Carbon Neutral Greenhouse: Economic Model Predictive Control Framework for Education

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***Abstract*—This paper presents a comprehensive framework aimed at enhancing education in modeling, optimal control, and nonlinear Model Predictive Control (MPC) through a practical greenhouse climate control model. The framework includes a detailed mathematical model of lettuce growth and greenhouse, which are influenced by real-time external weather conditions obtained via an application programming interface (API). Using this data, the MPC-based approach dynamically adjusts greenhouse conditions, optimizing plant growth, energy consumption, and minimizing the social cost of CO_2. Simulations demonstrate the effectiveness of this approach in balancing energy use with crop yield and reducing CO_2 emissions, contributing to economic efficiency and environmental sustainability.**

The primary contribution of this study is its educational value, providing students with a hands-on platform to understand the complexities of MPC and the trade-offs between profitability and sustainability in agricultural systems. By leveraging real-world data and dynamic simulations, this model allows students to explore and apply control theories in a practical context, fostering deeper learning and problem-solving skills. This makes the framework a valuable tool not only for optimizing lettuce production but also for enriching control systems education. The educational platform for this framework can be accessed at ecompc4greenhouse.streamlit.app.

***Index Terms*—Model Predictive Control, Lettuce Growth Optimization, Greenhouse Energy Management, Precision Agriculture, Economic Yield Optimization**

I. Introduction

In the rapidly evolving field of engineering, there is an increasing demand for graduates who possess not only theoretical knowledge but also practical skills applicable in real-world scenarios. Technical university education requires a solid foundation in theory coupled with opportunities for practical learning, often gained through participation in projects, solving real-world problems, and conducting experiments. The benefits of using interactive tools in control theory instruction have been highlighted in previous works, such as those by [1] and [2]. Importantly, practical learning does not always rely on physical experiments with costy equipment in labs; simulations and interactive tasks can serve as effective alternatives, offering new learning opportunities.

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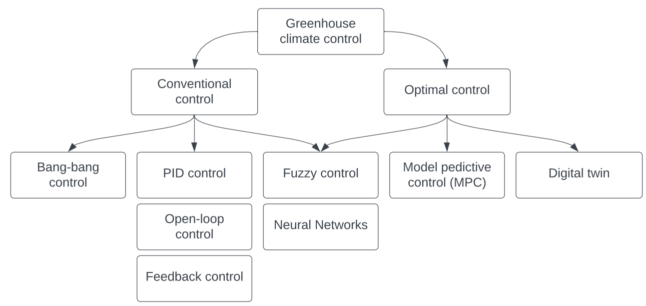

Fig. 1. A simplified diagram representing greenhouse control algorithms. Image adapted from [7].

Current farming practices are labor-intensive, seasonal, constrained by irrigation, and rely on subsidized inputs, leading to environmental issues such as eutrophication, deforestation and soil degradation. With nearly 70% of global water resources consumed by agriculture [3], greenhouses offer a solution by providing controlled environments that enhance productivity beyond what open-field cultivation can achieve. However, these systems face challenges, such as fluctuating internal temperatures that can harm crops. Effective climate management, through controlled ventilation and heating, is essential for maintaining optimal conditions and improving yields [4].

Solar radiation is vital for plant growth and energy generation in greenhouses. Key metrics include Global Horizontal Irradiance (GHI) and Photosynthetically Active Radiation (PAR), the latter directly influencing photosynthesis. Recent research has advanced models for accurate PAR prediction [5], [6], while various control methods, such as adaptive control, nonlinear feedback control, fuzzy control, robust control, and optimal control, have been explored to enhance greenhouse environments and resource use efficiency.

Adaptive control adjusts parameters based on real-time feedback [8], while nonlinear feedback control addresses system complexities with advanced algorithms [9]. Fuzzy control manages imprecise data and uncertainties [10], and robust control ensures stability despite disturbances [11]. Optimum control fine-tunes actions for better outcomes [3], [12]. Despite their strengths, these approaches often require complex implementation, with frequent adjustments leading to higher energy consumption and wear on actuators.

Consequently, PID controllers remain popular for their simplicity and effectiveness. However, IoT and machine learning are also being integrated into greenhouse control, as demonstrated by Wang et al. [13], who combined these technologies with PID for real-time monitoring. Nonetheless, managing greenhouse systems using PID can be challenging due to the need for multiple controllers and extensive tuning. This process is time-consuming and optimization-dependent, often lacking guaranteed optimal results. Consequently, MPC has emerged as a preferred approach for greenhouse climate control [14], enabling continuous adjustment of setpoints through sample-by-sample online optimization. This approach, however, increases computational demands.

Integrating advanced control techniques into education has become increasingly important. Recent studies [15], [16] have shown that web-based simulation platforms significantly enhance students' problem-solving skills by bridging the gap between theory and practice. Inspired by this approach, our framework aims to provide a similar educational experience within greenhouse climate control, focusing on modeling, optimal control, and nonlinear economic Model Predictive Control (NEMPC).

This study presents a web interface for optimizing greenhouse climate control, to achieve enhanced crop yields, energy efficiency and reduction in CO_2 emissions. Utilizing principles of thermodynamics, fluid dynamics, and mass transfer, along with real weather and carbon intensity forecasts we developed realistic hybrid simulation environment employed by NEMPC to adjust ventilation, heating, humidification, and CO_2 enrichment in real-time. Beyond technical contributions, the framework serves as an educational tool, allowing students to engage with real-world data and explore the economic and sustainability trade-offs in agricultural systems. Thus, this versatile platform enhances control education by combining theoretical concepts with practical skills in automatic control.

II. Methodology

III. Greenhouse Climate Model

In this section we provide a mathematical model of the greenhouse environment, focusing on wind, temperature, humidity, and CO_2 concentration dynamics, that simplifies the GES software [17], based on the Gembloux Dynamic Greenhouse Climate Model (GDGCM) [18] and on the thesis by Vanthoor [19].

A. Temperature Dynamics

The temperature dynamics inside the greenhouse are modeled by considering the energy exchange due to convection, radiation, and conduction — Fig. 2. The temperatures of different components (e.g., cover, internal air, vegetation, tray, etc.) are described using the following equations.

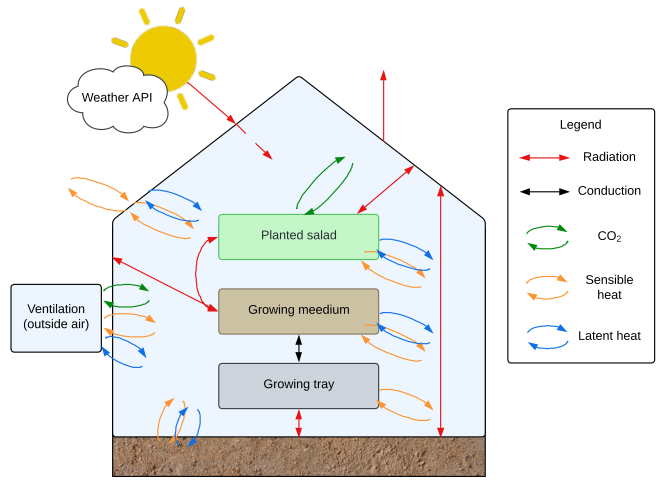

Fig. 2. A simplified diagram of the heat, mass and CO_2 exchanges modelled within the framework. Image adapted from [17].

The convective heat transfer between two surfaces is given by

$$\mathrm{Nu} = \max\left(\mathrm{Nu}_G, \mathrm{Nu}_R\right), \tag{1}$$

where Nu_G and Nu_R are the Nusselt numbers for free and forced convection, respectively

$$\mathrm{Nu}_G = 0.5 \cdot \left(\frac{\mathrm{Gr}}{10^5}\right)^{0.25} + 0.13 \cdot \left(\frac{\mathrm{Gr}}{10^5}\right)^{0.33} \tag{2}$$

$$\mathrm{Nu}_R = 0.6 \cdot \left(\frac{\mathrm{Re}}{20000}\right)^{0.5} + 0.032 \cdot \left(\frac{\mathrm{Re}}{20000}\right)^{0.8}, \tag{3}$$

where Re represents the Reynolds number, and Gr represents the Grashof number.

The heat flux due to convection is then calculated as

$$Q_{\mathrm{conv}} = A \cdot \mathrm{Nu} \cdot \lambda \cdot \frac{T_1 - T_2}{d}, \tag{4}$$

where A represents the area of a compartment, and d represents the characteristic length of a compartment.

The radiative heat transfer between two surfaces is described by

$$Q_{\mathrm{rad}} = \frac{\varepsilon_1 \cdot \varepsilon_2}{1 - \rho_1 \cdot \rho_2 \cdot F_{12} \cdot F_{21}} \cdot \sigma \cdot A_1 \cdot F_{12} \cdot \left(T_1^4 - T_2^4\right), \tag{5}$$

where σ is the Stefan-Boltzmann constant, F_{12} is the view factor from surface 1 to surface 2, T_1 and T_2 representing the temperatures of the surfaces, and ε and ρ are the emissivity and reflectivity of the surfaces, respectively.

The conductive heat transfer through a medium is given by

$$Q_{\mathrm{cond}} = \frac{A \cdot \lambda}{d} \cdot (T_1 - T_2), \tag{6}$$

where λ is the thermal conductivity of a compartment, and d is the thickness of the conducting layer.

B. Humidity Dynamics

The humidity within the greenhouse is modeled by considering the mass transfer of water vapor. The specific humidity is calculated as:

$$\text{SH} = \exp\left(11.56 - \frac{4030}{T + 235}\right). \tag{7}$$

The moisture content in the air is given by:

$$C_w = \text{SH} \times \rho_{\text{air}}, \tag{8}$$

where ρ_{air} is the density of air.

The mass transfer of water vapor due to convection is:

$$Q_v = \frac{A \cdot H_{\text{fg}}}{\rho \cdot c} \cdot \frac{\text{Sh}}{\text{Le}} \cdot \frac{\lambda}{d} \cdot \left(C - C_{\text{sat},T}\right), \tag{9}$$

where H_{fg} is the latent heat of vaporization, Sh is the Sherwood number, and Le is the Lewis number, λ is the thermal conductivity, d is the characteristic length, A is the heat exchange surface area, ρ is the density of the vapor, c is the specific heat capacity, C is the actual vapor concentration, and $C_{\text{sat},T}$ is the vapor concentration at temperature T.

C. Carbon Dioxide Concentration Dynamics

The CO_2 concentration within the greenhouse is affected by photosynthesis and external conditions. The external CO_2 concentration is computed as:

$$C_{\text{ext}} = \frac{4 \times 10^{-4} \cdot M_c \cdot P_{\text{atm}}}{R \cdot T_{\text{ext}}}, \tag{10}$$

where M_c is the molar mass of CO_2, P_{atm} is the atmospheric pressure, R is the gas constant, and T_{ext} is the external air temperature in Kelvin.

The internal CO_2 concentration in parts per million (ppm) is given by:

$$C_{\text{int, ppm}} = \frac{C_c \cdot R \cdot T_i}{M_c \cdot P_{\text{atm}}} \times 10^6, \tag{11}$$

where C_c is the CO_2 density, and T_{in} is the internal air temperature in Kelvin.

The greenhouse climate model integrates the physical models of temperature, humidity, and CO_2 concentration into a dynamic system represented by a state vector $\mathbf{z}$ (11×1) = $[T_c, T_i, T_v, T_m, T_p, T_f, T_s, C_w, C_c, x_{\text{sdw}}, x_{\text{nsdw}}]$, and input vector $\mathbf{u}$ (2×1) = [Ventilation, Heating]. The T_c represents the cover temperature, T_i the internal air temperature, T_v the planted salad temperature, T_m the growing medium temperature, T_p the tray temperature, T_f the floor temperature, and T_s the temperature of the soil layer. Additionally, C_w denotes the density of water vapor, C_c the CO_2 density, x_{sdw} the structural dry weight of the plant, and x_{nsdw} the non-structural dry weight of the plant.

TABLE I
SUMMARY OF ACTUATOR MODELS AND PARAMETERS

Actuator	Label	Unit
Heater	Q_{heater}	W
Fan	R_{fan}	m^3/s
Humidifier	V_{humid}	l/h
CO_2 Generator	G_{CO2}	kg/h

D. Actuation Control Systems

An actuator is a critical component within a system responsible for generating force, torque, or displacement in a controlled manner [20]. In our implementation, actuators operate by converting an input control signal from the system into the appropriate mechanical energy required to regulate environmental variables [21]. These actuators serve to maintain optimal conditions for crop growth by adjusting temperature, humidity, ventilation, and CO_2 concentration. Each actuator's functionality is modeled to simulate its contribution to the overall energy balance, operating costs, and CO_2 emissions of the greenhouse. Below, we describe the main equations used to model these actuators, summarized in Table I.

We model the actuators by adjusting the control signal, $u(t)$, which ranges from 0 to 100%, where 0% represents no activation, and 100% corresponds to the maximum actuation level. The actuation level, $a(u)$, is then calculated as:

$$a(u) = \frac{u}{100} \cdot a_{\text{max}} \tag{12}$$

where a_{max} represents the scale of the specific actuator, such as the maximum heating power or airflow.

The **power consumption** of each actuator, $P(u)$, is determined by:

$$P(u) = \frac{p_{\text{unit}}}{\eta} \cdot a(u) \tag{13}$$

where p_{unit} is the power per unit of actuation, and η represents the efficiency of the actuator.

The **total energy cost**, $C_{\text{energy}}(u)$, in EUR is calculated as:

$$C_{\text{energy}}(u) = \frac{E_{\text{cost}} \cdot \Delta t}{1000 \cdot 3600} \cdot P(u) \tag{14}$$

where E_{cost} is the cost of energy in EUR per kWh, and Δt is the time step in seconds.

The **CO_2 emissions**, $E_{\text{CO2}}(u)$, generated by each actuator are given by:

$$E_{\text{CO2}}(u) = \frac{I_{\text{CO2}} \cdot \Delta t}{1000 \cdot 36000} \cdot P(u) \tag{15}$$

where I_{CO2} is the carbon intensity in gCO_2eq/kWh [22]. The associated cost of these emissions is:

$$C_{\text{CO2}}(u) = C_{\text{CO2cost}} \cdot E_{\text{CO2}}(u) \tag{16}$$

where C_{CO2cost} is the social cost of CO_2 in EUR/gCO_2eq.

The **heater actuator**'s heating power, Q_{heater}, is determined based on the desired setpoint temperature, T_{sp}, and air volume of the greenhouse, V:

$$Q_{\text{heater}} = \rho_{\text{air}} \cdot c_{\text{air}} \cdot V \cdot (T_{\text{sp}} - T_{\text{ambient}}) \cdot \frac{Q_{\text{air}}}{3600} \tag{17}$$

where ρ_{air} is the density of air, c_{air} is the specific heat capacity of air, and Q_{air} represents the fresh air exchange rate per hour.

The **fan actuator** controls the air exchange rate. The ventilation rate, R_{fan}, is based on the air changes per hour (Q_{air}) and greenhouse volume:

$$R_{\text{fan}} = V \cdot \frac{Q_{\text{air}}}{3600} \tag{18}$$

The **humidifier actuator** controls the humidity level within the greenhouse. The humidification rate, V_{humid}, is calculated based on the air volume and the difference in absolute humidity at 40% and 80% relative humidity:

$$V_{\text{humid}} = V \cdot \frac{(\phi_{a,80} - \phi_{a,40})}{\rho_{\text{water}}} \tag{19}$$

where $\phi_{a,80}$ and $\phi_{a,40}$ are the absolute humidity levels at 80% and 40% relative humidity, and ρ_{water} is the density of water.

The **CO_2 actuator** increases the CO_2 concentration within the greenhouse. The CO_2 generation rate, G_{CO2}, is based on the desired change of the CO_2 density per hour, $\dot{c}_{co2}$ and air volume:

$$G_{\text{CO2}} = \dot{c}_{co2} \cdot V \tag{20}$$

where G_{CO2} is the CO_2 generation in kg/h.

IV. Nonlinear economic model predictive control

A nonlinear economic model predictive control (NEMPC) is adopted to maximize the profit from growing lettuce in a greenhouse. The objective of the proposed economic MPC for greenhouse control is to optimize the economic performance of the greenhouse system by controlling its actuators, such as heating, ventilation, and CO_2 injection. This is achieved by maximizing lettuce yield while minimizing operating costs over a finite prediction horizon. The nonlinear model predictive control framework incorporates the dynamics of the greenhouse and time-varying external conditions such as climate.

A. System Dynamics

The greenhouse system is modeled by a set of nonlinear state equations (see Section III) that describe the evolution of the greenhouse states, such as temperature, humidity, and biomass. The discrete-time nonlinear system is given by:

$$x(t+1) = f\left(x(t), u(t), \text{TVP}(t)\right), \tag{21}$$

where $x(t) \in \mathbb{R}^{n_x}$ represents the state vector at time step t, $u(t) \in \mathbb{R}^{n_u}$ represents the control input vector (actuators), and $\text{TVP}(t)$ are time-varying parameters that include external climate conditions such as temperature, radiation, and humidity.

B. Economic Objective Function

The goal of the economic MPC is to maximize the revenue from lettuce production while minimizing the costs associated with actuator use. The objective function is composed of two terms: the profit from biomass accumulation and the costs of actuators.

The revenue from lettuce production is proportional to the change in biomass between the initial state and the current state, expressed as:

$$R(t) = P_L \cdot \frac{(x_{\text{sdw}}(t) + x_{\text{nsdw}}(t)) - (x_{0,\text{sdw}} + x_{0,\text{nsdw}})}{\rho_{dw}} \cdot A_c, \tag{22}$$

where P_L is the price of lettuce per gram, A_c is the cultivated area, and x_{sdw} and x_{nsdw} are the biomass-related states.

In addition, the cost of operating the actuators at each time step is given by:

$$C_u(t) = \sum_i \left(C_{\text{energy}}(u_i(t)) + C_{\text{CO2}}(u_i(t))\right), \tag{23}$$

where $C_{\text{energy}}(u_i(t))$ is the cost associated with the actuator signal $u_i(t)$ and $C_{\text{CO2}}(u_i(t))$ represents the cost related to CO_2 emissions from the actuator.

Thus, the total cost at each time step is:

$$l_t = -R(t) + C_u(t). \tag{24}$$

C. Optimization Problem Formulation

The objective of the nonlinear economic MPC is to minimize the sum of the stage costs l_t over a finite prediction horizon N, subject to system dynamics and constraints. The optimization problem is formulated as follows:

$$\min_{\{u(t)\}_{t=0}^{N-1}} \sum_{t=0}^{N-1} l_t(x(t), u(t)), \tag{25}$$

subject to:

$$\begin{aligned}
x(t+1) &= f(x(t), u(t), \text{TVP}(t)), && (26)\\
u_{\min} &\leq u(t) \leq u_{\max}, \quad \forall t = 0, \ldots, N-1, && (27)\\
x_{\min} &\leq x(t) \leq x_{\max}, \quad \forall t = 0, \ldots, N, && (28)\\
x(0) &= x_{\text{initial}}. && (29)
\end{aligned}$$

Here, $x_{\min}$ and $x_{\max}$ represent the bounds on the state variables, and $u_{\min}$ and $u_{\max}$ define the bounds on the control inputs, i.e., actuator signals.

D. Time-Varying Parameters (TVP)

The external climate conditions are modeled as time-varying parameters (TVP), which influence the system dynamics. These parameters include variables such as outdoor temperature, solar radiation, and humidity, and are provided by real-time climate data. These parameters are incorporated into the state equations, influencing the evolution of the greenhouse states.

V. Educational Web Interface

Figure V demonstrates the interactive web-based educational tool. Via four layers of user customization of the greenhouse, participants grasped the main benefits of optimal control a d challenges related to non-linearity. The first layer is the greenhouse structure, where the user can select the shape of the greenhouse, affecting the energy exchange with the environment and suggested scaling of the actuation units. The second layer is the orientation and location of the greenhouse, which affects the solar radiation and the weather conditions. Here, we establish a connection to weather and carbon intensity forecast APIs to provide real-time data along with forecasts and history replays. The third layer is the actuation units, where the user can overwrite the suggested scaling and select the actuators for the heating, ventilation, humidification, and CO_2 enrichment. Meanwhile, the fourth layer is the control strategy, where the user can influence the control parameters, including the objective function and constraints of the economic MPC controller. While the user is customizing the greenhouse, the web interface provides real-time feedback. The user can also simulate the greenhouse operation over a selected period of time and analyze the results in terms of energy consumption, crop yield, and economic output.

Fig. 3. This figure illustrates an interactive web-based educational tool designed to teach students the principles of NEMPC applied to greenhouse climate management. Users can design greenhouses by adjusting parameters such as shape, location, and orientation while integrating real-time weather forecasts. The tool computes optimal control inputs for climate devices (e.g., fans, heaters, humidifiers, CO_2 generators) to maximize crop profit, demonstrated here for lettuce growth. Key outputs include profit calculations, energy usage, CO_2 emissions, and detailed climate simulation results.

VI. Results

In the first set of simulations, we analyzed the nonlinear behavior of the greenhouse under varying climate conditions and steps in actuation. We observed how different actuations influence the growth of the structural and non-structural dry weight of the plant. The simulations were run under a mild climate of Bratislava (Slovakia), from 11th October for a 24-hour window. Figure 4 shows that under given climate conditions, the influence of ventilation and humidification is insignificant on growth. Nevertheless, it has a positive effect on convection and the overall transfer of energy. Meanwhile, intense heating positively affects the conversion of non-structural dry weight into structural but does not influence the overall non-structural dry weight buildup. CO_2 enrichment has a significant impact on non-structural plant growth.

The second set of simulations compares the performance of the proposed NEMPC algorithm with a no-control scenario. The parameters of NEMPC are as follows in Table II. Results in Table III demonstrate that the proposed economic MPC algorithm increased crop yield by 9% and increased profit by more than 4% in just 15 days of growth. The cost function of the NEMPC algorithm also included the social cost of the carbon intensity of used energy sources, which reduced CO_2 consumption by 98% while decreasing the growth 4 times, compared to a scenario where the social cost of CO_2 was not minimized. This means that there is a significant trade-off between the economic output and the carbon intensity of the energy sources. While the primary objective of the farmers might be to maximize the economic output, consideration of the environmental impact of the production should be assessed.

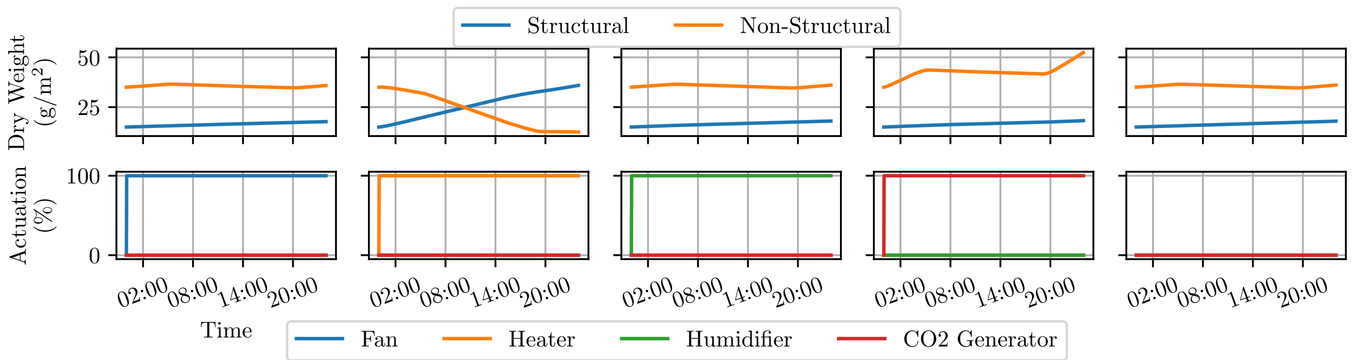

Fig. 4. Responses of structural and non-structural dry weight on step changes from off to maximum in following actuations from the left to the right: ventilation, heating, humidification, and CO_2 enrichment.

TABLE II
PARAMETERS OF THE NEMPC ALGORITHM.

Parameter	Value	Unit
Prediction horizon	10	min
Control horizon	10	min
Number of steps	10 801	—
Sampling time	120	s

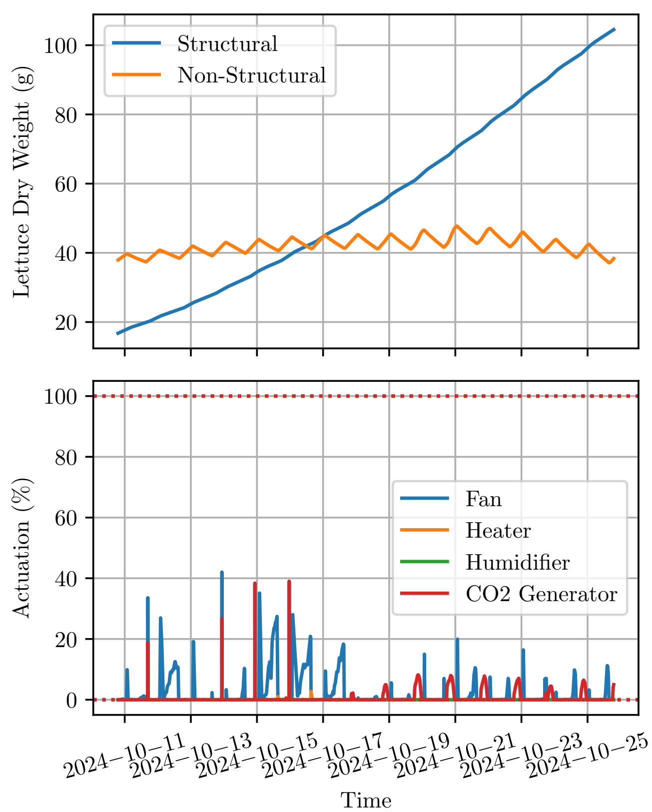

Fig. 5. A simplified diagram of the heat, mass and CO_2 exchanges modeled within the framework. Image adapted from [17].

TABLE III
COMPARISON OF THE NEMPC ALGORITHM WITH A NO CONTROL SCENARIO.

Parameter	No control	NEMPC (CO_2)	NEMPC ($)
Lettuce profit	858.32	940.19	4120.63
Energy (Fan)	0.00	−0.03	−0.16
Energy (Heater)	0.00	−0.45	−21.68
Energy (Humidifier)	0.00	−0.05	0.00
Energy (CO2 Generator)	0.00	−9.95	−697.59
CO2 (Fan)	0.00	−0.08	−0.51
CO2 (Heater)	0.00	−1.48	−70.84
CO2 (Humidifier)	0.00	−0.17	−0.01
CO2 (CO2 Generator)	0.00	−32.52	−2279.72
Total	858.32	895.45	1050.12

To assess the educational impact of our proposed paper, we conducted a survey among students who interacted with the web-based application. The survey measured the participants' prior knowledge and their learning outcomes in four key areas: mathematical modeling, optimal process control, economic process control, and model predictive control (MPC).

The results show a varied range of initial expertise levels in both modeling and process control, with participants rating their skills from novice (1) to advanced (5). Despite this variation, the application demonstrated a significant educational benefit across all experience levels.

a) Low-Skilled Users: Participants with minimal prior knowledge, such as Karolína and Miska, reported moderate improvements in understanding mathematical modeling, optimal control, and economic control, with a strong positive impact noted for MPC. These results suggest that the framework is accessible to beginners and helps build foundational knowledge.

b) High-Skilled Users: More experienced participants, such as Sofiia and Martin, rated the application as highly beneficial in all four categories. They noted substantial improvements in their understanding of complex control techniques, particularly in mathematical modeling and MPC, validating the educational potential of the framework for users with advanced backgrounds.

c) General Feedback: The participants' qualitative feedback further highlights the application's potential. Participants emphasized that with additional information, the tool could be used by a broader audience, including industrial farmers, to design and optimize greenhouse placement in practical settings. This points to the dual benefit of the application: it not only enhances student learning but could also have real-world applicability in sustainable greenhouse design.

These findings suggest that the proposed framework effectively supports educational objectives, promoting understanding across a spectrum of learners. It also has the potential to be adapted for broader use beyond educational contexts, providing valuable insights into the design of sustainable greenhouse systems.

VII. Conclusion

References

[1] A. Emami-naeini and K. Diehl, "The role of interactive graphic tools in teaching control theory," *IFAC Proceedings Volumes*, vol. 25, no. 12, pp. 53–58, 1991, iFAC Symposium on Advances in Control Education, Boston, MA, USA, 24-25 June 1991. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1474667017500889

[2] J. Guzmán, S. Dormido, and M. Berenguel, "Interactivity in education: An experience in the automatic control field," *Computer Applications in Engineering Education*, vol. 21, 06 2013.

[3] P. Debroy, P. Majumder, A. Das *et al.*, "Model-based predictive greenhouse parameter control of aquaponic system," *Environmental Science and Pollution Research*, vol. 31, pp. 48 423–48 449, 2024. [Online]. Available: https://doi.org/10.1007/s11356-024-34418-z

[4] G. Wu, Q. Yang, H. Fang, Y. Zhang, H. Zheng, Z. Zhu *et al.*, "Photothermal/day lighting performance analysis of a multifunctional solid compound parabolic concentrator for an active solar greenhouse roof," *Solar Energy*, vol. 180, pp. 92–103, 2019.

[5] E. Iddio, L. Wang, Y. Thomas, G. McMorrow, and A. Denzer, "Energy efficient operation and modeling for greenhouses: A literature review," *Renewable and Sustainable Energy Reviews*, vol. 117, p. 109480, 2020.

[6] S. M. Lu, S. Zainali, B. Stridh, A. Avelin, S. Amaducci, M. Colauzzi *et al.*, "Photosynthetically active radiation decomposition models for agrivoltaic systems applications," *Solar Energy*, vol. 244, pp. 536–549, 2022.

[7] M.-P. Trépanier and L. Gosselin, "Impact of setpoint control on indoor greenhouse climate modeling," in *Energy Informatics*. Cham: Springer Nature Switzerland, 2024, pp. 215–233.

[8] Y. Tian, "Adaptive control and supply chain management of intelligent agricultural greenhouse by intelligent fuzzy auxiliary cognitive system," *Expert Systems*, vol. 41, no. 5, p. e13117, 2024. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/exsy.13117

[9] L. Bood, K. NN, and A. M. Y, "Dual stage cascade controller for temperature control in greenhouse," *Bulletin of Electrical Engineering and Informatics*, vol. 12, no. 1, pp. 51–58, 2023.

[10] J. Riahi, H. Nasri, A. Mami, and S. Vergura, "Effectiveness of the fuzzy logic control to manage the microclimate inside a smart insulated greenhouse," *Smart Cities*, vol. 7, no. 3, pp. 1304–1329, 2024. [Online]. Available: https://www.mdpi.com/2624-6511/7/3/55

[11] W. Zhang, X. Cao, Y. Yao, A. Zhang, X. Xiao, and D. Luo, "Robust model-based reinforcement learning for autonomous greenhouse control," in *Proceedings of the Asian Conference on Machine Learning*. PMLR, 2021, pp. 1208–1223.

[12] J. L. Svensen, X. Cheng, S. Boersma, and C. Sun, "Chance-constrained stochastic mpc of greenhouse production systems with parametric uncertainty," *Computers and Electronics in Agriculture*, vol. 217, p. 108578, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169923009663

[13] C. Wang, "Intelligent agricultural greenhouse control system based on internet of things and machine learning," *arXiv preprint*, vol. arXiv:2402.09488, 2024, arXiv preprint.

[14] G. Hu and F. You, "Model predictive control for greenhouse condition adjustment and crop production prediction," in *Computer Aided Chemical Engineering*. Elsevier, 2022, vol. 51, pp. 1051–1056.

[15] Z. Wang, R. Zhao, Z. Zhao, H. Zhou, and Y. Shen, "A virtual quadrotor simulation platform for control education," *IFAC-PapersOnLine*, vol. 58, no. 16, pp. 101–106, 2024, 2nd IFAC Workshop on Aerospace Control Education - WACE 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2405896324012382

[16] K. Žáková, J. Matišák, and J. Šefčík, "Contribution to pid and pida interactive educational tools," *IFAC-PapersOnLine*, vol. 58, no. 7, pp. 115–119, 2024, 4th IFAC Conference on Advances in Proportional-Integral-Derivate Control PID 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S240589632400733X

[17] rmward61, "Eeci/ges: First release of ges software," *Energy Efficient Cities Initiative, University of Cambridge*, 2019. [Online]. Available: https://zenodo.org/record/2594716

[18] E. Mashonjowa, F. Ronsse, J. Pieters, and R. Lemeur, "Modelling heat and mass transfer in a naturally ventilated greenhouse in zimbabwe," *Communications in agricultural and applied biological sciences*, vol. 72, pp. 239–43, 02 2007.

[19] B. Vanthoor, "A model-based greenhouse design method," Ph.D. dissertation, Wageningen University and Research, [s.l.], 2011. [Online]. Available: https://edepot.wur.nl/170301

[20] M. Escudier and T. Atkins, *A Dictionary of Mechanical Engineering*. Oxford University Press, 2019. [Online]. Available: https://doi.org/10.1093/acref/9780198832102.001.0001

[21] A. J. Butterfield and J. Szymanski, Eds., *A Dictionary of Electronics and Electrical Engineering*. Oxford University Press, 2018. [Online]. Available: https://doi.org/10.1093/acref/9780198725725.001.0001

[22] Electricity Maps ApS, "Electricity maps," 2022, electricity Maps ApS - Univate, Njalsgade 76, 2300 Copenhagen. [Online]. Available: https://www.electricitymaps.com