Model Predictive Control Design for Efficient Air-Cooled Thermal Management in Contained Data Centers

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Abstract— **This paper presents a study on thermal management in data centers by applying an efficient air cooling control strategy using model predictive control (MPC). A transient thermal model is representing a contained data centre is used. The primary control objective is to achieve real-time optimization of cooling power, ensuring server temperature reference tracking while keeping the cooling power at its minimum, all within specific temperature and power constraints in accordance to the EU CoC and ASHRAE standards, to provide the secure and efficient performance of the data center's thermal management system. The effectiveness of the proposed controller is demonstrated through some simulations, looking into realistic scenarios. Observation is done especially to the inlet and server temperatures, and the cooling power consumption. The results highlight the proposed MPC efficient performance which shows the potential of this optimal control method to be applied to model based temperature control design in real contained data centers.**

Index Terms— **Data center energy consumption, model predictive control, row/rack-level cooling.**

I. INTRODUCTION

A data center (DC) is a facility composed of networked computers, storage systems and computing infrastructure that organizations use to assemble, process, store and disseminate large amounts of data. As digital transformation continues to accelerate across the globe, the rising demand for DCs inevitably leads to increased energy consumption, carbon emissions, and water usage. Simultaneously, global awareness regarding sustainability is on the rise, prompting the call for more efficient use of energy to run a DC [1], [2].

Recently, the energy consumption of DCs has become a focal point of concern. Recent International Energy Agency (IEA) report [3] states that in 2022, data centers consumed an estimated 460 terawatt-hours (TWh) globally, which was approximately 2% of global electricity consumption. This is estimated to double up to more than 1000 TWh in 2026, particularly with the increase of computations for artificial intelligence (AI) and the growing demand in cryptocurrency mining. Besides obviously the computing power, a significant portion of this energy consumption is attributed to the cooling system. These two are most energy intensive processes in DC operation. Multiple servers operating in close proximity produce a considerable amount of heat and high temperatures may lead to lower IT performance or equipment damage.

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To prevent server failures, it is crucial to maintain the temperature of a central processing unit (CPU) below a threshold using cooling control. Traditionally, cooling infrastructure in DCs has been predominantly room-based [4], [5]. Moreover, operating cooling system with high redundant capacity to make sure the temperature is always below the upper limit, is also a common practice in the industry, which creates a huge waste of energy. As power densities in racks increase, row-based and rack-based cooling solutions are needed in high-power-density DCs [6]. Traditional cooling control methods such as ON/OFF or PID based control become inefficient as they can sometimes cause temperature fluctuations, especially when cooling units are close to servers.

With the involvement of temperature constraints and the need to minimize energy consumption, model predictive control (MPC) is seen as a suitable potential method to use. There have been a growing number of research applying MPC for DC cooling system. These works can mainly be divided into two groups. The first group applies model based MPC, relying on simplified models of DC [7]–[10], representing the relation between the cooling power with the temperature being controlled, either the inlet temperature or the server temperature. Despite the generality of this approach, the fact that the interaction between temperature components in a DC makes it unrealistic and impossible to obtain optimality. The second group applies scenario-based strategies and applying predictive based control [11]–[13]. While they are more realistic, these strategies create high reliant on operational data from the DCs being controlled, thus the approach is mainly ad-hoc, working only for the specific DCs being controlled.

In this study, we propose a possible solution that addresses the drawbacks of the two mentioned approaches is proposed. The main contributions of this paper are summarized as follows. We propose a general model based MPC design for a rack/row level air-cooled model of a contained DC. A transient thermal model developed by [14], which gives a more realistic representation of a contained DC is used. A multi-objective MPC is designed, to maintain server temperatures at desired levels while simultaneously keeping the cooling power consumption at its minimum to achieve a feasible thermal management in accordance with DC standards.

The remainder of the paper is structured as follows. Section II presents the DC dynamic model for which the control design is based. The control design and simulations are presented in Sections III and IV, respectively. Furthermore, the results are analyzed in V. Finally, Section VI draws the conclusions and suggests further directions.

Manuscript 569 submitted to 2024 10th International Conference on Control, Decision and Information Technologies (CoDIT). Received March 31, 2024.

II. Data center transient thermal modeling

In this section, we provide a summary introducing a model of a contained DC developed in [14], based on a concise representation of DC thermal management using the Transient Thermal System Modeling (TTSM). A contained DC, also known as a modular DC, is a DC where the server racks are placed inside a container or cooling enclosure.

TTSM presents a methodology for analyzing instantaneous thermal fluctuations within buildings, offering predictive insights into heat transformation. The dynamic model of the contained DC that will be used in this study is derived using the model-driven framework (MDF), which is a first principle modeling. Thus, the MDF method is formulated by Ordinary Differential Equations (ODEs), leveraging the lumped-capacitance method and operating under predefined assumptions, as outlined in Assumption 1, to offer a comprehensive TTSM solution for relevant structures.

Assumption 1: The provided model incorporates the following assumptions as outlined by [13] in relation to the compact representation: 1) Server racks are consolidated into a singular unit, implying that each rack accommodates a single server unit. 2) All energy consumed by servers is exclusively transformed into heat. 3) Cooling power is employed to characterize the cooling demand generated by the cooling system. 4) The temperature within each lump is assumed to be well-mixed and homogeneous. 5) The model disregards cold air bypass and hot air recirculation, with both the cold and hot aisles contained. 6) Thermal conductivity in the model integrates three modes of heat transfer: thermal conduction, convection, and radiation.

The resulted model of the contained DC, as derived in detail in [14], is presented as the following 4th order differential equation:

$$\begin{aligned}
\frac{dT_c}{dt} &= \frac{l_r}{C_r}(T_r - T_c) + \frac{l_s}{C_r}(T_s - T_c) + \frac{l_o}{C_r}(T_o - T_c), \\
\frac{dT_i}{dt} &= \frac{-P_c}{C_i} + \frac{l_i}{C_i}(T_c - T_i), \\
\frac{dT_s}{dt} &= \frac{P_s}{C_s} + \frac{F_s H_a}{C_s}(T_i - T_s) + \frac{l_s}{C_s}(T_c - T_s), \\
\frac{dT_o}{dt} &= \frac{F_s H_a}{C_o}(T_s - T_o) + \frac{l_o}{C_o}(T_c - T_o).
\end{aligned} \tag{1}$$

The inputs to the system are the room temperature, $T_r(t)$, the server power, $P_s(t)$ and the cooling power, $P_c(t)$, while the outputs of the system are the temperatures of the cooling enclosure, $T_c(t)$, the inlet air, $T_i(t)$, the server, $T_s(t)$ and the outlet air, $T_o(t)$. The system parameters with their assigned values are listed in Table I. Moreover, a circuit diagram representation of the resistance–capacitance thermal modeling of (1) is depicted in Fig. 1. The thermal system is simply analogized to an electric circuit, comprising thermal conductance and thermal capacitance.

We leverage this MDF model framework obtained through experimentation for the purpose of model-based control

TABLE I

Parameters of the described DC model

Par	Description	Value	Unit
l_r	Thermal conductance of room	2.455	$^\circ$C/W
l_i	Thermal conductance of inlet air	80	$^\circ$C/W
l_o	Thermal conductance of outlet air	0.009	$^\circ$C/W
l_s	Thermal conductance of servers	1.457	$^\circ$C/W
C_r	Thermal capacitance of room air	3800	J/$^\circ$C
C_i	Thermal capacitance of inlet air	153300	J/$^\circ$C
C_o	Thermal capacitance of outlet air	275	J/$^\circ$C
C_s	Thermal capacitance of servers	2×10^5	J/$^\circ$C
F_s	Flow rate of air passing through servers	28.450	kg/s
H_a	Specific heat of air at constant pressure	7.450	J/kg.$^\circ$C

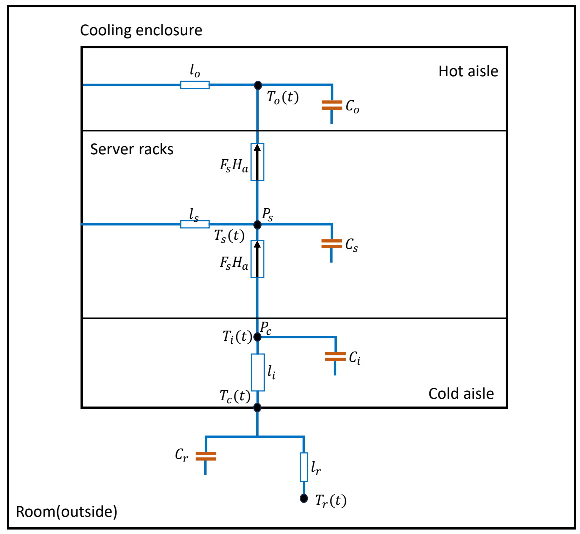

Fig. 1. Representation of the given resistance–capacitance thermal transfer model of a DC [14]

design. Thus, writing (1) in a standard linear state-space form

$$\begin{cases} \dot{x}(t) = Ax(t) + Bu(t) + p(t) \\ y(t) = Cx(t), \end{cases} \tag{2}$$

we have the systems matrices as:

$$A = \begin{bmatrix} -\frac{l_r+l_s+l_o}{C_r} & 0 & \frac{l_s}{C_r} & \frac{l_o}{C_r} \\ \frac{l_i}{C_i} & -\frac{l_i}{C_i} & 0 & 0 \\ \frac{l_s}{C_s} & \frac{F_s H_a}{C_s} & -\frac{F_s H_a + l_s}{C_s} & 0 \\ \frac{l_o}{C_o} & 0 & \frac{F_s H_a}{C_o} & -\frac{F_s H_a + l_o}{C_o} \end{bmatrix},$$

$$B = \begin{bmatrix} 0 & -\frac{1}{C_i} & 0 & 0 \end{bmatrix}^T,$$

$$p(t) = \begin{bmatrix} \frac{l_r}{C_r} T_r(t) & 0 & \frac{1}{C_s} P_s(t) & 0 \end{bmatrix}^T.$$

In this state-space form, we have the state vector $x(t) = [T_c,\ T_i,\ T_s,\ T_o]^T$ and we regard the cooling power as the control input $u(t) = P_c(t)$. The vector $p(t)$ includes the effects of room temperature, $T_r(t)$ and the server power, $P_s(t)$ to the thermal dynamic of the DC. The server power depends on the loads of the server. We use the model (2) to design a MPC strategy at the row/rack level for the

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temperature management in a data center for the goal of constructive control design and optimization.

III. MPC CONTROLLER DESIGN

In this section, we present the problem formulation and the MPC control design. In this study, the control design objective is to regulate the server temperature for some even scenarios that could happen in real DC center operation, while at the same time minimizing the cooling power consumption. Controlling the server temperature effectively also let the control system manages the heat dissipation, ensuring critical components operate within safe temperature ranges and minimizing the risk of overheating-related failures. This strategy enables real-time adjustments of cooling system parameters in response to changing environmental conditions and workload demands, optimizing energy efficiency by aligning cooling efforts with actual thermal requirements. By prioritizing energy-conscious thermal management strategies, such as reducing cooling power while maintaining server and inlet temperatures within specified limits, the system can achieve substantial energy savings without compromising performance, thus enhancing overall system resilience, efficiency, and sustainability.

The discrete-time MPC design is applied to this control problem. Therefore, the discretized version of the model (2) is first obtained, using a standard ZOH method with the sampling time t_s. The discretization of the system and input matrices A and B are denoted as A_d and B_d.

While the the server temperature T_s is considered as the output of interest for the tracking problem, it is assumed that all the states are measurable. The minimization problem is then formulates as

$$\begin{aligned} \min_{u} \quad & J(k) = \sum_{j=0}^{N_p} \left\| T_s(k+j) - \hat{T}_s(k+j|k) \right\|_Q^2 \\ & \qquad + \sum_{j=0}^{N_c} \|\Delta u(k+j)\|_R^2 \\ \text{s.t.} \quad & u_{min} \leq u(k) \leq u_{max} \\ & T_i \leq \alpha \\ & T_s \leq \beta \end{aligned} \tag{3}$$

where k is the time instance, N_p is the prediction horizon, N_c is the control horizon, $T_s(k+j)$ is the desired value of the server temperature and $\hat{T}_s(k+j|k)$ is the predicted server temperature at time instance $k+j$. Furthermore, t_s is the sampling time of the controller and $\Delta u(k+j) = u(k+j) - u(k+j-1)$ is the variation of the control input signal. Moreover, Q and R are strictly positive definite weighting matrices to be tuned. A higher value of Q indicates putting more importance on the setpoint tracking and a higher value of R indicates to putting more priority on the control input minimization. The thresholds α and β are predefined constants based on the safety measures and standards proposed by the energy efficiency guidelines for data centers, such as EU Code of Conduct (CoC) and ASHRAE standards for data centers [1], [2].

The N_p-th prediction step of the output signal in $J(k)$ is formulated as

$$\hat{Y}(k+N_p|k) = \Phi\hat{x}(k|k) + \Gamma_1 u(k-1) + \Gamma_2 \Delta U \tag{4}$$

where

$$\hat{Y}(k+N_p|k) = \begin{bmatrix} \hat{y}(k+1|k) \\ \hat{y}(k+2|k) \\ \vdots \\ \hat{y}(k+N_p|k) \end{bmatrix}, \Phi = \begin{bmatrix} C_d A_d \\ C_d A_d^2 \\ \vdots \\ C_d A_d^{N_p} \end{bmatrix},$$

$$\Gamma_1 = \begin{bmatrix} C_d B_d \\ C_d A_d B_d + C_d B_d \\ \vdots \\ \sum_{j=1}^{N_p} C_d A_d^{j-1} B_d \end{bmatrix},$$

$$\Gamma_2 = \begin{bmatrix} C_d B_d & \cdots & 0 \\ C_d A_d B_d & \cdots & 0 \\ \vdots & \ddots & \vdots \\ \sum_{j=1}^{N_p} C_d A_d^{j-1} B_d & \cdots & \sum_{j=1}^{N_p-N_c+1} C_d A_d^{j-1} B_d \end{bmatrix},$$

$$\Delta U = \begin{bmatrix} \Delta u(k) \\ \Delta u(k+1) \\ \vdots \\ \Delta u(k+N_c-1) \end{bmatrix}.$$

Moreover, the general diagram of the MPC procedure is illustrated in Fig. 2.

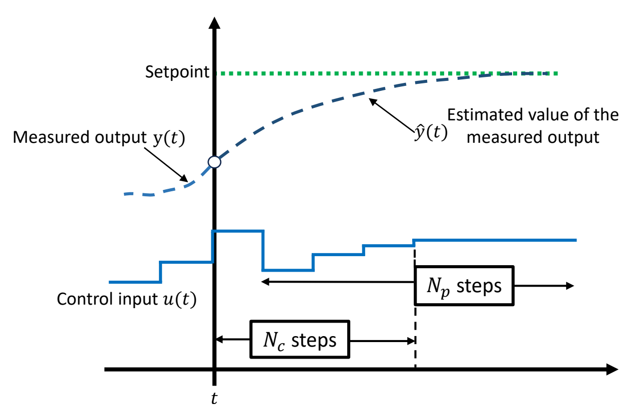

Fig. 2. General MPC diagram

The problem formulation (3) facilitates the determination of the optimal cooling power set to be implemented in the DC spanning from time instance k to $k+N_c$. Simulation results for some scenarios are presented in the next section, to showcase the presented control scheme.

IV. SIMULATIONS

In this section we apply the discrete-time MPC strategy to the contained DC model (2), considering two scenarios using MATLAB/Simulink, to test the performance of the proposed MPC in solving the control problem as formulated in (3).

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A. Simulation setup

In the simulation, we set the parameters of the system as given in Table I. These parameters are chosen within the constraints given in [14]. The discretization of the model is done with sampling time $t_s = 10$ sec. Additionally, the prediction and control horizons are set to $N_p = 20$ and $N_c = 10$, respectively to achieve appropriate prediction accuracy and satisfy control performance while maintaining computational efficiency. The cooling power is assumed to be varying between $u_{min} = 1000$ W and $u_{max} = 5500$ W. According to EU CoC and ASHRAE standards for energy efficiency for DCs, the inlet air and the server temperatures are required to below or no higher than $\alpha = 28°\text{C}$ and $\beta = 70°\text{C}$, respectively [1], [2]. Additionally, the room temperature is assumed to fluctuate between 23°C and 25°C.

In the next subsections, two scenarios are simulated to test the controller performance. The first is a simple scenario considering the server temperature control for a given step change to the reference temperature. The second is a more complex scenario considering a realistic operation when there are server load changes, which is represented by the server power changes.

B. Scenario I: Server temperature control with a step change of the reference temperature

This Scenario I is selected as changing the reference signal (setpoint) for server temperature in data centers may be necessary for different reasons to ensure optimal performance and energy efficiency. Seasonal changes in ambient temperature often require adjustments to the temperature setpoints, with higher temperatures tolerated during colder months and lower temperatures preferred in warmer weather. Additionally, adjustments may be needed during cooling system maintenance or in response to environmental factors like humidity. Energy cost management and emergency situations, such as cooling system failures, also call for setpoint modifications to balance energy consumption and prevent equipment overheating. By proactively managing setpoints in these cases, data center operators can optimize cooling efficiency, reduce energy costs, and ensure the reliability of critical infrastructure [15].

In this simulation, a constant reference temperature is initially set to $T_{s,ref} = 50°\text{C}$ and then changed to $T_{s,ref} = 60°\text{C}$ after 4000 sec (or 01:06:40 hours) of operation. The weighting coefficients are chosen to be $Q = 10^3$ and $R = 10$, putting the priority to the control strategy on minimizing the reference tracking error, which is the difference between actual server temperature T_s and the reference $T_{s,ref}$.

As shown in Fig. 3, the controller effectively manages to alter the cooling power to bring the server temperature to the desired level within a reasonable time. This indicates that the controller handles dynamic environmental conditions and workload changes. Additionally, during the simulation process, the server temperature is kept under the defined threshold $\beta = 70°\text{C}$ which guarantees the effective performance of the controller.

Fig. 4 also illustrates the control input signal over the entire simulation period. It is evident that the cooling power remains within the bounds of $u_{\min}$ and $u_{\max}$. This stability in control effort underscores the reliability and consistency of the cooling system in maintaining optimal operating conditions for the servers.

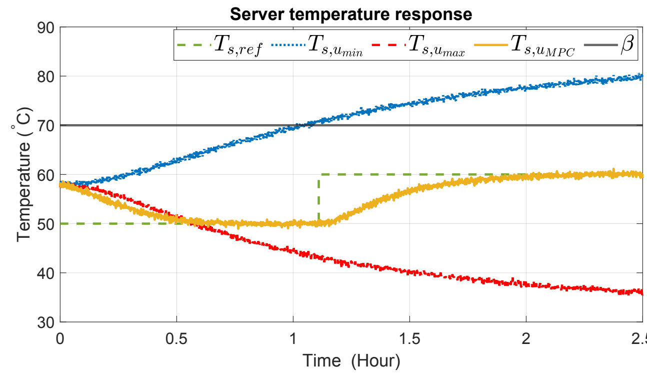

Fig. 3. Server temperature output response in Scenario I

Furthermore, Fig. 5 showcases the response of inlet air temperature throughout the system operation. It is evident from this figure that the inlet air temperature remains below the threshold $\alpha = 28°\text{C}$ throughout the simulation period that ensures the safe performance of the DC. This consistency in maintaining the inlet air temperature within acceptable limits highlights the efficiency of the cooling system in regulating environmental conditions within the DC.

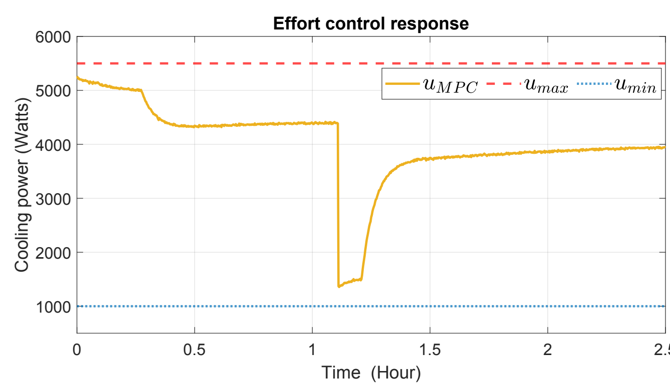

Fig. 4. Cooling power evolution in Scenario I

C. Scenario II: Server temperature control with sudden changes in server power

In this Scenario II, we extend the Scenario I by also considering the event of sudden changes in the server power. Fluctuations in server power occurs throughout the server operation, due to the changes in server workloads whether it is during normal operation and more so during specific events, e.g. big breaking news, polling deadlines, hardware upgrade etc., that may create sudden jumps in the server workloads, thus also the server power. These changes in

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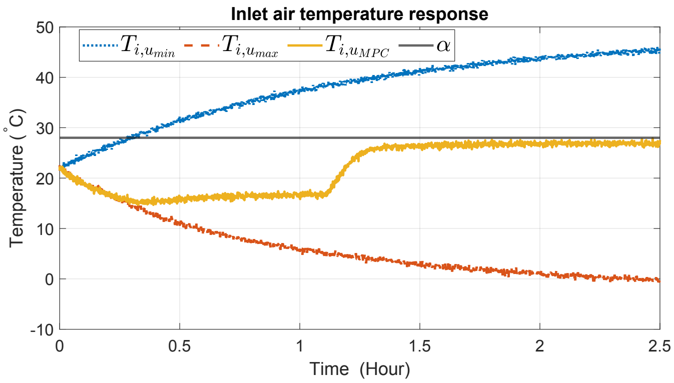

Fig. 5. Inlet air temperature output response in Scenario I

power server will affect the server temperature, hence extra control action is required to compensate this event, which is illustrated in this simulation scenario.

As shown in Fig. 6, during the 12 hours simulation, setpoint changes are made to the server temperature at $t_1 = 5600$ sec (or 01:33:20 hour) and $t_2 = 26600$ sec (or 07:23:20 hour). As observed in this figure, the controller effectively manages to alter the cooling power to bring the server temperature to the setpoints. Besides, sudden server power changes are introduced at 3000 sec (or 00:50:00 hour), 10000 sec (or 02:46:40 hour) and 35000 sec (or 09:43:20 hour) to represent the changes in the IT loads over the simulation time. As illustrated, the controller can effectively react to these server power changes and reduce the negative impacts of IT load changes or variation on the server and inlet temperatures adaptively. Additionally, throughout the whole operation duration, the server temperature stays below the threshold $\beta = 70°\mathrm{C}$ which guarantees the safe operating temperature of the server.

Moreover, Fig. 7 shows the control input signal over the entire simulation period. It is evident that the cooling power remains within the bounds of $u_{\min}$ and $u_{\max}$. The ability of the controller to stay within the allowable range underscores the reliability and consistency of the cooling control system in maintaining optimal operating conditions for the servers.

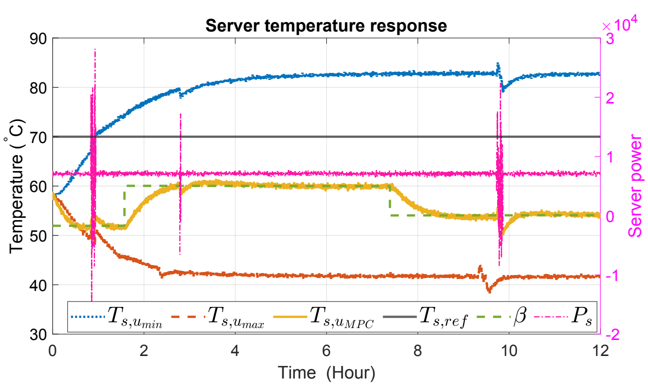

Fig. 6. Server temperature output response in Scenario II

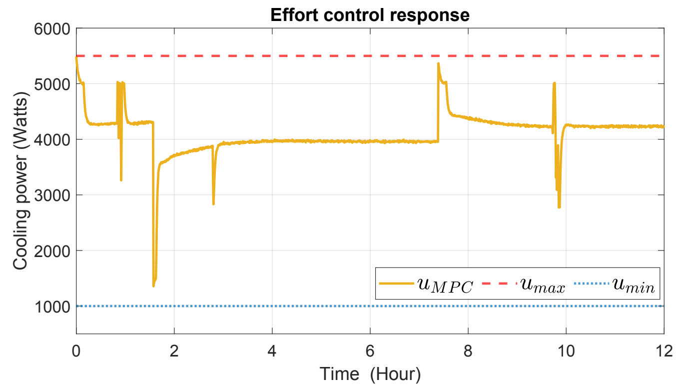

Fig. 7. Cooling power evolution in Scenario II

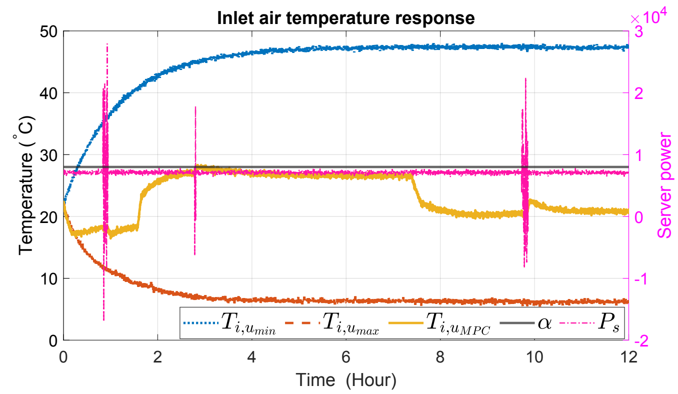

Fig. 8. Inlet air temperature output response in Scenario II

Similar to the case in Scenario I, as seen in Fig. 8, in this Scenario II can also be observed that the inlet air temperature remains below the threshold $\alpha = 28°\mathrm{C}$ throughout the entirety of the simulation period that ensures the safe performance of the DC.

Consequently, the simulations demonstrate the efficacy of the control system in adapting to dynamic workload changes and environmental disturbances while ensuring stable server temperatures and optimal cooling system performance. These findings provide valuable insights for optimizing DC operations and enhancing overall system reliability.

V. Analysis

As highlighted earlier, the efficacy of efficient cooling control systems in air-cooled DCs cannot be overstated, given their pivotal role in enhancing operational efficiency, increasing system reliability, and promoting environmental sustainability. Through more accurate temperature regulation, these systems mitigate the risk of equipment failures and operational disruptions, thereby ensuring uninterrupted functionality of critical infrastructure.

Furthermore, as demonstrated in the preceding section, the adoption of online cooling control strategies, such as MPC methods, enables DCs to achieve heightened effectiveness in transient thermal management of DCs. By systematically addressing constraints and offering a flexible cost function formulation, MPC allows for the articulation of desired tradeoffs between minimizing cooling power and accurately tracking server temperature reference signals. Consequently, tuning the control becomes more manageable by adjusting the weights R and Q in (3), which directly align with control objectives. The choice of weights depends on the relative importance of reference tracking accuracy and control effort minimization in the specific application. Generally, higher weights are assigned to terms that are more critical for achieving desired control performance. Moreover, such tailored controllers exhibit enhanced adaptability in improving cooling performance by dynamically responding to fluctuations in IT loads, thus ensuring timely and precise delivery of necessary cooling power to the servers.

VI. Conclusions

This paper has introduced a model predictive control (MPC) design applied to a realistic transient thermal system model of a contained data center, specifically aimed at enhancing thermal management in air-cooled data centers. This study has expanded its scope by incorporating a sophisticated control design for the model. The core objective remains the real-time optimization of cooling power, ensuring precise temperature reference tracking, and minimizing control effort, all while adhering to specified constraints to guarantee the safe and efficient performance of the data center's thermal management system. The MATLAB/Simulink simulations representing two scenarios affirm the efficacy of the proposed controller, showcasing its efficient performance in the face of changing reference signals. This work contributes valuable insights and a practical solution towards advancing the field of thermal management in air-cooled data center environments.

Future directions of exploration aims at extending this study to a wider context considering the case when the data center is not fully contained, where there is influence from one rack section with another. Moreover, exploring the setup where more than one cooling sources are applied, e.g. combination of air cooling and liquid cooling, which will require the formulation of a multi-input multi-output (MIMO) MPC controller, is another future direction. Additionally, there is a prospect for adapting the thermal management system to real-life case studies, applying and testing the proposed MPC to a real contained data center cooling system, thereby enhancing the applicability and robustness of the developed control framework.

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