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Study of Adaptive Model Predictive Control for Cyber-Physical Home Systems

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Abstract. With the inception of connected devices in smart homes, the need for user adaptive and context-aware systems have been increasing steadily. In this paper, we present an adaptive model predictive control (MPC) based controller for cyber-physical home systems (CPHS) environment. The adaptive MPC controller is integrated into the existing Energy Efficient Thermal Comfort Control (EETCC) system that was developed specifically for the experimental smart house, iHouse. The proposed adaptive MPC is designed in a real time manner for temperature reference tracking scenario where it is evaluated and verified in a CPHS simulation using raw environmental data from the iHouse.

Keywords: adaptive, model predictive control, smart homes, cyber-physical systems

1 Introduction

Recent growth in home automation research affirms the importance on enhancing the quality of life (QoL) in residential and commercial buildings [1–6]. Home automation typically requires key elements such as sensing, actuation and control. These key elements forms the cores of cyber-physical systems (CPS), which justifies its place in smart home environments. One of the active research in smart homes domain are energy efficient thermal comfort, where building architecture, envelop, heating, ventilation and air conditioning (HVAC) and control are within its scope. Model based controls such as model predictive control (MPC) have gained traction throughout the years especially in applications such as thermal comfort control [1, 7, 6]. Some of the advantages of MPC in thermal comfort control application are its capability to apply anticipated control strategies in lieu of corrective strategies while simultaneously handling multiple objectives and constraints. However, model based control normally require expert knowledge of the entire process to design and tune the plant model to accurately represent the actual control plant. Practical implementations of model based control for smart homes are generally unrealistic as every room or building have different thermal and insulation characteristics.

In this paper, the objective is to address presents an adaptive MPC controller for cyber-physical home systems (CPHS) environment. The main goal for this paper is twofold: (i) to implement adaptive MPC based temperature controller for CPHS; and (ii) to implement real time control based on CPS approach. With adaptive model based control, model tuning effort should be reduced significantly as it automatically identify the plant characteristics and tune the controller parameters at runtime. The rest of the paper is organized as follows. Section 2 introduces the background on relevant topics to this paper. The experimental house and its system, adaptive MPC controller and online model estimator details are described in Section 3. Proposed controllers are simulated during autumn season while its results and discussions are presented in Section 4. Finally, some relevant conclusions are summarized in Section 5.

2 Research Background

2.1 Cyber-Physical Home Systems

CPS are described as systems where their physical and computational elements are strictly interlinked together by networking elements [4]. This mechanism is incorporated into smart home environment to form CPHS, where it is comprised of the physical and cyber worlds interlinked together by various communication networks. Sensing and actuating domain are part of the physical world in a CPHS environment while the computing elements such as data storage and supervisory control are part the control domain in the cyber world. One of the implementation of smart homes are the iHouse, which is an advanced experimental smart house, located at Nomi City, Ishikawa prefecture, Japan. It is a conventional two-floor Japanese-styled house featuring more than 300 sensors, home appliances, and electronic house devices that are connected using ECHONET Lite version 1.1 and ECHONET version 3.6 [4]. The EETCC system designed in previous work was based on the CPS approach, where its implementation in the iHouse can be found in [4]. The EETCC system tightly coupled appropriate sensors and actuators together while a state based supervisory controller performs relevant control to maintain the thermal comfort level in a room. The state based supervisory controller is a rule based algorithm those objective is to promote energy efficiency by prioritizing the use of natural resources to maintain the thermal comfort level in a room rather than the use of HVAC. However, this supervisory controller suffers from non-optimal control strategies as it senses the changes in thermal comfort level without anticipating any future events.

3 Adaptive MPC for EETCC System

The control plant in this paper is based on the iHouse, where various types of networked sensors and actuators are linked together to provide the necessary feedback parameters and output controls to the proposed controller. The EETCC system introduced in [4] is used as the CPHS platform, where its architecture is illustrated in Fig. 1. The EETCC system is comprised of three main components: (i) controller; (ii) network and communication; and (iii) plant.

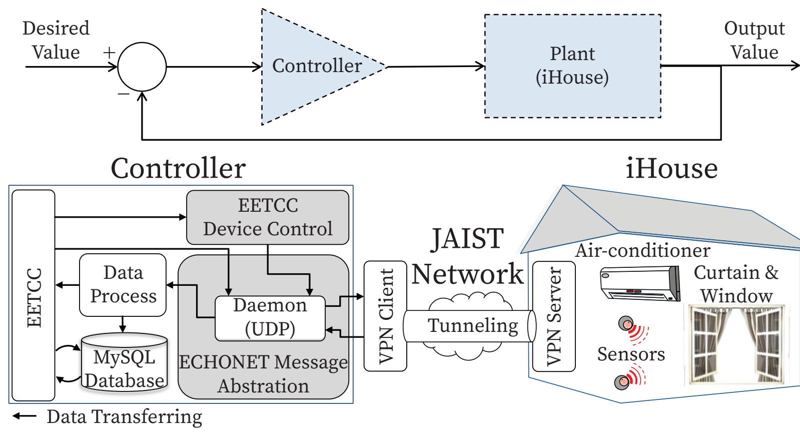

Fig. 1. Architecture of EETCC system.

In this paper, an adaptive MPC is employed as the local level control of the HVAC while the EETCC algorithm introduced in [4] is employed as supervisory level control in the iHouse EETCC system. Proportional Integral (PI) control algorithm is commonly implemented as local level control due to its low requirement for computing resource while supervisory level control are commonly governed by rule-based control (RBC) and optimal control algorithms such as MPC that are resource intensive. An example of such setup can be found in [1]. Advancement in embedded computing allows MPC to be used in local level control that are real time in general.

3.1 Adaptive Model Predictive Control

In this section, an adaptive MPC with online model estimation system is introduced. The plant in this context is the iHouse bedroom, subjected to outdoor environment disturbances as well as HVAC as its input. This is illustrated in Fig. 2. The MPC controller block is comprised of MPC internal plant model and state estimator as its prediction block, and the optimization block that computes input optimization with respect to the imposed cost and constraints.

The thermodynamic characteristics of the plant modeled using heat equations are comprehensively explained in [6]. Since the controller is a discrete MPC, the plant is transformed into a thermal resistor-capacitor (RC) model those form is a discrete state-space model as shown in [6]. Hence, a discrete state-space model can be given by the following equations

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + Wv(k) \\ y(k) &= Cx(k) + v(k) \end{aligned} \tag{1}$$

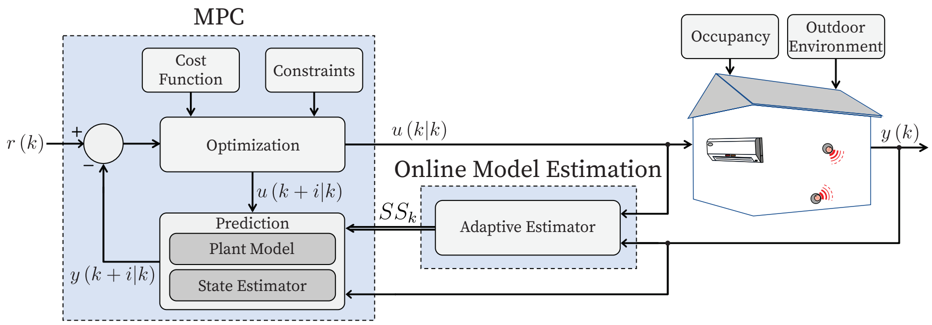

Fig. 2. Adaptive MPC system model.

where x is the state vector, u is the input vector, y is the output vector while A, B, C and W are constant state-space matrices of coefficients. $v(k)$ is the disturbance vector at interval k that is consisted of heat gain from outdoor temperature and solar radiation. The MPC internal plant model in this paper is a simplified plant, which only considers the HVAC input and room temperature output. Outdoor environmental disturbances are excluded from MPC prediction.

The MPC controller and online model estimation block are both in discrete time while the plant is in continuous time. Zero hold order discretization is employed for the inputs and outputs of the EETCC system controller, where the signals are held constant during the sampling period until the next sampling instance. This introduced delay into the system which deteriorates the closed loop performance of non-adaptive MPC controller. Hence, the working of how adaptive MPC with online state estimation can reduce internal model discrepancy as well as managing input delay issues are explained in the following subsections.

State Estimation Besides the internal plant model, state estimation is also one of the components in MPC prediction block. This section briefly describe a general state estimator in a MPC controller, Kalman filter (KF) as well as the linear time varying Kalman filter (LTVKF) state estimator in adaptive MPC. The state estimate of a MPC controller in the MPC toolbox provided by Simulink is described in [8], where the controller internal state estimation at interval k and the updated state estimation at interval $k+1$ are given by

$$x_c(k \mid k) = x_c^{rev}(k \mid k-1) + M_k e(k) \tag{2}$$

$$x_c(k+1 \mid k) = A_c x_c^{rev}(k \mid k-1) + B_u u^{opt}(k) + B_v v(k) + L_k e(k) \tag{3}$$

where $x_c^{rev}(k \mid k-1)$ is the predicted state estimate at interval k, $e(k)$ is the difference between measured state and predicted state estimate at interval k, $u^{opt}(k)$ is the optimal input computed by MPC at interval k, $v(k)$ is the input disturbance at interval k, A_c is the internal plant model state-space matrices of coefficients, B_u and B_v are the internal plant state vector for input control and disturbance, L_k and M_k are the KF gain matrices at interval k. Conventional

MPC pre-calculate the KF gain matrices during initialization of the MPC controller and keep the gain matrices constant throughout the entire runtime of the controller. This relies on the accuracy of the internal plant model during design stage, which requires expert knowledge of the entire control process and tedious parameter tuning to accurately represent the actual control plant. However, this shortcomings can be alleviated by employing adaptive MPC. Basically, adaptive MPC works by updating of the KF gain matrices at every interval of k, which calibrates the controller internal state according to the latest measurement. The KF gain matrices at interval k are given by

$$L_k = \left(A_k P_{k|k-1} C_{m,k}^T + N\right)\left(C_{m,k} P_{k|k-1} C_{m,k}^T + R\right)^{-1} \tag{4}$$

$$M_k = P_{k|k-1} C_{m,k}^T \left(C_{m,k} P_{k|k-1} C_{m,k}^T + R\right)^{-1} \tag{5}$$

where $P_{k|k-1}$ is the state estimate error covariance matrix at interval k based on the measured state at interval $k-1$, A_k and $C_{m,k}$ are the state-space matrices of coefficients updated at interval k, N and R are the state estimation constant covariance matrices [8].

Optimization Problem One of the advantages of MPC is its ability to handle multiple objectives and constraints. MPC generally solves a quadratic problem (QP) at each interval to find the optimal control input with respect to the objectives and constraints. This paper implements a temperature reference tracking MPC controller bounded by the HVAC capability and plant temperature boundary. A general objective or cost function that penalizes reference signal deviation, large change in control input and constraint violations can be given by

$$\begin{aligned} J_k = & \sum_{i=1}^{n_y} \left\{ w_i^y \left[r\left(k+1|k\right) - y\left(k+1|k\right) \right] \right\}^2 \\ & + \sum_{i=0}^{n_u-1} \left\{ w_i^{\Delta u} \left[\Delta u\left(k+1|k\right) \right] \right\}^2 + \rho_e \varepsilon_k^2 \\ \text{s.t.} & \\ & y_{min} \leq y\left(k+1|k\right) \leq y_{max} \\ & u_{min} \leq u\left(k+1|k\right) \leq u_{max} \end{aligned} \tag{6}$$

where n_y is the controller prediction horizon, n_u is the input control horizon, w_i^y is the plant output tuning gain at ith prediction step, $w_i^{\Delta u}$ is the change in input control tuning gain at ith prediction step, r is the reference signal, y is the predicted plant output and $\Delta u\left(k+1|k\right)$ is the change in the optimal input control at time $k+i$ computed at interval k, ρ_e is the constraint violation penalty gain and ε_k is the constraint slack variable at interval k. The HVAC minimum and maximum saturation points are given by u_{min} and u_{max} respectively while the plant minimum and maximum room temperature are given by y_{min} and y_{max}.

3.2 Online Model Estimation

The workings of adaptive MPC are described in the previous section, where it relies on model parameters updates at every interval to tune its internal state estimator. This section briefly describes the online model estimator that is used in this paper to update the adaptive MPC internal state estimator. Several methods are employed in literature related to online model estimation in buildings, such as extended KF (EKF) in [2], unscented KF (UKF) in [2, 9, 3] and controlled autoregressive integrated moving average (CARIMA) in [10]. Besides, previous work on the iHouse involves an autoregressive moving average (ARMA) model based offline estimation in [5]. This paper takes a different approach on model estimation of the iHouse, where online estimation is employed and input from HVAC is also taken into account. An autoregressive moving average with exogenous input (ARMAX) model is used in this paper to represent the iHouse. Thus, the plant dynamic thermal behavior can be expressed in a black box ARMAX model as

$$A(q)y(t) = B(q)u(t - nk) + C(q)e(t) \tag{7}$$

where y is the plant room temperature, u is HVAC control input, e is the noise term with zero mean. The parameters of autoregressive (AR) are given by $A(q) = 1 + a_1 q^{-1} + \cdots + a_{na} q^{-na}$ and $a_1, \cdots, a_{na}$, where na is the AR order. The parameters of exogeneous (X) input are given by $B(q) = b_1 + b_2 q^{-1} + \cdots + b_{nb} q^{-nb+1}$ and $b_1, \cdots, b_{nb}$, where nb is the X input order. The parameters of moving average (MA) are given by $C(q) = 1 + c_1 q^{-1} + \cdots + c_{nc} q^{-nc}$ and $c_1, \cdots, c_{nc}$, where nc is the MA order. Since the MPC internal model in this paper is intended to be a simplified plant model, the na, nb and nc are configured as first order to reduce its complexity.

Two estimation algorithms are employed to identify the ARMAX model parameters: (i) normalized least mean square (LMS) and (ii) KF algorithm. This two parameter estimation algorithms can be generally described by

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)\left[y(t) - \hat{y}(t)\right] \tag{8}$$

where $\hat{\theta}$ is the estimated ARMAX model parameter, K is the prediction error gain, y is the measured output and $\hat{y}$ is the predicted output. In-depth details of the two algorithms can be found in [11]. Although the ARMAX model parameters can be pre-estimated if the initial conditions are known, an initial guess is used instead during the initialization process to represent a more realistic deployment of such system. Besides, KF algorithm is capable of managing parameter estimation uncertainty during initialization by tuning the initial parameter covariance. Typically, a large initial parameter covariance is used when high uncertainty exists in the initial estimation. Uncertainty in the state equations and process noises can also be managed by tuning KF parameter covariance. While Simulink does not allow online tuning of the delay parameter, the expected delay value can be pre-configured in the online model estimator. Furthermore, the ARMAX model is converted into an equivalent state-space form before propagating the updated parameters to the adaptive MPC controller.

4 Numerical Evaluation

This section examines the performance of the proposed adaptive MPC controller with online model estimation in a CPHS environment, where a conventional MPC controller is employed as baseline controller. The term "MPC" and "conventional MPC" are used indistinguishably in this section. The simulation is built based on an actual bedroom in the iHouse and simulated on Simulink R2017b. Environmental sensors are polled and stored in the EETCC database at an interval of 10 seconds. Hence, the zero hold order sampling interval is also set to 10 seconds while MPC prediction and control horizon are configured to 2 minutes. Besides, the simulation outdoor environment is based on measured data from the iHouse on 1st November 2013 as shown in Fig. 3 while the simulation is performed on a MacBook Pro with Intel Core i7 processor at 3.1 GHz and 16 GB. The remaining simulation parameters are listed in Table 1.

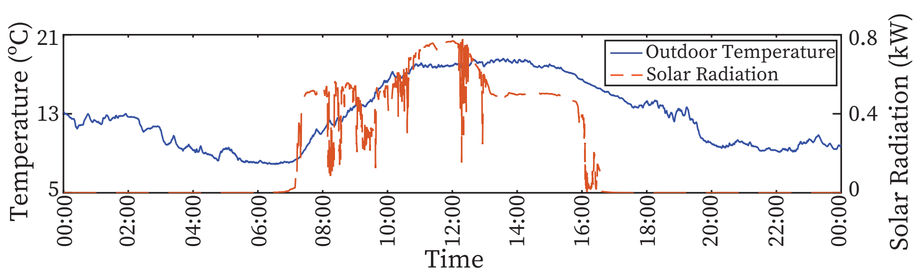

Fig. 3. Outdoor environment on 1st November 2013.

Table 1. Simulation parameters and settings.

Parameter	**Value**
Volume of room ($L \times W \times H$), V_{room}	$5.005 \times 4.095 \times 2.4\,\mathrm{m}^3$
Density of air	$1.2\,\mathrm{kg/m}^3$
Specific heat capacity of air	$1.005\,\mathrm{kJ/kg^\circ C}$
Air volume flow rate, CFM	$300\,\mathrm{ft}^3/\mathrm{min}$
Minimum cooling load of HVAC, u_{min}	$5\,\mathrm{kW}$
Maximum cooling load of HVAC, u_{max}	$6.3\,\mathrm{kW}$
Coefficient of performance, COP	3.44
Area of window type 1, A_{w1}	$1.815\,\mathrm{m}^2$
Area of window type 2, A_{w2}	$0.66\,\mathrm{m}^2$
U-value of window type 1, u_{w1}	$3.4\,\mathrm{W/m^{2\circ}C}$
U-value of window type 1, u_{w2}	$1.7\,\mathrm{W/m^{2\circ}C}$
Solar transmittance of window type 1, g_{w1}	0.79
Solar transmittance of window type 2, g_{w2}	0.41

4.1 Results and Discussion

Both MPC and adaptive MPC controllers are subjected to the same cost function and constraints as shown in Eqn. (6). Since the cost function is a reference tracking, a step signal of 25 °C is applied as the reference at 00:00 to the end of the simulation. Besides, normalized LMS and KF algorithm in the online model estimator are both evaluated as part of the adaptive MPC controller. Responses of all MPC controllers and online model estimators during initialization are shown in Figure 4. MPC reached steady state faster than both adaptive MPC controllers as the online model estimators requires a number of iterations before achieving stabilization. The online model estimator system matrix, A converged from its initial value to a stable value during the first two minutes of initialization process. During this period, the adaptive MPC applied large rate of change for the input to reach both ends of the HVAC constraints to quickly identify and tune the ARMAX model to the characteristics of the plant. Updated state space parameters are propagated to the adaptive MPC at the same time, where HVAC control inputs are promptly corrected from maximum cooling mode to heating mode as observed in Figure 4. Similar input response is also observed in [10].

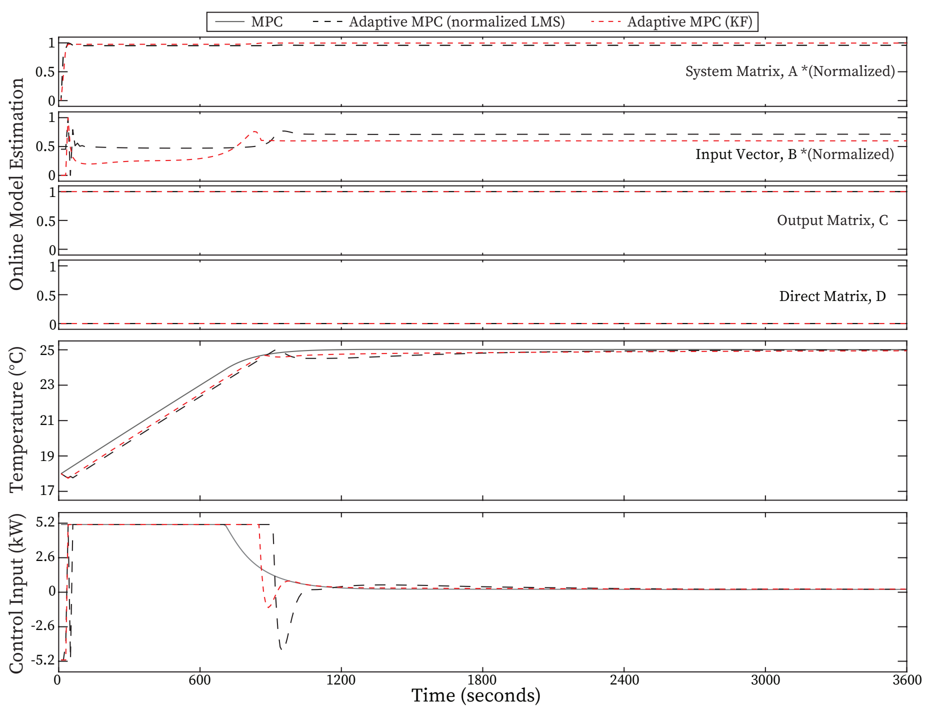

Fig. 4. Initial responses of MPC and adaptive MPC for iHouse bedroom. Note: system matrix and input vector are normalized.

Since the performance of adaptive MPC is dependent on the online model estimator, adaptive MPC with KF based online model estimator performed better as it offered faster convergences, less oscillations and overshoots than normalized LMS algorithm as shown in Figure 4. Besides, the steady state responses of all MPC controllers and online model estimators when subjected to disturbance from outdoor environment are shown in Figure 5. Unlike adaptive MPC, MPC is susceptible to random disturbances as it is unable to correct its internal model errors. The upper output error of MPC is $0.173\,^{\circ}$C while the lower output error is $0.168\,^{\circ}$C. The upper output errors for adaptive MPC with normalized LMS and KF based online model estimators are $0.0246\,^{\circ}$C and $0.0141\,^{\circ}$C while the lower output errors are $0.0208\,^{\circ}$C and $0.0183\,^{\circ}$C respectively. Although KF performed better than normalized LMS, KF is computationally heavier. However, computational load from various online model estimator algorithms are insignificant as it only constitute not more than 1.5% of the total simulation time while MPC optimization process constitute more than 86.5%. Average simulation time for MPC and adaptive MPC with online model estimation is 43.6 and 291.3 seconds, where the difference is more than six times. Thus, trade-offs between performance and computational cost should be assessed for practical implementations.

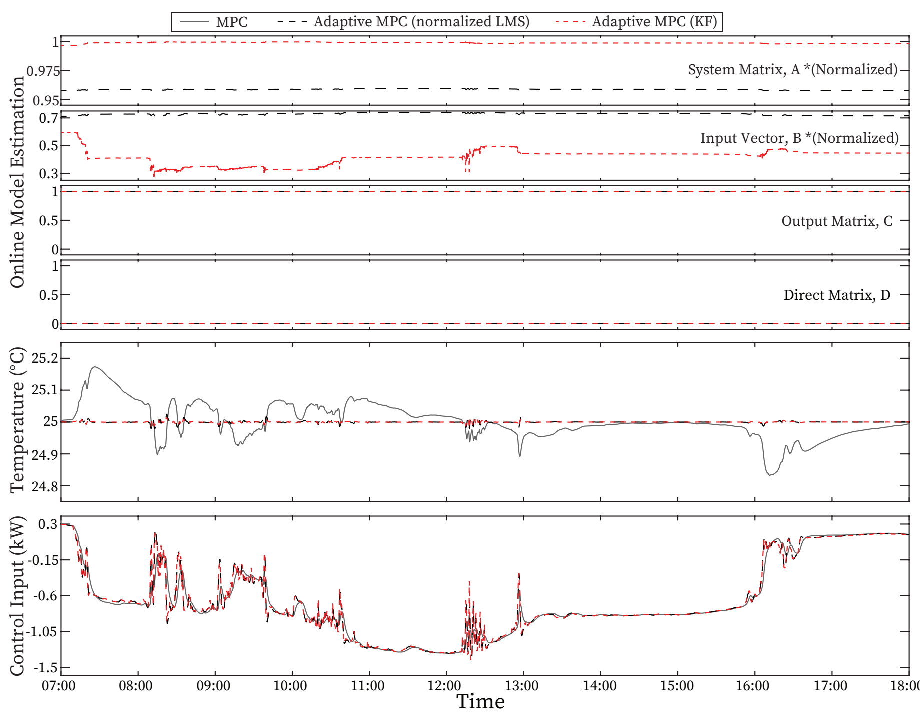

Fig. 5. Steady state responses of MPC and adaptive MPC with disturbance for iHouse bedroom. Note: system matrix and input vector are normalized.

5 Concluding Remarks

This paper summarizes the implementation details of real time adaptive MPC with online model estimation in CPHS environment. The adaptive MPC with various online model estimators are simulated and benchmarked against a conventional MPC controller to evaluate the performance and advantage of adaptive capability in a CPHS environment. Both adaptive MPC with KF and normalized LMS based online model estimators showed improvements in temperature reference tracking scenarios. However, computation required will increase if self adaptive capability and strict reference regulation are required. System designers should take note of the trade-offs between performance and computation cost for practical implementations of predictive control in a CPHS environment.

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