Experimental Evaluation of Data-Driven Predictive Indoor Thermal Management

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ABSTRACT

This paper considers the problem of thermal management in a typical shared indoor space that may be equipped with multiple heterogeneous heat sources and have different temperature requirements in different sections (thermal zones) of the shared space. Utilizing an on-campus smart conference room as a testbed, we discuss the practical challenges involved in real-time data-driven model learning, when a simple first-order dynamical model is used to capture the dependencies between the heat controls and the air temperatures measured at sensor locations. The data-driven model is then utilized for predictive control of the thermal environment towards minimizing the error between the desired and attained temperatures, and the integrated solution is evaluated against a standard thermal control employed by the BMS.

CCS CONCEPTS

• **General and reference → Experimentation**; *Evaluation.*

KEYWORDS

Thermal management, Data driven learning, Predictive control.

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1 INTRODUCTION

Use of occupant input about their thermal preferences, or real-time thermal control feedback from users, have been proposed as a means of attaining personalized comfort in shared indoor environments, and evaluated in several recent studies [2], [3], [1],[8],[9], [5], [6]. However, even if user comfort preferences/feedback are available, and are assumed to have been declared truthfully, incorporating them into thermal control of shared indoor spaces involves considerable challenges. Typically, large indoor spaces are not in thermal equilibrium spatially, and there can be significant temperature differences between the different sections of the space at any given time. Furthermore, the large indoor spaces are often associated with multiple (possibly heterogeneous types of) heat sources, located in different parts of the space, and the dependency between the heat controls and the spatial thermal map is generally not known, and difficult to model.

Towards modeling indoor thermal environments at reasonable complexity, researchers have often used a multi-zonal lumped parameter model, such as the RC model used in our prior work [4],[5]. However, identifying the thermal zones for open spaces can be challenging [11], and the zones could also be dynamically evolving over time [10]. While detailed spatial or zonal models are needed for high-fidelity simulations of the indoor thermal environment, they are typically not necessary for control purposes. Therefore, given the challenges in estimating the model parameters that can accurately capture the thermal dynamics and differences across the indoor space, we undertake an alternative approach where the dependence between the heat controls (inputs) and temperatures at some specified sensor locations (outputs) is learned using a simple dynamical model. Through our experimentation in a medium-size conference room with open layout, we further show how the size of the model (in terms of the parameters to be estimated) can be further reduced by ignoring some dependencies or averaging over time. We then use our simplified model for *predictive* thermal control in our test bed, and demonstrate that it is able to meet the requested temperatures at the sensor locations much more closely as compared to a standard thermostatic set-point based feedback control algorithm that the BMS implements. While the benefits of data predictive control (DPC) has been evaluated in [7] through numerical studies using synthetic building models, the novel contribution of our work is in the *experimental* evaluation of the benefits of *data-driven learning* of the the indoor thermal environment followed by *predictive* thermal control based on that model.

2 MODEL AND FORMULATION

2.1 Temperature Evolution Model

Temperature evolution of multi-zone indoor spaces is often modeled as a linear first-order dynamical system with an RC network modeling the heat retention in and across the different thermal zones of the space, as in our prior work [4], [5]. In our experimental test bed (described later in Section 3), which is representative of an open work/office space, we are interested in data-driven learning of a "black box" model that represents the dependency between the temperatures measured at some given sensor locations, and the different heat sources for that space. Therefore, a zone based thermal model is inappropriate. However, motivated by the linearity of the RC zonal models, we consider the following discrete-time model, where $n \times 1$ vector y represents the temperatures at the n sensor locations, and $m \times 1$ vector u represents the control inputs ($u > 0$

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for heating and < 0 for cooling) associated with the m heat sources:

$$y(k+1) = Ay(k) + Bu(k) + dy_\infty(k) + w(k). \quad (1)$$

In (1), A, B, d, w are matrices/vectors that would need to be estimated through data-driven learning. In Section 3, we will see how this model can be further simplified to be able to estimate it efficiently in real-time, while still retaining the accuracy needed for purposes of predictive thermal control.

2.2 Predictive Control Objective

Our control objective is to maintain an indoor thermal environment that is comfortable for its occupants while saving energy as much as possible. Occupants can be localized with a variety of Internet-of-Things (IoT) based mechanisms (such as Bluetooth based localization [3]), and occupants' thermal preferences can be translated to preferred temperature set-points at the sensor locations.[1] Let y_d denote the vector of desired temperatures at the sensor locations thus computed. Then our thermal control objective to be minimized over a window of K time units starting at $k_0 + 1$, is

$$J(k_0) = \sum_{k=k_0+1}^{k_0+K} [(y(k)-y_d(k))^T P(y(k)-y_d(k)) + u^T(k)Qu(k)], \quad (2)$$

where square diagonal matrices P, Q are chosen appropriately to trade-off between occupant discomfort and energy usage, and possibly providing differential weighting between different sensor locations and/or different heat inputs. While our objective J assumes quadratic cost functions, the framework applies as long as this dependency can be modeled as increasing, convex functions.

Occupancies and user locations in office environments can often be predicted reasonably well in advance, based on work and meeting schedules, and historical data. Thus, if y_d can be estimated in advance, the objective function J in (2) can be optimized predictively. Through such predictive control, the space can be put in "energy saver" mode during unoccupied periods, it will automatically pre-heat/pre-cool to bring the temperature the user locations to the desired values before it gets occupied. Furthermore, as the occupancy changes through the day, or the positions of the occupants change, the thermal control system will re-optimize automatically and adaptively. In our predictive thermal control solution, J in (2) is minimized over a rolling window, utilizing the predicted/estimated values y_d over the next time window. This optimization is subject to the dynamics (1), where the unknown parameters of the model are obtained through online learning.

3 DATA DRIVEN MODEL LEARNING

Before we list the practical challenges involved in data-driven learning of the model and describe how these were resolved, we describe the test facility that is used in all of our experimentation.

3.1 Experimental Test bed

The layout of the test bed is shown in Figure 1. There are four controllable heat sources, and the heat output of each source is controlled by controlling its output valve. Out of the four heat sources, two sources are wall-attached radiators, as shown in the figure. The other two sources are Air Handling Units (AHU) - one blows hot air while the other blows cold air. The output of the AHUs enter the room through the four inlet air ducts on the ceiling, as shown in the figure. For the purpose of experiments, five wall-mounted wireless temperature sensors were evenly distributed across the space, indicated by red boxes in the figure. The sensors measure temperature once every minute, and report the measurements wirelessly to a server located on one side of the room.

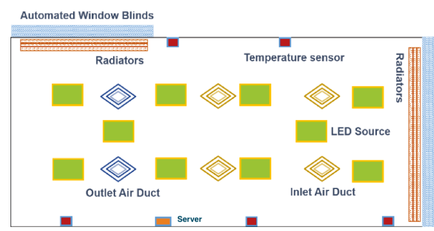


Figure 1: Layout of the Smart Conference Room (SCR) test bed showing different heat sources and sensor locations.

3.2 Effect of Measurement Timescale and Heat Input Aggregation

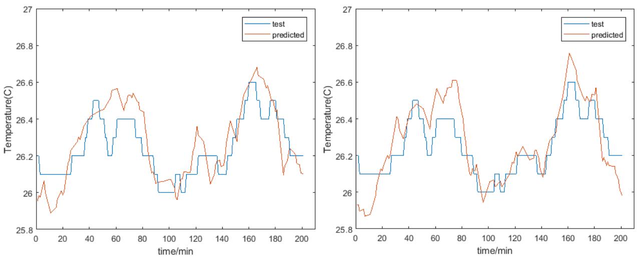
For experimental purposes, the time-step that was used for model learning was set to 5 minutes. Temperature measurements in time-steps shorter than 5 minutes tend to be small and noisy, posing problems in correct estimation of the model parameters in (1). However, even with a time-step set to 5 minutes, $y(k+1)$ was very close to $y(k)$ in (1), resulting in unusually low values of B, the parameter that captures the effect of heat input on temperature. An alternative to that would be to only consider temperature dynamics over longer time-scales (say, 30 mins) – for the purpose of model learning – and "scale it down" to a unit time-step.

We however observed that the one-step prediction capability of the model improves significantly when the heat inputs in each time-step is represented separately in the N time-step dynamics (in our case, N=(30 min)/(5 min) = 6), instead of aggregating them into a single heat input variable over the N time steps. In other words, for the purpose of data-driven parameter estimation, the N-step temperature dynamics is represented as

$$y(k+N) = \hat{A}y(k) + \hat{B}u(k, k+N) + \hat{d}y_\infty(k) + \hat{w}(k), \quad (3)$$

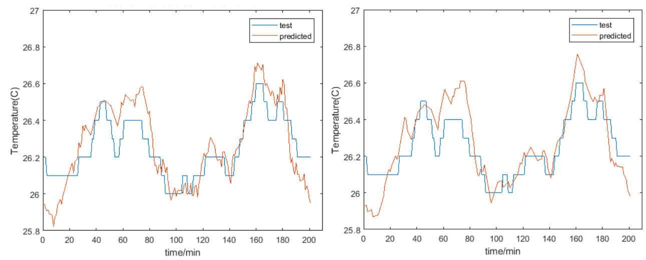
where $u(k, k+N) = (u(k), u(k+1), \cdots u(k+N-1))$ is the *vector* of heat inputs provided over the N time steps $k, k+1, \cdots, k+N-1$. Figure 3 illustrates one-step (or 5-min) prediction results obtained using the data-driven model learned through this process ((b)), along with an approach where the heat input over the N steps (30-min) is aggregated ((a)). Comparing Figure 3 (a) and (b), we see that despite some initial inaccuracy (which exists for both approaches), the learning based on (3) is able to predict the finer details of the temperature curve better than the case where the heat input is aggregated. For the experimental results presented in the rest of the paper, we use this approach for estimating the model parameters.

[1] An occupant's temperature preference could be assigned to the closest sensor, or could be "split" across multiple neighboring sensors, depending on the occupant's location with respect to the sensor field.



(a) Heat input summed over a 30-min intervals used for model learning **(b) Heat input over 5-min intervals used separately for model learning**

Figure 2: Comparison of the one-step temperatures predicted by data-driven learning with experimental values (test), with ((a)) and without ((b)) summing of the heat input over $N(= 6)$ 5-min time steps.



(a) Neighboring sensor correlation terms used for model learning **(b) Only self-correlation terms used for model learning**

Figure 3: Effect of considering cross-correlations between sensor temperatures in estimating model parameters.

3.3 Effect of Ambient Temperature and Cross-Correlation between Sensors

Our analysis of experimental data showed that using the dependency on the ambient temperature, as captured by the term $\hat{d}y_\infty(k)$ in (3), in training the model generated significant offsets between the predicted and actual values. The ambient temperature changes in much slower timescales over which the model estimation is done, and therefore unless a significant amount of historical data is used, it is unlikely to have sufficient richness (variation) in y_∞ to allow a good estimate of $\hat{d}$ (and consequently, d). Since our goal is do adaptive, real-time estimation that can quickly learn about changes in the model, we instead chose not to include the term dy_∞ in our model parameter estimation. This is reasonable - since the rate of variation of y_∞ is relative slow (a couple of degrees per hour, at the most) as compared to the model learning timescale (tens of minutes), any variation of dy_∞ will be captured in the noise term w which is estimated at the latter, faster timescale. This approach removed the offset and produced more accurate prediction by our data-driven model.

Secondly, note that the A matrix in (1) contains n^2 elements in general, which poses a problem in estimating all the parameters accurately when the number of sensors (n) is large. Even for a modest value of $n = 5$ as in our case, it requires estimation of 25 temperature correlation parameters, which is difficult to do reliability without large volume of *independent* data points. One alternative would be to consider only the correlation terms corresponding to neighboring sensors, i.e., $A_{ij} = 0$ is assumed to be zero if sensors i and j are not "near" each other. Determination of the neighborhood relationship can be done in a variety of ways, using only information on sensor location and possibly the layout of the space.

Figure 3 (a) illustrates one-step prediction using this approach. While we observe that the temperatures predicted by our model are quite close to the experimentally observed temperatures, the predicted temperatures includes some fluctuations. This "noise" is greatly reduced when we perform data-driven learning and prediction using self-correlation terms only, i.e., only 5 self-correlation terms (A_{ii}) are considered, and all cross-correlation terms ($A_{ij}, i \neq j$) are assumed to be zero. This is observed from 3 (b) which illustrates this case; we see that the predicted temperature curve is much smoother than that in (b). Thus, based on the above discussion, the final model we use in our experiments can be simply written as

$$y_i(k+1) = a_i y_i(k) + B_i u(k) + w_i(k), \tag{4}$$

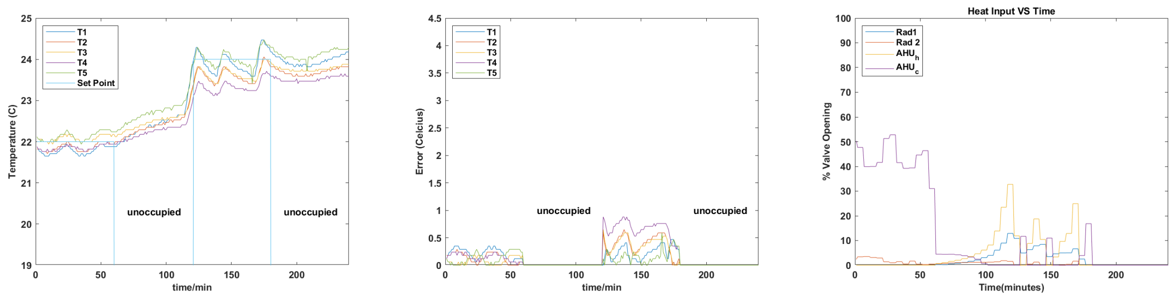
where scalar $a_i = A_{ii}$, vector B_i is the ith row of B in (1), and scalar w_i is a noise term that captures both the effect of ambient temperature and other uncontrollable heat sources on sensor i.

4 EXPERIMENTAL EVALUATION

We conducted several experiments, in which different meeting schedules and occupant preferences were physically simulated over five-hour test periods in our test bed (SCR). The thermal environment of the SCR is impacted by two ambients: the outside temperature ($y_{1,\infty}$), and temperature inside the building in which the SCR is located ($y_{2,\infty}$). For comparability, the experiments were performed on days (and hours) with approximately same $y_{1,\infty}$; $y_{2,\infty}$ was maintained around 23°C for all the experiments. Below, we present the results from one such scenario where the results obtained by our data-driven learning and predictive control approach are compared with a standard BMS approach. The BMS algorithm uses a set-point based proportional controller for maintaining the temperature set points for individual zones/rooms within the building.

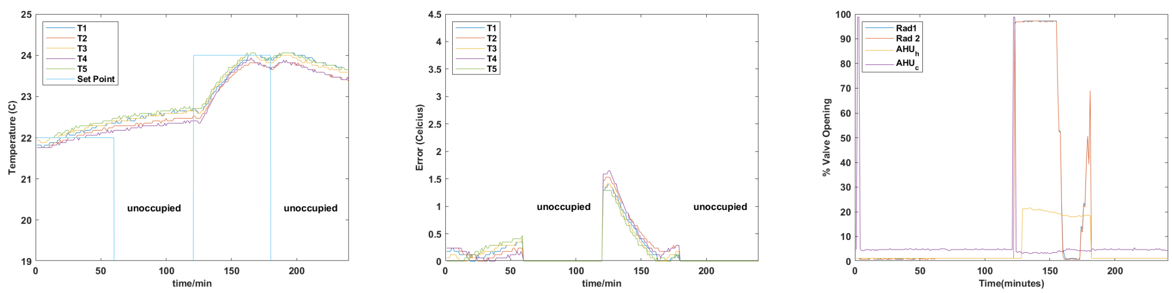
Typically, the conference room is utilized to host group meetings and presentations at different times of the day. In the example scenario whose results are presented next, hours 1 and 3 are assumed to have scheduled meetings, and there were no meetings scheduled in hours 2 and 4 of the 4-hour period. The individuals attending each meeting, and their temperature preferences, are assumed to be known (declared) in advance. In this specific scenario, it was assumed that the occupant (meeting attendee) temperature preferences were averaged to obtain a preferred temperature to be maintained at all sensor locations during the meeting period. This temperature preference was 22°C and 24°C in hours 1 and 3, respectively. There were no preferred temperatures or set points during hours 2 and 4 (when there were no meetings).

Figures 4 and 5 show the results for the two cases: the proposed Data-driven Learning and Predictive Control (DLPC) approach, and the existing BMS thermal control algorithm. Before the start of hour 1, both DLPC and BMS reach close to the desired temperatures (22°C) for the first meeting. However, during hour 1, we see that DLPC is able to maintain a temperature that is very close to the desired temperature throughout the hour; on the other hand, for



(a) Temperature measured at the 5 sensors, and desired temperature **(b) Difference between attained and desired temperatures at the 5 sensors** **(c) Heat Input, expressed as valve opening percentage, from the 4 sources**

Figure 4: Results for our approach that uses data-driven model learning and predictive control (DLPC)



(a) Temperature measured at the 5 sensors, and desired temperature **(b) Difference between attained and desired temperatures at the 5 sensors** **(c) Heat Input, expressed as valve opening percentage, from the 4 sources**

Figure 5: Results for the set-point based proportional controller used by the building management system (BMS)

BMS, the temperatures slightly increase over the hour. During hour 2, no meeting is scheduled, and therefore the BMS shuts down the heat inputs during that hour, other than maintaining a minimum level of cooling input from the AHU cooling unit. On the other hand, DLPC uses the two radiator heat inputs, particularly in the second half of that hour, in anticipation of the next meeting (in hour 3). DLPC is able to attain close to the desired temperatures of ($24^{\circ}C$) by the beginning of the next meeting, and maintains that throughout the meeting time. Under BMS, on the other hand, the sensor temperatures are only around $22.5^{\circ}C$ at the beginning of hour 3. BMS then turns on both the radiators at full capacity; however, it is only able to get close to the desired temperature of $24^{\circ}C$ towards the end of the hour. Comparing Figures 4 (b) and 5 (b), we see that the maximum deviation of temperature (from the desired temperature) at the sensors during that hour is less than a degree under DLPC; under BMS, this deviation is close to two degrees. This illustrates the benefits of predictive control in terms of attaining the desired temperatures during occupancy periods. Since there was no meeting scheduled or planned after hour 4, DLPC shuts down all heat inputs during that hour. With no occupants during that time, the BMS also shuts down the heat inputs, except for maintaining a minimal level of AHU cooling input, as it was part of the standard BMS control setting.

5 CONCLUDING REMARKS

In this paper, we presented and evaluated DLPC, a thermal control solution for indoor spaces that combines data-driven model learning with predictive control of heterogeneous heat inputs associated with the space. Supported by our experimental study, we discussed the challenges involved in real-time estimation of model parameters and ways to resolve them, and demonstrated that DLPC is able to attain temperatures close to the desired ones at all times (even as occupancies changed), unlike the standard BMS algorithm.

One limitation of our study is the lack of direct comparison between the energy usage (cost) of DLPC and BMS approaches. Comparing the aggregate valve opening values in Figures 4 (c) and 5 (c), we observe that while DLPC utilized slightly more cooling input than BMS, the latter used significantly more of all three heating inputs as compared to BMS. While the relationship between value opening and energy usage is not easily quantifiable, based on the valve opening results we would expect that the energy usage under DLPC will be comparable to that under BMS, and perhaps better. Further, the predictive DLPC approach results in a smoother energy usage pattern than the reactive BMS algorithm.

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REFERENCES

[1] E. Azar. 2012. Agent-based modeling of occupants and their impact on energy use in commercial buildings. *J. Comput. Civil Eng.* 26, 4 (2012), 506–518.

[2] V. L. Erickson and A. E. Cerpa. 2012. Thermovote: Participatory Sensing for Efficient Building HVAC Conditioning. In *Proceedings of the Fourth ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings (BuildSys '12)*. ACM, New York, NY, USA, 9–16. https://doi.org/10.1145/2422531.2422534

[3] S. K. Gupta, S. Atkinson, Ian O'Boyle, J. Drogo, K. Kar, S. Mishra, and J. T. Wen. 2016. BEES: Real-time occupant feedback and environmental learning framework for collaborative thermal management in multi-zone, multi-occupant buildings. *Energy and Buildings* 125 (2016), 142 – 152. https://doi.org/10.1016/j.enbuild.2016.04.084

[4] S. K. Gupta, K. Kar, S. Mishra, and J. T. Wen. [n. d.]. Singular Perturbation Method for Smart Building Temperature Control Using Occupant Feedback. *Asian Journal of Control* 20, 1 ([n. d.]), 386–402. https://doi.org/10.1002/asjc.1587 arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/asjc.1587

[5] S. K. Gupta, K. Kar, S. Mishra, and J. T. Wen. 2015. Collaborative Energy and Thermal Comfort Management Through Distributed Consensus Algorithms. *IEEE Transactions on Automation Science and Engineering* 12, 4 (Oct 2015), 1285–1296. https://doi.org/10.1109/TASE.2015.2468730

[6] S. K. Gupta, K. Kar, S. Mishra, and J. T. Wen. 2018. Incentive-Based Mechanism for Truthful Occupant Comfort Feedback in Human-in-the-Loop Building Thermal Management. *IEEE Systems Journal* (2018), 1–12. https://doi.org/10.1109/JSYST.2017.2771528

[7] A. Jain, M. Behl, and R. Mangharam. 2017. Data Predictive Control for building energy management. In *2017 American Control Conference (ACC)*. 44–49. https://doi.org/10.23919/ACC.2017.7962928

[8] R. K. Jain, J. E. Taylor, and G. Peschiera. 2012. Assessing eco-feedback interface usage and design to drive energy efficiency in buildings. *Energy and Buildings* 48 (2012), 8 – 17. https://doi.org/10.1016/j.enbuild.2011.12.033

[9] L. Klein, J-Y. Kwak, G. Kavulya, F. Jazizadeh, B. Becerik-Gerber, P. Varakantham, and M. Tambe. 2012. Coordinating occupant behavior for building energy and comfort management using multi-agent systems. *Automation in Construction* 22 (2012), 525 – 536. https://doi.org/10.1016/j.autcon.2011.11.012 Planning Future Cities-Selected papers from the 2010 eCAADe Conference.

[10] M. Minakais, S. Mishra, J. T. Wen, L. Lagace, and T. Castiglia. 2015. Design and instrumentation of an intelligent building testbed. In *2015 IEEE International Conference on Automation Science and Engineering (CASE)*. 1–6. https://doi.org/10.1109/CoASE.2015.7294032

[11] M. Minakais, J. T. Wen, S. Mishra, R. Zhou, Z. Wang, and A. Shah. 2014. Office building model identification and control design. In *2014 American Control Conference*. 1051–1056. https://doi.org/10.1109/ACC.2014.6859286