Modeling and Identification of Data Center HVAC System with Super-Multipoint Temperature Sensing System

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Abstract: This paper investigates a heating, ventilation, and air-conditioning (HVAC) system in a data center equipped with a previously developed super-multipoint temperature sensing system. This system is expected to be a key technology for reducing the total power consumption of the HVAC system by controlling the inlet temperature distribution of the servers in real time. For this purpose, we present an overview of our fan-control system based on model predictive control. The main objective of this paper is to identify a dynamical model of temperature variations, in order to predict the future evolution of the distribution. However, the spatially high-density temperature data provided by the sensing system is not suited to the needed model accuracy, and the present modeling problem is differentiated from standard ones. We thus present a systematic scheme for the spatial density reduction of sensors by using spectral clustering and graph theory and associated techniques to acquire the dynamical model. Through simulation with real data, we finally show that the developed model achieves an accuracy of 0.58 degrees Celsius on average.

Key Words: HVAC system, data center, system modeling, data reduction, machine learning.

1. Introduction

Data centers are expanding rapidly in both size and scope in response to the recent information explosion. Accordingly, the power consumed by such centers is increasing drastically, and roughly half the total power used by data centers is consumed by their heating, ventilation, and air-conditioning (HVAC) systems [1]. Therefore, smart HVAC management systems are expected as a key technology to render data centers environmentally and economically sustainable.

A general requirement when controlling a data center is to keep devices such as CPUs, memory units, and power supplies cooler than some specified temperature in order to avoid triggering an alarm. This could be achieved by controlling the temperature of each server by optimally allocating IT workloads among servers [2]. However, not all current data centers are capable of such load allocation. Hence, we focus on a different approach, namely, controlling the cold air supplied to the server. Recent technological advances in temperature sensing systems allow high-resolution data to be fed back in real time. In this regard, this paper employs our previously developed super-multipoint sensing system based on optical fibers [3], which is capable of providing thousands of data at each time instant. The sensing system is expected as a potential key technology for improving control performance.

Unlike conventional sensing systems, integrating the aforementioned sensing system with real-time control algorithms brings new challenges associated with the large volumes of data. Among the many issues that have to be addressed, this study is aimed at developing a dynamical model of the temperature distribution. We are motivated in this aim by a promising HVAC control methodology, namely model predictive control (MPC), for which several models have been presented in the literature [2], [4]–[8]. However, because of insufficient numbers of sensors, the models presented in those papers had limited spatial resolutions. More importantly, this particular modeling technique cannot be applied directly to the large amounts of data provided by our super-multipoint sensing system. As an alternative approach Arghode and Joshi [9] used a computational fluid dynamics (CFD) model to estimate temperature distributions on a rack surface of a cold aisle. However, CFD models are not always suitable for real-time control algorithms such as MPC because of their complexity.

Another area of active investigation is the modeling and control of HVAC systems in commercial/residential buildings, for which MPC is regarded as one of the most promising control approaches [10], [11]. Atam and Helsen [12] gave a comprehensive survey of various ways to model an HVAC system for a multi-zone building. They emphasized that the model must be both accurate and computationally tractable, and many modeling approaches have been advanced in pursuit of that objective [13]–[17]. Sturzenegger et al. [18] developed the Building Resistance-Capacitance (RC) Modeling software toolbox for the thermal modeling of buildings, applications of which are reported in [19], [20]. All of the aforementioned works rely more or less on the RC model as the internal thermal model. However, in the case of a data center, and in particular the modeling of the inlet temperature distribution of the server racks, we need to presume an open environment without any apparent partitions. The RC model is not expected to be valid in such cases, which is why in this paper we adopt a data-oriented system-identification approach instead.

In this paper, we first introduce an overview of the test system that is shown in Fig. 1 and that includes the super-multipoint
sensing system. The cooling system involves two fans underneath the floor to control the amount and location of cool air that is blown upward. We then model the entire system as a control system and present an MPC-based fan-control policy. The main objective of this paper is to identify the dynamical model that should be used to predict the inlet temperature distribution of the servers from the massive data provided by the sensing system. However, in the field of system identification, there is no technical solution to identify large-scale dynamical systems from the massive data [21]. To address this challenge, we present a systematic scheme for the spatial density reduction of sensors; for this, we use spectral clustering, graph theory and associated techniques to obtain a precise dynamical model. Finally, the accuracy of the proposed model is demonstrated using real data from the test system.

The main contributions of this paper are as follows:

- a novel system and control view for a data center equipped with a super-multipoint temperature sensing system, together with a new fan-control scheme;
- a novel system identification technique involving a systematic reduction scheme of the huge sensor outputs;
- verification of the developed model through simulation with real data.

Some of the concepts presented in this paper have been published as a conference version [22]. However, from the viewpoint of the commercial application, we need to improve the techniques used in [22]. The new improvements in this paper are as follows:

- [22] used the standard sub-space identification technique known as N4SID, which places strong dimensionality limitations on both the input and output data due to the heavy computational burden. To avoid these issues and improve the model accuracy, the present paper uses an auto-regressive exogenous (ARX) model instead.

- Whereas [22] used the mutual information to extract the essential outputs, the present paper uses a distance measure based on power spectral density (PSD) instead to shorten the computation time.

- Whereas [22] showed results for only one fixed fan mode, the present paper contributes new verification results for mixed fan modes based on MPC policy. Consequently, we obtain a dynamical model that gives an average prediction error of 0.58°C.

2. System Modeling of Data Center and Fan Control Policy

This paper addresses the management of the HVAC system in the data-center testbed shown in Fig. 1. The system consists of two server racks, one air conditioner, optical fibers to measure the temperature distributions, and two fans installed under the floor. Top and side views of the room are shown schematically in Fig. 2, where the arrows depict the typical airflow pattern. The racks are divided into areas \( D := \{D_1, \ldots, D_{20}\} \) as shown in the lower part of Fig. 2. Two of these areas contain real servers, whereas the other 18 contain heaters that are used to imitate servers from a thermal perspective. Air is chilled by the air conditioner and then sent to the server room through an underfloor duct, as illustrated by the dark-gray arrows in Fig. 2. This cold air then enters each server in the racks from the cold aisle and is expelled as hot air on either wall side, as illustrated in Fig. 2 by the light-gray arrows. Most of this hot air is discharged via the ceiling space that is linked with the air conditioner, but some
circulates back to the cold aisle. In what follows, we model this process as a control system.

We first introduce the sensors and the measured output. The testbed is equipped with the super-multipoint temperature sensing system that was presented by our research group [3]. In that system, an optical fiber is wound around the inlet surface of each rack, as shown by the dark-gray lines in Fig. 3, where both racks are viewed from the cold aisle. The sensing system detects the temperature at 10 cm intervals along the fiber with a sampling period \( \Delta T = 30 \text{ s} \). There are 723 measurement points \( Y = \{ Y_1, \ldots, Y_{723} \} \) in our testbed, as illustrated by the dots in Fig. 3; measurements at time \( t \) are denoted by \( y(t) = (y_1(t), y_2(t), \ldots, y_{723}(t)) \). We note that the number of sensing points depends on the length of the fiber, which is determined by the size of the data center.

Next, we identify the actuators and control input. The amount and location of the cold air that is blown upward is controlled by selecting one of four different individual modes \( U_0 := \{ O, L, M, H \} \) (\( O \): Off, \( L \): Light, \( M \): Medium, and \( H \): Heavy) for each fan in the underfloor duct. The fan system therefore has 16 potential combined modes \( U := U_0 \times U_0 \). However, for simplicity throughout this paper, we use only the four combined modes in which both fans share a common individual mode. We thus denote the pairs \( (O, O), (L, L), (M, M), \) and \( (H, H) \) simply as \( O, L, M, \) and \( H \), respectively. The HVAC system has two potential control variables: the fan mode and the set-point temperature of the air conditioner. These are generally set independently because of the different time scales on which they operate. Specifically, the settling time of the fan control is roughly 1 min whereas that of the set-point control is roughly 15 min. Therefore, we choose to focus on controlling only the fans while holding the set-point temperature fixed.

The upper part of Fig. 4 shows a visualized distribution of rack inlet temperature provided by the aforementioned sensing system for fan mode \( O \) in the case that only the lower left-hand server in the figure has a high workload and therefore a high temperature. This might necessitate lowering the set point of the air conditioner to cool just this specific location, which would cause wasteful power consumption [2]. In contrast, the lower part of Fig. 4 illustrates the temperature distribution for fan mode \( H \) under the same heat conditions as those in the upper part of Fig. 4. It can be seen that the locations of the cold and hot regions differ according to the fan mode. This raises the possibility that appropriate fan control could avoid having to lower the set point, thereby avoiding unnecessary power consumption [5].

Finally, we regard the heat generated by each server as a disturbance. We denote the heat from server \( D_k \) at time \( t \) by \( d_k(t) \text{ kW} (\geq 0) \), and the collection of \( d_k(t) \) by \( D(t) \). Traditionally, such internal server information was not provided to system operators. However, more data centers are doing so now, which is why we assume that \( d \) is measurable in real time. In summary, the entire process of the control system is illustrated in Fig. 5.

Next, we give an overview of the fan-control policy in order to identify which model should be built. Here, we employ a promising methodology for HVAC control, namely MPC. This requires us to predict the future evolution of the temperature distribution \( \hat{y}(t), \hat{y}(t + \Delta T), \ldots, \hat{y}(t + n_1 \Delta T) \) for a profile of future fan modes \( u(t), u(t + \Delta T), \ldots, u(t + n_1 \Delta T) \) based on the current measurements \( \hat{y}(t) = y(t) + d(t) \) in order to determine the best input profile in the sense of an appropriately designated cost function \( J^* \).

Note that it is desirable from an engineering perspective to...
avoid changing the fan mode frequently in order to extend the machine life while mitigating mechanical fatigue. To reflect this requirement, we assume that the fan mode is fixed in the prediction horizon from $t$ to $t+n_1\Delta T$. This also makes the modeling process more feasible from a technical perspective. Indeed, it would be difficult to parameterize the evolution of $\hat{y}$ with respect to the time sequence of $u$ because of the high nonlinearity associated with drastic changes in the airflow. In contrast, if the fan mode is fixed for a period of time, we expect the trajectories of $y$ to be fairly consistent. In this case, we have only four different models to compute, each corresponding to a fan mode. The entire fan-control system is summarized schematically in Fig. 6.

According to the above policy, we consider a discrete linear-time-invariant (LTI) system model

$$\hat{y}(t+\Delta T) = \tilde{A}(u)\hat{y}(t) + \tilde{B}(u)d(t), \quad (1)$$

where $u \in U$, $\tilde{A}(u) \in \mathbb{R}^{23 \times 23}$, and $d(t) \in \mathbb{R}^{20}$. The parameter $\tilde{A}(u)$ means the equilibrium states for the fixed fan mode $u$ and $\hat{y}(u) = A(u)\hat{y}(u)$ holds. Equation (1) is similar to that used by [11]. Note that the system matrices $A$ and $B$ depend on the fixed fan mode $u \in U$. We acknowledge that some readers might think that it would be better to add intermediate state variables other than the outputs in (1) in order to make the model more accurate. This is true, but it would require the design of an estimator of the states at the control stage. In the present system, it is difficult to estimate a state from the past data of $\hat{y}$ generated by a different fan mode, since the physical meaning of the state variables is not necessarily common among fan modes $u \in U$. That is why we choose the particular form of (1).

### 3. Parameter Identification and Data Reduction

The main challenge in this paper is to identify the huge matrices $A(u)$ and $B(u)$ in (1) for each fixed fan mode $u \in U$. This paper presents a new parameter estimation scheme for the fixed fan mode $u = L$, and the scheme is applied to the remaining fan modes in the same way.

For this purpose, we randomly change the heat input $d_k = [0, 1, 2, 3] \text{ kW}$, $k = 1, \ldots, 20$, and store the input data $d(t)$ and measured outputs $y(t)$ at every time $t \in T$ for a period $T = \{T_1, T_2, \ldots, T_n\}$, where the air conditioner keeps the temperature at 21°C. In this paper, we identify all the parameters in $A(u)$ and $B(u)$ by using the so-called least-squares method, a standard system-identification method for parametric models such as (1). Now, let us denote by $\phi(t) := [(y(t))^T, (d(t))^T]^T$ the output and input data at time $t \in T$, and by $\theta_u = [A(u), B(u)]^T$ the parameter matrices. The notation $^T$ denotes the transposition of a matrix or a vector. Because the ARX model represented by (1) is a linear regression model, the unknown parameters $\theta_u$ that minimize the sum of the square of the errors defined by

$$\sum_{t=2}^{n} \| \phi(T_t) - \phi(T_{t-1}) \|_2^2$$

are given analytically by

$$\theta_u := [A(u), B(u)]^T = [\Phi^T \Phi]^{-1} \Phi^T z \quad (3)$$

if $\Phi^T \Phi$ is invertible, where $z := [y(T_2), \ldots, y(T_n)]^T$, $\Phi := [\phi(T_1), \ldots, \phi(T_{n-1})]^T$, and $\| \cdot \|$ represents the Euclidean norm [21]. To satisfy the invertibility of $\Phi^T \Phi$, we need to remove the 10 monotonic heat data. Hence, the appropriate input dimension of (1) is reduced from 20 to 10, the reduced set of which is denoted by $D_1$. $D_2$ is shown in Fig. 7 and selected in order to be sensitive to the temperature variations caused by the fan control, considering the results of Fig. 4. In fact, Parolini et al. [2] reported that some servers in most current data centers are basically idling at constant load, and the reduction process is needed.

However, when we apply (3) to the original data with the 723 output dimensions, the average root-mean-squared error (RMSE) between the measured data and that estimated with (1) and (3) converges to roughly 1°C; based on our experience, such an error is too large to allow the MPC policy to be implemented. Fortunately, we found that this estimation error could be reduced sufficiently by selecting the output signals appropriately from the 723 points.

We thus present a systematic procedure for extracting the essential outputs from the set of 723 outputs via the technique clustering similar outputs, which is the main challenge of this section. Specifically, we execute the following procedure for...
Next, we compute the dynamical model using only the data of \( \mathcal{D}_r \) and \( \mathcal{Y}_r \) as
\[
\hat{y}'(t + \Delta T) = A_r(u)\hat{y}'(t) + B_r(u)d'(t),
\]
where \( d' := (d_j)_{j \in \mathcal{X}_r} \) and \( \hat{y}' := (\hat{y}_j)_{j \in \mathcal{Y}_r} \). As with (1)–(5), the matrices \( A_r(u) \) and \( B_r(u) \) minimizing the least-squares error are given by
\[
[A_r(u), B_r(u)] = \left[ \Phi_1^T \Phi_1 \right]^{-1} \Phi_1^T z_r,
\]
where \( z_r := \{y'(T_1), \ldots, y'(T_n)\}^\top, \Phi_r := [\varphi_r(T_1), \ldots, \varphi_r(T_{n-1})]^\top, \) and \( \varphi_r(t) := \{(y'(t))^\top, (d'(t))^\top\}^\top, t \in T \). Once the representative signals \( \hat{y}'(t), t = t, t + \Delta T, \ldots, t + n_1\Delta T \) are estimated using (4) and (5), we can estimate the trajectories of the remaining points \( Y_j \in \mathcal{Y}\setminus\mathcal{Y}_r \) to restore the full-scale model given by (1). Specifically, the predicted value \( \hat{y}_j(t) \) of the point \( Y_j \in \mathcal{Y}\setminus\mathcal{Y}_r \) at time \( t \) is given by linear regression on the data of \( \mathcal{Y}_r \) as
\[
\hat{y}_j(t) = \sum_{r \in \mathcal{Y}_r} \beta_{jr} \hat{y}_r(t),
\]
where \( \beta_{jr} \) is a regression coefficient from \( Y_r \in \mathcal{Y}_r \) to \( Y_j \) calculated in advance by the least-squares method.

### 4. Verification

Through the process described in Section 3, we have in (4)–(6) a model for predicting all the output data. In this section, we use real data to demonstrate the effectiveness of the proposed scheme.

To begin with, under the settings given above in Section 3, we identify a reduced model given by (4) for the data set for the identification. Specifically, after subtracting the mean \( \bar{y}(u) \) from the measured output data for identification and scaling the signals, we apply the above parameter-estimation technique. Then, Fig. 9 illustrates the data for validation (black lines) and the estimate (gray lines) based on the model given by (4) and (5) at a portion of representative points. Note that the input data set for validation is different from that of the identification. Furthermore, the initial values of the dynamical model given by (4) are updated after every 10 time horizons (5 min), which is the future horizon \( n_f \) of the cost function that we assume in experimental verification of our proposed fan-control system shown in Fig. 6. We see from Fig. 9 that the time evolution of the estimate at each point is very nearly an evolution of the relatively slow dynamical response of the measured data. Moreover, the average of the RMSE at each representative point is 0.31°C. This precision is finer than both the temperature accuracy of the sensing technology, approximately 0.5°C [3], and natural temperature variations that are between one and a few degrees centigrade [7]. Therefore, in a similar way to that of [7], we

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4 If the reduction scheme is applied to all 723 sensing data instead of only roughly 70 in each loop, each value of \( \lambda_j - \lambda_{j-1} \) in Step 2 is too small for the division.

5 Except for the selection of the similarity measure or entropy between data, there is little difference between the PSD-based approach in Step 1 and the mutual information-based approach presented by [22].
have shown that the precision of our approach is sufficiently acceptable.

We next estimate the trajectories of the remaining points \( Y_j \in \mathcal{Y} \backslash \mathcal{Y}_r \) by using (6). Figure 10 illustrates a portion of the time evolutions of all outputs similarly to Fig. 9. The mean RMSE at each point in all outputs is 0.32°C, which is acceptable from the above reasoning. We see from Figs. 9 and 10 that the proposed identification scheme is valid. In this paper, we demonstrate only the case with \( u = L \), but we fully expect that the other control modes can be dealt with in the same way. The results are listed in Table 1, which indicates that the identified model

| Number of elements in \( \mathcal{Y} \) | \( O \) | \( L \) | \( M \) | \( H \) |
|--------------------------------------|------|------|------|------|
| Number of elements in \( \mathcal{Y}_r \) | 67   | 65   | 73   | 61   |
| Average of RMSE in \( \mathcal{Y} \) (°C) | 0.34 | 0.31 | 0.38 | 0.31 |
| Average of RMSE in \( \mathcal{Y} \) (°C) | 0.33 | 0.32 | 0.39 | 0.31 |
| Average of RMSE in \( \mathcal{Y} \) (°C) for Eqs. (1) and (3) | 0.41 | 0.36 | 0.43 | 0.37 |

accuracies for the other fan modes are valid to the same extent as that of fan mode \( L \).

Finally, we verify the effectiveness of the data-center model
with mixed fan modes activated, which is the desired model shown in Section 2. The desired model is first verified by using the data set of the mixed fan modes shown in the upper part of Fig. 11 and the randomly changed heat input. We assume that the data set of the mixed fan modes is an ideal control trajectory generated by the MPC policy. Then, the measured temperature and the estimate at \(Y_{19}, Y_{262}, Y_{465},\) and \(Y_{651}\) are described by the black and gray lines in Fig. 11, respectively. We see from Fig. 11 that the time evolution of the estimate at \(Y_{19}\) is similar to that of the slow dynamical response of the measured data. Meanwhile, the estimate at \(Y_{465}\) is roughly 0.5°C higher than the measured value as a whole. In addition, the time evolutions of the estimates at \(Y_{262}\) and \(Y_{651}\) do not completely agree with the measured value. Overall, the average of the RMSE at each output is 0.77°C, which is basically poor. Fortunately, from our empirical knowledge, we see that the steady-state error for each fan mode remains constant despite the profile of the heat \(d(t)\) changing randomly. This is because varying the fan modes changes the stationary distribution of cold air in the room. Hence, we take account of the gaps obtained by the pre-identification process in advance, and replace the values \(\hat{y}(u)\) with the mean of the measured output data. The results for the modified model are shown by gray lines in Fig. 12. Surprisingly, we see from this figure that the behavior of the estimate almost coincides with that of the measured data. Moreover, the average RMSE for the 723 outputs is 0.58°C, which is sufficient for the dynamical model of the data center in the same way as the analysis for a fixed fan mode.

If we use the basic system identification model given by (1) and (3) instead of (4)–(6), the average RMSEs for the estimate without/with the correction term are 1.08°C and 0.82°C, respectively. We see from Table 1 and the above results that the estimate performance of the original method is eventually worse than that of the proposed method, although the gap between them is relatively small in this case.

In summary, we conclude that the proposed data-center model and its parameter-estimation scheme with output reduction are valid and superior to the original method. Therefore, we expect that the fan-control system based on MPC shown in Section 2 can be realized successfully, which is left as future work after this paper.

5. Conclusions

This paper has investigated a server cooling system in a data center that has fans placed under the floor and that is equipped with super-multipoint temperature-sensing technology. We began by presenting the concept of a fan-control system based on MPC to cool the heat-generating servers effectively. To realize the control scheme, we required a dynamical model of the temperature variation for each fan mode in order to predict the future evolution of the distribution. We therefore presented a scheme for systematically reducing the output dimension (along with associated techniques) to obtain the dynamical model precisely in the presence of the large volume of data provided by the sensing system. The accuracy of the developed model was demonstrated finally using real data for all fan-control modes. We obtained a dynamical model with an average prediction error of 0.58°C.

Because the proposed method involves systematic state reduction with ensuing model accuracy, it could potentially be app-
Fig. 12 Time evolution of operated fan modes (upper), measured values (black lines) and estimates with correction (gray lines) based on four dynamical models for mixed fan modes at $Y_{19}$, $Y_{262}$, $Y_{465}$, and $Y_{651}$.

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