CHEMICAL ENGINEERING TRANSACTIONS

VOL. 103, 2023

A publication of AIDIC

The Italian Association
of Chemical Engineering
Online at www.cetjournal.it

Guest Editors: Petar S. Varbanov, Panos Seferlis, Yee Van Fan, Athanasios Papadopoulos

ISBN 979-12-81206-02-1; **ISSN** 2283-9216

DOI: 10.3303/CET23103016

Energy Management for Plant Factory with Deep Learning and Predictive Control

Guoqing Hu*, Fengqi You

Cornell University, Ithaca, NY, 14853, USA
gh429@cornell.edu

This study introduces a novel cyber-physical-biological system for energy management and crop production in plant factories. The goal is to minimize energy consumption while maintaining operational efficiency in sustainable food production. The CPBS integrates various control variables, including temperature, humidity, lighting, and CO_2 levels, and accurately captures plant biological dynamics while predicting crop growth within controlled environments. To achieve this, physics-informed deep learning techniques are utilized to develop computationally efficient digital twins of the plant factory's internal microclimate and crop states. By incorporating Artificial Intelligence (AI), the control objectives are fine-tuned to minimize energy usage and resource expenses, ensuring sustainable crop production rates under different daytime scenarios. The results demonstrate an impressive 8.75 % reduction in energy usage compared to alternative control methods, enhancing operational efficiency and promoting sustainability in plant factories. The proposed approach offers a promising solution for achieving sustainable food production with minimized energy consumption in controlled environments.

1. Introduction

Over recent decades, advancements in food production technology have made remarkable progress in addressing the challenges posed by population growth (Engler and Krarti, 2021). One such advanced plant cultivation technology is the plant factory, which promises to ensure sustainable food production by creating optimal growing conditions for crops while requiring less cultivation area (Sannan et al., 2023). Plant factories are controlled environment agriculture (CEA) facilities that provide the ideal growing conditions for the crops. To further enhance crop production, advanced control technologies have been developed and incorporated into the plant factory (Shamshiri et al., 2018). However, the high initial capital investment in the control system for the plant factory poses a challenge to consistent operation. Such high maintenance cost restricts the prevalence of plant factory application in many areas (Kozai, 2013). Due to the requirement of a high density of sensors per unit area, the producers need to allocate many resources for monitoring every aspect of the crop states (Liang et al. 2018). High-fidelity and computationally efficient digital twins of plant factories could help to substantially reduce the budget needs for the sensor installation and improve the control decision for the automatic system. Several plant factory digital twins have been developed to describe the dynamics of these factories. The classification and regression trees algorithm was used to construct a model for predicting temperature parameters within the plant factory (Zhang et al., 2021). Conversely, digital twins for crop growth have also been developed to consider the crop's responses and impact on the dynamics of the CEA facility rather than focusing solely on the microclimate within the facility (de Koning, 1994). A study suggested that 80 % of energy consumption could potentially be reduced if energy and resources are allocated judiciously within the CEA facility (Cuce et al., 2016). Therefore, integrated digital twins of plant factories should be proposed. In today's era of explosive data growth and diverse data types, artificial intelligence (AI) has been developed and employed to refine modeling approaches by improving accuracy and computational capability (Li et al., 2023). However, traditional AI methods, leveraging black-box methods (Ajagekar et al., 2023), fall short of predicting the nonlinear dynamics within the CEA facility due to limited data accessibility in the early stages of crop cultivation (Zaks and Kucharik, 2011). To tackle this challenge, physics-informed deep learning (PIDL) approaches can mitigate this problem by requiring significantly less data.

Paper Received: 04 April 2023; Revised: 22 July 2023; Accepted: 28 July 2023
Please cite this article as: Hu G., You F., 2023, Energy Management for Plant Factory with Deep Learning and Predictive Control, Chemical Engineering Transactions, 103, 91-96 DOI:10.3303/CET23103016

Equally important to high-fidelity digital twins is the optimization of energy management in plant factories (Liu et al., 2023). The primary emphasis for energy management in plant factories is on lighting control, which accounts for 60 % of the factory's energy consumption (Xu et al., 2021). However, not only the lighting, temperature, humidity, and CO_2 control are also essential for maintaining the ideal growing environment for the crop. Rather than focusing solely on one aspect of control efforts, all potential actuators are considered in the plant factory, moving towards a comprehensive cyber-physical-biological system (CPBS) (Hu and You, 2022). There are various optimal control algorithms developed, including proportional-integrated-derivative (PID) control (Kiam Heong et al., 2005), lead-lag control, etc. However, the aforementioned control algorithms can exclusively be adopted for a single-input-single-output (SISO) system, and a plant factory is a multiple-input-multiple-output (MIMO) system, which considers multiple control inputs, such as temperature, humidity, CO_2, lighting control, and multiple output states. Hence, the design of multiple PID controllers and their coordinated functioning should be approached with caution, as the failure of a single PID controller has the potential to jeopardize the functionality of the entire decision-making system. Consequently, model predictive control (MPC) is leveraged in this control framework. MPC is a model-based control strategy that determines the optimal control sequence by solving a sequence of numerical optimization problems with constraints over a specific horizon based on the prediction model. The first input in the optimal sequence is sent into the system, and the entire computation is repetitively performed at subsequent control intervals following a receding horizon approach. MPC stands out as a more suitable approach for optimal control in plant factories due to its MIMO system (Chen et al., 2023) compared to alternative control algorithms. However, the effectiveness of MPC is contingent upon the uncertainties of prediction (Hu and You, 2023). Significant errors in the forecasting model can skew the control results away from the desired constraints. For instance, if there is a large forecast error, the optimal control decisions informed by predictive data might allocate inadequate heating/cooling energy required to uphold ideal growth conditions, resulting in diminished crop yield and quality. To augment resilience to these forecast uncertainties, robust MPC (RMPC) has been introduced, considering uncertain disturbances (Chen and You, 2022). RMPC provides a buffer against forecast uncertainties, but it could potentially yield overly cautious outcomes: excessive leeway might be given to avoid violating constraints. This issue could necessitate additional control efforts (Shang et al., 2019). Therefore, a data-driven RMPC should be proposed to both effectively hedge against the effects of uncertainty while lowering power consumption.

This study introduces an AI-enabled comprehensive and robust control system to optimize energy consumption and crop yield in plant factories. To create a comprehensive control system, Deep learning is employed to estimate a nonlinear dynamic model, considering various energy inputs such as heating, cooling, humidification, dehumidification, ventilation, CO_2 enrichment, and lighting. A versatile approach is designed to calculate separate state-space models (SSM) at each control interval. These individual models were approximated using data from our neural network, capturing diverse conditions during different intervals. Within each interval, a linear representation of the system's states is obtained, ensuring accurate linearization over the nonlinear model. This greatly enhanced the overall robustness and responsiveness of the control system. These specifically computed SSMs served as the basis for decision-making within the MPC framework. For each control interval, the optimal control strategy was determined based on its corresponding SSM, enabling more tailored and adaptive control actions considering the plant factory's microclimate, crop states, and control actuators.

2. Integrating physics and deep learning to the dynamic model for plant factory optimization

Both photosynthesis and respiration processes are considered in this crop model to monitor better the carbohydrate contained within the plants, as these two biological processes are deemed as two of the key factors in describing the plant crops. As one of the bases of plant growth, the photosynthesis process can capture energy from sunlight and convert it into biochemical energy stored within the plant (Evans, 2013). In this study, the process of photosynthesis is modeled. The net photosynthesis rate described in (Farquhar and von Caemmerer, 1982) can be formulated as:

$$M_{c,i,buf} = M_{carb} h_{air,buf} \left(P - R\right) \tag{1}$$

where M_{carb} is the molar mass of CH_2O and $h_{air,buf}$ is the inhibition of the photosynthesis rate by saturation of the leaves with carbohydrates, P is the gross canopy photosynthesis rate, and R is the photorespiration during the photosynthesis process. The inhibition coefficient $h_{air,buf}$ is introduced to describe the scenario when carbohydrate within the buffer reaches the plant’s maximum storage capacity, and P is the gross canopy photosynthesis rate. R is the photorespiration rate described in (Farquhar and von Caemmerer, 1982). Respiration of the plant can release the biochemical energy stored within the plant to support growth, reproduction, and other life processes, and is formulated as follows (Heuvelink, 1996):

$$MC_{org,air} = c_{Org} Q_m^{0.1(T_{can}-25)} C_{org} \left(1 - e^{-c_{RGR} RGR}\right) \tag{2}$$

where c_{Org} is the maintenance respiration coefficient of the plant organ, Q_m is the value for temperature effect on maintenance respiration, C_{Org} is the carbohydrate weight of the plant organ, RGR is the net relative growth rate, and c_{RGR} is the regression coefficient for maintenance respiration. The effects of artificial controls, including the control of temperature, humidity, and lighting, should be studied to enhance the model's accuracy.

The temperature control of indoor climate is one of the key factors for sustaining the crops' lives. The heating model is constructed based on the radiation, convection, and conduction between the nutrition solution, plants, and lighting. The internal air temperature is assumed to be uniform within the cultivation facilities (Vanthoor, 2011). The heating model can be constructed based on the heating transfer equations listed below:

$$\frac{\partial T_i}{\partial t} = \frac{QV_{v,i} + Q_{heat} - Q_{vent} + QT_{st}}{V \rho_i c_i} \tag{3}$$

$$\frac{\partial T_v}{\partial t} = \frac{QR_{l,v} - QT_{st}}{c_v A_v \mu} \tag{4}$$

where V is the volume of the container, ρ is the air density, c_i is the heat capacity of internal air, c_v is the heat capacity of plants, A_v is the plant cultivation area, and μ is the surface density. After the construction of the revised heating model, the water vapor density and CO_2 concentration can be calculated below,

$$\frac{dC_w}{dt} = \frac{\sum \dot{q}_P + \dot{q}_{trans}}{VH_g} + \dot{m}_{hum} - \dot{m}_{dehum} + \dot{m}_{vent} \tag{5}$$

where $\Sigma\dot{q}_P$ is the sum of the energy transfer rate due to the phase change of the water vapor within the cultivation facility, $\dot{m}_{hum}$, $\dot{m}_{dehum}$, $\dot{m}_{vent}$ are water vapor mass flow rate by humidifier, dehumidifier, and ventilation. Finally, the growth rate with respect to the time of the fruit, leaf, and stem can be found as follow:

$$\frac{dR_{fruit}}{dt} = \frac{\left(\frac{dC_{fruit}}{dt}\right)}{C_{fruit}} - R_{fruit} \tag{6}$$

$$\frac{dR_{leaf}}{dt} = \frac{\left(\frac{dC_{leaf}}{dt} + M_{c,leaf,prune}\right)}{C_{leaf}} - R_{leaf} \tag{7}$$

$$\frac{dR_{stem}}{dt} = \frac{\frac{dC_{stem}}{dt}}{C_{stem}} - R_{stem} \tag{8}$$

where R_{fruit} is the relative growth rate of the fruit, R_{leaf} is the relative growth rate of the leaf, and R_{stem} is the relative growth rate of the stem. By formulating these equations, the growth conditions of crops and cultivation environments are numerically and mutually connected. Due to the stiffness of the differential equation for plant factory dynamics, regular integration methods may either fail to accurately predict the states or require tremendous computational power when the step size or the grid size is not properly settled (Nasiri and Dargazany, 2022). PIDL is deemed as one powerful neural network architecture for modeling the cultivation facility's nonlinear dynamics with a small error (Luan et al., 2011). The training dataset is created using the physical differential equations described above. Subsequently, this dataset is utilized to train the PIDL. The training set of integrated function $\hat{x}(u,t)$ and differential function $\hat{\dot{x}}(u,t)$, which both have a sample size of N are initialized for unifying the scale between different states as follows:

$$x(u,t) = \left(\hat{x}(u,t) - \frac{\sum \hat{x}(u,t)}{N}\right) / \sigma_f \tag{9}$$

$$\dot{x}(u,t) = \left(\dot{x}(u,t) - \frac{\sum \dot{x}(u,t)}{N}\right) / \sigma_d \tag{10}$$

where σ_f and σ_d are the standard deviation values of the integrated function training datasets and of the differential function training datasets. Afterward, in order to construct the PIDL for integrating the stiff ODE, the neural network $\bar{x}(u,t,a)$ with the trainable parameters α to integrate the ODE $\dot{x}(u,t)$, (Xiao et al., 2023). Specifically, this neural network is trained within the training dataset. The loss function is defined as (Chen et al., 2023):

$$\Gamma(u,t) = w_f \Gamma_f(u,t) + w_d \Gamma_d(u,t) \tag{11}$$

where Γ_f is the supervised loss term defined as:

$$\Gamma_f = \frac{1}{N}\Sigma\left|\tilde{x}(u,t,\alpha) - x(u,t)\right|^2 \tag{12}$$

and Γ_d is the unsupervised loss term defined as:

$$\Gamma_d(u,t) = \frac{1}{N}\Sigma\left|\dot{x}(u,t,\alpha) - \dot{x}(u,t)\right|^2 \tag{13}$$

and w_f is the weight for the integrated function loss, and w_d is the weight for the differential function loss. The differential function loss is then compared with the differential equations of the plant factory's dynamics proposed earlier. Finally, the predicted values are converted back to the state as follows:

$$\tilde{x}(u,t) = \sigma_f \tilde{x}(u,t,\alpha) + \frac{\Sigma\hat{x}(u,t)}{N} \tag{14}$$

After the PIDL model construction for describing the dynamics within the plant factory, the smart control system needs to be designed to both maximize the power usage efficiency and sustain crop production.

3. Case study for lettuce production in the plant factory under different daytime length

Leafy greens continue to be highly significant crops in the fresh produce market, raising the need for advancements in cultivation technology (Uyttendaele et al., 2016). Among leafy greens, lettuce stands out as a widely cultivated crop in various controlled environment facilities, particularly in plant factories (Shimizu et al., 2011). In response to the demand for improved control systems in plant factories, simulations are conducted to investigate lettuce growth under different durations of daytime scenarios. The purpose of this controlled case study is to regulate the climate within a plant factory, with the primary objectives being energy conservation and maximizing production yield. To achieve these goals, specific constraints have been established as follows: During the daytime, the temperature must not exceed 29 °C, and the lower limit is set at 24 °C. The upper limit for relative humidity during this period is 90 %, while the lower limit is 80 % (Ramírez-Arias et al., 2012). For the dark time, the temperature should not exceed 24 °C, and the lower limit is set at 16 °C. The relative humidity range during this time is defined as 65 % to 75 % (Hamidane et al., 2023). The initial conditions for the study are based on the values: (a) The starting temperature condition for all values is set at 25 °C; (b) The initial relative humidity is settled at 70 %; (c) The initial CO_2 concentration is set to 1,000 ppm.

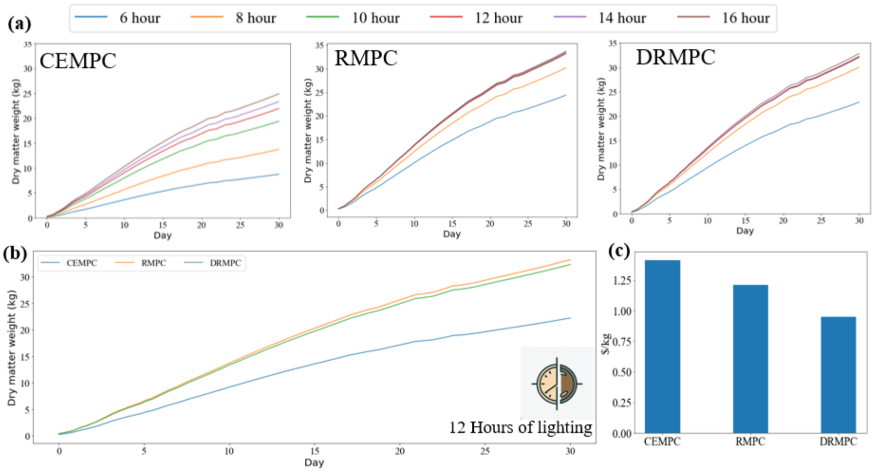

Figure 1: The crop growth under different scenarios. (a) Different control systems crop growth curves under different daytime lengths (6 h, 8 h, 10 h, 12 h, 14 h, 16 h). (b) The crop growth curves of different control systems under the daytime length of 12 h. (c) The cost-to-yield ratio comparison between different control systems

Table 1: The statistical summary of the control systems' performances

	CEMPC	RMPC	DRMPC
Temperature violation (%)	85.41	1.32	2.32
Humidity violation (%)	87.52	1.41	2.67
CO_2 concentration violation (%)	88.42	1.08	2.78
Power consumption ($/m^2)	15.61	18.52	16.33
Water consumption ($/m^2)	4.1	5.3	4.5
Resource consumption ($/m^2)	6.2	7.8	6.9

In this study, a consistent approach is adopted for all MPC frameworks. The prediction horizon is set to encompass six-time steps, and the sampling interval is defined as 15 min. To solve the optimization problems associated with these frameworks, CVXPY is used as the optimization library and utilizes the GUROBI solver. The simulation process is executed on a laptop equipped with an Intel Core i7-11800 H processor operating at a frequency of 2.3 GHz, alongside 16 GB. of RAM. The plant factory undergoes evaluation using three different control strategies: certainty equivalent MPC (CEMPC), robust MPC (RMPC), and data-driven Robust MPC (DRMPC), all aimed at indoor climate control and energy optimization. The control duration spans 30 days, approximately equivalent to the entire crop cycle of lettuce. Regarding the impact of different daytime lengths on lettuce growth suggested in Figure 1, the observed significant production increments when extending the daytime length from 6 to 8 h, 8 to 10 h, and 10 to 12 h indicate the importance of providing adequate light exposure to the crops. This finding aligns with previous research emphasizing the role of light in photosynthesis and crop productivity. However, beyond the 12 h mark, the production increments become less prominent, suggesting diminishing returns in terms of yield improvement. This information can be valuable for growers who aim to optimize their lighting strategies and strike a balance between crop productivity and energy consumption. Table 1 offers a statistical summary of the controllers' performances, providing quantitative metrics to evaluate their effectiveness. Metrics such as production yield, energy consumption, and resource usage can be valuable indicators of control system performance. These statistics enable a comprehensive comparison of the different strategies, aiding decision-making processes for plant factory optimization. It is worth noting that although RMPC achieves a higher production rate compared to the other strategies, the cost-yield ratio displayed in Figure 3c demonstrates that the proposed DRMPC framework emerges as the most profitable option. This finding highlights the significance of incorporating data-driven approaches and considering uncertainties in the control system. By leveraging real-time data and optimizing control objectives based on machine learning techniques, the DRMPC framework maximizes production yield while simultaneously reducing energy and resource requirements. Conversely, CEMPC, despite its lower energy and resource demands, falls short in crop production compared to RMPC and DRMPC due to its failure to account for model uncertainties. The larger violations of temperature, humidity, and CO_2 constraints observed in CEMPC indicate the adverse effects of not considering uncertainties in the control system.

4. Conclusions

This study presented a novel cyber-physical-biological framework tailored for plant factories, addressing the challenges of accurately modeling biological dynamics, optimizing control decisions, and predicting crop growth under varying daylight conditions. Our approach combines PIDL with efficient computational models to achieve these objectives. By leveraging this approach, high-fidelity models were developed that capture the intricate relationships between environmental factors and crop growth, enabling accurate simulation and analysis. Our models are computationally efficient through adaptive linearization feedback, facilitating real-time decision-making and control adjustments. A key aspect is the optimization of control parameters such as temperature, humidity, lighting, and CO_2 levels using artificial intelligence. This AI-driven approach strikes a balance between energy usage, resource expenses, and sustainable crop production rates. To demonstrate the optimal performance of our control framework, extensive simulations compare our AI model with traditional methods (CEMPC and RMPC with box-shaped uncertainty set), showcasing a 10.25 % reduction in simulation time and improved responsiveness to dynamic conditions. Notably, our control framework achieves an 8.75 % reduction in energy usage compared to conventional approaches. By dynamically adjusting environmental conditions based on real-time data and AI-optimized objectives, efficient resource utilization is achieved while maintaining crop production rates. Our framework offers significant economic and environmental benefits for plant factories. Regarding future work, our intention is to expand this method by conducting real-world experiments in order to gather additional data. This will not only enhance the accuracy of the model but also enable us to ascertain the optimal number of samples required for training.

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