

DYNAMIC DECOUPLING OF PID CONTROL LOOPS FOR MULTIVARIABLE PROCESSES: A GREENHOUSE MICROCLIMATE CASE STUDY

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ABSTRACT

This paper presents the development and implementation of a multivariable control system for a greenhouse microclimate, using individual monovariate Proportional-Integral-Derivative (PID) controllers coupled with a multivariable dynamic decoupler. The proposed architecture integrates temperature, humidity and soil moisture sensors with actuators managing heating, ventilation and irrigation.

The system is designed to automatically adjust the environmental parameters according to the specific plant that is being cultivated. Because every plant species requires a distinct microclimate for optimal development, the control algorithm dynamically adapts to the target crop by incorporating its recommended optimal temperature, humidity and soil moisture setpoints. The simulation tests demonstrate improved results, compared with classical PID control. The system shows potential for cost-effective automation of small and medium greenhouses, contributing to sustainable agriculture and smart-farming initiatives.

Keywords: multivariable control, greenhouse, PID algorithm, dynamic decoupling, energy efficiency

INTRODUCTION

Greenhouse cultivation has become one of the most important technologies supporting sustainable food production by enabling precise control of environmental conditions throughout the plant-growing cycle. Temperature, relative humidity and soil moisture strongly influence photosynthesis, transpiration, nutrient absorption and crop productivity, making automatic climate control an essential component of modern greenhouse management [2],[3],[15],[18],[20],[23],[24].

Recent developments in smart agriculture integrate wireless sensor networks, Internet of Things (IoT) platforms and distributed monitoring systems to acquire real-time environmental information and improve decision-making capabilities [3],[15],[18-22]. These technologies allow continuous monitoring of greenhouse conditions while reducing labor requirements and improving resource efficiency.

Among automatic control methods, PID controllers remain the most widely implemented because of their robustness, simplicity and low computational requirements [1],[10],[13]. However, conventional PID controllers are primarily designed for single-input single-output

systems and their performance deteriorates when strong interactions exist between the multiple controlled variables.

The greenhouse microclimate represents a nonlinear multi-input multi-output (MIMO) process where temperature, humidity and soil moisture continuously influence each other. For example, increasing ventilation decreases both temperature and humidity, while increasing heating rate modifies greenhouse temperature but also, indirectly, the soil moisture and the air humidity [7], [12],[24].

Several advanced multivariable control strategies have been proposed to overcome these limitations. Model Predictive Control (MPC) has demonstrated excellent performance in handling process constraints and multivariable interactions, while optimizing energy consumption [8],[25]. Feedback linearization techniques have also been successfully combined with predictive control to compensate nonlinear dynamics [6]. More recently, Artificial Intelligence techniques, including reinforcement learning, adaptive algorithms and fuzzy control have shown promising results for greenhouse climate optimization [9],[11],[14],[16], [17],[21],[22].

Despite their superior control performance, many advanced approaches require accurate mathematical models, extensive training datasets or considerable computational resources, making their implementation difficult for small and medium greenhouse installations [5],[9],[13],[17].

Therefore, the objective of this paper is to develop a low-cost multivariable greenhouse control architecture that preserves the simplicity of conventional PID controllers while significantly reducing loop interactions through dynamic decoupling. In addition, the proposed system incorporates a plant database containing optimal environmental conditions, allowing automatic selection of temperature, humidity and soil moisture setpoints according to the cultivated crop. Unlike AI-based or MPC-based approaches, the proposed solution does not require detailed nonlinear modelling or extensive computational resources, making it suitable for practical greenhouse automation.

Although the proposed methodology is demonstrated using a greenhouse microclimate control system, the underlying dynamic decoupling approach can be applied to a large class of multivariable processes characterized by strong interactions among control loops. In particular, the proposed methodology may be relevant to industrial MIMO control applications encountered in the oil and gas sector, where effective decoupling of interacting process variables is essential for achieving stable and high-performance operation.

PROPOSED SYSTEM ARCHITECTURE

Based on the literature review presented above, the proposed control structure was designed to combine the benefits of the advanced control methods, while maintaining the simplicity of the classical methods.

Table 1 summarizes the main criteria that define the different control methods that have been implemented to control the parameters associated with a greenhouse, as well as the criteria that will define the proposed control structure.

Table 1. Main features for the different control methods used to control the greenhouse parameters.

Method	Complexity	Requires model	AI training	Efficiency	Cost
PID	Low	No	No	Low	Low
MPC	High	Yes	No	High	High
Reinforcement Learning	Very High	No	Yes	High	High
Fuzzy	Medium	Rules	No	Medium	Medium
Proposed	Low	Approximate	No	High	Low

As can be seen from Table 1, the proposed control structure will provide the advantages of having high efficiency, low complexity and low implementation cost.

The proposed control system (Figure 1) contains three main layers:

- **Basic layer:** consists of temperature, humidity and soil moisture sensors, to measure the process variables, and heater, fans, sprinkler and water pump to control the greenhouse process variables.
- **Multivariable control layer:** consists of the classical PID controllers, for the low-level control and the multivariable dynamic decoupler.
- **Decision-making layer:** establishes the setpoints for each control loop and the order of changes depending on the priority of the parameter to be adjusted, considering the type of plant being grown.

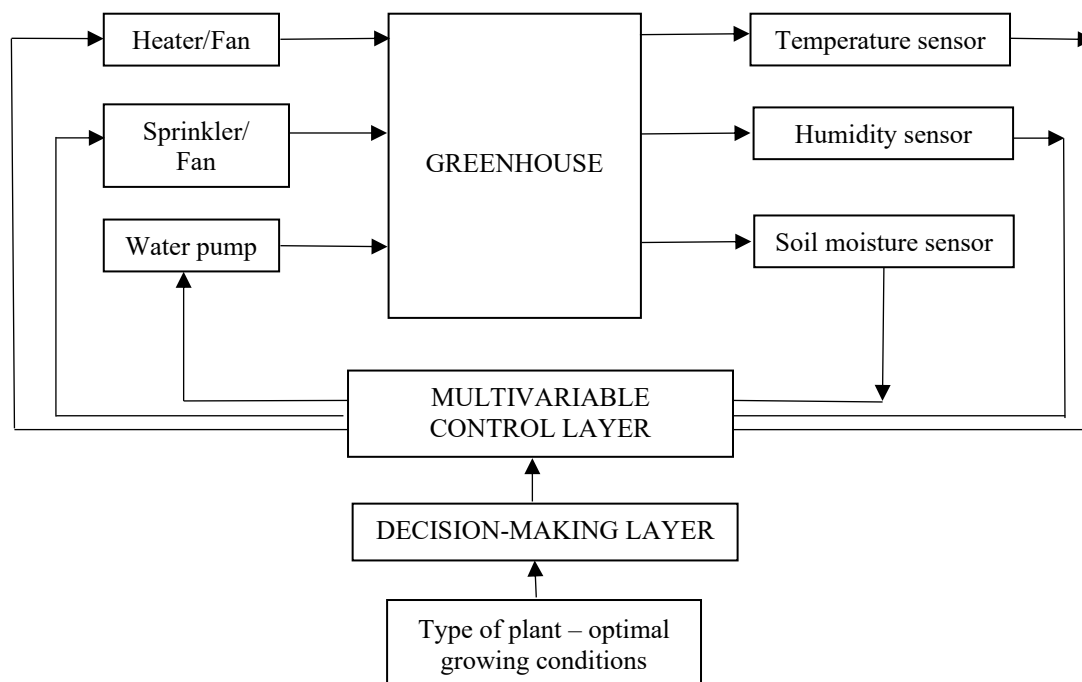


Figure 1. The proposed system architecture.

Figure 2 shows the block diagram of the proposed greenhouse control system. The greenhouse control system is programmed to not allow the Fan1 and Sprinkler to run simultaneously. If humidity is a priority for plants, the Sprinkler will run, if the temperature becomes critically high, the Sprinkler stops and the Fan1 starts for quick ventilation, even if this will temporarily lower the humidity.

The optimal growing conditions for plants involve balancing temperature, humidity and soil moisture to facilitate photosynthesis and growth. General optimal ranges include temperatures between 15–30°C, relative humidity between 50–90% and soil moisture content ranging from 50% to 90%, depending on plant species. Each crop species is represented by a record containing the optimal temperature, humidity and soil moisture ranges. When the user selects the cultivated crop, the corresponding setpoints are automatically loaded into the decision layer.

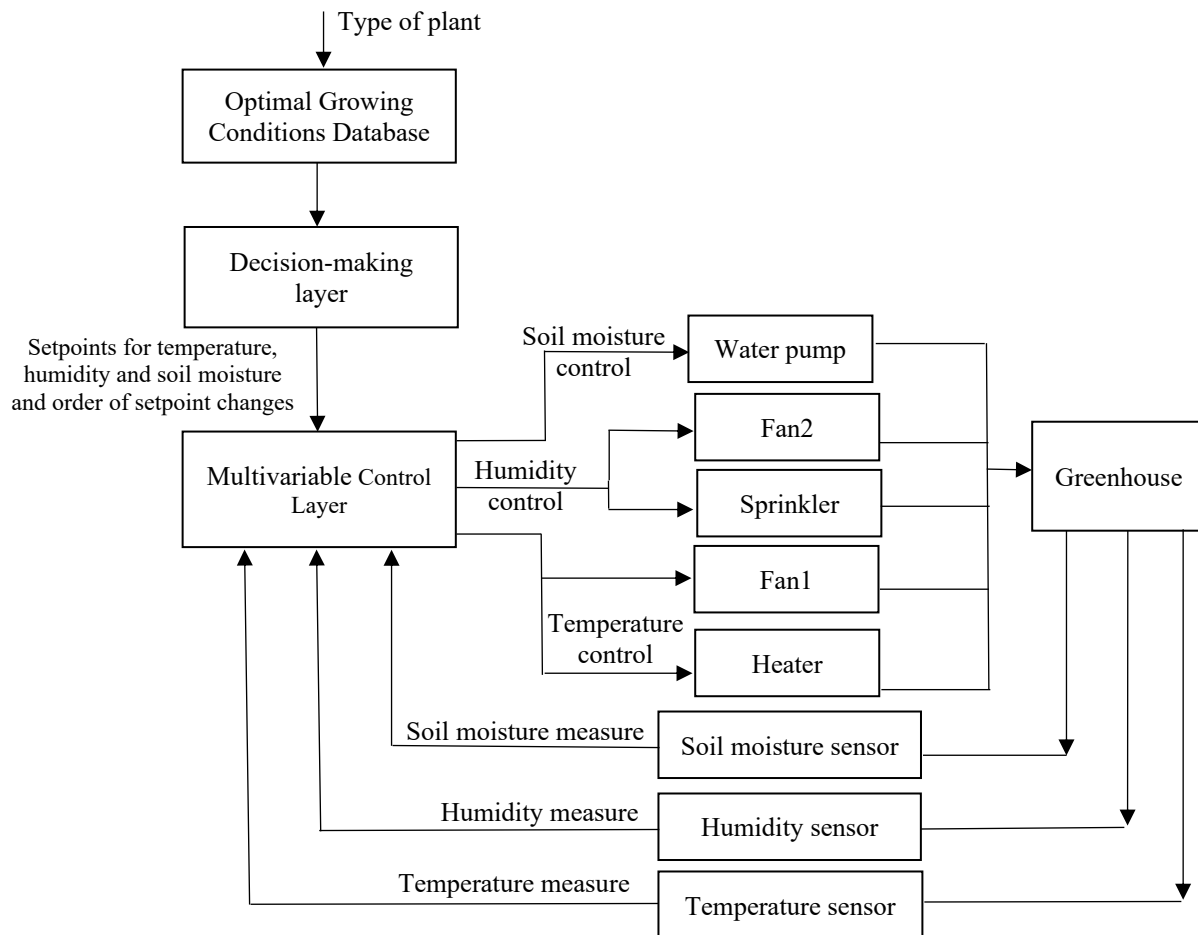


Figure 2. Block diagram of the proposed greenhouse control system.

Table 2 summarizes the optimal growth requirements (that were used in this application) for tomatoes, cucumbers, lettuce, peppers, green onions, strawberries and blueberries [26]. The values are general targets for the growing season and may vary slightly depending on the specific growth stage.

Table 2. Optimal growth requirements for different types of plants.

Types of plants	Optimal Temperature (°C)	Optimal Humidity (%)	Optimal Soil Moisture
Tomato	21–29°C (Day) 15–21°C (Night)	65–75%	70–80%
Cucumber	20–28°C	70–80%	80–85%
Lettuce	15–18°C	50–70%	70–80%
Pepper	21–29°C	60–70%	70–80%
Green onions	15–30°C	90–98%	70–80%
Strawberries	18–25°C (Day) 12–18°C (Night)	65–75%	50–80%
Blueberries	18–25°C	50–70%	50–80%

THE MULTIVARIABLE CONTROL ALGORITHM

In order to better understand the process behavior, a number of simulations were performed, that consisted of step changes of the manipulated variables (heater, fan1, sprinkler, fan2, water pump outputs) and recording the values of the process outputs (temperature, humidity and soil moisture), over time. Some of the simulation results are presented below, in Figures 3-10.

Figures 3-6 show the process response (temperature, humidity, soil moisture variation) to control variable (fan, heater, sprinkler and water pump) step change.

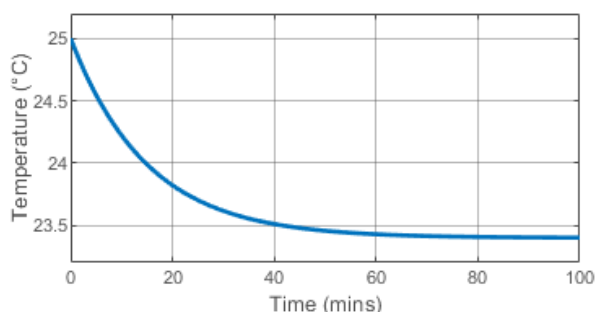


Figure 3. Greenhouse temperature variation at a 10% variation of the fan actuator.

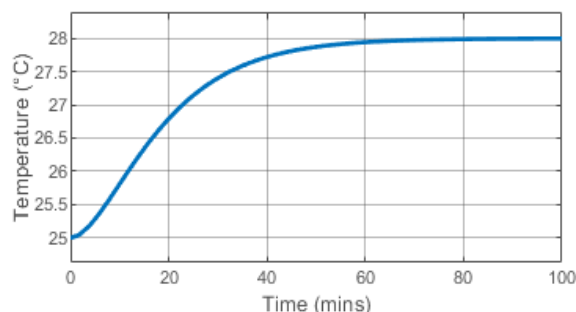


Figure 4. Greenhouse temperature variation at a 10% variation of the heater actuator.

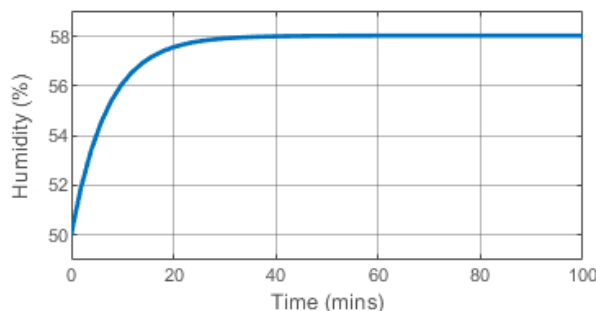


Figure 5. Greenhouse humidity variation at a 10% variation of the sprinkler actuator.

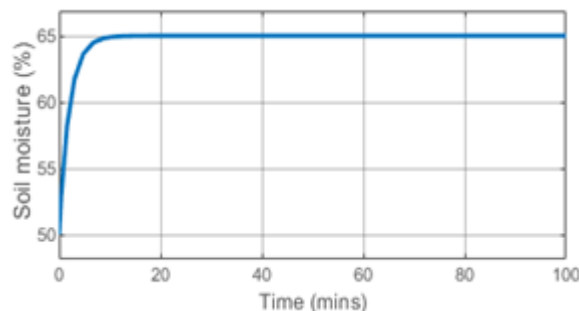


Figure 6. Greenhouse soil moisture variation at a 10% variation of the water pump actuator.

The greenhouse dynamics showed different interactions between loops. For example, turning on Fan1 (in order to lower the temperature) will often lower also the Humidity; turning on the Sprinkler (to raise humidity) will lower the Temperature. Also, increasing the soil moisture and the temperature setpoints will lead to a higher evaporation from the soil surface, which naturally raises the ambient Humidity. Figures 7-10 show different types of unwanted process cross-interactions.

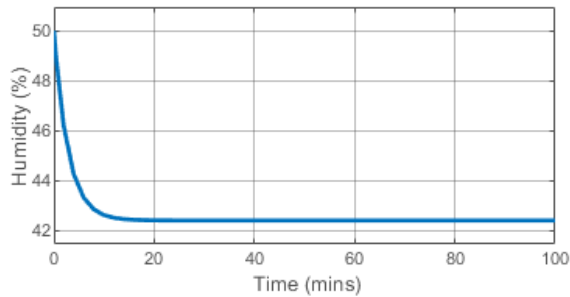


Figure 7. Greenhouse humidity variation at a 10% variation of the fan actuator.

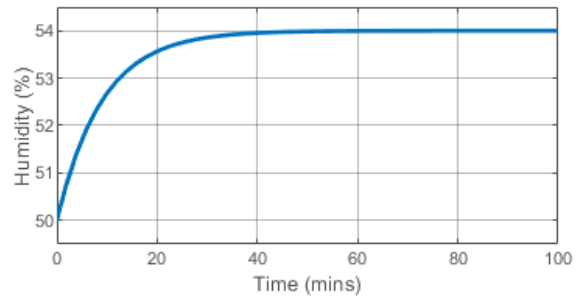


Figure 8. Greenhouse humidity variation at a 10% variation of the heater actuator.

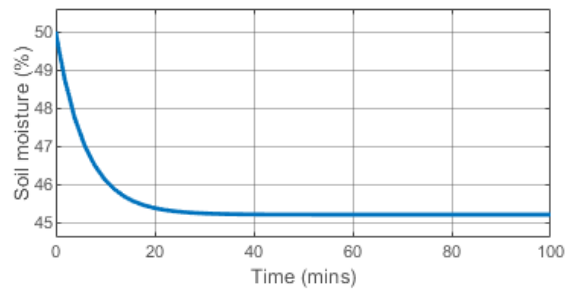


Figure 9. Greenhouse soil moisture variation at a 10% variation of the heater actuator.

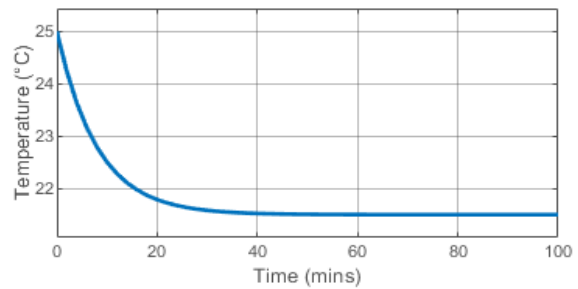


Figure 10. Greenhouse temperature variation at a 10% variation of the sprinkler actuator.

Following the performed simulations, the below multivariable process block diagram (Figure 11) can be highlighted, in which appear the direct-interaction channels (drawn with a solid black line) and the unwanted, dominant cross-interaction channels (drawn with a red dotted line).

Using the process step responses, models of process were determined for direct (G_P) and cross-interaction (G_{CI}) process channels. These models are represented as first-order (for each G_P or G_{CI} , excepting G_{P1}) or second order (for G_{P1}) transfer functions [4]:

$$G_{Pi} = \frac{K_{Pi}}{T_{Pi}s + 1}, i = 2,3,4,5 \quad (1)$$

$$G_{P1} = \frac{K_{P1}}{(T_{P1}s + 1)^2} \quad (2)$$

$$G_{Cii} = \frac{K_{Cii}}{T_{Cii}s + 1}, i = 1,2,3,4,5,6 \quad (3)$$

where K_{Pi} are the process amplifications on direct-interaction channels (Fan1-Temperature, Sprinkler-Humidity, Fan2-Humidity, Water Pump-Soil Moisture), T_{Pi} are the process time constants on direct-interaction channels (Fan1-Temperature, Sprinkler-Humidity, Fan2-Humidity, Water Pump-Soil Moisture), K_{PI} is the process amplification on Heater-Temperature direct-interaction channel, T_{PI} is the process time constant on Heater-Temperature direct-interaction channel, K_{Cii} are the process amplifications on dominant cross-interaction channels (Heater-Humidity, Fan1-Humidity, Water Pump-Humidity, Sprinkler-Temperature, Fan2-Temperature, Heater-Soil Moisture) and T_{Cii} are the process time constants on dominant cross-interaction channels (Heater-Humidity, Fan1-Humidity, Water Pump-Humidity, Sprinkler-Temperature, Fan2-Temperature, Heater-Soil Moisture).

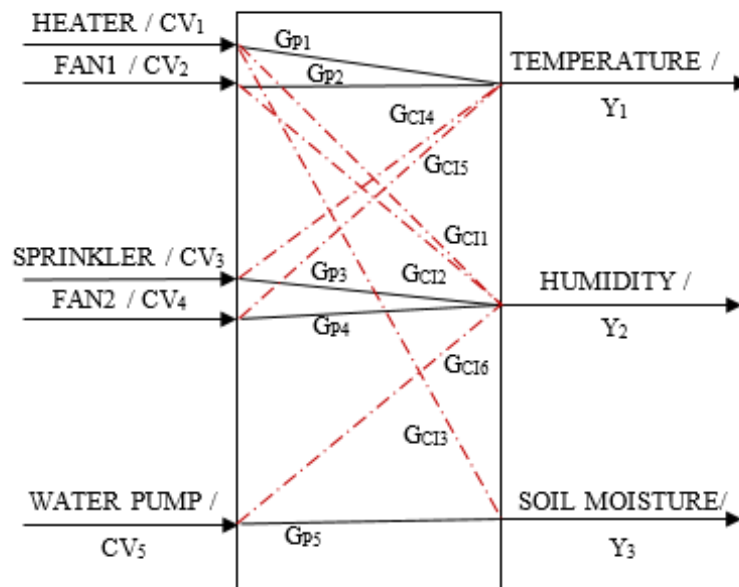


Figure 11. The multivariable process block diagram:
 CV_i – Control Variable; G_{Pi} – Process (direct-interaction) transfer function; Y_i – Process (direct-interaction + cross-interaction) output; G_{Cii} – Cross-Interaction transfer functions.

The greenhouse microclimate is maintained using the PID (Proportional-Integral-Derivative) algorithm, one for each control loop (temperature, humidity and soil moisture).

The PID algorithm has the general equation [4]:

$$c(t) = K_R \left(e(t) + K_I \int_0^t e(\tau) d\tau + K_D \frac{de}{dt} \right), \quad (4)$$

where $e(t)$ is the error between the desired and the measured value of the controlled variable (temperature, humidity or soil moisture) and K_P , K_I and K_D are the PID tuning parameters.

The tuning parameters were determined for each control loop based on greenhouse dynamics to the step change in the control variable, using the following tuning formulas [4]:

$$K_R = \frac{1}{K_P \left(1 + \frac{5\tau}{T_{tr}}\right)} \quad (5)$$

$$K_I = \frac{3}{T_{tr}} \quad (6)$$

$$K_D = 0 \quad (7)$$

where K_P is the process amplification, T_{tr} is the transient time and τ is the process time delay. The values of each PID controller are summarized in Table 3.

Table 3. The tuning parameter values.

	Heater-Temperature control loop	Fan1-Temperature control loop	Sprinkler-Humidity control loop	Fan2-Humidity control loop	Water pump-Soil moisture control loop
K_P	2.90	0.78	0.75	0.80	0.60
K_I	0.07	0.06	0.14	0.10	0.50
K_D	0	0	0	0	0

The derivative action was omitted to avoid derivative amplification of sensors noise that can affect the closed-loop stability. To compensate the unwanted cross-interactions (drawn with a red dotted line in Figure 11), the following general control system structure, with dynamic decoupling, was considered (Figure 12).

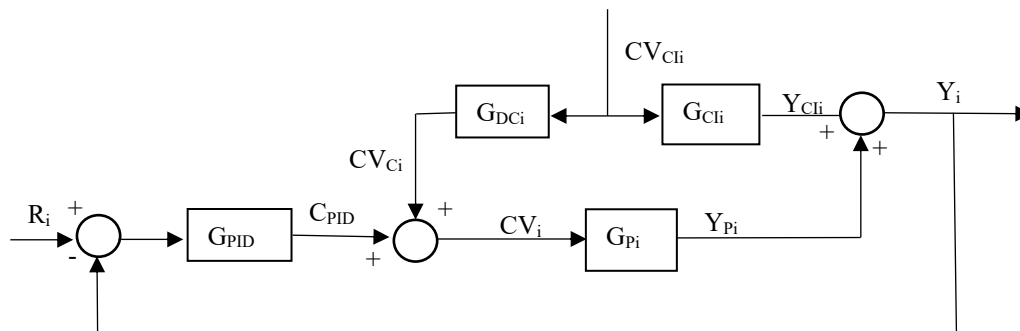


Figure 12. Control system structure with dynamic decoupling: R_i – setpoint, G_{PID} – PID controller transfer function, C_{PID} – PID Control Variable, CV_{Ci} – Compensators Control Variable, CV_i – Control Variable, G_{Pi} – Process (direct-interaction) transfer function, Y_{Pi} – Process (direct-interaction) output, Y_{Cli} – process Cross-Interaction output, Y_i – Process (direct-interaction + cross-interaction) output, G_{Cli} – Cross-Interaction transfer functions, CV_{Cli} – Control Variable for Cross-Interaction channel, G_{DCi} – Dynamic decoupler transfer functions.

This general control system structure, with dynamic decoupling, was particularized for each of the monovariable control loops. Only the dominant interaction channels were considered for dynamic decoupling. The dominant interaction channels were identified using the relative magnitude of the steady-state gains. This selection was intended to retain the dominant coupling

effects while limiting the complexity of the decoupling structure. If the control loop controls the Temperature, the considered control variables from the cross-interaction channels (whose effects must be compensated) are the Sprinkler output, the Fan2 output and the Water Pump output; if the controlled variable is the Humidity, the considered control variables from the cross-interaction channels (whose effects must be compensated) are the Heater output and the Fan1 output; if the controlled variable is the Soil Moisture, the considered control variable from the cross-interaction channel (whose effect must be compensated) is the Heater output.

Assuming that all the elements of the control system are linear, the operational relationship that expresses the dynamic dependence of the process output on the inputs, has the form:

$$Y_i(s) = Y_{Pi}(s) + Y_{Cii}(s) \quad (8)$$

$$Y_i(s) = G_{Pi}(s)CV_i(s) + G_{Cii}(s)CV_{Cii}(s) \quad (9)$$

$$Y_i(s) = G_{Pi}(s)[G_{PID}(s)(R_i(s) - Y_i(s)) + G_{DCi}(s)CV_{Cii}(s)] + G_{Cii}(s)CV_{Cii}(s) \quad (10)$$

$$Y_i(s) = \frac{G_{Pi}(s)G_{PID}(s)}{1 + G_{Pi}(s)G_{PID}(s)}R_i(s) + \frac{G_{Pi}(s)G_{DCi}(s) + G_{Cii}(s)}{1 + G_{Pi}(s)G_{PID}(s)}CV_{Cii}(s) \quad (11)$$

The perfect control conditions:

$$\frac{G_{Pi}(s)G_{PID}(s)}{1 + G_{Pi}(s)G_{PID}(s)} = 1, \frac{G_{Pi}(s)G_{DCi}(s) + G_{Cii}(s)}{1 + G_{Pi}(s)G_{PID}(s)} = 0, \quad (12)$$

are fulfilled when the dynamic decoupler has ideal transfer function [4]:

$$G_{DCi}(s) = -\frac{G_{Cii}(s)}{G_{Pi}(s)}, \quad (13)$$

where G_{Cii} is the transfer function of the cross-interaction channel i and G_{Pi} is the process transfer function for the direct-interaction channel i . These transfer functions were determined in the previous step.

RESULTS AND DISCUSSIONS

The tests consisted of modifying the control loop setpoints, both in the case of using simple PID loops and in the case of using dynamic decoupling. Figures 13-19 show some of the system response when using PID controllers, without dynamic decoupling.

Figure 13 shows the temperature response to a setpoint increase from 25°C to 30°C. The temperature controller successfully controls the temperature toward the new reference value, demonstrating the basic capability of the PID controller. However, the response is obtained without compensation of the interactions with the humidity and soil moisture control loops.

Figure 14 illustrates the effect of the temperature setpoint change on the greenhouse humidity. Although the manipulated variable is associated with temperature control, the change in temperature produces a variation in humidity due to the inherent coupling between the greenhouse environmental variables. This response confirms the presence of a cross-interaction channel from the temperature control loop to the humidity variable.

Figure 15 presents the soil moisture response resulting from the temperature setpoint increase. The variation in soil moisture, despite the fact that its setpoint remains unchanged, indicates the indirect influence of temperature control on the soil moisture dynamics. This cross-interaction is associated with increased evaporation and moisture transfer caused by changes in the greenhouse thermal conditions. Figure 16 shows the humidity response to a setpoint increase from 50% to 60%. The PID controller successfully tracks the new humidity reference, confirming the effectiveness of the individual control loop under nominal conditions.

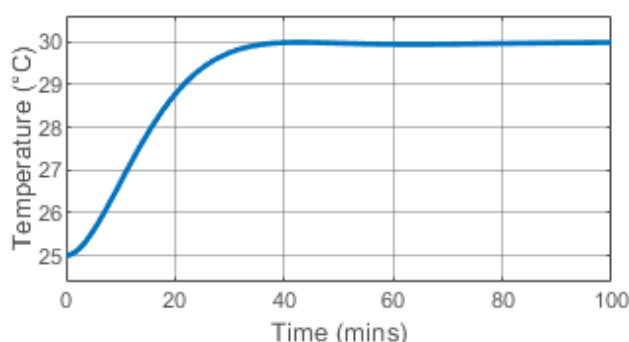


Figure 13. Greenhouse temperature variation at a setpoint variation from 25°C to 30°C of the temperature controller.

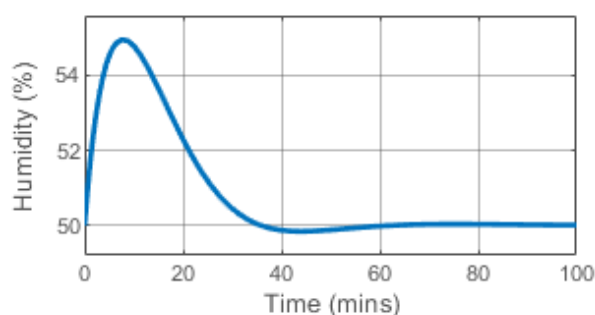


Figure 14. Greenhouse humidity variation at a setpoint variation from 25°C to 30°C of the temperature controller, having the humidity setpoint at 50%.

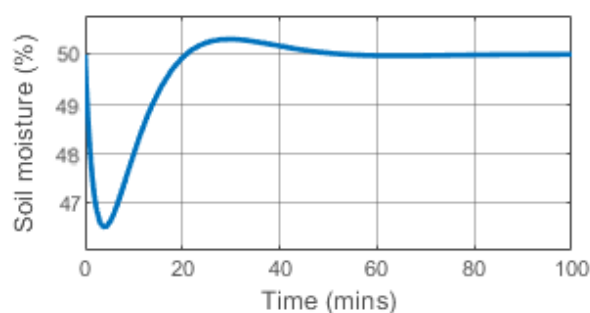


Figure 15. Greenhouse soil moisture variation at a setpoint variation from 25°C to 30°C of the temperature controller, having the soil moisture setpoint at 50%.

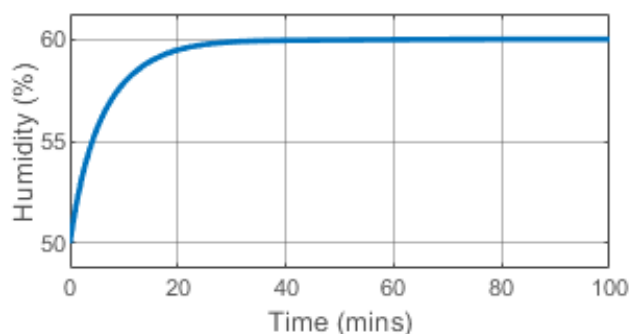


Figure 16. Greenhouse humidity variation at a setpoint variation from 50% to 60% of the humidity controller.

Figure 17 shows the temperature variation as a consequence of the humidity setpoint change from 50% to 60%. Although the temperature setpoint remains unchanged, a temperature deviation occurs. This result confirms the existence of a cross-interaction channel from the humidity control loop to the temperature variable.

Figure 18 presents the soil moisture response associated with the humidity setpoint variation. The deviation of soil moisture from its initial operating condition, despite the absence of a direct soil moisture setpoint change, demonstrates the interaction between humidity control and soil moisture dynamics. This behavior further illustrates the multivariable nature of the greenhouse process and the limitations of independently tuned PID controllers.

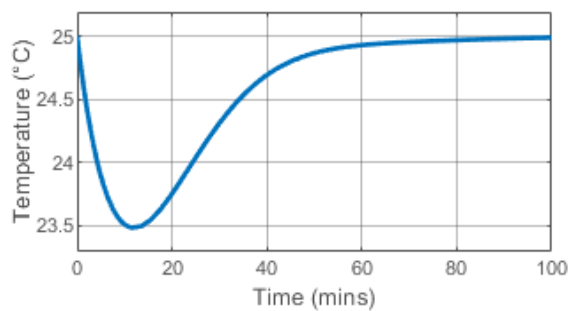


Figure 17. Greenhouse temperature variation at a humidity setpoint variation from 50% to 60% of the humidity controller, having the temperature setpoint at 25°C.

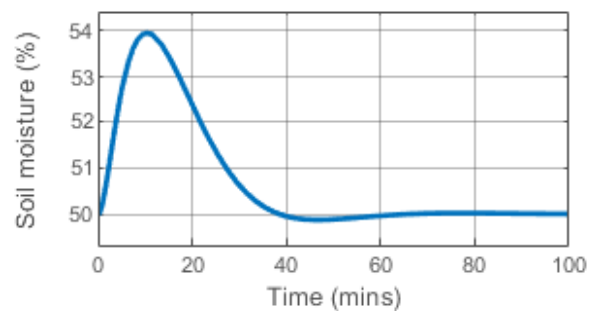


Figure 18. Greenhouse soil moisture variation at a setpoint variation from 50% to 60% of the humidity controller, having the soil moisture setpoint at 50%.

Figure 19 shows the response of the soil moisture control loop to a setpoint increase from 50% to 60%. The controlled variable follows the new reference, demonstrating the tracking capability of the PID controller. In the absence of dynamic decoupling, however, changes in soil moisture may also influence the other greenhouse variables through evaporation and moisture exchange, contributing to the overall coupling among the control loops.

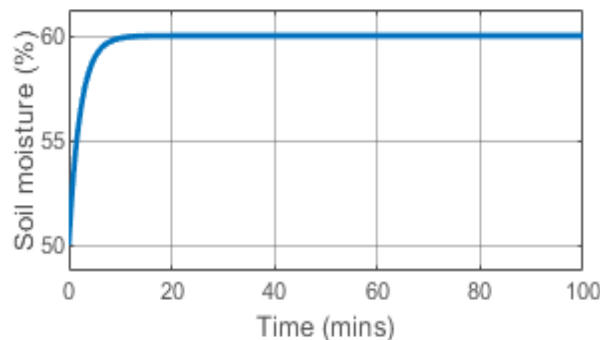


Figure 19. Greenhouse soil moisture variation at a setpoint variation from 50% to 60% of the soil moisture controller.

Overall, Figures 13–19 demonstrate that conventional independent PID controllers provide a good setpoint tracking for the individual controlled variables, but the unwanted cross-interactions remain between the temperature, humidity and soil moisture loops. A change in

one setpoint can therefore induce deviations in the other controlled variables, even when their respective reference values remain unchanged. These results provide the motivation for evaluating the effectiveness of the proposed dynamic decoupling strategy presented in the following simulations. Figures 20-31 show the system response when using PID controllers with dynamic decoupling.

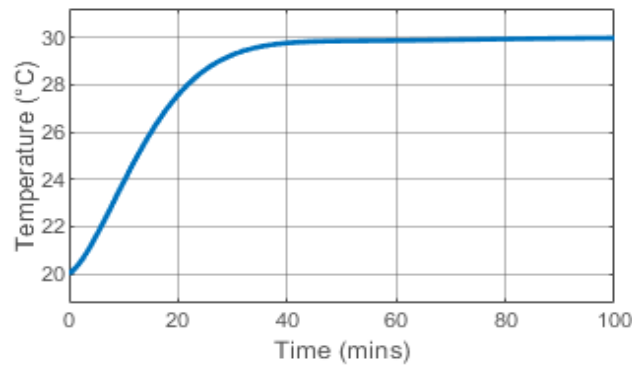


Figure 20. Greenhouse temperature variation at a setpoint variation from 20°C to 30°C of the temperature controller, using dynamic decoupling.

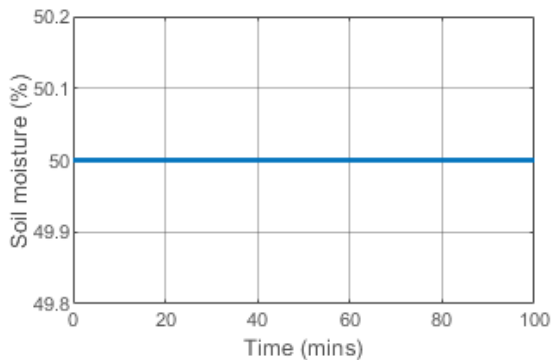


Figure 21. Greenhouse soil moisture variation at a setpoint variation from 20°C to 30°C of the temperature controller, using dynamic decoupling.

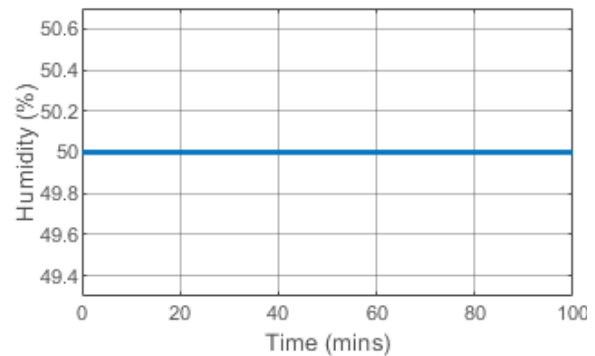


Figure 22. Greenhouse humidity variation at a setpoint variation from 20°C to 30°C of the temperature controller, using dynamic decoupling.

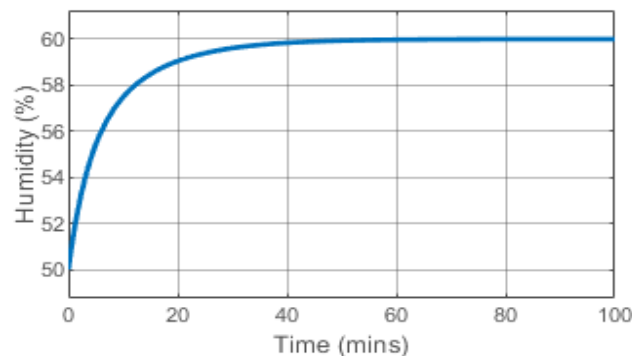


Figure 23. Greenhouse humidity variation at a setpoint variation from 50% to 60% of the humidity controller, using dynamic decoupling.

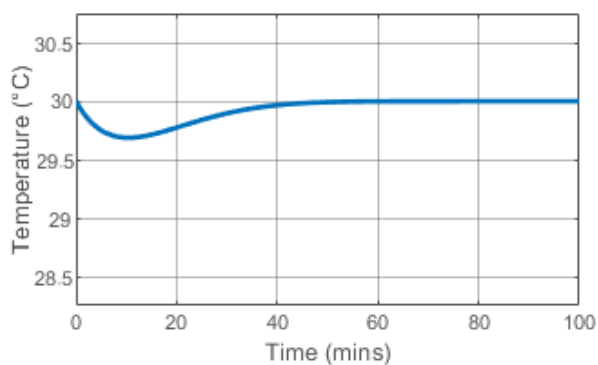


Figure 24. Greenhouse temperature variation at a setpoint variation from 50% to 60% of the humidity controller, using dynamic decoupling.

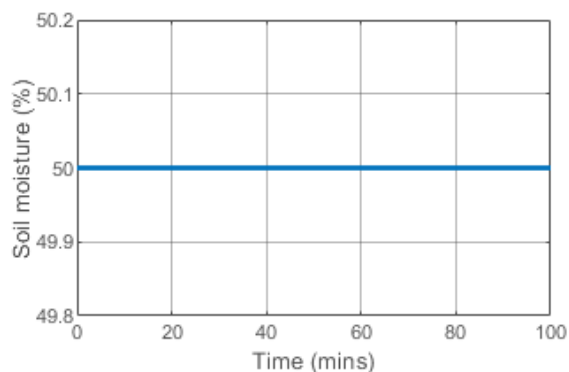


Figure 25. Greenhouse soil moisture variation at a setpoint variation from 50% to 60% of the humidity controller, using dynamic decoupling.

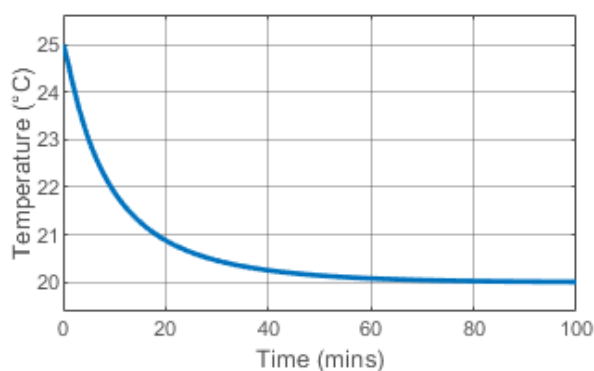


Figure 26. Greenhouse temperature variation at a setpoint variation from 25°C to 20°C of the temperature controller, using dynamic decoupling.

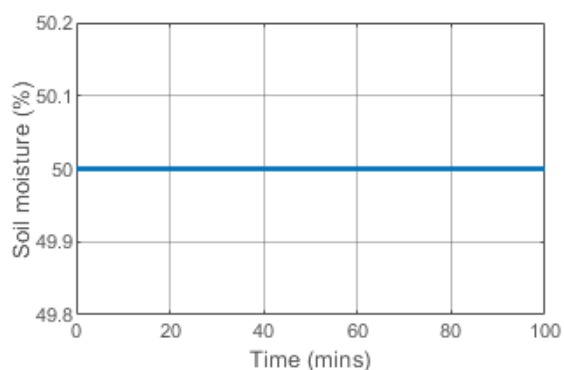


Figure 27. Greenhouse soil moisture variation at a setpoint variation from 25°C to 20°C of the temperature controller, using dynamic decoupling.

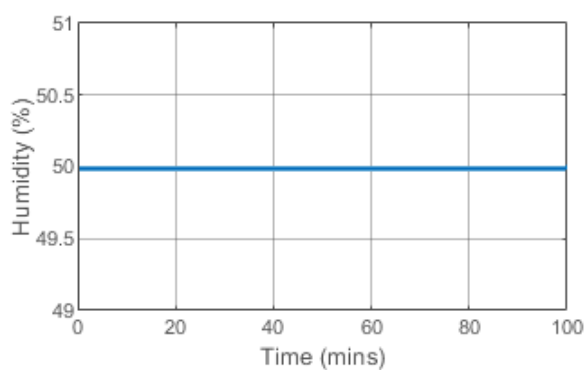


Figure 28. Greenhouse humidity variation at a setpoint variation from 25°C to 20°C of the temperature controller, using dynamic decoupling.

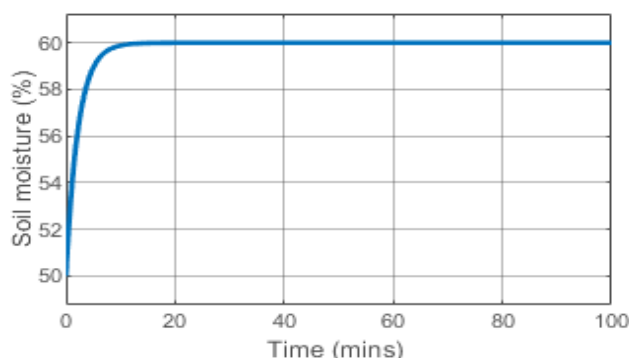


Figure 29. Greenhouse soil moisture variation at a setpoint variation from 50% to 60% of the soil moisture controller, using dynamic decoupling.

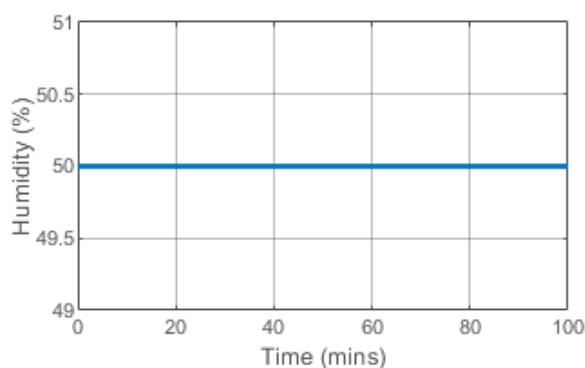


Figure 30. Greenhouse humidity variation at a setpoint variation from 50% to 60% of the soil moisture controller, using dynamic decoupling.

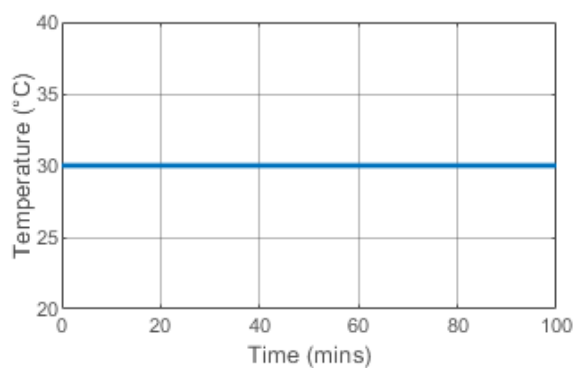


Figure 31. Greenhouse temperature variation at a setpoint variation from 50% to 60% of the soil moisture controller, using dynamic decoupling.

The simulation results demonstrate that the proposed multivariable decoupling strategy substantially reduces the interaction effects between greenhouse climate variables. Compared with conventional PID control, the disturbances generated by actuator interactions are compensated before propagating through the remaining control loops.

Figures 20–31 clearly illustrate the attenuation of cross-coupling effects after introducing the dynamic decouplers. As can be seen from the above figures, only the humidity control produces a minor temperature deviation compared with the uncompensated case.

Another important advantage of the proposed architecture is its modularity. Since each loop preserves a conventional PID controller, existing greenhouse installations may be upgraded simply by adding the dynamic decoupler without replacing the entire control infrastructure.

The integration of the crop database further increases system flexibility, allowing automatic adaptation of the desired environmental conditions to different plant species without modifying the underlying control algorithm.

Figure 32 shows the graphical user interface of the MATLAB application developed for greenhouse control. The interface allows the user to select the crop species to be cultivated.

Based on the selected crop, the application automatically loads the corresponding optimal temperature, humidity and soil moisture setpoints from the embedded crop database.

The decision-making algorithm then establishes the sequence and timing of the setpoint updates, ensuring coordinated transitions between operating conditions while minimizing interactions between the control loops and preventing undesirable system behavior.

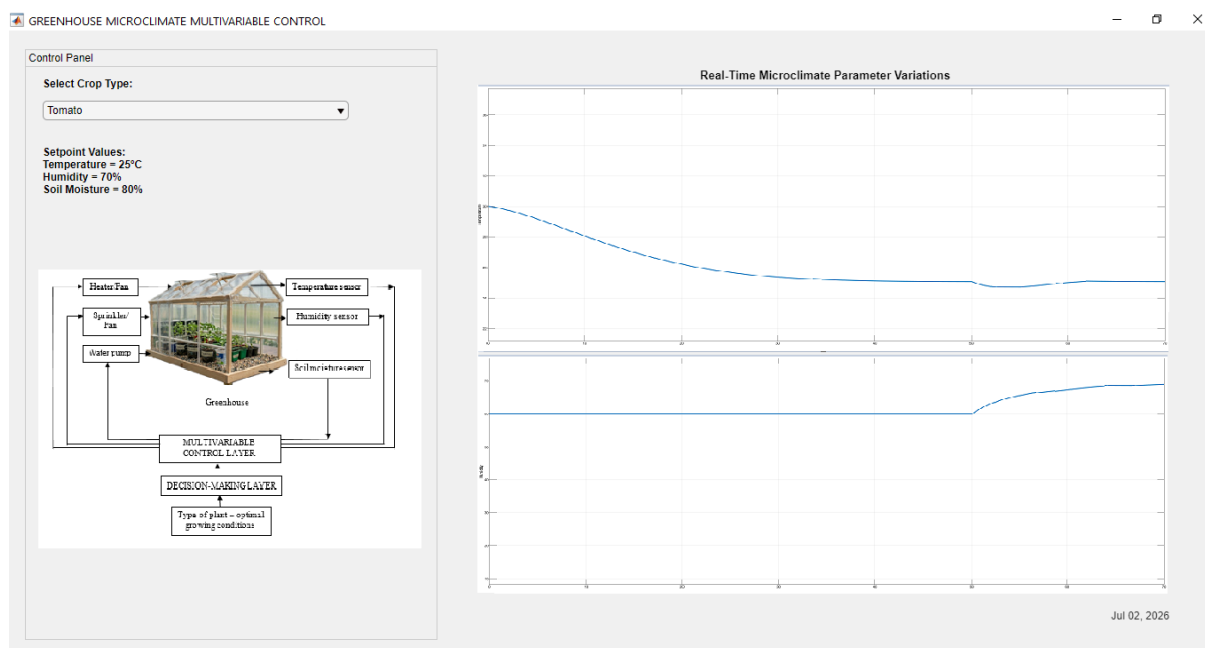


Figure 32. Application interface.

Overall, the proposed solution combines the simplicity of classical PID control with the dynamic decoupling system that compensates the dominant cross-coupling effects between the control loops, offering an attractive compromise between implementation complexity and control performance.

A limitation of the present study is that the proposed greenhouse control system has been evaluated exclusively in a simulation environment, without a physical implementation of the hardware components.

Nevertheless, the simulation-based framework provides a valuable preliminary validation of the proposed control strategy, enabling the analysis of system performance and the interaction between the controlled environmental parameters before its implementation on a physical prototype.

Experimental validation on a fully implemented greenhouse prototype represents a natural direction for a future research.

Synthesizing, the advantages of the proposed control strategy are:

- reduced interaction between temperature, humidity and soil moisture loops;
- faster stabilization after setpoint changes;
- lower steady-state error;

- improved environmental stability;
- less wear on actuators due to smoother control actions;
- improved energy efficiency;
- low implementation cost;
- compatibility with existing PID-based greenhouse controllers.

CONCLUSIONS

This paper presented a multivariable greenhouse microclimate control system based on conventional PID controllers improved with dynamic decouplers designed to reduce the interactions among temperature, humidity and soil moisture control loops. Unlike advanced predictive or artificial intelligence-based controllers, the proposed approach preserves the simplicity of classical PID control, while significantly improving multivariable performance.

Simulation investigations demonstrated that dynamic decoupling effectively attenuates the cross-interaction effects between environmental variables.

In addition to reducing the cross-interactions, the simulations indicated settling times of approximately 40 minutes for the temperature and humidity control loops and 10 minutes for the soil moisture control loop, as well as zero steady-state error, confirming the effectiveness of the proposed control strategy.

An additional contribution of the proposed architecture is the integration of a decision-making layer containing optimal growing conditions for multiple crop species. This enables automatic adaptation of greenhouse operating conditions without modifying the underlying control structure, increasing flexibility for practical agricultural applications.

Another contribution of this study is that it provides a systematic basis for subsequent hardware implementation and experimental validation.

Compared with model predictive control or artificial intelligence approaches, the proposed solution does not require complex mathematical models or extensive computational resources, making it particularly attractive for small and medium greenhouses, where implementation cost and reliability remain critical factors.

Future research will focus on extending the multivariable controller to additional environmental variables such as CO₂ concentration and light intensity, integrating energy optimization strategies and validating the proposed architecture under varying outdoor weather conditions and long-term cultivation cycles.

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