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RESEARCH ARTICLE

Real-time Greenhouse Climate Control with Deep Learning

Pham Van Khanh[1], Le Thi Thuy Giang[1], Do Thi Loan[1]

[1] Institute of Information Technology (IIT), Vietnam Academy of Science and Technology (VAST), A3 building, No. 18, Hoang Quoc Viet Street, Nghia Do ward, Cau Giay district, Ha Noi, Vietnam

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***Corresponding Author:**

khanhvietdm@gmail.com

ABSTRACT

This study focuses on the implementation of control strategies based on Nonlinear Model Predictive Control (NMPC) and Deep Neural Networks (DNN) to regulate key environmental variables in greenhouses. The NMPC method is used to optimize these control variables by minimizing a cost function that penalizes deviations of the state variables from their reference trajectories. This involves solving a nonlinear optimization problem at each time step over a finite prediction horizon. The training data generated from the NMPC optimization process is then used to train a DNN, with the goal of estimating the optimal control actions computed by the NMPC. The DNN model is trained using supervised learning, minimizing the mean squared error between the predicted and actual control actions. Once trained, the DNN can make real-time control decisions with significantly reduced computational requirements compared to NMPC. Simulation results are presented to compare the performance of the NMPC and DNN controllers against reference trajectories.

INTRODUCTION

In recent years, greenhouse cultivation has become increasingly important in modern agriculture, providing a controlled environment for high-quality crops to thrive regardless of external weather conditions. The ability to precisely control environmental variables such as temperature, humidity, CO2 concentration, and nutrient levels is crucial for optimizing crop growth, maximizing yield, and improving crop quality. However, effectively managing these variables presents significant challenges due to their complex and nonlinear interactions, as well as the dynamic nature of the greenhouse environment.

Traditional control strategies, such as Proportional-Integral-Derivative (PID) controllers, have been widely used for greenhouse climate control. Although these methods are relatively easy to implement, they often fail to address the highly nonlinear and multivariable nature of greenhouse systems (Searchinger et al, 2019). To overcome these limitations, advanced control strategies like Model Predictive Control (MPC) have been developed. MPC is a robust optimization-based control method capable of handling constrained multivariable control problems, making it suitable for greenhouse climate management (Liu et al, 2023).

Nonlinear Model Predictive Control (NMPC) extends the capabilities of standard MPC by incorporating nonlinear models of the greenhouse environment. This allows for more accurate predictions of system behavior and improved control performance (Hassanien et al, 2016). NMPC optimizes control actions by minimizing a cost function that penalizes deviations from the desired setpoints over a finite prediction horizon. Despite its advantages, NMPC is computationally intensive, making real-time implementation challenging, especially in large-scale greenhouses (Iddio et la, 2020).

To alleviate the computational burden of NMPC, recent research has explored the use of machine learning techniques, particularly Deep Neural Networks (DNNs), to estimate the NMPC control policy (Ren et al, 2022). DNNs have the ability to learn complex mappings from high-dimensional input data to control actions, providing a fast and efficient way to generate control decisions once trained. By leveraging data generated from NMPC simulations, DNNs can be trained to predict optimal control actions, thereby combining the accuracy of NMPC with the real-time efficiency of neural networks (Hu et al, 2011).

This study aims to develop and compare the performance of NMPC- and DNN-based control strategies for greenhouse climate control. The key state variables considered in this study include air temperature, CO2 concentration, absolute humidity, crop biomass, crop temperature, soil moisture, nutrient concentration in irrigation water, and wind speed inside the greenhouse. The control variables include solar radiation, heating, cooling, irrigation, ventilation, fertilization, and humidification (Su et al, 2016).

By integrating advanced control methods with machine learning, this study seeks to enhance the efficiency and performance of greenhouse climate management, ultimately contributing to more sustainable and productive agricultural practices.

The application of advanced control strategies in greenhouse climate management has been extensively studied to enhance crop production and optimize environmental conditions. Traditional control methods such as Proportional-Integral-Derivative (PID) controllers, though popular due to their simplicity, often struggle with the complex nonlinear dynamics of the greenhouse environment (Searchinger et al, 2019). This has led to the exploration of more sophisticated approaches, such as Model Predictive Control (MPC) and its nonlinear variant, Nonlinear Model Predictive Control (NMPC) (Liu et al, 2023).

Model Predictive Control (MPC) in Greenhouses has been widely researched and applied in greenhouse climate control due to its ability to handle multivariable systems and constraints. Van Straten et al. (2009) provided a comprehensive framework for greenhouse climate control using MPC, emphasizing its effectiveness in managing the nonlinear interactions between climate variables. They demonstrated that MPC could significantly improve control performance compared to conventional methods (Hassanien et al, 2016).

In subsequent studies, researchers focused on enhancing the predictive capabilities of MPC by incorporating more detailed models of the greenhouse environment. For example, Gabel et al. (2017) developed an MPC framework that integrated energy balance equations to more accurately predict temperature and humidity dynamics. Their results showed that MPC could maintain more stable climate conditions, thereby promoting better crop growth (Iddio et al, 2020; Al-khresheh et al., 2022).

While linear MPC has proven beneficial, the inherently nonlinear nature of greenhouse systems necessitates the use of NMPC. NMPC can capture the complex nonlinear interactions within the greenhouse, leading to improved control accuracy. Boulard and Wang (2002) implemented NMPC in greenhouse climate control, using a nonlinear model that accounted for both physical and biological processes. Their findings indicated that NMPC outperformed linear MPC in terms of both accuracy and robustness (Ren et al, 2022; Al-khresheh., 2021).

However, the computational demand of NMPC is significantly higher due to the need to solve nonlinear optimization problems in real-time. This limitation has driven research into methods to reduce the computational complexity while retaining the benefits of NMPC (Hu et al, 2011; Jam et al., 2011).

Machine learning, particularly deep learning, has emerged as a promising solution to address the computational challenges of NMPC. Deep Neural Networks (DNNs) can approximate complex functions and have been applied to various control problems. Researchers have explored the use of DNNs to learn control policies derived from NMPC, enabling real-time control decisions with reduced computational effort (Su et al, 2016; Al-Zaqeba et al., 2024).

For example, Parisini et al (2019) proposed a framework in which DNNs were trained to predict control actions computed by NMPC. By leveraging data generated from NMPC simulations, they demonstrated that DNNs could achieve equivalent control performance with significantly lower computational requirements (Van Beveren et al, 2015). Similarly, Lee et al (2020) used reinforcement learning to train neural networks for greenhouse climate control, showing that the learned policies could adapt to changing environmental conditions more effectively than traditional methods (Ram´ırez-Arias et al, 2012).

Recent studies have focused on integrating MPC and machine learning to leverage the strengths of both approaches. The DNN provides quick initial control decisions, while MPC refines these decisions to ensure optimal performance. This integrated approach has shown promise in achieving both high accuracy and computational efficiency (van Ooteghem , 2007).

The research landscape in greenhouse climate control is rich with innovations aimed at enhancing control accuracy and efficiency. While traditional methods like PID controllers are still in use, advanced techniques such as NMPC and machine learning are paving the way for more sophisticated and efficient control strategies. This study builds on these advancements by comparing the performance of NMPC- and DNN-based controllers, aiming to combine the robustness of NMPC with the real-time capabilities of DNNs, thereby offering a practical solution for modern greenhouse management.

The remainder of this paper is structured as follows: section 2 presents the mathematical modeling of the greenhouse environment and the formulation of the NMPC problem. Section 3 describes the process of training the DNN using data generated from NMPC optimizations. Section 4 provides the simulation setup and results, comparing the performance of the NMPC and DNN controllers. Finally, section 5 concludes the study and discusses potential future work in this field.

2. METHODOLOGY

This study aims to compare the performance of Nonlinear Model Predictive Control (NMPC) and Deep Neural Network (DNN)-based control strategies for managing greenhouse climate conditions. The methodology is divided into several key steps: system modeling, NMPC formulation and optimization, DNN training, and simulation for performance evaluation.

2.1. System Modeling

The greenhouse environment is modeled using a set of nonlinear differential equations that describe the dynamics of key state variables. The primary state variables considered are:

T: Air temperature in the greenhouse $(°C)$.

C: CO_2 concentration in the greenhouse (ppm).

H_a : Absolute humidity of the air (kg / m^3) .

B : Crop biomass (kg / m^2) .

T_{crop} : Crop temperature $\left(^{\circ}C\right)$.

H_{soil} : Soil humidity.

$N_{nutrient}$: Nutrient concentration in irrigation water.

V_{wind} : Wind speed inside the greenhouse.

The control variables are:

Q_{sun} : Solar radiation.

Q_{heat} : Heating.

Q_{cool} : Cooling.

$Q_{irrigation}$: Irrigation.

$Q_{ventilation}$: Ventilation.

$Q_{fertilization}$: Fertilization.

$Q_{humidification}$: Humidification.

The system dynamics are defined by the following equations:

$$T(t+1) = T(t) + \Delta_t . \frac{Q_{sun} + Q_{heat} - Q_{cool}}{c_{p\_ga}} \tag{1}$$

$$C(t+1) = C(t) + \Delta_t . \frac{k_{CO_2}}{k_{sa}} .(\phi_{CO_2} .T) \tag{2}$$

$$H_a(t+1) = H_a(t) + \Delta_t . \frac{k_{CO_2}}{k_{sa}} .(\phi_{CO_2} - C) \tag{3}$$

$$B(t+1) = B(t) + \Delta_t . \frac{k_{CO_2} .\phi_{CO_2} .T}{k_{sa}} \tag{4}$$

$$T_{crop}(t+1) = T_{crop}(t) + \Delta_t .(Q_{heat} - Q_{cool} - Q_{ventilation}) \tag{5}$$

$$H_{soil}(t+1) = H_{soil}(t) + \Delta_t .Q_{irrigation} \tag{6}$$

$$N_{nutrient}(t+1) = N_{nutrient}(t) + \Delta_t .Q_{fertilizatiom} \tag{7}$$

$$V_{wind}(t+1) = V_{\mathrm{wind}}(t) + \Delta_t .Q_{ventilation} \tag{8}$$

2.2. NMPC Formulation and Optimization

The NMPC problem is formulated to minimize a cost function over a finite prediction horizon NNN. The cost function penalizes deviations of the state variables from their reference trajectories and the control variables from their reference values. The cost function $J_c(u)$ is defined as:

$$J_c(u) = \sum_{i=0}^{N-1} \left[(x(i) - x_{ref})^T Q (x(i) - x_{ref}) + (u(i) - u_{ref}) \right] + (x(N) - x_{ref})^T P (x(N) - x_{ref}) \tag{9}$$

Where:

$x(i)$: State vector at time step i .

x_{ref} : Reference state vector.

$u(i)$: Control vector at time step i .

u_{ref} : Reference control vector.

Q, R, P : Weighting matrices,

The optimization problem is solved at each time step to obtain the optimal control actions u^* :

$$u^* = \arg\min_u J_c(u). \tag{10}$$

3. DNN Training

To reduce the computational burden of solving the NMPC optimization problem in real-time, a Deep Neural Network (DNN) is trained to estimate the NMPC control policy. The DNN is trained using data generated from NMPC simulations. The training process includes the following steps:

Data Generation: Create a dataset by running NMPC simulations and recording the state variables and control variables.

Model Architecture: Design a multi-layer DNN to map state variables to control variables.

Training: Train the DNN to minimize the Mean Squared Error (MSE) between the predicted control actions and the NMPC control actions:

$$\min_{\Theta} \frac{1}{N_D} \sum_{i=1}^{N_D} (u_{DNN}(x_i; \Theta) - u_i)^2 \tag{11}$$

where Θ represents the DNN parameters, N_D is the number of training samples, x_i is the state vector, and u_i is the control vector from NMPC.

The performance of both the NMPC and DNN controllers is evaluated through simulation. The evaluation process includes:

Simulation Setup: Initialize the state variables and set reference trajectories for the simulation period.

NMPC Simulation: Run the NMPC controller and record the state variables and control variables.

DNN Simulation: Run the DNN controller and record the state variables and control variables.

Comparison: Compare the performance of the NMPC and DNN controllers in terms of tracking accuracy and computational efficiency. The results are visualized through graphs showing the trajectories of state variables under both control strategies.

By following this methodology, the study aims to demonstrate the feasibility of using DNNs to approximate NMPC for real-time greenhouse climate control, thereby achieving a balance between control performance and computational efficiency.

NMPC Algorithm Flowchart

Step 1. Initialization:

Initial state x(0)

Initial values for control variables u(0)

Model parameters and weight matrices Q,R,P

Step 2. Prediction:

Use the nonlinear dynamic model to predict future states $x(t+1), x(t+2), \ldots x(t+N)$ based on u(0), u(1),...u(N-1)

Step 3. Cost Function Calculation:

Define the cost function $J_c(u)$

Include constraints and weightings Q,R,P

Step 4. Solve Optimization Problem:

Use an optimization algorithm (e.g., SLSQP) to find the sequence of optimal control variables u^* that minimize the cost function $u^* = \arg\min_u J_c(u)$

Step 5. Apply Control Variable:

Apply the first control variable in the sequence u(t) to the system

Step 6. Update State:

Update the system's state $x(t+1) = (x(t), u(0))$

Step 7. Iterate the Process:

Shift the prediction window to the next time step and repeat from Step 2

Step 8. Simulation and Evaluation:

Perform simulations to evaluate the NMPC algorithm’s performance

Record and analyze the results.

4. SIMULATION AND RESULTS

As discussed in the previous sections, we use a two-level hierarchical control strategy to first create realistic reference trajectories for the inputs and states, and then track them using a DNN. The OCP problem (11) is solved with input constraints $0 \le u \le 1$ and soft constraints on the state variables, with x_{min}=[18, 500, 60] and x_{max}=[26, 900, 90]. Constraints on the state C′ are often relaxed in units of ppm. Additionally, the hard constraint set X is defined as follows:

X=[14,30]×[300,1000]×[10,100]×[0,100]

Now, the above OCP problem is solved with a sampling time of Δt_0=300s over a single day with T=86400s, resulting in N_0=288 samples. On the other hand, the NMPC is solved every 300s with Δt_c=60s and a prediction horizon of N=5. The closed-loop gain matrices are chosen as Q=100.I_4, R=I_4 , and P=Q.

4.1. Training the DNN Controller to Track References

To obtain a sufficiently large data matrix D, we consider 8 months of disturbance data during the operation of the greenhouse. This results in 285,000 data pairs, with 80% used for training and the remainder for testing the accuracy of the network. Adam, a stochastic gradient optimization method, is used for training through TensorFlow. The final state value of the previous day is used as the initial condition for the optimization problem and to track the references for the next day.

To solve optimization problems (11) and (12), we use CasADi in conjunction with IPOPT. Furthermore, the nonlinear dynamics are discretized using the collocation method for predictive control implementation, and integrals are computed using the SUNDIALS tool. To provide a good approximation for π_{MPC} in finding the number of parameters N_θ, a random search using KerasTuner has been implemented to determine hyperparameters such as N_h, N_l, and β. The DNN model consists of 5 hidden layers with approximately 4,000 parameters, trained with a batch size of 512 data, a learning rate of 0.001, and occupies less than 14 kB of memory.

4.2. Performance of the DNN Controller

The simulation results comparing the tracking performance of NMPC and DNN against the reference trajectory generated by the upper-level OCP over a day are shown in Figure 1. The initial state vector consists of the real-time state values from the previous day. Both NMPC optimization and DNN inference are performed on a personal computer (PC).

First, note that in both scenarios, the states exceed the soft constraints but adhere to the hard constraints defined by the set X. The CO2 concentration increases during the initial phase of solar radiation and is maintained at this level. Biomass production starts when the temperature reaches around 19°C. It can be observed that both NMPC and DNN are able to track the reference trajectories. Figure 1 shows a comparison of the NMPC and DNN controllers under 10% uncertainty of relative to forecast data. It can be seen that the performance of the DNN is nearly identical to that of the NMPC controller. However, the biomass output of the DNN controller is approximately 1.2497 kg/m², slightly higher than the NMPC's 1.2512 kg/m².

The performance of the controllers was analyzed using the closed-loop cost function $S = V(x(N_s)) - \sum_{i=1}^{L} L(x(i),u(i))$ of greenhouse operation over one day for different levels of uncertainty in disturbance d. Table 1 presents the total operating cost L_i and the final/crop cost VVV of greenhouse operation over one day. With complete knowledge of disturbance ddd, the total net cost using NMPC is lower than that of DNN. However, in the presence of uncertainty in d, DNN outperforms NMPC.

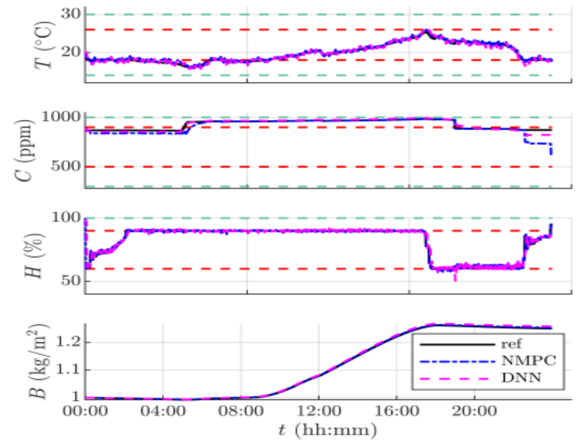

Fig. 1 Comparison of the convergence of states in NMPCvs. DNN under 10% uncertainty of d **with respect to forecast data. The red and green dashed lines indicate the soft and hard constraints of the states respectively. The hard constraint lower bound of RH – 10% is not shown here.**

5. CONCLUSION

This study successfully implemented a hierarchical control system based on Nonlinear Model Predictive Control (NMPC) and Deep Neural Networks (DNN) for greenhouse climate management. Through simulations, we compared the performance of these two methods in controlling key state variables such as temperature, CO2 concentration, humidity, and crop biomass.

The results show that both NMPC and DNN can effectively track the reference trajectory. However, the DNN outperformed NMPC in terms of computational speed, achieving inference times four times faster on a personal computer while maintaining nearly equivalent accuracy. This makes DNN a suitable solution for real-time control applications in large-scale greenhouse environments where computational demands are a challenge.

Moreover, the DNN's ability to accurately estimate under uncertain disturbance forecasts indicates that it can effectively replace NMPC in many practical situations. With low memory requirements and fast computation times, DNN holds great potential for deployment on low-power embedded devices, saving both energy and costs.

Future work will focus on testing and practically deploying the DNN-based controller on low-cost embedded devices in real greenhouse systems. This will help evaluate the model's applicability under real-world operating conditions and identify further potential optimizations to enhance the control system's performance.

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