Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 59-23 (2025) 443–448

A Cascaded Economic Model Predictive Control Approach to Greenhouse Climate Control

Ioannis Panagopoulos* Robert D. McAllister* Simon van Mourik Tamás Keviczky***

* *Delft Center for Systems and Control, Delft University of Technology, The Netherlands (e-mail: i.panagopoulos@tudelft.nl, r.d.mcallister@tudelft.nl, t.keviczky@tudelft.nl)*

** *Agricultural Biosystems Engineering, Wageningen University and Research, The Netherlands (e-mail: simon.vanmourik@wur.nl)*

Abstract: This paper introduces a cascaded climate control framework in which a primary economic model predictive controller (EMPC) determines climate bounds for a secondary rule-based controller, based on industrial practice. The proposed controller may therefore serve as a blueprint for control design for existing greenhouse climate control systems while retaining the reliability and safety of legacy systems. The framework's performance is evaluated through simulations of a lettuce greenhouse model and compared against a state-of-the-art EMPC that controls all actuators directly. The results show that the proposed approach achieves comparable performance to the ideal state-of-the-art EMPC, demonstrating negligible performance loss from retaining rule-based control in the climate control system.

Keywords: cascade control, economic MPC, lettuce greenhouse, controlled environment agriculture, rule-based control

1. INTRODUCTION

Since the early 1990s, several research directions have been pursued to optimize greenhouse climate control. One frequently studied approach involves model-based optimal control methodologies based on crop growth. Initially introduced by Challa and van Straten (1993) and then further explored by van Henten (1994) and Tap (2000), these methods share a common focus on economic optimization, aiming to maximize net revenue, typically defined as crop yield gains minus greenhouse operational costs.

The integration of optimal control in controlled environment agriculture (CEA) has been widely explored in literature. For instance, Iddio et al. (2020) provides examples of economic model predictive control (EMPC) in CEA. Furthermore, EMPC has been applied to address parametric uncertainties (Boersma et al., 2022) and weather forecast errors in climate control (Kuijpers et al., 2022). Additionally, van Mourik et al. (2023) investigated economic climate control through stochastic dynamic programming, while Morcego et al. (2023) explored its integration within a reinforcement learning framework. Another notable contribution from van Henten and Bontsema (2009), is the introduction of economic climate control in hierarchical control architectures that exploit temporal decomposition of climate-crop dynamics.

These methodologies have consistently demonstrated their potential to enhance energy efficiency and crop yield in numerical simulations. However, they are not readily applicable at an industrial scale. As highlighted by van Straten and van Henten (2010), real-world greenhouses predominantly rely on complex, heuristically designed Rule-Based Controllers (RBCs). RBCs receive climate boundary signals that define the desired climate space. Using the current greenhouse climate states, control inputs are computed through switching rules and proportional controllers, which adjust the system to maintain or steer the climate within the specified climate bounds. RBCs are expected to remain central due to their reliability, safety, and the industry's preference for incremental integration over radical system overhauls (van Straten, 1999). State-of-the-art research overlooks RBCs in greenhouse climate control, posing a key barrier to industry adoption. Therefore, a shift in perspective is needed to bridge the gap between optimal control strategies and practical greenhouse applications.

In this study, we adopt an industry-oriented perspective on greenhouse climate control. We propose designing automated climate control as a cascaded control system. In this framework, a primary EMPC determines optimal climate bounds while accounting for economic impact. These bounds are then transmitted to a secondary controller, the RBC, which directly regulates the greenhouse

⋆ The Synergia project is organized and led by Wageningen University and Research in close cooperation with Next Food Collective as well as the Universities of Delft, Twente, Eindhoven, and Nijmegen. The authors have declared that no competing interest exist in the writing of this publication. Funding for this research was obtained from the Dutch Research Council (NWO grant 17626), IMEC-One Planet and other private parties.

10.1016/j.ifacol.2025.11.828

actuators, forming a closed-loop cascaded control system, as illustrated in Figure 1. To assess the performance of the proposed framework, we consider a state-of-the-art direct EMPC scheme as a benchmark, representing ideal control performance. In this initial study, we assume full-state feeback for both control strategies.

This paper proposes an MPC approach for the cascaded climate control loop and evaluates its performance using a simulated experiment on a greenhouse lettuce model. Section 2 introduces the lettuce greenhouse model. Section 3 describes the RBC implemented in this study. Section 4 details the proposed EMPC formulation. Section 5 presents the benchmark EMPC and the simulation results. Section 6 discusses the findings and Section 7 concludes the work.

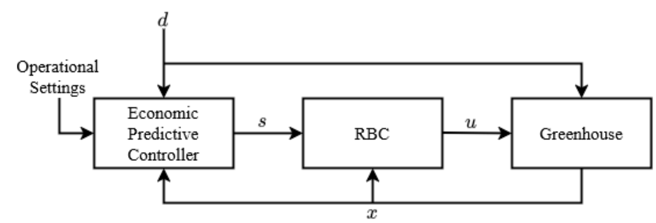

Fig. 1. Closed-loop cascaded climate control framework integrating an economic predictive controller to determine the optimal climate bounds and an RBC for climate implementation. Here, d represents the weather conditions, s indicates the climate bounds acting as RBC's input signals, u corresponds to greenhouse control inputs for heating, ventilation, and CO_2 control, and x represents the full-state feedback, including the climate-crop measurements from the sensors.

2. LETTUCE GREENHOUSE MODEL

In this study, we employ a greenhouse lettuce model taken from van Henten (1994). The model is discretized using the fourth-order Runge-Kutta method with time step $T_\mathrm{s} =$ 15 min, formulated as:

$$\begin{aligned} x(k+1) &= f\big(x(k), u(k), d(k)\big), \\ y(k) &= h\big(x(k)\big), \end{aligned} \tag{1}$$

with discrete time $k \in \mathbb{Z}_{\geq 0}$, $f(\cdot) : \mathbb{R}^4 \times \mathbb{R}^3 \times \mathbb{R}^4 \rightarrow \mathbb{R}^4$ and $h(\cdot) : \mathbb{R}^4 \rightarrow \mathbb{R}^4$ are nonlinear functions. The model states are $x(k) \in \mathbb{R}^4$, outputs $y(k) \in \mathbb{R}^4$, control inputs $u(k) \in \mathbb{R}^3$ and weather disturbances $d(k) \in \mathbb{R}^4$. Their vectors are defined as,

$$\begin{aligned} &x = (x_\mathrm{dw},\ x_{\mathrm{CO_2}},\ x_\mathrm{T},\ x_\mathrm{H})^T, \quad u = (u_{\mathrm{CO_2}},\ u_\mathrm{vent},\ u_\mathrm{heat})^T, \\ &y = (y_\mathrm{dw},\ y_{\mathrm{CO_2}},\ y_\mathrm{T},\ y_\mathrm{RH})^T, \quad d = (d_\mathrm{I},\ d_{\mathrm{CO_2}},\ d_\mathrm{T},\ d_\mathrm{H})^T \end{aligned} \tag{2}$$

where x_dw denotes the lettuce dry weight in $\mathrm{kg \cdot m^{-2}}$, $x_{\mathrm{CO_2}}$ the indoor CO_2 concentration in $\mathrm{kg \cdot m^{-3}}$, x_T the air temperature in ^{o}C, x_H the humidity in $\mathrm{kg \cdot m^{-3}}$, $u_{\mathrm{CO_2}}$ the supply rate of CO_2 in $\mathrm{mg \cdot m^{-2} \cdot s^{-1}}$, u_vent the ventilation rate through the vents in $\mathrm{L \cdot m^{-2} \cdot s^{-1}}$ (liters per greenhouse area per second), u_heat the energy supply by the heating system in $\mathrm{W \cdot m^{-2}}$, y_dw the dry weight in $\mathrm{g \cdot m^{-2}}$, $y_{\mathrm{CO_2}}$ the indoor CO_2 concentration in $\mathrm{ppm \cdot 10^3}$, y_T air temperature in ^{o}C, y_RH relative humidity in %, d_I the incoming radiation in $\mathrm{W \cdot m^{-2}}$, $d_{\mathrm{CO_2}}$ the outdoor CO_2 concentration in $\mathrm{kg \cdot m^{-3}}$, d_T the outdoor temperature in ^{o}C, d_H the outdoor humidity content in $\mathrm{kg \cdot m^{-3}}$.

3. RULE-BASED CLIMATE CONTROL

In practice, greenhouse temperature control typically operates based on two boundary signals: the *heating line* (s_heat) and the *ventilation line* (s_vent). When the air temperature drops below the *heating line*, heating is activated and scales proportionally to the temperature difference. Conversely, when the air temperature exceeds the *ventilation line*, the ventilation rate scales proportionally to the temperature difference. A dead-band is applied between these two lines to prevent simultaneous heating and cooling actions. Humidity control follows a similar principle; when relative humidity exceeds the *relative humidity line* (s_RHmax) the ventilation rate scales proportionally to the humidity difference. In cases where both temperature and humidity require regulation, the ventilation rate is determined by the maximum of the two control demands. The control logic governing temperature and humidity is depicted in Figure 2. In addition, CO_2 levels are regulated using the CO_2 *line* ($s_{\mathrm{CO_2}}$). When CO_2 drops below the CO_2 *line*, CO_2 injection is activated and scales proportionally to the CO_2 difference.

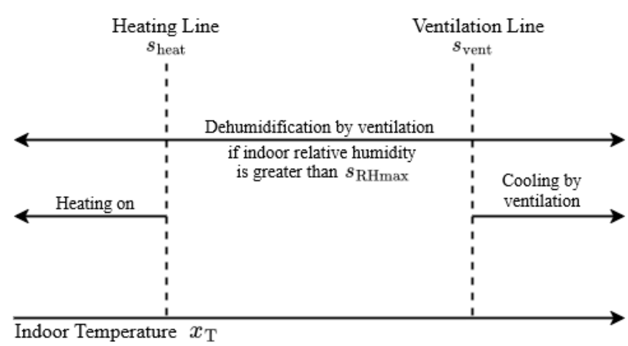

Fig. 2. Control rules of heating and ventilation for temperature and humidity control. Here x_T denotes the indoor air temperature, s_heat is the heating line, s_vent is the ventilation line, and s_RHmax represents the maximum allowed relative humidity. Ventilation is used to keep the indoor humidity below s_RHmax at all times, regardless of x_T. Heating is activated when $x_\mathrm{T} \leq s_\mathrm{heat}$, while ventilation provides cooling when $x_\mathrm{T} \geq s_\mathrm{vent}$. For $x_\mathrm{T} \geq s_\mathrm{vent}$, the ventilation is set to the maximum value needed for either temperature control or relative humidity control.

The RBC presented in this study is integrated into an optimization problem that is solved using gradient-based methods. Gradient-based methods require continuously differentiable functions to guarantee reliable and stable convergence. Therefore, all functions within the RBC are smoothed to ensure continuous gradients.

The mathematical representation of the RBC is based on the smoothed proportional controller as defined in Katzin (2021). Specifically, the heating and CO_2 control actions are computed using the sigmoid-based formulation shown in (3):

$$g_{(\cdot)}(w(k), s_{(\cdot)}(k)) = \frac{v_{(\cdot)}}{1+\exp\left(-2\frac{\ln(100)}{\rho_{(\cdot)}}(-w(k)+s_{(\cdot)}(k)-0.5\rho_{(\cdot)})\right)} \tag{3}$$

Here, $w(k)$ is the measured value (i.e., temperature or CO_2), $s_{(\cdot)}(k) \in \{s_{\mathrm{heat}}(k),\ s_{CO_2}(k)\}$, $\rho_{(\cdot)}$ specifies the proportional control bandwidth (P-band), and $v_{(\cdot)}$ denotes the maximum control action. The heating and CO_2 control inputs are calculated as:

$$u_{\mathrm{heat}}(k) = g_{\mathrm{heat}}(x_{\mathrm{T}}(k), s_{\mathrm{heat}}(k)) \tag{4}$$
$$u_{CO_2}(k) = g_{CO_2}(x_{CO_2}(k), s_{CO_2}(k)) \tag{5}$$

To ensure the smooth implementation of the ventilation rule, the modified *log-sum-exp function*:

$$\begin{aligned} u_{\mathrm{vent}}(k) = \ln\big(&\exp\left(g_{\mathrm{vent}}(x_{\mathrm{T}}, s_{\mathrm{vent}})\right) \\ &+ \exp\left(g_{\mathrm{RH}}(y_{\mathrm{RH}}, s_{\mathrm{RHmax}})\right) - 1\big). \end{aligned} \tag{6}$$

is used, where g_{vent} and g_{RH} are ventilation rates calculated for temperature and humidity, respectively, using a sigmoid function similar to (3), with the term $(-w(k) + s_{(\cdot)}(k) - 0.5\rho_{(\cdot)})$ replaced by $(w(k) - s_{(\cdot)}(k) - 0.5\rho_{(\cdot)})$ to reverse the direction.

The RBC tuning parameters are detailed in Table 1.

Table 1. RBC parameters

	CO_2	vent	heat	RHmax
$v_{(\cdot)}$	$1.2\,\mathrm{mg\,m^{-2}\,s^{-1}}$	$7.5\,\mathrm{L\,m^{-2}\,s^{-1}}$	$150\,\mathrm{W\,m^{-2}}$	$7.5\,\mathrm{L\,m^{-2}\,s^{-1}}$
$\rho_{(\cdot)}$	$10^{-3}\,\mathrm{kg\,m^{-3}}$	$5\,^{o}\mathrm{C}$	$6\,^{o}\mathrm{C}$	$15\,\%$

4. ECONOMIC NONLINEAR MPC WITH RBC INTEGRATION

We propose an economic climate controller using MPC that indirectly controls greenhouse actuators by optimizing climate boundary trajectories as inputs to an RBC. These trajectories aim to achieve optimal climate conditions that maximize net revenue. As with any MPC framework, the key components are a predictive model, an optimization problem, and constraints that define the feasible solution space. Consistent with the receding horizon principle, the proposed controller solves the optimization problem at each time instant and applies only the first optimal decision.

4.1 Prediction Model

The prediction model in this work relies on a detailed understanding of the coupled RBC-greenhouse system dynamics. Integrating the RBC into the prediction model is critical for accurately capturing system behavior. However, this integration introduces additional nonlinearities into the MPC problem, which may impede convergence of standard nonlinear solvers.

The prediction model is formulated as:

$$\begin{aligned} &u(k) = g(s(k), x(k)), \\ &x(k+1) = f(x(k), u(k), d(k)), \\ &y(k) = h(x(k)), \end{aligned} \tag{7}$$

where $f(\cdot)$ and $h(\cdot)$ represent the greenhouse dynamics, $s \in \mathbb{R}^4$ a vector containing the desired climate bounds, and $g : \mathbb{R}^4 \times \mathbb{R}^4 \to \mathbb{R}^3$ is the RBC model representing the right hand side of (3) and (6).

For simplicity, the controller operates under nominal conditions, assuming full-state feedback where $x(k)$ is either directly measured or perfectly estimated.

4.2 Optimization Problem

At each time instant k_0, the following optimization problem is solved:

$$\begin{aligned} \min_{x,u,s} \quad & \sum_{k=k_0}^{k_0+N} \ell(x(k), u(k), s(k)) \\ \text{s.t.} \quad & u(k) = g(s(k), x(k)), \\ & x(k+1) = f(x(k), u(k), d(k)), \\ & y(k) = h(x(k)), \\ & 0 \le s_{\mathrm{vent}}(k) - s_{\mathrm{heat}}(k) \le 30, \\ & \underline{s} \le s(k) \le \overline{s}, \\ & \underline{y} \le y(k) \le \overline{y}, \quad k = k_0, \dots, k_0 + N, \end{aligned} \tag{8}$$

where $\underline{s}$ and $\overline{s}$ are the lower and upper limits of $s = (s_{CO_2},\ s_{\mathrm{vent}},\ s_{\mathrm{heat}},\ s_{\mathrm{RHmax}}\ )^T$, $\underline{y}$ and $\overline{y}$ define greenhouse output limits. The climate limits used reflect standard practice and their values are:

$$\begin{aligned} \underline{s} &= (0,\ 0,\ 0,\ 65)^T, \quad \overline{s} = (0.0035,\ 35,\ 35,\ 95)^T \\ \underline{y} &= (0,\ 0.4,\ 10,\ 40)^T, \quad \overline{y} = (\infty,\ 1.6,\ 25,\ 80)^T \end{aligned} \tag{9}$$

The inequality constraint on $s_{\mathrm{vent}}(k) - s_{\mathrm{heat}}(k)$ is imposed to prevent concurrent activation of heating and cooling for temperature control. Upper and lower limits are not applied on u as they are enforced indirectly through $g_{(\cdot)}$.

4.3 Cost Function

The cost function of (8) has to reflect the maximization of the plant growth and the minimization of the energy use. These economic factors are accounted for via the stage cost:

$$\ell_e(x(k), u(k)) = -c_{\mathrm{dw}}\Delta x_{\mathrm{dw}}(k) + c_u^T u(k) \tag{10}$$

where $c_{\mathrm{dw}} > 0$, $c_u^T \in \mathbb{R}^3$ are weights for the dry weight change (Δx_{dw}), and actuation effort (u).

Due to the nature of the RBC, multiple climate bound trajectories can generate identical control inputs. For example, any heating line below the current greenhouse temperature results in zero heating input. Thus, if the optimal action is to avoid heating, any selection of s_{heat} below the current greenhouse temperature is equally optimal. This behavior complicates the optimization problem, potentially causing numerical instability in the solver. To address this, a quadratic penalty is applied to $\Delta s(k)$, facilitating convergence. This approach also prevents abrupt changes in $s(k)$, which would be impractical in real-world operations. Thus, the stage cost $\ell(\cdot)$ in (8) is defined as:

$$\begin{aligned} \ell(x(k), u(k), s(k)) = \ell_e&(x(k), u(k)) \\ &+ \Delta s(k)^T C_s \Delta s(k) \end{aligned} \tag{11}$$

where C_s is a diagonal (positive semidefinite) weighting matrix penalizing the climate bounds rate-of-change (Δs).

Simulation details and results, along with a comparison to a benchmark algorithm are presented in the next section.

5. SIMULATION RESULTS

The weather data $d(k)$ used for the simulations are real-world measurements from ASHRAE (2001), representing weather conditions in Amsterdam, the Netherlands. The dataset, originally sampled every 5 minutes, was resampled to a $T_\mathrm{s} = 15$ min sampling period to align with the simulation requirements. The simulation spans a duration of 28 days corresponding to $N_s = 28 \cdot 24 \cdot 4$ timesteps. A prediction horizon of 6 hours, discretized into $N = 6 \cdot 4$ timesteps was chosen for consistency with other model predictive climate control studies on the same lettuce model (Boersma et al., 2022; Morcego et al., 2023).

The weighting factors for the objective function (11) were selected to balance yield, energy consumption, and climate bound fluctuations. Specifically, the parameters were set as follows: $c_\mathrm{dw} = 16$, $c_u = \left(378 \cdot 10^{-6},\ 0,\ 5715 \cdot 10^{-9}\right)^T$, and $C_s = \mathrm{diag}\left(0,\ 10^{-5},\ 10^{-6},\ 10^{-6}\right)$.

For benchmarking, a direct EMPC was employed with full access to greenhouse actuators and complete state feedback, as typically assumed in the scientific literature. Its purpose is to represent the achievable control performance under ideal conditions, providing a reference for evaluating the performance impact of introducing the RBC in the climate control loop. The benchmark direct EMPC is formulated as follows:

$$
\begin{aligned}
\min_{x,u} \quad & \sum_{k=k_0}^{k_0+N} \ell_e(x(k), u(k)) \\
\text{s.t.} \quad & x(k+1) = f(x(k), u(k), d(k)), \\
& y(k) = h(x(k)), \\
& \underline{u} \leq u(k) \leq \overline{u}, \\
& \underline{y} \leq y(k) \leq \overline{y}, \quad k = k_0, \ldots, k_0 + N,
\end{aligned}
\tag{12}
$$

where the input constraints are $\underline{u} = (0,\ 0,\ 0)^T$ and $\overline{u} = (1.2,\ 7.5,\ 150)^T$ as specified in Boersma et al. (2022).

The optimization problems (8) and (12) were solved using the open-source algorithm differentiation software CasADi from Andersson et al. (2018) and the nonlinear optimization solver IPOPT from Wächter and Biegler (2006) within a Python environment. The implementation used direct multi-shooting and leveraged the IPOPT warm-start option to improve computational efficiency. Additionally, an initial guess based on shifted previous optimal decisions was used to aid convergence. For these settings, the proposed controller in (8) required 0.58 seconds, on average, to compute new control signals, whereas the direct EMPC required an average of 0.07 seconds per iteration.

Figure 3 illustrates the simulation results for day 26. The top panel shows the simulated weather data d (black lines), while the middle panel displays the greenhouse control input trajectories u. The benchmark and proposed controller inputs are represented by orange and purple dashed lines, respectively. The bottom panel presents the applied control signals s (red and cyan lines) alongside the climate-crop outputs y.

Day 26 was selected for analysis due to the activation of all control inputs s in response to high outdoor temperatures (d_T). During this day, ventilation was necessary to maintain the greenhouse temperature y_T below 25 ^{o}C. In contrast, on cooler days, the controller avoids ventilation for temperature control to prioritize energy savings.

The Python code used for both simulation and analysis is publicly available at: `https://github.com/ipanagopoulos/Cascaded-EMPC-RBC-Lettuce-GH`.

5.1 Performance Metrics

The comparison between the two control approaches (direct EMPC and EMPC-RBC) focuses on three key metrics: final yield, CO_2 consumption, and heating energy consumption. Table 2 summarizes these quantities over the 28-day simulation period, presenting absolute values, absolute differences, and relative differences, with the benchmark direct EMPC algorithm used as the reference. Table 2 shows that the proposed control approach performs comparably to the benchmark algorithm. Interpreting these results requires analyzing the relative differences in terms of energy efficiency, defined as the final yield per unit of energy cost, using EMPC as the baseline. The EMPC with RBC exhibited a 0.38% reduction in CO_2 efficiency and a 0.21% reduction in heat energy efficiency. The CO_2 mass exchange through the vents, shows that the EMPC-RBC approach resulted in 0.6% more CO_2 loss to the outdoor environment compared to the pure EMPC. Conversely, the difference on heating energy loss through the vents between the two control approaches was negligible. The slightly increased CO_2 loss is likely an indirect consequence of suboptimal ventilation decisions imposed by the cascading control structure. Unlike the direct EMPC approach, which directly controls ventilation, the RBC-enforced ventilation rules restrict the climate controller's ability to optimize ventilation fully, leading to higher CO_2 losses.

Table 2. Simulation results in terms of final dry yield, CO_2 consumption, and heating energy consumption.

	Final Yield [g m^{-2}]	Total CO_2 Use [g m^{-2}]	Total Heating Use [kWh m^{-2}]
Direct EMPC	291.43	901.78	22.86
EMPC with RBC	286.89	891.12	22.56
Abs. Diff.	4.54	10.66	0.30
Rel. Diff. [%]	-1.56	-1.18	-1.31

6. DISCUSSION

The exclusion of legacy RBC used in practical applications from the greenhouse climate control loop is a common assumption in the optimal greenhouse climate control literature. This paper challenges that convention by proposing optimal control methods that better reflect practical implementations. Specifically, we demonstrate that it is possible to achieve results comparable to the ideal EMPC of (12) with the cascaded control architecture in Figure 1, albeit with nearly eight times the mean execution time per iteration. This increased computational cost stems from incorporating the nonlinear RBC logic into the optimization problem. However, this remains computationally acceptable, as the EMPC-RBC requires less than 1 second per iteration, well within the 15-minute system time step.

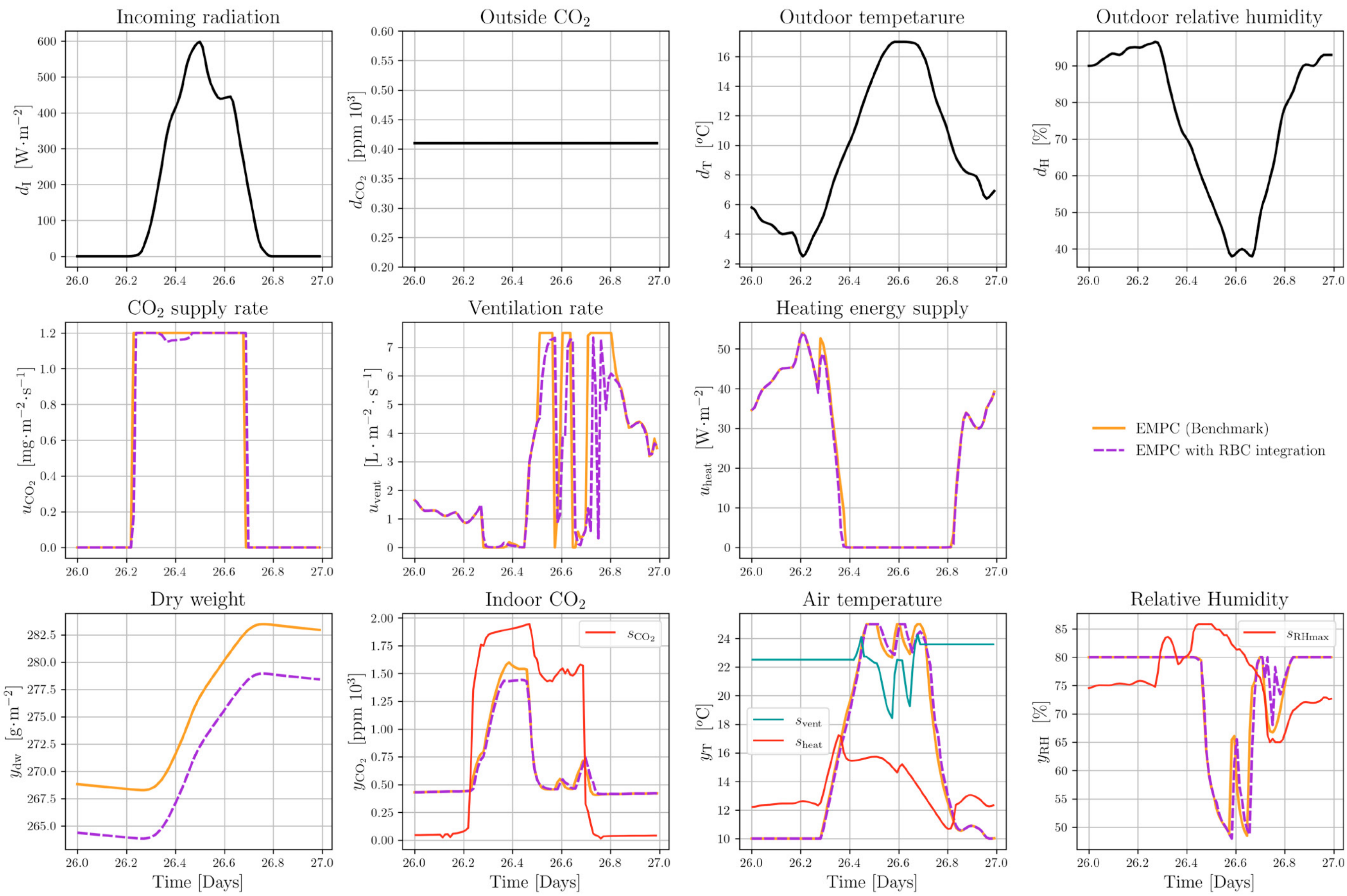

Fig. 3. Simulation results for Day 26: the top panel presents weather disturbances (d), the middle panel shows control inputs (u) with orange and purple lines representing the direct EMPC and the EMPC with RBC, respectively, and the bottom panel illustrates output measurements (y) using purple and orange lines, alongside control signals (s) depicted in cyan and red.

Finally, solver stability and convergence were consistently maintained throughout the simulated study.

A key advantage of the proposed approach is its alignment with typical greenhouse practice where growers conventionally manage greenhouse conditions by adjusting climate bounds. The proposed design enhances the interpretability of control decisions, as the primary EMPC regulates climate through climate bounds rather than direct greenhouse actuator control. In contrast, the benchmark EMPC returns actuator trajectories, which are less intuitive for practitioners and thereby limiting its practical adoption. Another advantage is that the RBC provides a layer of operational safety by ensuring responsive greenhouse actuation, even when the primary EMPC encounters numerical problems or solver failures. Conversely, a solver failure with direct EMPC can disrupt the entire control loop.

Despite these benefits, certain limitations must be acknowledged. The absence of performance degradation in our results may be due to the simplified nature of the RBC compared to a more complex industrial climate control system. Additionally, our approach assumes full-state feedback and does not account for uncertainty. Future work will focus on extending the framework to real-world applications, with particular attention to the impact of RBC integration in climate control loops. We plan to leverage more sophisticated greenhouse simulators and incorporate advanced RBC frameworks that include essential greenhouse control features, such as thermal and blackout screens, artificial lighting, and fogging systems. To ensure realism, the model should closely mimic real-world RBC behavior while being smooth to ensure continuous gradients. These additions are expected to increase the overall problem complexity, and the scalability of the proposed approach under more complex RBCs remains to be assessed. Moreover, to enhance robustness and bridge the gap between simulation and real-world application, we will address state estimation challenges and assess the proposed approach under uncertainty.

In this study, we used an EMPC approach, a widely studied algorithm in the literature, as the benchmark. A major challenge in greenhouse climate control research lies in the lack of standardization, as studies often employ diverse greenhouse models as ground truth or distinct parameterizations. This inconsistency complicates the reproducibility of the results and hinders comparison between studies. Given its established role as a reference in the community (Boersma et al., 2022), we adopt the algorithm in (12) as a benchmark for studies using the lettuce model described in van Henten (1994). To facilitate reproducibility and implementation, we provide the corresponding software and data in a publicly available repository (Panagopoulos et al., 2025), enabling future research to build upon a standardized framework.

Finally, the proposed cascaded method is compared against the ideal EMPC. However, greenhouse climate control in practice is governed by climate bounds, and a direct comparison with current industrial practices is missing. Establishing benchmarks based on standard growing practices would allow for such a comparison.

7. CONCLUSION

This paper proposes a climate control framework aligned with industrial practices by integrating a typical representative legacy RBC into the climate control loop. Specifically, a cascaded control architecture is employed, where the primary EMPC controller optimizes the climate boundary trajectories passed to the secondary RBC. The key challenges in designing the proposed EMPC controller are ensuring a smooth representation of the RBC model and formulating the economic objective function in the presence of non-unique optimal solutions. The results demonstrate that this approach achieves comparable performance to the direct EMPC benchmark, with slightly reduced energy consumption at the cost of a minor decrease in yield. The yield reduction is attributed to the restrictive ventilation control imposed by the RBC. Nonetheless, the findings suggest that integrating an RBC into the climate control loop does not significantly degrade performance. Whether this conclusion holds for other types or more complex RBCs remains to be investigated. The study further highlights the need for standardized benchmarks to improve reproducibility and comparability in greenhouse control research. Future work focuses on applying the proposed framework to more complex greenhouse models with advanced RBCs, while addressing state estimation challenges and uncertainty to enhance robustness and bridge the gap between simulation and real-world application.

ACKNOWLEDGEMENTS

The authors would like to express their gratitude to Hoogendoorn and Van der Hoeven. Their insights, expertise, and valuable feedback on RBCs used in greenhouse practice have been instrumental in shaping this research.

REFERENCES

Andersson, J., Gillis, J., Horn, G., Rawlings, J., and Diehl, M. (2018). Casadi: a software framework for nonlinear optimization and optimal control. *Mathematical Programming Computation*, 11.

ASHRAE, A. (2001). International weather for energy calculations (iwec weather files) users manual and cd-rom. *ASHRAE, Atlanta*.

Boersma, S., Sun, C., and van Mourik, S. (2022). Robust sample-based model predictive control of a greenhouse system with parametric uncertainty. *IFAC-PapersOnLine*, 55(32), 177–182. 7th IFAC Conference on Sensing, Control and Automation Technologies for Agriculture AGRICONTROL 2022.

Challa, H. and van Straten, G. (1993). Optimal diurnal climate control in greenhouses as related to greenhouse management and crop requirements. *The computerized greenhouse: automatic control application in plant production*, 119–138.

Iddio, E., Wang, L., Thomas, Y., McMorrow, G., and Denzer, A. (2020). Energy efficient operation and modeling for greenhouses: A literature review. *Renewable and Sustainable Energy Reviews*, 117, 109480.

Katzin, D. (2021). *Energy saving by LED lighting in greenhouses: A process-based modelling approach*. internal phd, wu, Wageningen University, Netherlands. doi: 10.18174/544434.

Kuijpers, W.J., Antunes, D.J., van Mourik, S., van Henten, E.J., and van de Molengraft, M.J. (2022). Weather forecast error modelling and performance analysis of automatic greenhouse climate control. *Biosystems Engineering*, 214, 207–229.

Morcego, B., Yin, W., Boersma, S., van Henten, E., Puig, V., and Sun, C. (2023). Reinforcement learning versus model predictive control on greenhouse climate control. *Computers and Electronics in Agriculture*, 215, 108372.

Panagopoulos, I., McAllister, R.D., Keviczky, T., and van Mourik, S. (2025). Economic Model Predictive Control with Rule Based Control Integration to Greenhouse Climate Control on a Lettuce Model. URL `https://github.com/ipanagopoulos/Cascaded-EMPC-RBC-Lettuce-GH`.

Tap, R. (2000). Economic-based optimal control of greenhouse tomato crop production. *Wageningen. Promotor: Prof.dr.ir. G. van Straten, co-promotor(en): Dr.ir. L.G. van Willigenburg. - Wageningen : R.F. Tap, 2000. - ISBN 90-5808-236-9*.

van Henten, E. and Bontsema, J. (2009). Time-scale decomposition of an optimal control problem in greenhouse climate management. *Control Engineering Practice*, 17(1), 88–96.

van Henten, E.J. (1994). *Greenhouse climate management : an optimal control approach*. Ph.D. thesis, Wageningen University & Research, Wageningen, Netherlands. *PhD Dissertation*.

van Mourik, S., van't Ooster, B., and Vellekoop, M. (2023). Plant performance in precision horticulture: Optimal climate control under stochastic uncertainty. URL `https://arxiv.org/abs/2303.14678`.

van Straten, G. and van Henten, E.J. (2010). Optimal greenhouse cultivation control: Survey and perspectives. *IFAC Proceedings Volumes*, 43(26), 18–33. 3rd IFAC Conference in Modelling and Control in Agriculture, Horticulture and Post-Harvest Processing - Agricontrol.

van Straten, G. (1999). Acceptance of optimal operation and control methods for greenhouse cultivation. *Annual Reviews in Control*, 23, 83–90.

Wächter, A. and Biegler, L. (2006). On the implementation of an interior-point filter line-search algorithm for large-scale nonlinear programming. *Mathematical programming*, 106, 25–57.