

Human-in-the-loop Model Predictive Operation for Energy Efficient HVAC Systems

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ABSTRACT

HVAC systems account for majority of energy consumption in buildings and play a vital role in energy efficiency and occupants' comfort. Efficient control of HVAC systems could reduce energy consumption while maintaining occupants' comfort at an acceptable level. Predictive control strategies that leverage the thermal capacity of buildings have been shown to be an effective approach in decreasing the energy consumption of buildings. One of the conventional methods in representing comfort in the formulation of predictive controllers is to consider a fixed temperature range as a constraint. However, this method does not account for differences in occupants' thermal preferences. Therefore, in this paper, we have compared the performance of two model-predictive controllers in terms of energy consumption and thermal satisfaction: the first one is a conventional controller constrained by a fixed temperature range and the second proposed controller is constrained by information from personal comfort profiles. The controllers were formulated as optimization problems using multivariate regression for predictive modeling and genetic algorithm for optimization. To represent human thermal preferences, probabilistic comfort profiles of occupants were developed by utilizing real-world thermal votes. The performance of these controllers was evaluated in a residential building through EnergyPlus simulations for different multi-occupancy scenarios of one, two, and four occupants. The proposed MPC controller improves thermal satisfaction by 15% while increasing energy consumption by 4% on average.

INTRODUCTION

Efficient control of HVAC systems results in reducing energy consumption and improving occupants' thermal comfort (West, Ward et al. 2014). In the literature, two main paradigms of reactive and predictive control of HVAC systems have been investigated (Shaikh, Nor et al. 2014). In these paradigms, building systems' control logic centers around taking *actions* (e.g., adjusting the thermostat setpoint) according to the *states* (e.g., the indoor temperature) of a system. In the reactive paradigm, control is based on the current state of a building for taking actions. However, in the predictive paradigm, future states of the system are considered in taking an action at the current time. Previous studies have demonstrated the efficacy of the predictive paradigm in reducing cost and energy consumption (Drgoňa, Arroyo et al. 2020). Predictive controllers employ the thermal capacity of buildings by precooling or preheating (Killian and Kozek 2016). To

account for occupants' perspective in the predictive control paradigm, different approaches have been used. The most commonly used approach relies on a fixed temperature range to provide satisfactory thermal conditions. Several examples of this approach could be found in the literature. Hu et al. (2019) have developed a predictive controller for a floor heating system and presumed fixed temperature ranges (20°C to 24°C during off-peak hours and 22°C to 25°C during on-peak hours) as thermal comfort constraints in their model. Huang et al. (2021) have evaluated the sensitivity of model-predictive control (MPC) techniques to different parameters and similarly constrained their MPC formulation with a fixed temperature range from 20°C to 24°C. Alternatively, generalized thermal comfort indices, such as Predicted Mean Vote (PMV) have been adopted in other studies. Examples of using PMV-based constraints in improving energy efficiency through predictive control paradigm could be found in the studies by Yang et al. (2020) and Carli et al. (2020) to name a few.

Studies have shown that occupants have varied ranges of thermal preferences and different levels of sensitivities to temperature variations for different modes of thermal conditioning based on age, gender, and other physiological factors (Liu, Schiavon et al. 2019). Therefore, considering these differences in thermal needs, algorithmic constraints of fixed temperature ranges could potentially result in occupants' discomfort. Relying on generic models, such as the PMV index, could not accurately represent the individual thermal needs as studies have shown (Van Hoof 2008). The advancement of sensors and Information and Communications Technologies, as reflected in modern smart thermostats that are capable of learning user preferences, has paved the way for integration of a more refined representation of occupants' need in the control formulation. Considering varied occupants' characteristics could result in improved energy efficiency and flexibility (Jung and Jazizadeh 2019). Accordingly, in this study, we have compared two MPC formulations with different human-related constraints: (1) an MPC formulation based on the conventional fixed temperature range to account for occupants' comfort, and (2) a proposed MPC framework with the integration of occupants' thermal comfort profiles. These controllers have been formulated as optimization problems, for which the objective function addresses the trade-off between energy consumption and occupants' comfort. We have used genetic algorithm (GA) to solve the optimization problems considering that GA has been widely used for MPC-based optimizations (Shaikh, Nor et al. 2014).

Different methods including white-box, black-box, and grey-box modeling could be used to develop models of building dynamics (Yao and Shekhar 2021). White-box models are physics-based and are developed based on the thermodynamic behavior of major components in a building. These models could be tuned to represent a building's dynamic with high accuracy. White-box models have been used in development and evaluation of HVAC control techniques (Huang, Lin et al. 2021). Black-box models are completely data-driven, and are used to develop a mapping between a number of independent variables and a dependent variable such as energy use in a building. Grey box models rely on a mixture of white-box and black-box models. A lower-fidelity physics-based model of a building is developed and its parameters are identified through data-driven methods. In this paper, using the black-box modeling approach and multivariate linear

regression analysis, we have developed two predictive models for cooling energy use and indoor temperature in a typical residential building for our analysis. Previous studies have shown that black-box models can be effectively used for predicting the thermodynamic behavior of buildings (Yoon, Baldick et al. 2014). Figure 1 shows the framework for the MPC-based controllers in this study including the independent variables used in developing predictive models. To simulate the learning process of thermal comfort profiles, real-world thermal comfort votes and their associated ambient conditions for several occupants have been used. The two controllers have been compared in terms of energy consumption and occupant comfort.

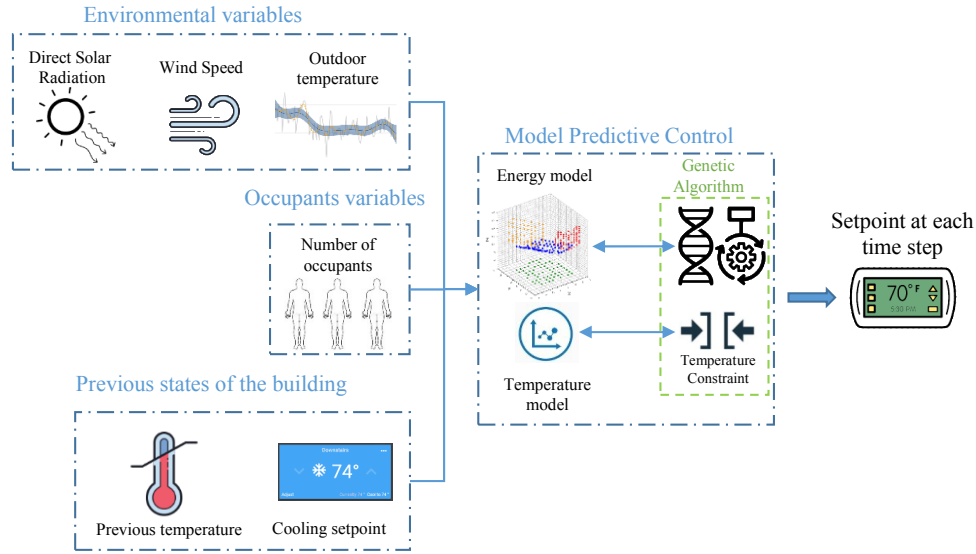


Figure 1 - The main framework for the investigation of MPC-based controllers

METHODOLOGY

In this section, we have described the details of the MPC formulation, the predictive modeling for thermodynamic response of the building, and thermal comfort modeling.

MPC formulation. As noted, MPC-based HVAC operations seek to optimize for energy efficiency over a future prediction horizon. The general MPC formulation, in this study, is as set in the following optimization problem:

$$\begin{aligned} \min \quad & \sum_{t=k}^{t=k+N} E(u_t) + \eta * D(u_t) \\ \text{s. t.} \quad & 20^{\circ}\text{C} \leq u_t \leq 30^{\circ}\text{C} \end{aligned}$$

where E and D denote energy and discomfort, respectively. In this equation, u_t represents an action at time step t . Actions include changes in setpoints that are constrained between 20°C and 30°C and N is the number of time steps on the prediction horizon for identifying an action at the current time step. Given the control logic in residential settings, thermostat setpoints could be effectively used as an action (control) variable as also commonly used in previous studies (Yoon, Baldick et

al. 2016, Ding, Du et al. 2020). The objective function is the summation of energy consumption and occupants' discomfort. Adjusting the value of η changes the trade-off between occupant comfort and energy consumption. For the two controllers in our study, the energy component of the objective function is the same but the discomfort component is different. For the conventional controller based on a fixed temperature range, discomfort at time t due to the action u is defined as follows:

$$D(u_t) = \begin{cases} T_t - 24 & \text{if } T_t > 24 \\ 20 - T_t & \text{if } T_t < 20 \end{cases}$$

where T_t is indoor temperature at time t . Discomfort at time t for the controller is defined based on occupants' comfort profiles as follows:

$$D(u_t) = \text{Thermal Error} = \sum_{occ.} |T_t - TP_{occ.}|$$

where $TP_{occ.}$ is the preferred indoor temperature for each occupant that is learned from their comfort profiles. Thermal comfort profiles are probabilistic distributions of comfort with respect to indoor temperature that are generated from the user-provided data. Therefore, preferred temperature is the temperature with the highest likelihood of comfort. Thermal error is the absolute value of the difference between the room temperature and the preferred indoor temperature for each occupant. The pseudo-code for the MPC is as presented in Figure 2 (a). The controller at time $t = k$ considers the next N steps and calculates the optimal set of actions from $t = k$ to $t = k + N$. It stores the current optimal action (u_t) in U^* and recedes to the next horizon. U^* is the set of optimal actions over the whole simulation process. Figure 2 (b) shows the process of MPC-based operations. As an example, at $t = 0$ and in step 1, the controller calculates the optimal set of actions from time 0 to 5. The optimal action at time 0 (u_0) is stored in U^* and the state (indoor temperature of the building) is updated based on u_0 . This process repeats for the next steps.

We have used 15-min intervals for simulation and control purposes. The prediction horizon was set to $N = 6$ time steps for 90 minutes. The MPC-based operations have been evaluated for August 1st and over 24 hours (96 time steps). For the GA algorithm, the initial population size of chromosomes was 100, mutation probability was 0.1, the crossover probability was 0.5, the parents' portion was 0.3, and the elite ratio was 0.01. The genetic algorithm explores the possible solutions by calculating the best answers at each time step, but it does not guarantee global optimum and might trap into a local optimum (Ramos Ruiz, Lucas Segarra et al. 2018). To address that limitation, we repeated the optimization 50 times to decrease the chance of trapping in local optima. Based on these parameters, the genetic algorithm runs took one minute for each MPC step.

Building dynamics predictive modeling. The building, in this study, is a single-family residential unit from Residential Prototype Building Models developed by Pacific Northwest National Laboratory (PNNL) based on the 2021 International Energy Conservation Code (IECC). The building area is 3565.64 ft² (~330 m²) with two thermal zones of living zone and attic zone. The HVAC system only conditions the living zone. To prepare a dataset for developing the models,

the cooling setpoints were randomly changed and several simulations were run in EnergyPlus to create different scenarios of operation (Hong, Chen et al. 2020).

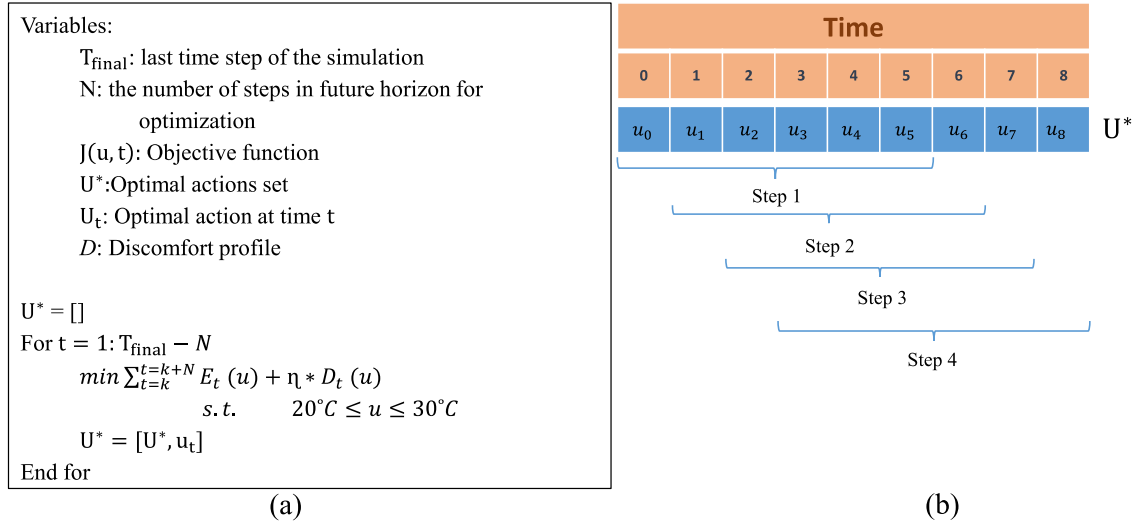


Figure 2 - (a) The pseudo-code for MPC, and (b) the process of MPC-based operations

These simulations were repeated for weather conditions in different geographical locations including Austin, Albuquerque, and Houston to capture a wider range of thermodynamic response of the building (Ding, Du et al. 2020). We only focused on the cooling mode during a warm season for these analyses. A multivariate regression model was developed for prediction of HVAC system's cooling energy at the next time step according to the current state of the building:

$$E(t+1) = -0.101 * T_s(t) + 0.032 * T(t) + 0.029 * T_o(t) + 0.006 * w_s(t) - 0.001 * r_s(t) + 0.001 * occ(t)$$

where T_s , T , and T_o are setpoint, room temperature, and outdoor temperature in $^\circ C$, respectively, and w_s , r_s , and Occ are wind speed (m/s), solar radiation in (W/m^2), and the number of occupants, respectively. The coefficient of determination (R^2) of this model is 0.78. Similarly, a second model for predicting the next time step indoor temperature was developed with an R^2 of 0.92:

$$T(t+1) = 0.53 * T_s(t) + 0.39 * T(t) + 0.05 * T_o(t)$$

Thermal comfort modeling. To simulate the process of learning from interactions of occupants with thermostats, we have adopted a probabilistic comfort profile development approach that relies on thermal votes and their corresponding ambient conditions. The comfort data from (Daum, Haldi et al. 2011) and (Jazizadeh, Ghahramani et al. 2014) were used in this study. The probabilistic comfort profiles are generated by combining probabilistic profiles of being comfortable, uncomfortably warm, and uncomfortably cool by employing Bayesian network modeling. More details of this probabilistic modeling approach could be found in (Jung and Jazizadeh 2019). Figure 3 shows an example profile, in which the preferred temperature is $23.05^\circ C$ (with a 100% likelihood

of being comfortable). As the temperature moves from the preferred temperature, the likelihood of comfort drops with different rates depending on the direction of temperature variation. In this study, in the MPC formulation, we have used thermal error index, which is the difference between temperature at time t and thermal preference for each occupant, which is the temperature with highest probability of comfort. For multi-occupancy scenarios, thermal error has been aggregated across different occupants at each temperature which is noted as $D(u_t)$. The lower values of $D(u_t)$ are associated with higher thermal satisfaction.

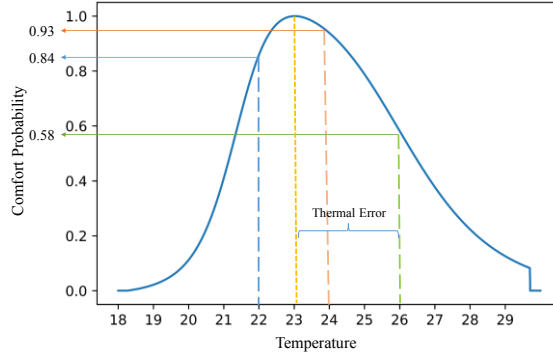


Figure 3 – An example thermal comfort profile for one occupant

Simulation scenarios and evaluation metrics. Fifteen thermal comfort profiles from real-world data have been generated. For one, two and four multi-occupancy scenarios, there are $C(15,1) = 15$, $C(15,2) = 105$ and $C(15,3) = 1365$ different number of combinations, respectively. We randomly selected four sample for each scenario. Upon identification of action vector by using the predictive models, the building performance from these control strategies has been simulated in EnergyPlus. Different scenarios have been compared for their energy usage and total thermal satisfaction. In addition, we have proposed to use Energy Productivity (EP) index that measure how each unit of energy use has contributed to thermal comfort of occupants. The unit of this index is (1/kWh).

$$EP = \frac{\text{Total comfort satisfaction}}{\text{Total energy consumption}}$$

Through a sensitivity analysis for $\eta = [1, 10, 100]$ we set $\eta = 10$ for running the MPC simulations to keep a balance in the trade-off between energy and comfort. Increasing the value of η leads to prioritizing comfort over energy.

RESULTS

Performance analysis of MPC-based operations. The performance of the controllers was evaluated on different multi-occupancy scenarios consisting of one, two, and four occupants for a summer day in Austin, Texas. Figure 4 (a) shows the outdoor temperature, cooling setpoint, and indoor temperature for an example comfort profile on August 1st – the simulated day as a sample

warm day. In this graph, we have used hourly values of each variable. The outdoor temperature started increasing at round 6 am and reaches the peak at 3 pm. Since MPC controllers use future information, precooling of a building starts at around 7 am by decreasing the morning setpoint (as shown in Figure 4 (b)).

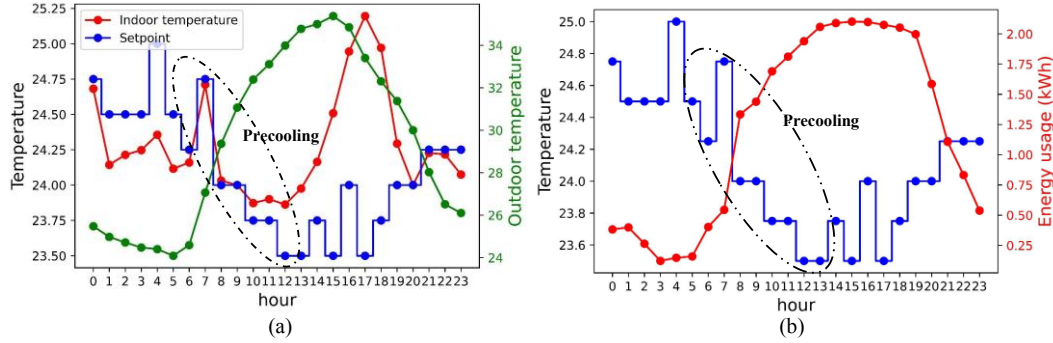


Figure 4 – The MPC results for one human subject (#6) during August 1st

Figure 5 (a) compares the energy usage of the controller with a temperature range from 20°C to 24°C and the proposed MPC controller for two human subjects (#14 and #2) in single occupancy scenarios. The thermal preferences of subjects #14 and #2 are 21.74°C and 24.69°C, respectively (Figure 5 (b)). The total energy usage of the conventional MPC controller and proposed comfort-driven MPC controller for subject #2 and subject #14 were 29.02 kWh, 26.70 kWh and 35.95 kWh, respectively. Higher preferred temperature values results in reduction of energy consumption. In terms of thermal satisfaction, the proposed controller considerably outperforms the conventional controller. In evaluating the comfort consequences of these controllers, we have used average thermal satisfaction during the simulation day. For subject #14, the average thermal satisfaction for the conventional MPC controller was 19, and 73 for the proposed MPC controller. The thermal satisfaction of subject #2 has been increased from 91 for the conventional MPC controller to 97 for the proposed MPC controller. The EP index for subject #14 for the proposed MPC controller is 2.03 (1/ kWh) and for the conventional MPC controller is 0.65 (1/kWh). This index for subject #2 has increased for the proposed MPC controller compared the conventional MPC controller from 3.21 (1/kWh) to 3.63 (1/kWh), respectively. In other words, for both subjects, the proposed controller increases the productivity of the controller. During the peak outdoor temperature from 2 to 5 pm, the energy usage of the conventional MPC controller and the proposed MPC controller were the same. The main reason is that the HVAC system of the building model is for all US regions and we used this model to identify the cooling load of a building during summer time in Austin, Texas that is a hot climate. In this extreme case, the HVAC system uses its maximum capacity to cool down the building and keep an acceptable indoor temperature.

Energy-saving and thermal satisfaction potential. The above examples show the performance variations for occupants with different comfort preferences. To evaluate the overall performance, the average performance from four simulations for different multi-occupancy scenarios were as presented in Table 1. In terms of thermal satisfaction, the proposed MPC controller outperformed

the conventional one in all scenarios. Thermal satisfaction for one-, two-, and four-occupant scenarios has increased by 32%, 7%, and 7%, respectively.

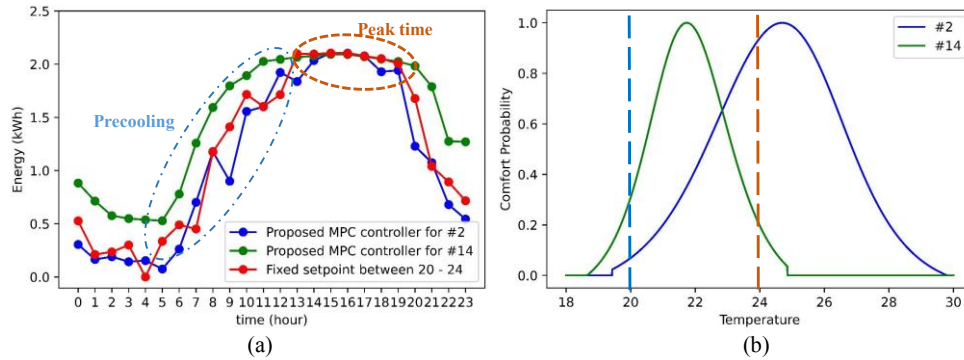


Figure 5 – (a) comparing the energy consumption of the conventional MPC controller (with fixed temperature range) and the proposed MPC controller for subject #14 and #2 (b) Thermal comfort profiles for subject #14 and #2

In terms of energy usage, the conventional MPC controller consumes 29.02 kWh, while the proposed MPC controller have used more energy for scenarios with one and four occupants. In scenarios with two occupants, the energy consumption of the proposed MPC controller is however reduced. Increase in the number of occupants has led to less standard deviation of energy consumption reflecting reduced flexibility in the operations. The EP indices for one, two, and four occupants are as calculated in Table 1. As the EP Index Ratios show the use of comfort-driven MPC has been shown to be more energy efficient compared to the conventional MPC.

Table 1 - Energy consumption and thermal satisfaction for different simulated scenarios

Number of occupants	Energy use – Comfort-driven MPC (kWh) (std)	Thermal satisfaction for proposed MPC (%)	EP Index – Comfort-driven MPC	Thermal satisfaction – Conventional MPC	EP Index – Conventional MPC	EP Index Ratio
1	31.42 (5.06)	86	2.74	65	2.24	1.22
2	28.47 (4.50)	64	2.25	60	2.07	1.09
4	30.73 (1.81)	60	1.95	56	1.93	1.01

In this study, there are a number of limitations that should be addressed in future investigations. We assumed that the residential unit in the simulation is fully occupied. Although this assumption could be valid for some households, future analysis could account for the effect of dynamic occupancy on the performance of MPC controllers. In this paper, we used black-box modeling for updating the state of the system at each time step. Black box models are simple representations of the building and physics-based modeling could be adopted to improve accuracy. Moreover, co-simulation with EnergyPlus at each MPC step could increase the accuracy of the analyses. Finally, using thermal error as the strategy for integrating personal comfort models could limit the benefit from comfort-driven MPC and other more effective techniques could be used to improve the efficiency (Jung and Jazizadeh 2019).

CONCLUSION

In this paper, the performance of two model-predictive controllers (MPC) has been compared. The first controller is constrained by a conventional assumption of comfort in predictive controllers, which is a fixed temperature range. Preferred temperatures from occupants' comfort profiles constrain the second controller that was proposed in this study. Fifteen actual comfort profiles of occupants have been created by using actual thermal votes and used in evaluations of these controllers. Both controllers were formulated as optimization problems. Black-box modeling of a residential building thermodynamic response through multivariate linear regression was adopted for predictive modeling and genetic algorithm was used as the heuristic to optimize the operations. The performance of the controllers were evaluated on different multi-occupancy scenarios consisting of one, two, and four occupants for a summer day in Austin, Texas. In terms of energy consumption, using a controller that fixes setpoint on 23°C consume 34.52 kWh. However, the conventional MPC controller consumes 29.02 kWh and the proposed MPC controller uses 30.20 kWh on average. Thermal satisfaction has been increased by 15% by using the proposed MPC controller over the conventional MPC controller across the multi-occupancy scenarios. In addition, a new index for evaluating energy productivity (EP) has been introduced to measure how each unit of energy use has contributed to thermal comfort of occupants. Our results indicate that the proposed MPC controller has a higher value of energy productivity compared to the conventional MPC controller.

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