyzing the relationships between input and output data within the model (Smarra et al., 2018). The dataset was

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structured such that the air temperature inside the greenhouse depended on its current and past state values (Shin et al., 2020).

The predictive model incorporates microclimate parameters as inputs, including predictive parameters such as the learning rate, random state, momentum, and bias functions. These elements were fine-tuned through trial and error to predict the air temperature inside the greenhouse, denoted as u_{Tin}'(k)[prediction]. The backpropagation model represents the greenhouse system, consisting of an input layer with eight parameters categorized into three variable groups: 1) environmental variables u(k-1) representing the previous stage, which include T_{in-1}, RH_{in-1}, RH_{out-1}, T_{out-1}, $SR_{in-1,}$ and SR_{out-1}; 2) supporting variable v(k-1), which is $T_{chiller-1}$; and 3) control variable w(k-1), which is F_{inv-1}.

The hidden layer (n) introduces additional parameters, while the output layer predicts the environmental variable u_{tin}'(k), spesifically T_{in} [prediction]. Subsequently, the actual environmental variables u_{tin}(k) [actual], comprising T_{in}, RH_{in}, RH_{out}, T_{out}, SR_{in} and SR_{out}, and $T_{chiller}$, along with u_{tin}'(k) [Prediction], were used to correct the biases through the backpropagation algorithm. The root-mean-square error (RMSE) and coefficient of determinant (R^2) parameters in Equations 2 and 3 were used to measure the performance of the prediction model (Kamilaris & Prenafeta-Boldú, 2018). The performance of the model is highly dependent on the accuracy of its system representation (Coccia et al., 2021), as the prediction results inform the process pathway to achieve the desired optimal condition (Yamashita et al., 2016).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(X_{obs,i}-X_{model,i}\right)^2}{n}} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(X_{obs,i}-X_{model,i}\right)^2}{\sum_{i=1}^{n}\left(X_{obs,i}-\bar{X}_{obs,i}\right)^2} \tag{3}$$

b. Optimizination Model

The fitness function serves as the objective function in the optimization process, calculating the fitness scores for both the predicted air temperature (T_{in}') and the cost of inverter frequency (F_{inv}). The goal of the fitness function is to minimize the error between the predicted output and the target values. An adaptive control model predicts future behavior u_{tin}'(k) and optimizes control variables w(k) using an optimization algorithm. The inverter frequency (F_{inv}) used as the control variable, operates within predefined upper and lower limits to reduce computational complexity. The fitness function is defined as Equation 4.

$$\mathrm{Fitness} = \left|\frac{\hat{y}-T_{target}^{N}}{T_{ba}^{N}-T_{target}^{N}}\right|^3 \tag{4}$$

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where, $\hat{y}$ is the predicted internal temperature from the ANN model, T^N_{target} is the lower target temperature, normalized between the maximum and minimum air temperatures at 20 Hz and 50 Hz inverter frequencies, and T^N_{ba} is the upper target temperature, normalized similarly.

The inverter frequency (F_{inv}) was adjusted within a limited range of 20, 30, 40, and 50 Hz, based on the optimization results and target temperature. The control settings were defined as follows:

- F_{inv} < 24,99 set to 20 Hz,
- 25 < F_{inv} < 34,99 set to 30 Hz,
- 35 < F_{inv} < 44,99 set to 40, and
- 45 < F_{inv} < 54,99 set to 50 Hz.

The target temperature (T_{ref}) was maintained at 28 °C.

c. Model Testing and Application

Historical data from three variable groups, namely u(k-1), v(k-1), and w(k-1), were used to predict the air temperature u_{Tin}'(k). The model was tested with parameter constraints to evaluate its performance based on the RMSE and R^2. The predictive model was then applied to a new dataset consisting of environmental variables u_{Tin}(k), supporting variables v(k), and predicted future air temperature u_{Tin}'(k+1). This trained model was integrated with the objective function and optimization algorithm to determine the optimal value of w(k) for aligning the predicted air temperature with the desired target. The predicted air temperature was compared with actual measurements, and the energy consumption was calculated based on motor rotation speed adjustments.

3 Results and Discussion

3.1 Data Exploration and Analysis

Changes in the air temperature inside the greenhouse depend on other micro parameters such as the outside air temperature, relative humidity, solar radiation, fan rotation speed, and chiller water temperature that flows to the cooling pad. For greenhouses not equipped with natural ventilation, fan rotation speed is an important variable that affects greenhouse air temperature changes. The faster the fan rotates, the lower the air temperature, even though the solar radiation is high.

Figure 3 shows the relationship between the air temperature in the greenhouse and solar radiation measured at four fan rotation speeds. On a 20 Hz inverter frequency scale (y1), the air exchange rate in the greenhouse is relatively low; therefore, if the solar radiation is high, the air temperature in the greenhouse will also increase. Furthermore, the fan spins faster at frequencies of 30 Hz (y2), 40 Hz (y3), and 50 Hz (y4), so there is more air exchange in the greenhouse, and the air temperature is lower. Faster fan rotation can lower the air temperature inside a greenhouse, even under high solar radiation conditions. Consequently, the air temperature fluctuation inside the greenhouse depends not only on the building structure, orientation, top material (Badji et al., 2022), ventilation (Ghani et al., 2020), and speed of the installed fans.

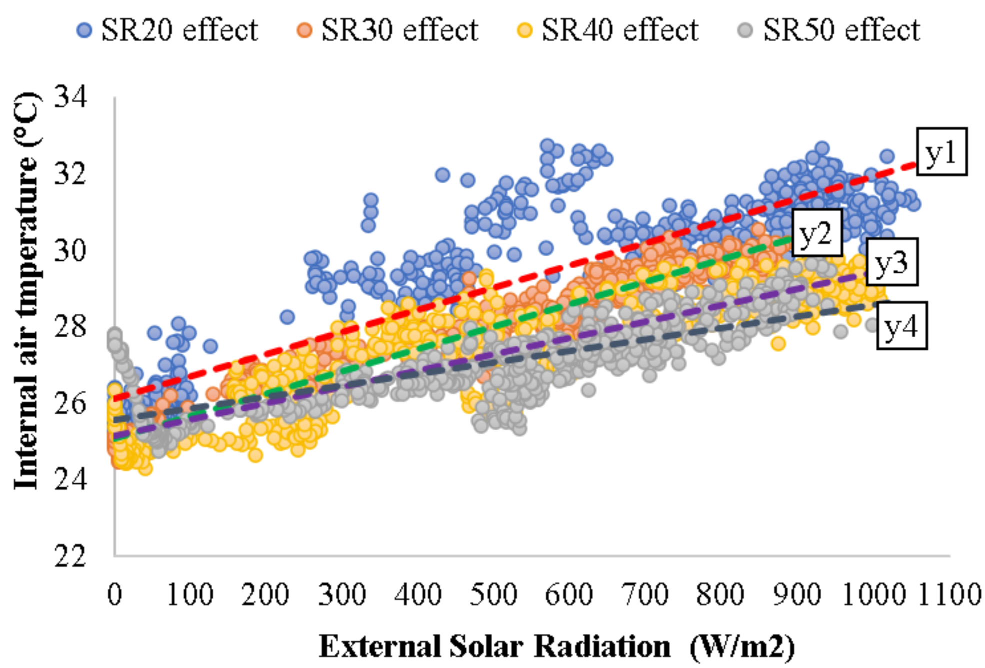

Figure 3. The relationship between greenhouse air temperature and solar radiation was measured at four fan rotation speeds.

Table 1. Relationship between solar energy intensity and greenhouse air temperature changes on four inverter frequency scales.

Frequency of inverter (Hz)	Average of Solar Radiation (W/m²)	Average of internal Temp (°C)	Regression	R^2
20	534,2	29	y1 = 0,0058x + 26,133	0,82
30	442,7	28	y2 = 0,0058x + 25,101	0,94
40	544,0	27,5	y3 = 0,0043x + 25,161	0,82
50	496,3	27	y4 = 0,003x + 25,569	0,55

The regression for each inverter frequency level in Table 1 shows that increasing the internal air temperature by one degree with an inverter frequency, the 20 Hz frequency requires 666,7 W/m², the 30 Hz frequency needs 672,2 W/m², the 30 Hz frequency requires 776 W/m², and the 50 Hz frequency requires 810 W/m². Alternatively, it can be said that changes in radiation more easily change the air temperature in a greenhouse at a low inverter frequency.

3.2 Performance of Prediction Model

Intervention Figure 4a shows a comparison of the expected and actual air temperatures of the greenhouse obtained from the prediction model. The data were concentrated between 24 °C and 33 °C, with a target temperature of 28 °C. Although the scattered temperature data appeared below the target, the model worked well at R^2 0,96. The model was then validated using a dataset measured on August 25, 2022, at the same target temperature. A comparison of the predicted air temperature with the actual air temperature, as shown in Figure 4b, shows promising results with R^2 0,92.

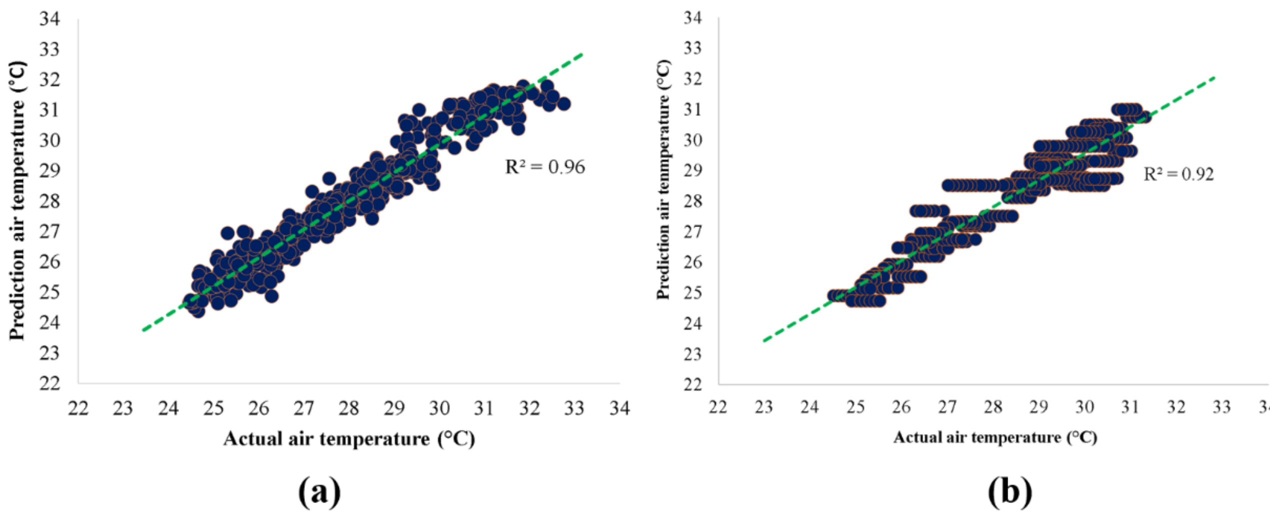

Figure 4. Comparison of actual and predicted air temperature data in greenhouse modeling results: **(a)** Training Performance and **(b)** Validation Performance.

The model validation results using measurement data from August 25, 2022, showed good Performance with R^2 of 0,92. The Performance of the prediction model was calculated at three different times, assuming that these periods represented changes in microclimate parameters in the greenhouse. R^2 and RMSE were determined at prediction times of 10, 15, and 20 min. The validation results show that the 10-minute prediction model has R^2 and RMSE values of 0,96 and 0,026, decreasing at 15 and 20 min of prediction time. This study uses a 10-minute prediction model because it has a better level of precision. The prediction model also provided different conditions for different numbers of hidden neurons. The model performance improved when the number of neurons in the hidden layer was increased from 7, 9, 11, and 13. The best performance is given to 11 neurons and is used as part of the structural model.

3.3 Effect of Prediction Model of Sunny and Cloudy Weather

The dataset was divided into sunny and cloudy climates based on ambient temperature and data variability. The model was trained based on each requirement to predict the air temperature inside the greenhouse. The measurement data from August 25, 2022, were used for sunny conditions, while the data from August 31, 2022, were used for cloudy conditions. Validation of the model for the bright condition showed a difference of ±2 °C between the inside and outside air temperatures. However, the involvement of other indicators results in a model performance that seems unaffected by high outside air temperature. The model accurately predicted the internal air temperature (R^2 = 0,92) predicts the air temperature inside. The model validation for cloudy conditions showed a lower difference between the inside and outside air temperatures (±3 °C). The model predicted the air temperature with high accuracy (R^2 = 0,90). Thus, the model worked well in conditioning the air temperature inside the greenhouse, even under sunny conditions. The validation results show that the prediction model with eight input parameters and 11 hidden neurons is considered good enough to be used in the following optimization process.

3.4 Optimizanition With Genetic Algorithm

Figures 5–8 show the optimization results using the genetic algorithm on all four inverter frequency scales.

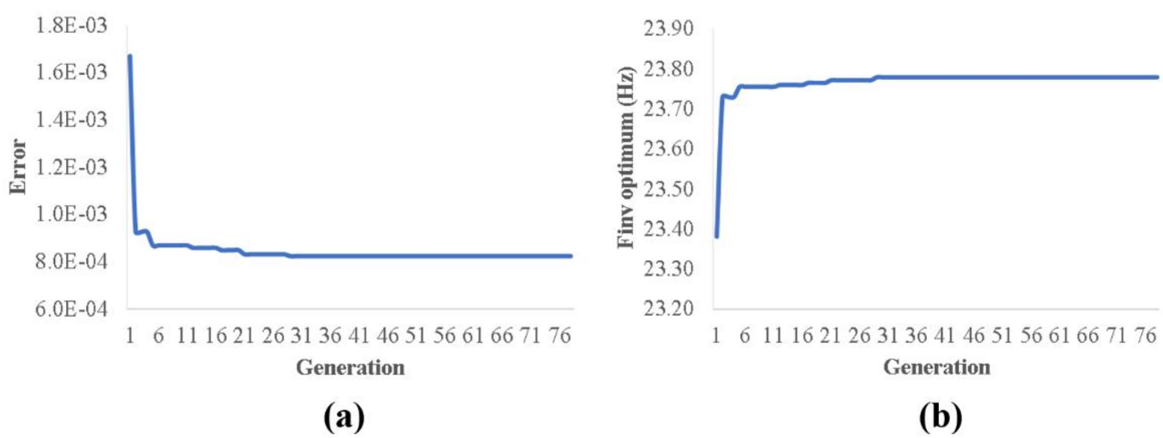

Figure 5. Graph of the optimization process at a frequency of 20 Hz: (**a**) changes in fitness value during the optimization process; (**b**) changes in the optimum value of the inverter frequency during the optimization process.

The optimization process works well in maintaining the air temperature inside the greenhouse. The iteration process for optimization starts with a high error value. The larger the iteration, the lower the error value until convergence to a certain value, where the generation value is identified. The change in the error value is in line with the inverter frequency value, which starts with the current value and increases until it converges simultaneously. The frequency value, when converged, was executed.

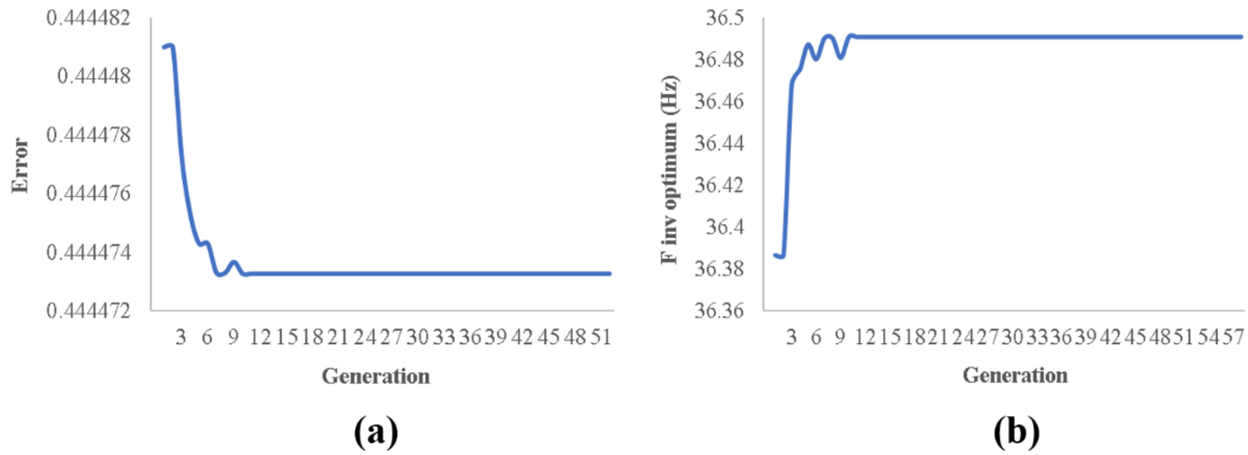

Figure 6. Graph of the optimization process at a frequency of 30 Hz: (**a**) changes in fitness value during the optimization process; (**b**) changes in the optimum value of the inverter frequency during the optimization process.

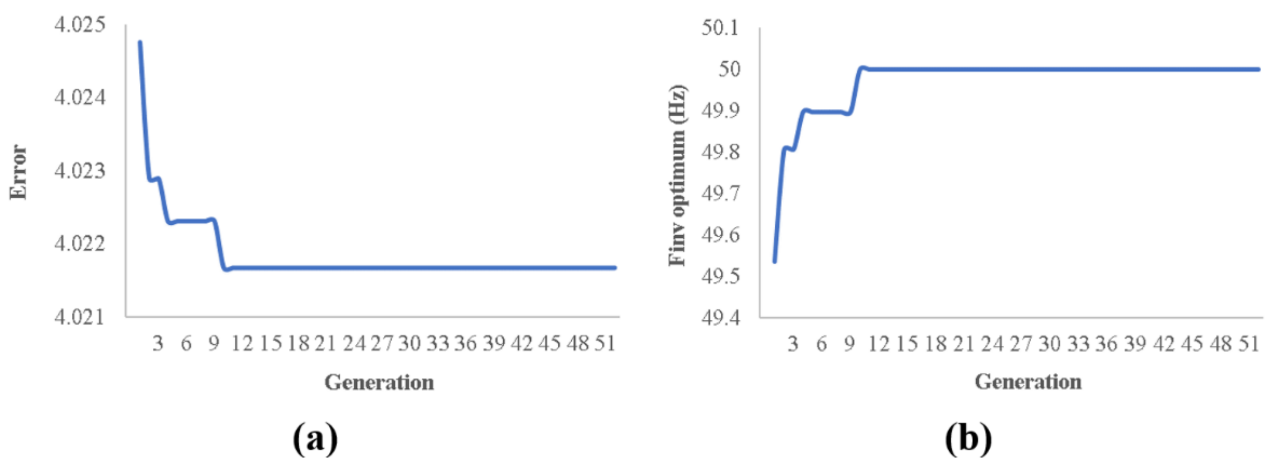

Figure 7. Graph of the optimization process at a frequency of 40 Hz: (**a**) changes in fitness value during the optimization process; (**b**) changes in the optimum value of the inverter frequency during the optimization process.

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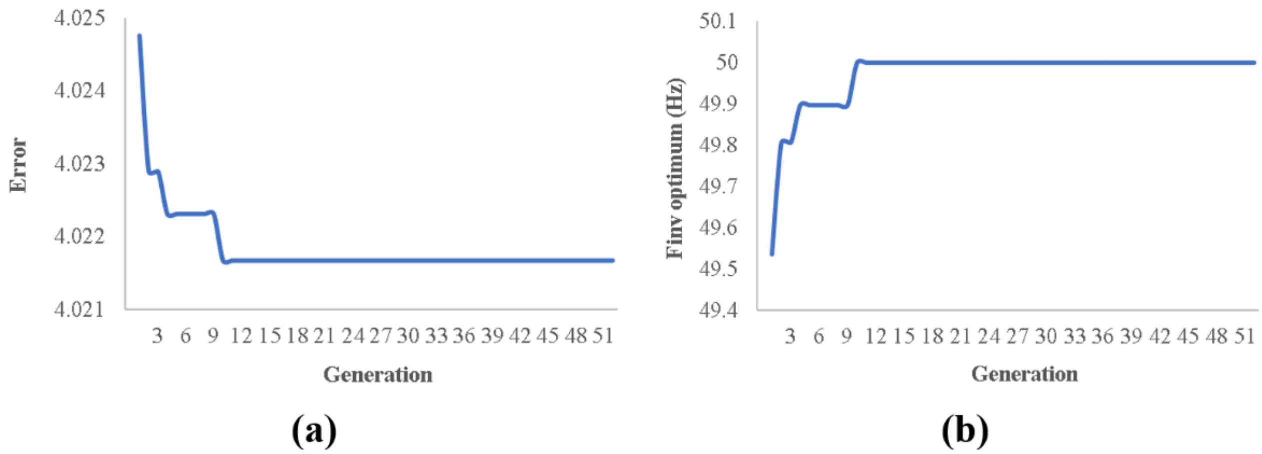


Figure 8. Graph of the optimization process at a frequency of 50 Hz: (**a**) changes in fitness value during the optimization process; (**b**) changes in the optimum value of the inverter frequency during the optimization process.

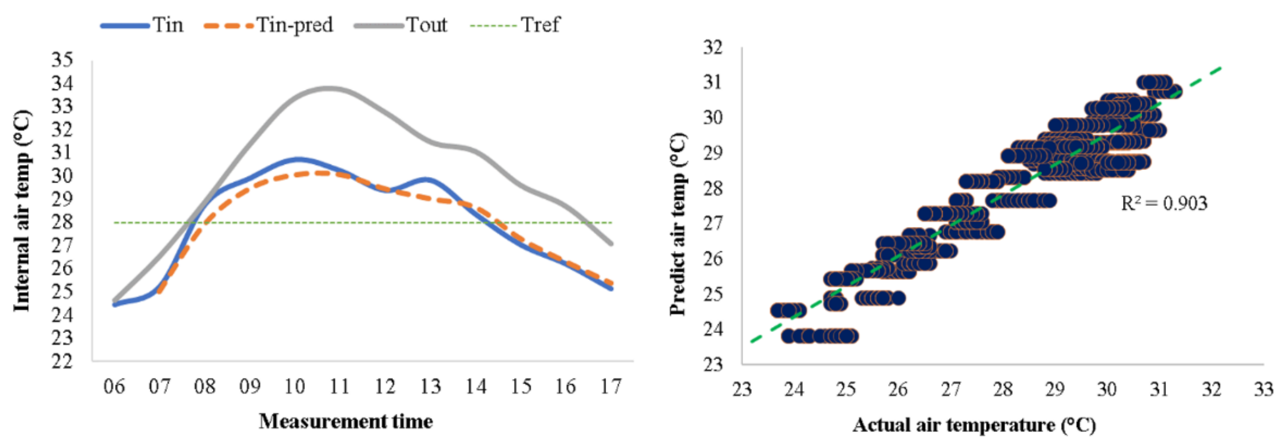
According to the control scale setting, 20 Hz optimization process convergence occurred in the 29th generation, 30 Hz in the 21st generation, 40 Hz in the 9th generation, and 50 Hz in the 10th generation.

The results showed that when the conditions were cloudy and the predicted air temperature was lower than the target, an optimization result of 20 Hz was obtained. However, this frequency was not executed by the control system because it still met the needs of the plants. A 30 Hz optimization was performed when the predicted air temperature increased. As the target temperature approached, a frequency of 40 Hz was recommended. In sunny weather, the optimization runs quite well. However, the limitation of the fan frequency, which is not more than 50 Hz, prevents the 50 Hz optimization from maintaining the air temperature according to the target.

3.5 Performance of Adaptive Model in Sunny and Cloudy Conditions

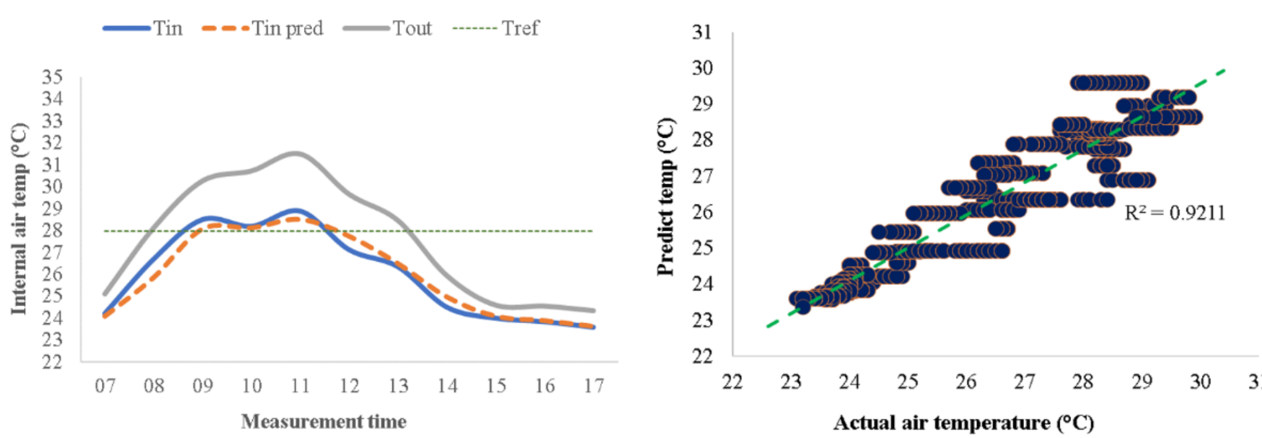
The performance of the adaptive model was evaluated based on a motor rotation speed assessment to maintain the internal predicted air temperature below the target temperature and the evaluation of electrical energy while the control model was running. The model attempts to maintain the target temperature when there are fluctuations in solar radiation and air temperature outside the greenhouse.

The prediction model for sunny conditions was validated using measurement data from August 26, 2022, using a control device that operated from 06:00 to 18:00. Figure 9a shows the trend of the predicted air temperature from the prediction model, the actual air temperature, the outside air temperature, and the target temperature integrated into the adaptive control model.



(a) (b)

Figure 9. Model performance in sunny conditions using the dataset on August 26, 2022 **(a)** the trend of air temperature predicted by the model, actual air temperature, outside air temperature, and target temperature, which is integrated into the adaptive control model; **(b)** comparison of the predicted and actual air temperatures in the greenhouse.



(a) (b)

Figure 10. Model performance in cloudy conditions using the data set on September 9, 2022 (**a**) the trend of air temperature predicted by the model, actual air temperature, outside, and target temperature, which is integrated into the adaptive control model; (**b**) comparison of the predicted and actual air temperatures in the greenhouse.

The model's performance, as shown in Figure 9b, had high accuracy, with R2 and RMSE values of 0,903 and 0,01, respectively. Compared with the target temperature, a temperature difference of ±2 °C was recorded when there was an increase in the air temperature outside the greenhouse.

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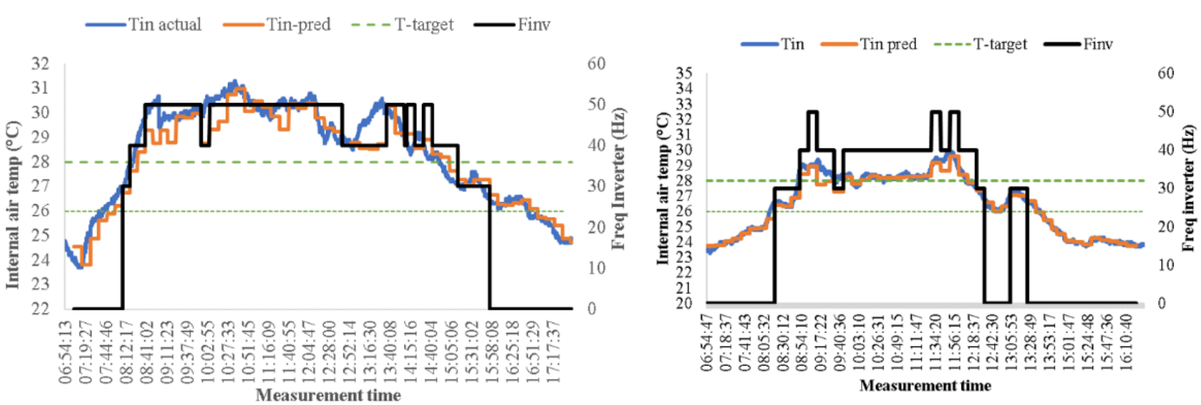
The prediction model for cloudy conditions was validated using measurement data from September 9, 2022, using a control device that operated from 06:00 to 18:00. Figure 10a shows the trend of the predicted air temperature from the prediction model, actual air temperature, outside air temperature, and target temperature, which was integrated into an adaptive control model under overcast conditions. As shown in Figure 10b, the model's Performance has high accuracy with R^2 and RMSE values of 0,92 and 0,01, respectively. Compared to the target, a maximum temperature difference of ±1 °C was recorded when the air temperature increased outside the greenhouse.

Figure 11a shows the performance of the model when optimizing the rotation speed of the fan motor through the inverter to maintain the air temperature inside the greenhouse at the target temperature (T_{ref}). The tolerance target temperature value was used as the target for setting the control variable (F_{inv}). The control was active when the predicted temperature was greater than Tref. In the morning, the fan was active at 08:06 when the predicted air temperature was > T_{ref}. Similarly, in the afternoon, the fan stopped at 16:00 when the air temperature prediction was < T_{ref}. The broken black line in the graph indicates an inactive fan condition because the predicted air temperature was below the target.



(a) (b)

Figure 11. Control air temperature inside the greenhouse: (**a**) sunny conditions using the data set on August 26, 2022; (**b**) cloudy conditions using the data set on September 9, 2022.

Figure 11b shows the performance of the model when the rotation speed of the fan motor is optimized through the inverter. In the morning, the fan was active at 08:30 when the predicted air temperature was > T_{ref}. From 12:45 to 13:15, the control system gave an order stopped because the air temperature prediction fell below T_{ref}. It was then active again for 10 min owing to an increase in the air temperature prediction, but at 13:40, the order to stop was given again until 18:00. The broken black line in the graph indicates an inactive fan condition because the predicted air temperature was below the target.

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The performance of the adaptive model under both cloudy and sunny conditions shows that the inverter frequency is consistently adjusted according to the model's optimization value. In the morning, afternoon, and evening, the inverter converged at frequencies of 0 Hz and 20 Hz, causing the fan to remain off. However, during the day, the inverter frequency increases to 30, 40, and 50 Hz, thereby conditioning the greenhouse to maintain the targeted air temperature. Trials conducted over one planting period of Purwoceng plants successfully maintained the plants until harvest at eight months age of 8 months.

3.6 Use of Electrinical Energy

The overall use of electrical devices in greenhouses places water coolers and fans as the devices that use the most electrical energy (80,60 kWh and 55,96 kWh) compared to other instruments. However, the average electrical-power usage from 06:00 to 18:00 was 189 kWh. The evaporative cooler works continuously, regardless of weather changes outside the greenhouse.

The adaptive model regulates the fan's performance under sunny and cloudy conditions, which means that it can stop when the air temperature inside the greenhouse is below the set target temperature. Figure 12 shows the results of the evaluation of electrical energy use during the two-week application of the adaptive model. The electrical energy consumption during the two-week application of the adaptive model was 152,88 kWh. This value was 19,12 % lower than that under normal conditions. In sunny conditions, using the data set on August 25, 2022, the amount of electrical energy consumed was 153,97 kWh, which was 18,54 % more efficient than under normal conditions. Under cloudy conditions using the dataset on September 9, 2022, electricity consumption reached 124,89 kWh, which was 33,93 % more efficient.

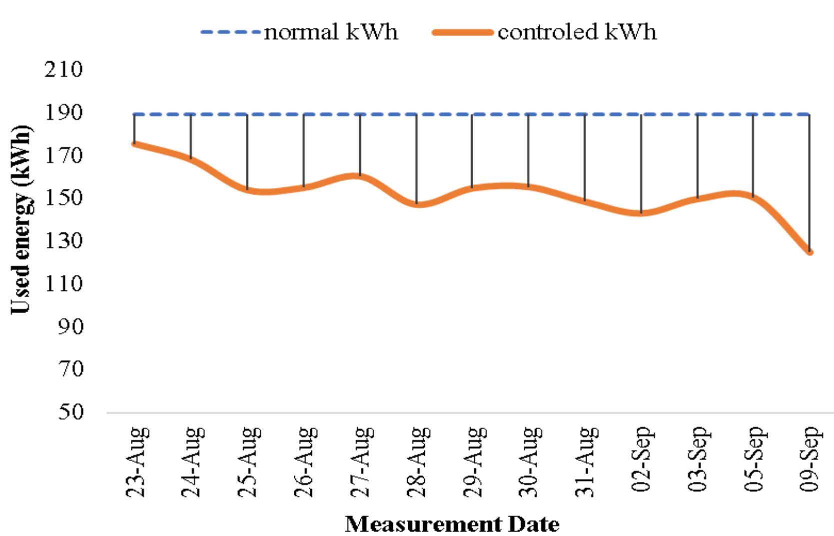

Figure 12. Trends in the use of electrical energy during the two-week application of the adaptive model.

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When applying the adaptive model, the electrical energy usage was high when it was sunny and low when it was cloudy. Optimizing the inverter frequency to maintain the air temperature inside the greenhouse tends to approach the target temperature when the model works in overcast conditions. Therefore, this adaptive model is suitable for tropical regions with ever-changing weather conditions. Bogors are areas with a high rainfall index and rapidly changing weather throughout the year (Adi et al., 2024; Khyber et al., 2021).

4. Conclusion

In this study, we successfully developed an adaptive model to optimize the air temperature and reduce the energy consumption in tropical greenhouses. By integrating a multilayer prediction model, objective function, and genetic algorithm, the study achieved significant advancements in maintaining optimal growing conditions with enhanced energy efficiency. The model demonstrated high accuracy in predicting air temperature and effectively adjusted fan rotation speeds to meet the target temperatures under varying climatic conditions. The practical application of the model resulted in substantial energy savings, particularly in regions with rapidly changing weather patterns.

The innovative approach of using historical climate data for a real-time adaptive model sets this study apart, and offers a scalable and economically viable solution for greenhouse management. The findings underscore the potential of data-driven predictive models to provide more adaptive and energy-efficient climate control, making them especially suitable for tropical areas such as Bogor, Indonesia.

Future research should aim to broaden the applicability of this model by testing it in different greenhouse structures and diverse climatic conditions. Incorporating real-time weather forecasting and exploring alternative cooling technologies and renewable energy sources can further enhance the performance of the model. Additionally, a detailed economic analysis across various greenhouse scales would provide deeper insight into its practical feasibility. This study lays a solid foundation for developing advanced greenhouse climate control systems, paving the way for sustainable and efficient agricultural practices.

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