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Chance-constrained stochastic MPC of greenhouse production systems with parametric uncertainty

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ABSTRACT

Greenhouse climate control is important to provide sufficient fresh food for the growing population in an economical and sustainable manner. However, the developed crop-climate models are generally complex with parametric uncertainties and far from describing the real system accurately, which affects adversely the control system's performance. To improve optimality and guarantee robustness during the control process, we develop and implement a stochastic model predictive control (MPC) scheme for greenhouse production systems considering parametric uncertainties. By leveraging the advantages of model linearization, the proposed chance-constrained MPC method enables a more straightforward formulation of uncertainty constraints and computationally cheaper optimization in comparison to directly using the nonlinear model. Finally, the efficacy of the proposed approach is demonstrated on a greenhouse climate control case study.

1. Introduction

Maintaining an appropriate growing climate to achieve optimal, economical and sustainable objectives is a major control problem in modern greenhouses (Chen et al., 2020). The performance of control systems rely on various environmental parameters, such as temperature, humidity, carbon dioxide levels, and photosynthetic radiation, etc., which define the desired environment. However, arising from environmental variations and sensor inaccuracies, parametric uncertainties can induce inaccurate control actions that may have a negative impact on the plant growth, development, and overall yield as shown in Van Henten (2003). In other words, when uncertainties are not properly accounted for, the control system may overcompensate or respond inadequately, resulting in energy wastage or suboptimal resource utilization. Hence, taking these parametric uncertainties into account becomes a critical issue when designing controllers for greenhouse production systems.

In the context of greenhouse climate control, various control methods have been proposed in the literature, such as the latest one contributed by Liu et al. (2023). A well-known practical control strategy is to maintain the ideal growing climate near steady levels via on-off rule-based control logic or PID controllers. However, these classic approaches lack the ability to effectively cope with the complex dynamics of greenhouse systems with multiple inputs multiple outputs, see e.g., Hamza et al. (2019), Lafont et al. (2013) and Wang et al. (2013). Despite the developments of the PID control to the multiple inputs and multiple outputs (MIMO) systems, see e.g., Vázquez and Morilla (2002), Astrom et al. (2001) and Saab (2017), it is still challenging to apply the PID control to greenhouse systems, since we need to consider the interactions between multiple inputs and outputs in the system with various constraints, which may require substantial tuning efforts for PID controllers. Furthermore, we need to seek for the trade-offs between different control objectives, such as disturbance rejection, setpoint tracking, and loop interaction. Balancing these objectives can also be difficult for the PID control. In contrast, model predictive control (MPC) has emerged and gained popularity as an appealing approach for multivariable constrained control, which is then implemented to support the operation of greenhouse production since the late nineties (Boodley, 1996; Blasco et al., 2007; Gruber et al., 2011; Montoya et al., 2016; Ito, 2012; Wang et al., 2008; Maciejowski, 2002; Kircher and Zhang, 2016). Despite advancements in climate control applications in greenhouses, the majority of them still operate under the assumption of complete knowledge about model parameters as in van Henten (1994), Blasco et al. (2007) and Ding et al. (2018). However, it is important to acknowledge that climate control models, specifically those concerning the interaction between crops and indoor climate, rarely align precisely with the actual dynamics due to parametric errors

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and other uncertain disturbances. Consequently, there is a need to adapt control actions to effectively handle and mitigate the impact of uncertainty in the models. While MPC provides a level of robustness to parameter uncertainties thanks to its receding-horizon implementation, its deterministic formulation often makes it insufficient for effectively handling uncertainties in the crop-climate model. This may degrade the performance of the control system as discussed in Fesharaki et al. (2017). Furthermore, considering that many farmers have contractual obligations for product delivery, having realistic expectations regarding production rates is crucial for them, as well as for the market and consumers. Given these factors, robustly formulating a control problem using MPC in the presence of parametric uncertainties becomes an essential yet complex challenge (Schaal and Christopher, 2010).

The existing literature on MPC control applied in greenhouse climate control shows limited efforts in effectively handling uncertainties, especially parametric errors. For example, in a study (Chen et al., 2020), a data-driven robust MPC approach is proposed to control temperature using historical data, but it primarily focused on external uncertainties related to weather prediction and did not account for parametric uncertainties. Another approach presented in Hamza et al. (2019) considers parametric uncertainties through fuzzy MPC design with simplified bounded constraints, but it lacked proper formulation and propagation of these uncertainties. Similarly, a PSO-based robust MPC is proposed in Xu and van Willegenburg (2018) for greenhouse climate control to address various uncertainties using an additive bounded disturbance, while explicit formulation of parametric uncertainty was not included. The authors in Gonzalez et al. (2013) and Boersma et al. (2022) developed a tube-based robust MPC for linear and nonlinear greenhouse climate control, respectively. These robust approaches tend to be conservative and stochastic approaches are favorable in this application. At last, Piñón et al. (2001) considers a nonlinear robust MPC. However, these approaches did not account for the physical constraints of the actuators in the greenhouse, which may lose the guarantee on the practical performance of the control system.

In this paper, we aim to bridge this gap through developing a stochastic MPC control scheme to explicitly address parametric errors lie within crop-climate model of greenhouse production system using chance constraints via explicit formulation and propagation of parametric uncertainty. This proposed control scheme will be able to optimize greenhouse production with robustness while having parametric errors in crop-climate model for real-life application. More precisely, this work focuses on the stochastic MPC approach for the control of greenhouse production systems. As the crop-climate model of greenhouse is mostly nonlinear, to reduce the computational cost of applying CC-MPC, model linearization is implemented firstly to the crop-climate model before employing it together with CC-MPC. By leveraging the advantages of linearization, the proposed approach enables a more straightforward uncertainty analysis and computationally cheaper optimization in comparison to directly using the nonlinear model. Specifically, in the proposed approach, a linear model is derived at each time step based on the current operating point of the nonlinear system. Subsequently, uncertain parameters are incorporated into the linear model as additive terms. This linearization simplifies the analysis of uncertainty propagation, allowing for the relatively simple formulations of probabilistic constraints. Additionally, utilizing the linear model instead of the original nonlinear model reduces the computational complexity of the optimization problem, resulting in more efficient computations.

The rest of the paper is organized as follows. Section 2 presents two crop-climate models of greenhouse which are used for control and simulation respectively, with the aim of optimizing the system and then testing the proposed control approach, accordingly. Then Section 3 presents the proposed chance-constrained MPC (CC-MPC) controller with model linearization. The proposed control method is then verified in Section 4 via simulation studies, and finally, conclusions of the this paper are made in Section 5.

Table 1
Meaning of the state $x(t)$, measurement $y(t)$, control signal $u(t)$ and disturbance $d(t)$.

$x_{dw}(t)$	Dry-weight (kg/m^2)	$y_{dw}(t)$	Dry-weight (g/m^2)
$x_{CO_2}(t)$	Indoor CO_2 (kg/m^3)	$y_{CO_2}(t)$	Indoor CO_2 (ppm)
$x_{temp}(t)$	Indoor temperature (deg°)	$y_{temp}(t)$	Indoor temperature (deg°)
$x_{hum}(t)$	Indoor humidity (kg/m^3)	$y_{hum}(t)$	Indoor humidity (%)
		$d_{rad}(t)$	Radiation (W/m^2)
$u_{CO_2}(t)$	CO_2 injection (mg/m^2/s)	$d_{CO_2}(t)$	Outdoor CO_2 (kg/m^3)
$u_{ven}(t)$	Ventilation (mm/s)	$d_{temp}(t)$	Outdoor temperature (deg°)
$u_{heat}(t)$	Heating (W/m^2)	$d_{hum}(t)$	Outdoor humidity (kg/m^3)

2. Crop and climate models

This section introduces two crop-climate models to describe the indoor climate in greenhouse, among which, one model which is nonlinear with high fidelity of the system is used for simulation and another simplified linearized model is used for control development. The simulation model, which will be used to validate the proposed controller, is firstly introduced in this section. Afterwards, the control model, which is used to generate the optimized control signals under defined control objectives, is also presented. Lettuce is selected as the crop in this research.

2.1. Nonlinear crop-climate simulation model

The indoor crop (lettuce) and climate simulation model that is used in this research is originally from van Henten (1994) and then formulated using the following state-space formulation:

$$\begin{aligned} \frac{\mathrm{d}x}{\mathrm{d}t} &= f_c\big(x(t), u(t), d(t), p\big), \\ y(t) &= g\big(x(t), p\big), \end{aligned} \tag{1}$$

with continuous time $t \in \mathbb{R}$, state $x(t) \in \mathbb{R}^4$, measurement $y(t) \in \mathbb{R}^4$, control signal $u(t) \in \mathbb{R}^3$, (weather) disturbance $d(t) \in \mathbb{R}^4$, parameter $p \in \mathbb{R}^{28}$ and nonlinear functions $f_c(\cdot), g(\cdot)$. These are defined in Appendix. Table 1 shows the meaning of the signals.

Fig. 1 depicts a schematic of the employed lettuce greenhouse model.

In order to solve the state-space formulation at (1), a numerical integration method is used. Based on which, the discretized version of (1) is defined as:

$$\begin{aligned} x(k+1) &= f\big(x(k), u(k), d(k), p\big), \\ y(k) &= g\big(x(k), p\big), \end{aligned} \tag{2}$$

with discrete time $k \in \mathbb{Z}^{0+}$. The explicit fourth order Runge Kutta integration method is used with sample period $h = t/k$.

2.2. Linear crop-climate control model

As CC-MPC involves lots of probabilistic natures during uncertainty propagations, a linearized model is developed for control purpose. The controller demanded linear model is built through approximating (1) in a region around an operating point $(\bar{x}, \bar{u}, \bar{d}, \bar{y})$. To represent the linearized model, new variables are defined that are centered around the operating point:

$$\begin{aligned} \Delta x(t) &= x(t) - \bar{x}, & \Delta u(t) &= u(t) - \bar{u}, \\ \Delta d(t) &= d(t) - \bar{d}, & \Delta y(t) &= y(t) - \bar{y}. \end{aligned} \tag{3}$$

Furthermore, we also incorporate the uncertainty of the parameters p in the linear model. Assume that the parameters follow a distributions with the mean value at $\bar{p}$, and that there is no correlation between any two parameters. Then, the linearized model in terms of the new variables is formulated as

$$\begin{aligned} \frac{\mathrm{d}\Delta x(t)}{\mathrm{d}t} &= A\Delta x(t) + B\Delta u(t) + E\Delta d(t) + F\Delta p(t), \\ \Delta y(t) &= C\Delta x(t), \end{aligned} \tag{4}$$

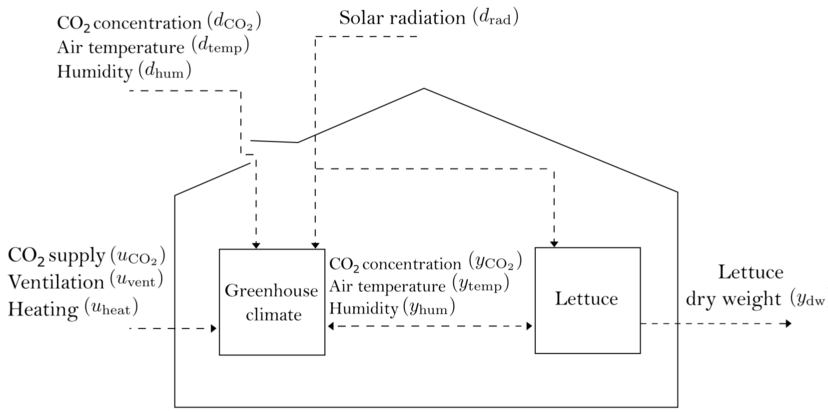

Fig. 1. Illustration of the employed lettuce greenhouse model, with the arrows indicating the dynamical interaction between the submodels. The control signal $u(t)$ and disturbance $d(t)$ are inputs that influence the measurement $y(t)$.

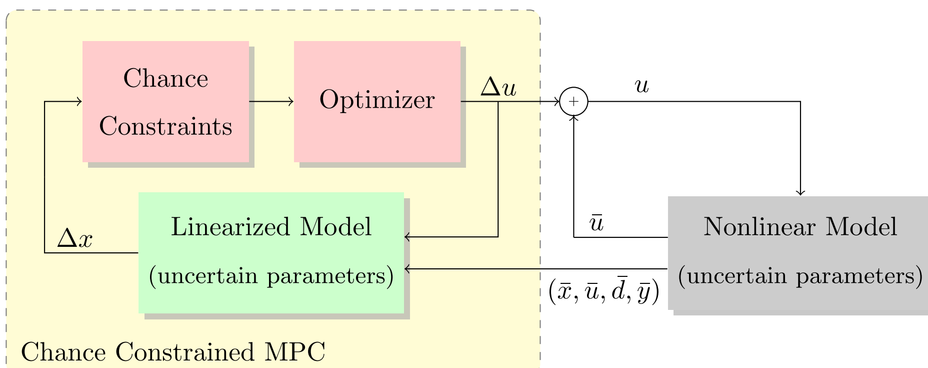

Fig. 2. Diagram of the chance constrained MPC.

where $\Delta p(t) := p(t) - \bar{p}$, and

$$A := \frac{\partial f_c}{\partial x}(\bar{x}, \bar{u}, \bar{d}, \bar{p}), \;\; B := \frac{\partial f_c}{\partial u}(\bar{x}, \bar{u}, \bar{d}, \bar{p}),$$

$$E := \frac{\partial f_c}{\partial d}(\bar{x}, \bar{u}, \bar{d}, \bar{p}), \quad F = \frac{\partial f_c}{\partial p}(\bar{x}, \bar{u}, \bar{d}, \bar{p}), \; C := \frac{\partial g}{\partial x}(\bar{x}, \bar{p}).$$

The controller model (4) is also discretized using the Runge Kutta integration method.

3. Chance constrained linear model predictive control

The parameters of any application systems, including the greenhouse production system, are in practice never exactly known. Therefore, it is necessary to take the uncertainty of model parameters into account with the controller. In addition, as we will use linearized model for CC-MPC control purpose, the linearization will also introduces modeling errors. These errors produced during the linearization process, will be considered as part of the uncertainty of the model parameters.

Therefore, the following controller takes both these uncertainties into account, via incorporating chance-constrained MPC (CC-MPC) discussed in Kouvaritakis and Cannon (2016), Svensen et al. (2021) and Schwarm and Nikolaou (1999). It is assumed that the parameters follow a distribution F, which (1) is preserved under summation and (2) has a possible bounded span of $[a, b]$, e.g., truncated Gaussian distribution. The overall diagram of the proposed method is shown in Fig. 2.

Moreover, this work assumes full knowledge of the parameter distributions.

3.1. Optimization problem

To anchor the MPC to the application and making sure that it keeps track of the nonlinear behavior, the controller linearizes the nonlinear model at every sample. The CC-MPC will then be updated at each sample by using the newly linearized model. This linear model is defined as:

$$\begin{aligned}
&\min_{u(k)} \; \mathbb{E}\left[\sum_{k=k_0}^{k_0+N_p} V\big(\Delta u(k), \Delta y(k)\big)\right], \\
\text{s.t.} \quad & \Delta x(k+1) = A_{k_0}\Delta x(k) + B_{k_0}\Delta u(k) + E_{k_0}\Delta d(k) + F_{k_0}\Delta p \\
& \Delta y(k) = C_{k_0}\Delta x(k), \quad \Delta p_k \sim \mathcal{F}_b^a\big(\Delta\mu_p, \Sigma_p\big) \\
& \Delta u_{\min} \leqslant \Delta u(k) \leqslant \Delta u_{\max}, \\
& |\Delta u(k) - \Delta u(k-1)| \leqslant \delta u, \\
& \mathcal{P}\big(\Delta y(k) \leqslant \Delta y_{\max}(k)\big) \geqslant \beta, \\
& \mathcal{P}\big(\Delta y_{\min}(k) \leqslant \Delta y(k)\big) \geqslant \beta, \quad \text{for } k = k_0, \ldots, k_0 + N_p, \\
& \Delta x(k_0) = x(k_0) - x^*(k_0),
\end{aligned} \tag{5}$$

where A_{k_0}, B_{k_0}, C_{k_0}, E_{k_0} and F_{k_0} are the linear system matrices linearized around the operating point $x(k_0), u(k_0), d(k_0), p(k_0)$. The probabilistic constraints are defined as scalar probabilities; possible without loss of generality as the joint-probability case can be written with scalar constraints and confidence levels β_i chosen to fulfill the joint confidence level β as in Grosso et al. (2014).

3.2. Cost function and constraints

The cost function of the MPC is chosen as the linear cost:

$$\begin{aligned}
\sum_{k=k_0}^{k_0+N_p} V\big(\Delta u(k), \Delta y(k)\big) = {} & -q_{y_{\text{dw}}} \cdot \Delta y_{\text{dw}}(k_0 + N_p) + \cdots \\
& \sum_{i=k_0}^{k_0+N_p} \big(q_{u_{\text{CO}_2}} \quad q_{u_{\text{vent}}} \quad q_{u_{\text{heat}}}\big)\, \Delta u(i),
\end{aligned} \tag{6}$$

with a maximizing terminal cost on the dry-weight $\Delta y_{\text{dw}}(k)$, and minimizing costs on the control signal over the prediction horizon. The relative expensive CO_2 injection $\Delta u_{CO_2}(k)$ is given a higher cost to scale it relative to the ventilation $\Delta u_{\text{vent}}(k)$ and heating $\Delta u_{\text{heat}}(k)$. The exact values are given in the section where the simulation results are presented.

The control signals and measurements are given the following operational limits in the MPC:

$$0 \leqslant \bar{y}_{\text{dw}} + \Delta y_{\text{dw}}(k), \quad k \in k_0 + (1 : N_p), \tag{7a}$$

$$0 \leqslant \bar{y}_{CO_2} + \Delta y_{CO_2}(k) \leq 2.75, \quad k \in k_0 + (1 : N_p), \tag{7b}$$

$$6.5 \leqslant \bar{y}_{\text{temp}} + \Delta y_{\text{temp}}(k) \leq 25, \quad k \in k_0 + (1 : N_p), \tag{7c}$$

$$0 \leqslant \bar{y}_{\text{hum}} + \Delta y_{\text{hum}}(k) \leqslant 70, \quad k \in k_0 + (1 : N_p), \tag{7d}$$

$$0 \leqslant \bar{y}_{\text{dw}} + \Delta u_{CO_2}(k) \leqslant 1.2, \quad k \in k_0 + (1 : N_p), \tag{7e}$$

$$0 \leqslant \bar{y}_{\text{dw}} + \Delta u_{\text{vent}}(k) \leqslant 7.5, \quad k \in k_0 + (1 : N_p), \tag{7f}$$

$$0 \leqslant \bar{y}_{\text{dw}} + \Delta u_{\text{heat}}(k) \leqslant 150, \quad k \in k_0 + (1 : N_p), \tag{7g}$$

$$|\Delta u_{CO_2}(k) - \Delta u_{CO_2}(k-1)| \leq 0.12, \quad k \in k_0 + (1 : N_p), \tag{7h}$$

$$|\Delta u_{\text{vent}}(k) - \Delta u_{\text{vent}}(k-1)| \leq 0.75, \quad k \in k_0 + (1 : N_p), \tag{7i}$$

$$|\Delta u_{\text{heat}}(k) - \Delta u_{\text{heat}}(k-1)| \leqslant 15, \quad k \in k_0 + (1 : N_p). \tag{7j}$$

3.3. Chance-constraint: Probabilistic constraints

The probabilistic constraints in (5) can be formulated in a deterministic form for simpler computation as shown in the following Kouvaritakis and Cannon (2016). For this, we will write the kth step ahead output, input and disturbances for the linear model as:

$$\begin{aligned}
\Delta y(k) &= \Psi_{k,k_0}\Delta x(k_0) + \Theta_{k,k_0} U(k) + \Gamma_{k,k_0} D(k) + \Xi_{k,k_0}\Delta p, \\
U(k) &= \begin{pmatrix}\Delta u(k_0)^T & \dots & \Delta u(k)^T\end{pmatrix}^T, \\
D(k) &= \begin{pmatrix}\Delta d(k_0)^T & \dots & \Delta d(k)^T\end{pmatrix}^T,
\end{aligned} \tag{8}$$

where Ψ_{k,k_0}, Θ_{k,k_0}, Γ_{k,k_0}, and Ξ_{k,k_0} are the matrices of the kth step ahead propagated linear model. For a probabilistic constraint knowing the constraint's distribution is a theoretic requirement; this is obtained from propagation of state, input and parameter distributions. In practise, if a distribution is not known, the Gaussian distribution is typical a qualified guess/approximation based on the central limit theorem, with mean and variance estimated from observations, e.g., an ensemble temperature forecast or parameter measurements.

3.3.1. Truncated distribution

While many probabilistic distributions has unlimited span (includes infinity), e.g. Gaussian, for applications there are always limits on what value something can take. E.g. temperature does not vary hundred degrees from one time to another. As such we need to consider distributions with limited spans, such as truncated distributions as shown in Nadarajah and Kotz (2006). With truncated distributions we can integrate know limits on the distributions to be propagated through the system. Consider a variable X following some non-truncated distribution:

$$\Phi_X(x) = \mathcal{P}\Big(X \leqslant x\Big), \quad X \sim \mathcal{F}(p). \tag{9}$$

If we know the actual variable Y is in the interval a and b, then Y can be formulated as a truncated X by:

$$Y \sim \mathcal{F}_a^b(p), \quad Y = \begin{cases} X, & a \leqslant X \leqslant b, \\ 0, & \text{else.}\end{cases} \tag{10}$$

For probabilistic constraints with truncated distributions, the following approach is used to obtain a non-truncated version of the constraints as discussed in Svensen et al. (2021), as part of obtaining an deterministic form of the constraint.

First, consider the CDF of Y, $\Phi_Y(y)$, for truncated distribution it can be written using CDFs of X as

$$\Phi_Y(y) = \mathcal{P}\Big(Y \leqslant y\Big) = \frac{\mathcal{P}\Big(X \leqslant y\Big) - \mathcal{P}\Big(X \leqslant a\Big)}{\mathcal{P}\Big(X \leqslant b\Big) - \mathcal{P}\Big(X \leqslant b\Big)} = \frac{\Phi_X(y) - \Phi_X(a)}{\Phi_X(b) - \Phi_X(a)}. \tag{11}$$

Utilizing this, the probabilistic constraint of a truncated distribution, can be formulated as:

$$\Phi_Y(y) \geqslant \beta \Leftrightarrow \Phi_X(y) \geqslant \bar{\beta}, \quad \text{with } \bar{\beta} := \Phi_X(a) + \beta(\Phi_X(b) - \Phi_X(a)), \tag{12}$$

providing an updated confidence level for the constraint. In the remaining discussion of this section, it is assumed that the above method is applied to every truncated distribution.

3.3.2. Deterministic constraints

Utilizing the CDF notation $\Phi_X(x) \geqslant \beta$ and it is corresponding quantile function $\Phi_X^{-1}(\beta) \leqslant x$, a deterministic constraint can be formulated for the linear model, consider the upper bound constraint:

$$\begin{aligned}
&\mathcal{P}\Big(\Psi_{k,k_0,i}\hat{x}(k_0) + \Theta_{k,k_0,i}U(k) + \Gamma_{k,k_0,i}D(k) + \Xi_{k,k_0,i}\hat{p} \leqslant \hat{y}_{\max,i}(k)\Big) \geqslant \beta_i \\
&\Leftrightarrow \Theta_{k,k_0,i}U(k) \leqslant \hat{y}_{\max,i}(k) - \Phi^{-1}_{\Psi_{k,k_0,i}\hat{x}(k_0)+\Gamma_{k,k_0,i}D(k)+\Xi_{k,k_0,i}\hat{p}}(\beta_i).
\end{aligned} \tag{13}$$

If we assume that the uncertainty is Gaussian distributed, then the constraint can be simplified to

$$\begin{aligned}
&\Theta_{k,k_0,i}U(k) + \Psi_{k,k_0,i}E\{\Delta x(k_0)\} + \Gamma_{k,k_0,i}E\{D(k)\} + \Xi_{k,k_0,i}E\{\hat{p}\} \\
&\leqslant \hat{y}_{\max,i}(k) - \sqrt{\sigma^2(\Psi_{k,k_0,i}\Delta x(k_0) + \Gamma_{k,k_0,i}D(k) + \Xi_{k,k_0,i}\hat{p})}\Phi^{-1}(\beta_i),
\end{aligned} \tag{14}$$

where $\Phi^{-1}(\beta)$ is the quantile function of the standard Gaussian distribution, and $\sigma^2(x)$ is the variance function. The quantile term can be interpreted as a tightening of the expected constraint.

Using the same approach, the lower bound constraints can be written as deterministic constraint:

$$\begin{aligned}
&\hat{y}_{\min,i}(k) + \sqrt{\sigma^2(\Psi_{k,k_0,i}\hat{x}(k_0) + \Gamma_{k,k_0,i}D(k) + \Xi_{k,k_0,i}\hat{p})}\Phi^{-1}(\beta_i) \\
&\leqslant \Theta_{k,k_0,i}U(k) + \Psi_{k,k_0,i}E\{\hat{x}(k_0)\} + \Gamma_{k,k_0,i}E\{D(k)\} + \Xi_{k,k_0,i}E\{\hat{p}\}.
\end{aligned} \tag{15}$$

The optimization program in (5) can then be formulated in a deterministic form:

$$\begin{aligned}
\min_{u(k)} \;& q_{y_{\text{dw}}} \cdot \mathbb{E}\Big[\Delta y_{\text{dw}}(k_0+N_p)\Big] + \sum_{i=k_0}^{k_0+N_p}\Big(q_{u_{CO_2}} \quad q_{u_{\text{vent}}} \quad q_{u_{\text{heat}}}\Big)\Delta u(i), \\
\text{s.t.} \;& \Delta x(k+1) = A_{k_0}\Delta x(k) + B_{k_0}\Delta u(k) + E_{k_0}\Delta d(k) + F_{k_0}\Delta p \\
& \Delta y(k) = C_{k_0}\Delta x(k), \quad \Delta p_k \sim \mathcal{F}_b^a\Big(\Delta\mu_p, \Sigma_p\Big) \\
& \Delta u_{\min} \leqslant \Delta u(k) \leqslant \Delta u_{\max}, \\
& -\delta u \leqslant \Delta u(k) - \Delta u(k-1) \leqslant \delta u, \quad \text{for } k = k_0, \dots, k_0 + N_p \\
& \hat{y}_{\min,i}(k) + \Omega\Phi^{-1}(\beta_i) \leqslant \Theta_{k,k_0,i}U(k) + \mu \leqslant \hat{y}_{\max,i}(k) - \Omega\Phi^{-1}(\beta_i), \\
& \Delta x(k_0) = x(k_0) - x^*(k_0) \\
& \mu = \Psi_{k,k_0,i}E\{\hat{x}(k_0)\} + \Gamma_{k,k_0,i}E\{D(k)\} + \Xi_{k,k_0,i}E\{\hat{p}\} \\
& \Omega = \sqrt{\sigma^2(\Psi_{k,k_0,i}\hat{x}(k_0) + \Gamma_{k,k_0,i}D(k) + \Xi_{k,k_0,i}\hat{p})},
\end{aligned} \tag{16}$$

4. Simulation results

The real-life weather data $d(k)$ is taken from Kempkes et al. (2014). It is collected during experiments done in the "the Venlow Energy greenhouse" located in Bleiswijk, Holland. The data points are sampled at 5 min and for our application re-sampled to the sample period h. Other settings are presented in Table 2. The weights $q_{y_{\text{dw}}}, q_{u_{CO_2}}, q_{u_{\text{vent}}}$, $q_{u_{\text{heat}}}$ are tuned to get an desired trade-off between yield and energy usage. The prediction horizon N_p is not taken too large so that the controller model stays relatively close to the simulation model.

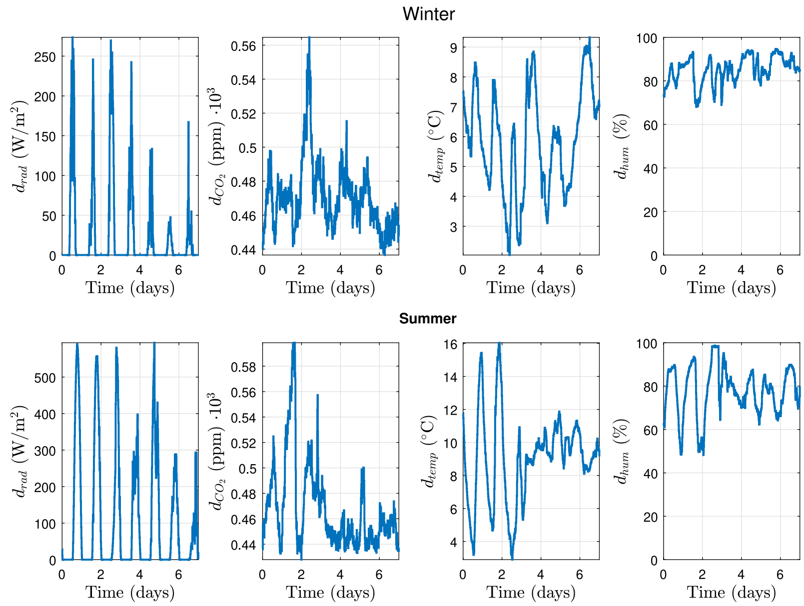

Fig. 3. Disturbances of the two simulation scenarios: winter scenario (first row) and summer scenario (second row).

Table 2
Simulation and controller settings.

Parameter	Value	Parameter	Value
h	15 min	$q_{y_{dw}}$	10^3
N_p	12 h	$\{q_{u_{CO_2}}, q_{u_{vent}}, q_{u_{heat}}\}$	$\{10, 1, 1\}$
N	40 days		

The open-source software CasADi presented in Andersson et al. (2019) and solver IPOPT explained in Wächter and Biegler (2006) are employed in a Matlab environment to solve (5), while following the direct single-shooting method and warm start option of IPOPT.

4.1. MPC performance comparison

To evaluate the proposed controller we utilize deterministic simulations of two scenarios. Fig. 3 show the disturbances affecting the system for the two scenarios. The top row is showing the winter scenario disturbance and the bottom row the summer scenario disturbance, which is a half year later.

Three controllers are used for the comparison: the nonlinear MPC (N-MPC), linear MPC (L-MPC) and the proposed chance-constraint MPC (CC-MPC). They are all given the correct parameters for the model, though the CC-MPC is told to run the constraints at a 80% confidence level, assuming the parameters are uncertain with a standard deviation of 15% and up to 30% error in the parameters. Table 3 shows the computational performances of the controllers. It can be seen that, as expected, the L-MPC compute faster than the other controllers, worst-case being faster than the mean times. For the CC-MPC the mean time is comparable to the N-MPC, while the worst-case is significant lower. The controllers has all comparable success rates in finding a feasible solution, possible indicating the presence of general infeasible solutions in the inputs.

The performances of the controllers has been quantified in Table 4 based on constraint violations. Only three constraints were violated across the controllers and scenarios, the remaining constraints has as such been omitted for clarity as the values are zero.

The control and output of the winter scenario is shown in Figs. 4 and 5 respectively. The CO_2 control of CC-MPC is generally seen to be delayed compared to N-MPC, and slightly less aggressive than L-MPC. For the ventilation and heating, the CC-MPC is seen to have less variation, but a higher mean. For the output, we see that N-MPC has a higher yield after 3 days, the and that CO_2 content is generally comparable with individual spikes for all controllers Generally, the temperature of the CC-MPC is slightly higher as a consequence for lowering the humidity away from the limit of 70%.

The control and output of the summer scenario is shown in Figs. 6 and 7 respectively. Looking at the control, we observed the same comparative behavior between the controllers as the winter scenario. The difference is longer and more frequent periods of inputs and higher amplitudes of the control signals, e.g., doubling the ventilation.

Evaluating the constraint violations in Table 4, we can see the CC-MPC violates the humidity 0.6–1.3% of the time, while it is 50%–52% and for 57%–72% the N-MPC and L-MPC respectively, giving a significantly improvement in constraint guarantees. The temperature constraints are more comparable with only a 1% improvement for CC-MPC in the summer scenario. For the length of violations the pattern repeat with a significant shorter periods. The size of the average humidity violations follows the same pattern, while the worst-case violation are more varied. With L-MPC being less depend on the season, the others improving in the summer time. The CC-MPC giving a clear improvement to the worst-case performance.

To evaluate each controllers dependency on knowing the correct parameter values, the seven day simulation of the winter where performed with a -20% offset on all model parameters. The constraint violations of the controllers were 5.9435% for CC-MPC, 66.2704% for L-MPC, and 56.1664% for N-MPC for the humidity upper limit respectively. For the lower temperature limit the violations were 0.2972% for CC-MPC, 0.4458% for L-MPC, and 0.4458% for N-MPC. We can see the CC-MPC increases a bit in violation percentage for humidity, where the L-MPC and N-MPC are in the same range as before, a bit increase and a bit decrease respectively, but still violating over half the samples. For the temperature, violation percentage decreases for the CC-MPC and is identical for L-MPC and N-MPC. All in all, the CC-MPC still show significant improvement with respect to L-MPC and N-MPC.

5. Conclusions & discussions

In this paper, we have proposed a novel control method for controlling the crop-climate model in greenhouse systems with uncertain parameters. The main procedure is based on the combination of chance constrained MPC with model linearization. The model linearization has

Table 3
Computation results.

	N-MPC		L-MPC		CC-MPC	
	W	S	W	S	W	S
Computation time	18.9523	20.9637	3.7828	4.2445	18.3974	23.9109
Max computation time	90.2651	54.9034	8.3843	6.4323	32.7165	35.2345
Optimization success rate	95.8395%	96.7311%	97.7712%	93.0163%	97.7712%	93.1649%

Table 4
The remaining constraints are excluded as there were no violations.

	N-MPC		L-MPC		CC-MPC	
	W	S	W	S	W	S
Constraint violations rate ($y_{3,max}$) [%]	0	2.6746	0	2.3774	0	1.6345
Constraint violations rate ($y_{3,min}$) [%]	0.4458	0	0.4458	0	0.4458	0
Constraint violations rate ($y_{4,max}$) [%]	51.8574	49.7771	71.7682	56.6122	1.3373	0.5944
avg. violations period ($y_{3,max}$) [samples]	0	0.0275	0	0.0244	0	0.0166
avg. violations period ($y_{3,min}$) [samples]	0.0045	0	0.0045	0	0.0045	0
avg. violations period ($y_{4,max}$) [samples]	1.0743	0.9822	2.5079	1.2955	0.0136	0.0060
max. violations period ($y_{3,max}$) [samples]	0	5	0	5	0	6
max. violations period ($y_{3,min}$) [samples]	3	0	3	0	3	0
max. violations period ($y_{4,max}$) [samples]	11	16	54	29	3	2
avg violation size ($y_{3,max}$) [°C]	0	0.0097	0	0.0175	0	0.0155
avg violation size ($y_{3,min}$) [°C]	−0.0010	0	−0.0008	0	−0.0012	0
avg violation size ($y_{4,max}$) [%]	0.2920	0.2747	0.3042	0.2976	0.0164	0.0101
max violation size ($y_{3,max}$) [°C]	0	0.8841	0	2.3099	0	2.4625
max violation size ($y_{3,min}$) [°C]	−0.3662	0	−0.2894	0	−0.3954	0
max violation size ($y_{4,max}$) [%]	14.1420	4.8998	5.7628	5.8798	4.1899	2.9587

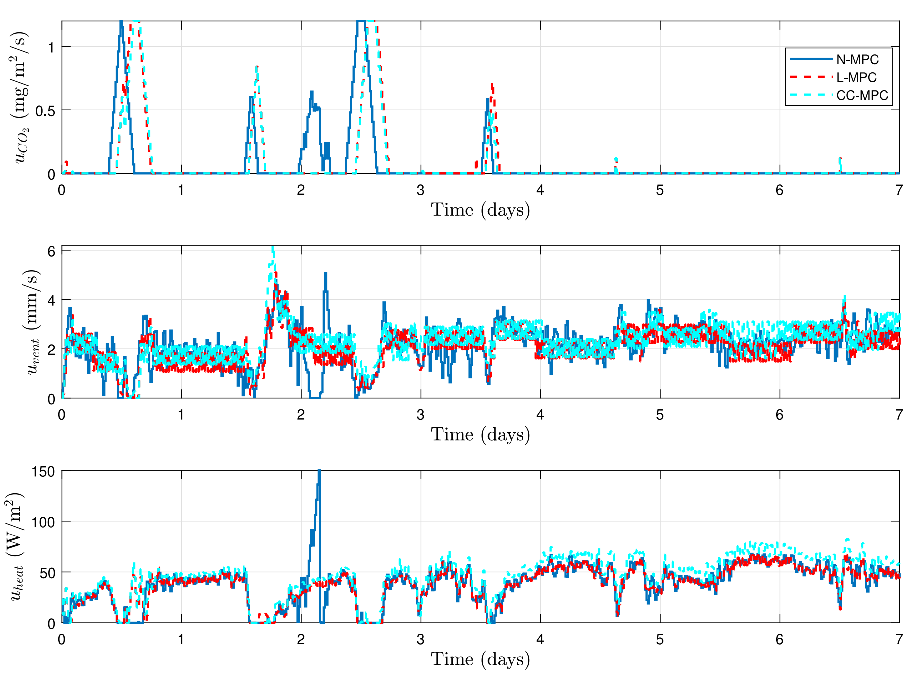

Fig. 4. The control signals for the winter scenario.

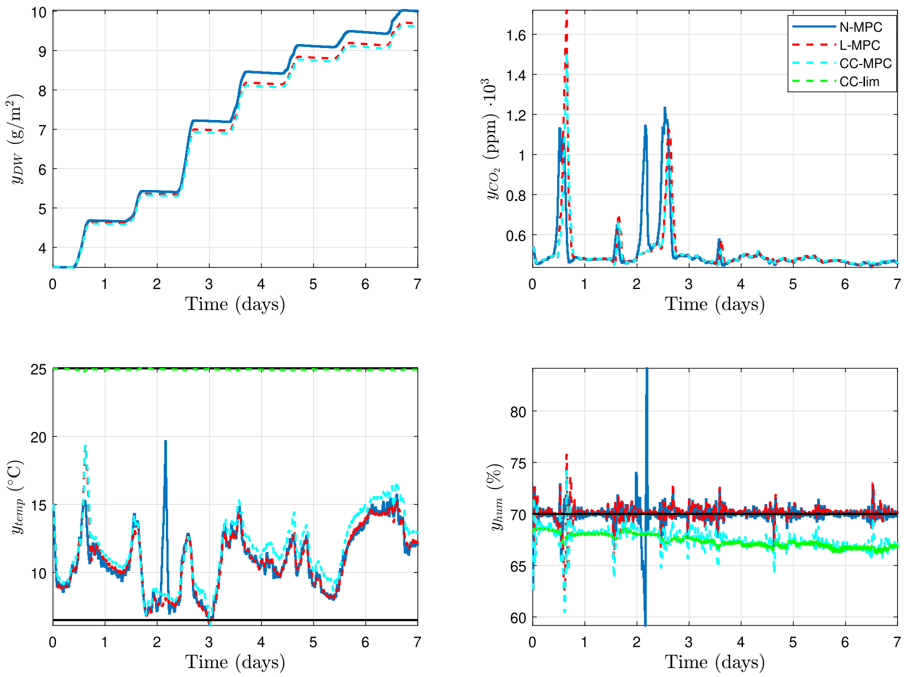

Fig. 5. The output signals for the winter scenario.

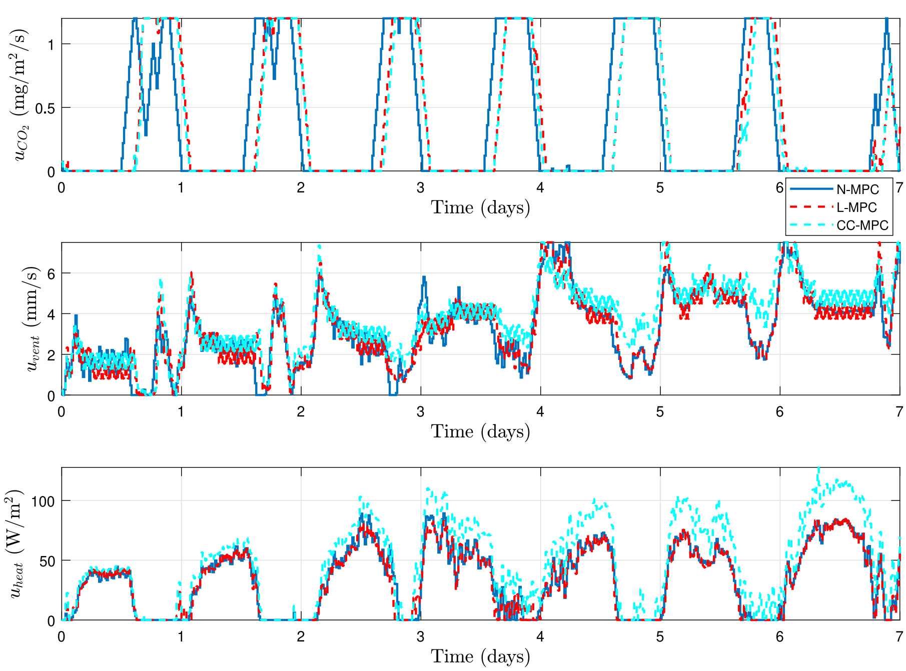

Fig. 6. The control signals for the summer scenario.

shown to be an effective approach to take into account uncertainties in model parameters, allowing for a direct formulation of uncertainties as optimization constraints, and facilitating the optimization procedure. Additionally, using linear models can reduce the computational cost for the optimization, enabling its potential application to large-scale greenhouse models as well. Through a case study on greenhouse control, we have demonstrated the effectiveness of our proposed method.

There are also some interesting observations shown in our simulation results. The control performance of the temperature shows a more robust result compared to that of the other state variables, with regards to uncertainty. This can be attributed to the cascade structure of the system, where temperature is an upstream variable and thereby is unaffected by other state variables such as crop yield and humidity. Stated differently, parametric uncertainties in other state variables do not exert influence over temperature. However, temperature can impact other state variables, and hence the parameter uncertainty in the differential equation of temperature will be propagated to the evolution of the other state variables. Though it also means less effect on robustness from the CC-MPC.

Applying MPC to greenhouse climate control has shown to be feasible in the real horticulture production, see for example, Mahmood et al. (2023) and Jung et al. (2020). This paper introduces a new contribution to the MPC control framework by incorporating the parameter uncertainties in the climate modeling, which enhances the reliability of

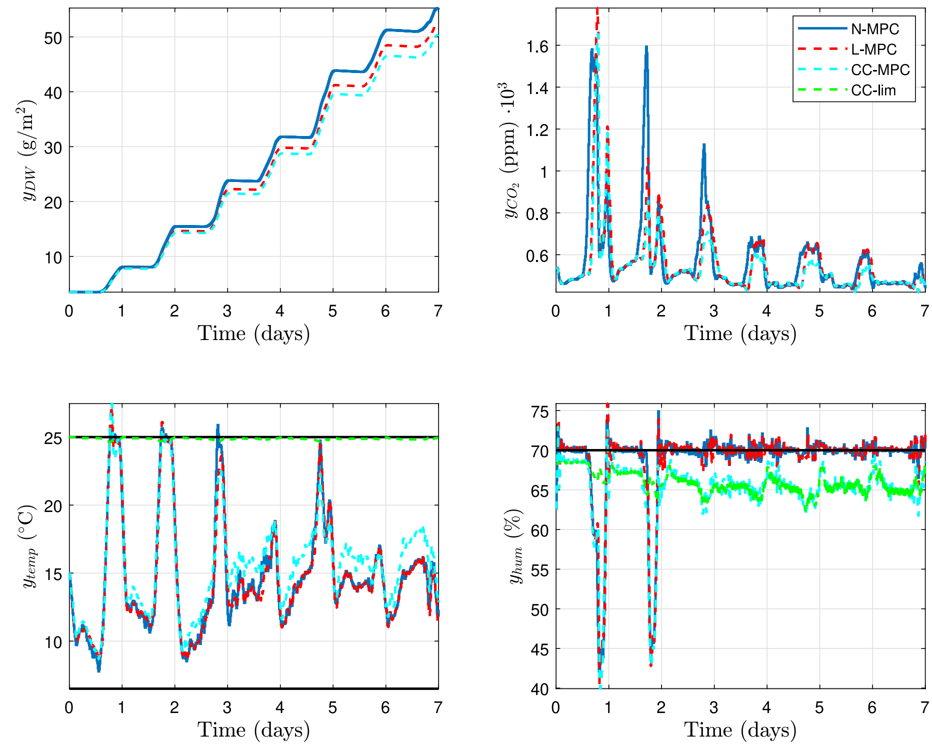

Fig. 7. The output signals for the summer scenario.

our control. Meanwhile, the feasibility of our approach also relies on the climate data and greenhouse climate model, since the controller relies on both elements to make real-time control decisions. As the accessibility of accurate and up-to-date weather data is increasing, and the quality of climate models continues to improve as discussed in van Henten and Bontsema (1991) and Katzin et al. (2022), the proposed method stands to become even more feasible for real-world applications with these ongoing developments.

Some problems for future research remain to be addressed. Within the context of our current result, all parameters are subjected to the same level of stochasticity. In the future, a valuable direction would involve different levels of uncertainty to each parameter and analyze the specific impact of uncertainty on individual parameters.

CRediT authorship contribution statement

Jan Lorenz Svensen: Investigation, Methodology, Resources, Software, Validation, Writing – original draft, Writing – review & editing. **Xiaodong Cheng:** Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Sjoerd Boersma:** Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Congcong Sun:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix. Nonlinear lettuce greenhouse model

The following lettuce greenhouse model is used:

$$\begin{pmatrix} \frac{\mathrm{d}x_{\mathrm{dw}}(t)}{\mathrm{d}t} \\ \frac{\mathrm{d}x_{\mathrm{CO_2}}(t)}{\mathrm{d}t} \\ \frac{\mathrm{d}x_{\mathrm{temp}}(t)}{\mathrm{d}t} \\ \frac{\mathrm{d}x_{\mathrm{hum}}(t)}{\mathrm{d}t} \end{pmatrix} = \underbrace{\begin{pmatrix} p_{1,1}\phi_{\mathrm{phot,c}}(t) - p_{1,2}x_{\mathrm{dw}}(t)2^{x_{\mathrm{temp}}(t)/10-5/2} \\ \frac{1}{p_{2,1}}\left(-\phi_{\mathrm{phot,c}}(t) + p_{2,2}x_{\mathrm{dw}}(t)2^{x_{\mathrm{temp}}(t)/10-5/2} + u_{\mathrm{CO_2}}(t)10^{-6} - \phi_{\mathrm{vent,c}}(t)\right) \\ \frac{1}{p_{3,1}}\left(u_{\mathrm{heat}}(t) - (p_{3,2}u_{\mathrm{vent}}(t)10^{-3} + p_{3,3})(x_{\mathrm{temp}}(t) - d_{\mathrm{temp}}(t)) + p_{3,4}d_{\mathrm{rad}}(t)\right) \\ \frac{1}{p_{4,1}}\left(\phi_{\mathrm{transp,h}}(t) - \phi_{\mathrm{vent,h}}(t)\right) \end{pmatrix}}_{f_{\mathrm{c}}(x(t),u(t),d(t),p)}$$

with

$$\begin{aligned} \phi_{\mathrm{phot,c}}(t) &= \left(1 - \exp\left(-p_{1,3}x_{\mathrm{dw}}(t)\right)\right)\left(p_{1,4}d_{\mathrm{rad}}(t)\left(-p_{1,5}x_{\mathrm{temp}}(t)^2 + \cdots \right.\right. \\ &\quad \left.\left. p_{1,6}x_{\mathrm{temp}}(t) - p_{1,7}\right)\left(x_{\mathrm{CO_2}}(t) - p_{1,8}\right)\right)/\varphi(t), \\ \varphi(t) &= p_{1,4}d_{\mathrm{rad}}(t) + \left(-p_{1,5}x_{\mathrm{temp}}(t)^2 + p_{1,6}x_{\mathrm{temp}}(t) - p_{1,7}\right) \\ &\quad \times \left(x_{\mathrm{CO_2}}(t) - p_{1,8}\right), \\ \phi_{\mathrm{vent,c}}(t) &= \left(u_{\mathrm{vent}}(t)10^{-3} + p_{2,3}\right)\left(x_{\mathrm{CO_2}}(t) - d_{\mathrm{CO_2}}(t)\right), \\ \phi_{\mathrm{vent,h}}(t) &= \left(u_{\mathrm{vent}}(t)10^{-3} + p_{2,3}\right)\left(x_{\mathrm{hum}}(t) - d_{\mathrm{hum}}(t)\right), \\ \phi_{\mathrm{transp,h}}(t) &= p_{4,2}\left(1 - \exp\left(-p_{1,3}x_{\mathrm{dw}}(t)\right)\right) \\ &\quad \left(\frac{p_{4,3}}{p_{4,4}(x_{\mathrm{temp}}(t) + p_{4,5})}\exp\left(\frac{p_{4,6}x_{\mathrm{temp}}(t)}{x_{\mathrm{temp}}(t) + p_{4,7}}\right) - x_{\mathrm{hum}}(t)\right). \end{aligned}$$

Here, $t \in \mathbb{R}$ is the continuous time and $\phi_{\mathrm{phot,c}}(t), \phi_{\mathrm{vent,c}}(t)$, $\phi_{\mathrm{transp,h}}(t)$ and $\phi_{\mathrm{vent,h}}(t)$ are the gross canopy photosynthesis rate, mass exchange of CO_2 through the vents, canopy transpiration and mass exchange of H_2O through the vents, respectively. The following output equation is

Table 5
Values of the model parameters that are taken from van Henten (1994).

Parameter	Value	Parameter	Value	Parameter	Value	Parameter	Value
$p_{1,1}$	0.544	$p_{2,1}$	4.1	$p_{3,1}$	$3\cdot 10^4$	$p_{4,1}$	4.1
$p_{1,2}$	$2.65 \cdot 10^{-7}$	$p_{2,2}$	$4.87 \cdot 10^{-7}$	$p_{3,2}$	1290	$p_{4,2}$	0.0036
$p_{1,3}$	53	$p_{2,3}$	$7.5 \cdot 10^{-6}$	$p_{3,3}$	6.1	$p_{4,3}$	9348
$p_{1,4}$	$3.55 \cdot 10^{-9}$	$p_{2,4}$	8.31	$p_{3,4}$	0.2	$p_{4,4}$	8314
$p_{1,5}$	$5.11 \cdot 10^{-6}$	$p_{2,5}$	273.15			$p_{4,5}$	273.15
$p_{1,6}$	$2.3 \cdot 10^{-4}$	$p_{2,6}$	101 325			$p_{4,6}$	17.4
$p_{1,7}$	$6.29 \cdot 10^{-4}$	$p_{2,7}$	0.044			$p_{4,7}$	239
$p_{1,8}$	$5.2 \cdot 10^{-5}$					$p_{4,8}$	17.269
						$p_{4,9}$	238.3

used:

$$\begin{pmatrix} y_{\mathrm{dw}}(t) \\ y_{\mathrm{CO_2}}(t) \\ y_{\mathrm{temp}}(t) \\ y_{\mathrm{hum}}(t) \end{pmatrix} = \underbrace{\begin{pmatrix} 10^3 x_{\mathrm{dw}}(t) \\ \frac{10^3 p_{2,4}\left(x_{\mathrm{temp}}(t)+p_{2,5}\right)}{p_{2,6}p_{2,7}} \cdot x_{\mathrm{CO_2}}(t) \\ x_{\mathrm{temp}}(t) \\ \frac{10^2 p_{2,4}\left(x_{\mathrm{temp}}(t)+p_{2,5}\right)}{11\cdot\exp\left(\frac{p_{4,8}x_{\mathrm{temp}}(t)}{x_{\mathrm{temp}}(t)+p_{4,9}}\right)} \cdot x_{\mathrm{hum}}(t) \end{pmatrix}}_{g(x(t),p)}$$

The model parameters $p_{i,j}$ are chosen according to van Henten (1994) and given in Table 5.

The above model is discretized using the explicit fourth order Runge–Kutta integration method. Consequently, the discrete-time model is defined as presented in (2). The initial state and control signal are defined as:

$$x(0) = \begin{pmatrix} 0.0035 & 0.001 & 15 & 0.008 \end{pmatrix}^T, \qquad u(0) = \begin{pmatrix} 0 & 0 & 0 \end{pmatrix}^T.$$

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