Graphical Abstract

Impact of Occupant Related Data on Identification and Model Predictive Control for Buildings

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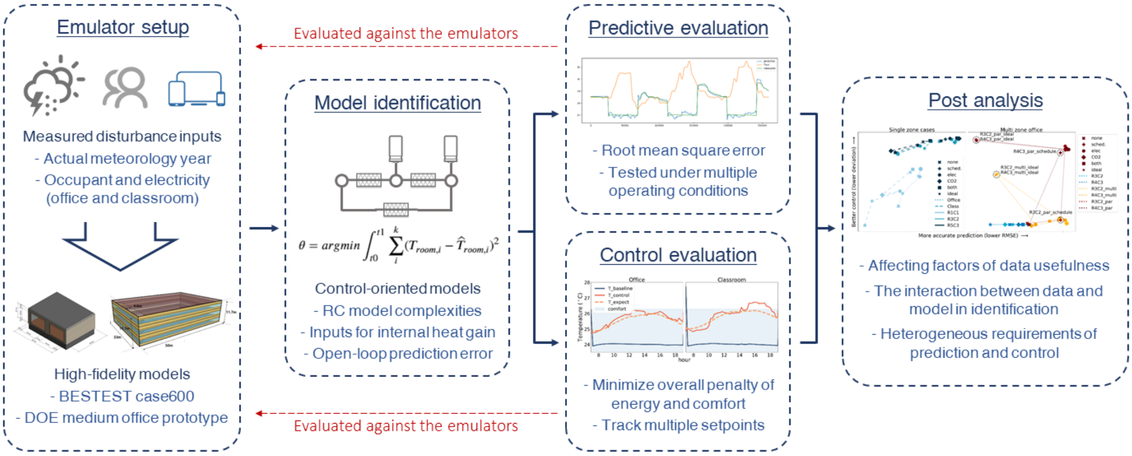

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Highlights

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- Over 10% energy saving and acceptable PMV achieved without occupant-related data.
- Occupant-related data is needed only if the internal heat gain has high variability.
- Adequate model with sufficient data yields physically representative identification.
- Better physical representation could lead to larger RMSE but more precise control.
- Sparse data and parsimonious modeling should be pursued in real-world implementation.

Impact of Occupant Related Data on Identification and Model Predictive Control for Buildings

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ABSTRACT

Model predictive control (MPC) has shown potential in improving building performance but is bottlenecked by the difficulty in constructing control-oriented models. The challenge lies in evaluating the sufficiency of the model and the data usage beforehand. This paper bridges the knowledge gaps in the interactions between data requirements, model quality, and control performance by integrating real-world measurements and simulation-based experiments. The data usage related to occupancy and Internal heat gain (IHG) was studied considering its importance and the absence of consensus in the literature. Varying occupant-related data sources were tested as RC model inputs, including none, schedule, electricity consumption, CO_2 ppm, and ideal measurement. Combinations of model inputs and complexities were examined for prediction and control in an office, a classroom, and multi-zone offices on one floor. The results indicated that the usefulness of data is jointly affected by three factors: measurement suitability, model complexity, and modeling purpose. Given the adequate model structure, satisfying prediction and control performance was achieved in offices with no detailed measurement. Meanwhile, electricity and CO_2 were needed together to capture the IHG influence and realize the good performance for classrooms. The experiments also uncovered the heterogeneous requirements on models from traditional prediction tests and the control tasks. Lower prediction error did not always mean better control. More importantly, we provided the first quantitative demonstration of the complementary relationship between model adequacy and data informativeness with respect to different purposes. This study advocates the pioneering idea of sparse data usage and parsimonious modeling, which promotes the actual application of MPC in buildings by guiding control-oriented model development.

1. Introduction

Buildings contribute more than a third of global greenhouse gas emissions and energy consumption, playing an important role in the trending campaign of reducing carbon emission [1]. There is an escalating need to apply optimal control for better building operating performance. For example, both occupant comfort and energy efficiency can be improved by integrating advanced sensing technologies and occupant-centric control [2]. Plus, the fast installation of renewable energy generation calls for more flexible buildings with demand response control [3].

1.1. MPC and control-oriented models

Model predictive control (MPC) is an established optimal control method that has succeeded in many industrial fields [4]. It determines the optimal control decision at every time step with three main components: disturbance forecasting, control-oriented modeling, and receding horizon optimization. MPC has been tested in buildings since the 1990s [5]. Able to incorporate various system dynamics and disturbances, it showed great potential in many applications, such as improving system performance and integrating renewable energy sources [6, 7].

Despite its potential, there was a limited number of actual applications during the past decades [8]. One major barrier is the cost of obtaining an adequate control-oriented model, which is the foundation of the entire framework [9]. Henze [10] reported that creating and calibrating the models account for 70% of the total effort in implementing MPC in buildings. Past studies have proposed various modeling methods for MPC, such as physics-based (white-box) models [11], data-driven (black-box) models [12], and hybrid (gray-box) models [13]. Physics-based models are based

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on physical equations and building metadata. They can predict under different operating conditions but have to undergo a troublesome calibration [14]. Data-driven models, on the contrary, only involve building operation data but could suffer extensibility issues [15]. Hybrid models combine physics-based and data-driven models, integrating physical equations, building information, and data-driven parameter estimation [16].

The Resistor-capacitor (RC) model is the typical hybrid model of choice because it shares the advantages of the other two model types and is suitable for optimization [17]. Unfortunately, it inherits the disadvantages from both sides as well. First, it requires both building physics knowledge for model creation and time-series operation data for identification. Zhan and Chong [18] proposed a Level of Detail (LoD) framework to quantify the data usage and pointed out the lack of consensus on which LoD to use. Besides, while having a simplified physical model structure, the parameters could be wrongly estimated if the training data does not properly describe the building dynamics. The poorly identified control-oriented model could jeopardize the prediction and control performance [19]. Lin et al. [20] suggested conducting excitation experiments for identification instead of using a larger amount of regular operation data. However, it is practically challenging to realize dedicated experiments and realistic disturbances simultaneously [21].

In addition to the difficulty in modeling building dynamics, it is even harder to determine how accurate a model should be and to assess the modeling effort in advance [22]. Bengea et al. [23] showed 5% more energy cost and 100% more comfort violation caused by 10% of model discrepancy. By contrast, RMSE was found to be an insufficient measure of control performance [24]. Atam and Helsen [16] suggested that control-oriented models should be carefully examined from multiple aspects, including model structure, parameter values, and predictive performance over the control horizon. These non-trivial approaches were designed for different situations and require intensive expert knowledge, making them hard to generalize in practice.

1.2. Sparse data and parsimonious modeling

The challenges of the scalable application of MPC in buildings can be attributed to the knowledge gaps between data requirements, model quality, and control performance. The first unresolved question is what data should be used to obtain the control-oriented model. There are various data sources over the building life cycles, such as the metadata from design and the time-series data from operations, among which many are not as useful for the modeling or control objectives [25]. Meanwhile, many important variables are typically immeasurable or unavailable in practice, such as surface temperature and heat flux. This leaves buildings hardly data-rich compared with other advanced control objects such as industrial process and robots, the status of which are closely monitored. Thus, it is essential to select the data that provides useful information for model identification. Using insufficient data could reduce a model's predictive performance [26]. On the other hand, it is not beneficial to simply use all available data. An excessive amount of data could not just increase the computational cost, but also dilute the embedded information and cause trouble in further analysis [19]. Hence, sparse data usage should be pursued when acquiring control-oriented models. The dictionary definition of sparse is "something small in number or amount and spread out over an area". In this context, it refers to the data that has relatively low volume and dimensionality but provides sufficient information to identify the control-oriented model with good quality.

The information contained in the data of a specific measurement is usually reflected in data length, time resolution, and distribution. For the dataset of a building, another significant factor is the type of data sources. For example, occupant behavior and the resulting internal heat gain (IHG) is a major source of uncertainty in building operations [27]. As the exact IHG cannot be measured, the question towards sparse data usage is what data source is needed to convey the information. Various data sources for IHG inputs have been used in control-oriented models. Some models used no input for IHG and expected the model to incorporate the uncertainty [12]. Under the shortage of real-time measurement, Váňa et al. [28] approximated the IHG with a ratio-based design schedule. As a more informative choice, the profiles were estimated based on the electricity consumption trend [29]. Among the measurements that are less available in building operations, CO_2 concentration was usually used for control-oriented modeling [30, 31]. As the role of occupants varies across building functions, the required data sources could also differ [32, 33].

Given sufficient data, the next challenge lies in designing the model. Similar to the recently promoted idea of "fit-for-purpose" modeling [34], the quality of a model should be assessed by its effectiveness in the control optimization, which involves extrapolation outside of the training data range. Due to the complicated building dynamics and exogenous disturbances, there is always an inevitable discrepancy between reality and what a model can explain [35]. Considering that a dataset can only account for part of the variability in building operations, model selection and identification should account for a trade-off between fitting the data and representing the building. Too complex models could lead to misspecification of the parameters [36, 37]. It has long been advocated to parsimoniously construct useful computational models and to avoid overparameterization when chasing lower errors [38, 39]. For MPC in buildings, parsimonious control-oriented modeling should aim stronger model capability in lieu of higher accuracy on normal testing data. The model capability evaluates how well a model can extrapolate in different conditions and support the control decision.

Sparse data and parsimonious modeling are interrelated and closely tied to the control performance. Therefore the key to realizing them in practice is linking the model quality and the control performance. Most past studies developed one model to fulfill the control purposes. There has been a huge variation in model complexity even just within the category of RC models [40]. However, due to the diversity across buildings, studies catering to specific buildings are typically not generalizable and cannot be aggregated for comparison. Consequently, well-defined experiments need to be conducted to better understand the influence of different model configurations. Only a few studies focused on this. Picard et al. [41] varied the number of states in the model and spotted the minimum amount that guarantees the control performance. Blum et al. [24] tested several practical factors of model identification and concluded with a couple of modeling suggestions. Arroyo et al. [42] found that a centralized multi-zone model and a simplified single-zone model achieved similar prediction and control performance. A comprehensive understanding of the relationship between model quality and control performance is lacking.

1.3. Research objectives

This paper has three research objectives:

1. Investigate how data inputs affect model identification and the resulting model capability. Identify the sparsest data required to acquire a reliable control-oriented model.
2. Study alternative data sources for internal heat gain in different building types as one aspect of data requirements.
3. Address the relationship between model quality and control performance, thereby steering parsimonious model development in actual MPC applications.

A simulation-based approach was integrated with real-world data to fulfill the objectives. RC model structures, paired with internal heat gain input types, were varied to investigate the interrelationships in three test cases. The models were extensively tested for extrapolation capability and control performance. In the rest of this paper, section 2 introduces the simulation framework and the experiment setup. Section 3 and 4 present the results of model identification and control experiments. Subsequently, section 5 discusses the theory of sparse data and parsimonious modeling based on observations from the experiment results. Upon concluding this study, we point out directions for further investigation.

2. Methodology

2.1. Simulation framework

Figure 1 shows the experiment framework, including the end-to-end emulation of implementing Model Predictive Control (MPC) in buildings. It consists of four main stages: emulator setup, model identification, model evaluation, and post-analysis. In each experiment, the high-fidelity emulator served as a real building to generate synthetic datasets while exposed to actual measurements of boundary conditions. The training and testing datasets were split to estimate the parameters of RC models and evaluate the identification results. Next, the MPC controller based on the identified RC model determined the control action through optimization, which was applied back to the emulators for control performance evaluation. Given the complete flexibility in dataset generation and the low cost of repeating experiments under the same boundary conditions, RC models with different complexities and inputs were comprehensively tested. Post-analysis was then carried out to establish the relationships between data requirements, model quality, and control performance.

- **Emulator model** We designed three test cases for better generalizability. The first test case is BESTEST Case600, which is a single-zone office case with light-weight construction [43]. The room was conditioned by a fan coil unit that supplies air at a constant 13°C. As the baseline control, a PI controller was used to adjust the supply airflow rate to meet the room temperature setpoint of 24°C, which generated the synthetic dataset. To represent the large uncertainties in internal heat gains (IHG) in actual offices, we collected the occupant number and electricity consumption (plug and lighting) of an office for three months. The measured profiles, instead of standard design

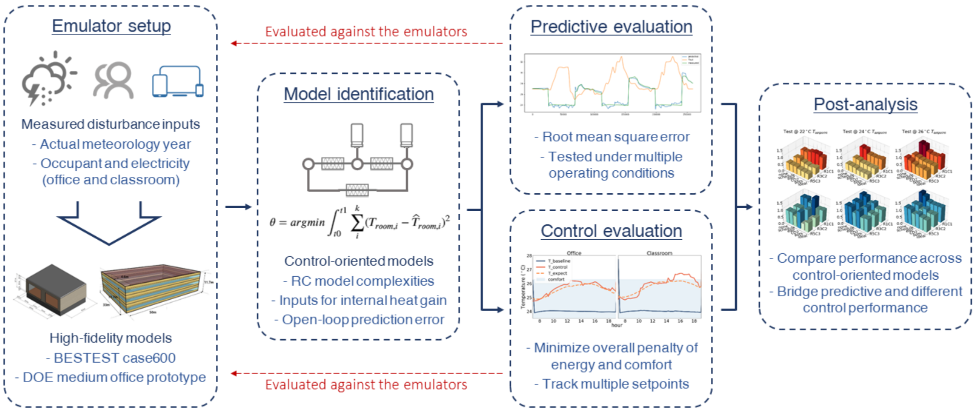

Figure 1: Structure of the framework that emulate the end-to-end process of implementing MPC.

schedules, were applied to emulate occupant, equipment, and lighting heat gains. The actual meteorological year (AMY) data in Singapore was utilized for external disturbances.

The second test case is a single-zone classroom case with the same geometry and HVAC system as the first test case. However, Wi-Fi access point connection number (as a proxy of occupant number) and electricity consumption (plug and lighting) were collected in an actual classroom and used as input schedules. Figure 2 plots one week of the collected data, from which the larger scale and irregularity of classroom profiles can be observed. Incorporating actual data from different types of room functions introduced variations in the role of occupants and their temporal characteristics.

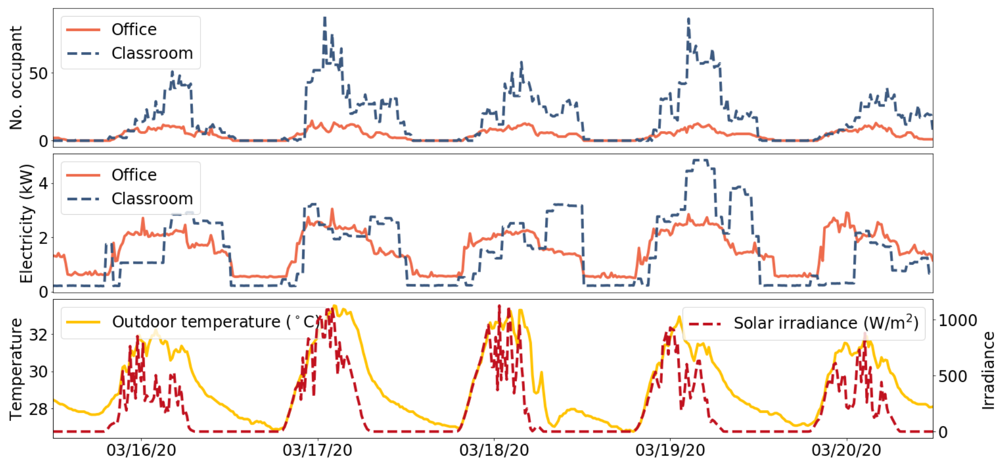

Figure 2: One week of measured data of internal and external disturbances.

The third test case is a multi-zone office on a single floor with five thermal zones (four perimeter zones and one core zone) that is based on the US Department of Energy medium office prototype building [44]. The internal gain profiles for each zone on each day were randomly sampled from the measured data of the office. While being also office-based, the multi-zone test case came with more complex system dynamics, such as the inter-zone heat transfer and the more complicated HVAC components. This is another critical factor that affects predictive and control performance. These emulators were built using the Modelica Buildings Library[1] and simulated for three months using PyFMI[2].

- **RC model** The RC models represent the simplified thermal dynamics of the room with a set of parameters θ (resistances, capacitances, and heat gain coefficients). More details about the model structures can be found in the section on experiment design. Synthetic data in a short period was used to estimate the parameters θ via Non-Linear Programming (NLP). Equation 1 defines the estimation problem, where x is the states, u is the inputs, d is the disturbances, k is the number of rooms, $t0$ and $t1$ are the start and end time of training data. The lower and upper bounds of parameter values (θ^{lb} and θ^{ub}) are based on prior knowledge. Ten days were randomly picked from the remaining days in the three months to evaluate the identified models. Both training and testing adopted relatively long prediction horizons without re-initialization to incorporate more information about the building dynamics. To examine the extrapolation capability of the RC models, Root Mean Squared Error (RMSE) was calculated against operation data with 22, 24, and 26 °C room temperature setpoint. For the multi-zone case, RMSE was calculated against the average temperature of five zones, as well as the room temperature of each zone.

$$
\begin{aligned}
&\theta = argmin \int_{t0}^{t1} \sum_{i}^{k} (T_{room,i} - \hat{T}_{room,i})^2 \\
&s.t. \quad \hat{T}_{room} = f(x, u, d, \theta) \\
&\qquad\; \theta^{lb} \leq \theta \leq \theta^{ub}
\end{aligned} \tag{1}
$$

- **MPC controller** Two control experiments were conducted to comprehensively evaluate the models' capability. First, Equation 2 formulates a typical MPC optimization task. The quadratic objective function penalizes the cooling power and thermal discomfort with weights q_u and q_t. Cooling power is represented by the control input m_{flow}, and thermal discomfort is quantified by the absolute value of Predicted Mean Vote (PMV) during the operating hours (7 am to 7 pm). The PMV was calculated assuming the relative humidity of 60% and quietly seated occupants with the typical summer indoor clothing [45]. The minimization is subject to the nominal airflow rate and comfort constraints. The prediction and control horizons are half an hour (two time steps), which is relatively short but enough for the indoor conditions to reach steady state. Longer horizons caused negligible change on the control actions in preliminary tests. The internal states were estimated using the Unscented Kalman Filter, and the boundary conditions were assumed to be known to eliminate its impact on the control performance. The control performance was evaluated on the randomly selected testing days according to the resulting energy consumption, average PMV, and discomfort hours.

$$
\begin{aligned}
&J = \int_{t_0}^{t_0+30min} \sum_{i}^{k} \left(q_u (m_{flow,i})^2 + q_t (PMV_i)^2 \right) \\
&s.t. \quad 0 \leq m_{flow,i} \leq m_{flow,norm} \\
&\qquad\; -0.5 \leq PMV \leq 0.5
\end{aligned} \tag{2}
$$

  Considering the trade-offs between comfort and energy, higher cooling temperature setpoints are often associated with lower energy consumption and higher discomfort risk. Therefore, these evaluation metrics cannot distinctly reflect the control performance. Meanwhile, good decision-making in all MPC tasks relies on accurate load prediction given future disturbances. Accordingly, we defined another control task of tracking the room temperature setpoint (equation 3), where the only objective is to maintain the room temperature by controlling the supply airflow rate. This control task was kept simple to eliminate other affecting factors and to study the effect of model mismatch. The control performance was quantified by average setpoint violations (°C) and subsequently evaluated under three temperature setpoints (22, 24, and 26°C) on randomly-selected days. Both control tasks

[1]https://simulationresearch.lbl.gov/modelica/
[2]https://jmodelica.org/pyfmi/

Table 1
Summarized design of experiments.

	Single-zone office	Single-zone classroom	Multi-zone office
High-fidelity emulator	BESTEST Case600		a floor of DOE medium office
Emulator inputs	occupant count and electricity consumption of an office	Wi-Fi count and electricity consumption of a classroom	randomly sampled office daily occupant and electricity profiles
Emulator outputs	room temperature, electricity consumption, CO2 concentration, internal heat gain, supply airflow rate		the single-zone measurements of each zone
RC model sturcture (number of parameters)	R1C1 (3), R3C2 (7), R5C3 (10)		R3C2 (7), R4C3 (9), R3C2_multi (15), R4C3_multi (17), R3C2_par (19), R4C3_par (21)[a]
RC model inputs	*common inputs*: outdoor temperature, global horizontal solar radiation, supply airflow rate *alternative inputs for internal heat gain (No. parameters)*: none (0), schedule[b](1), electricity consumption (2), CO_2 ppm (2), elec+CO_2 (electricity and CO_2 ppm, 3), ideal measurement (0)		
Training data	three days of normal operation with 24°C setpoint		one day with time-varying temperature setpoint[c]

[a] Constructions with the same material were restricted to have proportional Rs and Cs in multi-RC models (R3C2_multi, R4C3_multi, R3C2_par, and R4C3_par) to limit the number of parameters to estimate.
[b] Standard schedules according to ASHRAE [46] were used for the offices, and the class schedules were queried from the university administration system for the classroom.
[c] One of the five zones took turns to increase temperature setpoint by 2°C, while the other four zones remained 24°C.

were solved via NLP using the interior point method.

$$J = \int_{t_0}^{t_0+30min} \sum_{i}^{k} (T_{room} - T_{setpoint})^2 \tag{3}$$
$$s.t. \quad 0 \le m_{flow,i} \le m_{flow,cap}$$

2.2. Design of experiments

Table 1 summarizes the key variables of the experimental design. Variations in the emulator configurations have been elaborated on in the previous section. The emulators output commonly available measurements, including room temperature, electricity consumption, CO2 concentration, and supply airflow rate. The exact amount of internal heat gain, typically immeasurable in practice, was also exported as an ideal situation for comparison.

RC models with increasing complexities were designed respectively for the single-zone and multi-zone cases. Figure 3 shows the schematic diagrams of all RC model structures, and the resulting total numbers of parameters of each model are specified in Table 1. Three levels of complexities were tested for the single-zone cases. R1C1 lumped the entire room into a capacitor $C1$ and a resistor $R1$ connecting the outdoor temperature node. Cooling power and internal heat gain were directly delivered to the room temperature node, so was solar heat gain but with a coefficient a. R3C2 modeled the wall as a separate capacitor C_{wall} and two resistors R_{wi} and R_{we}. Another resistor R_{infil} was added to model the infiltration. Solar heat gain was then absorbed by the wall and room node with coefficients a_{int} and a_{wall}. R5C3 considered the heat transfer through the floor with three extra parameters R_{fi}, R_{fe}, and C_{floor}. Since the floor was exposed to a constant ground temperature, this configuration was expected to capture separate dynamics different from the wall.

For the multi-zone case, R1C1 was too simplified to obtain comparable results and therefore excluded. R3C2 and R4C3 simplified the multi-zone dynamics as one zone and only modeled the average room temperature in response to the total cooling power. As the multi-zone emulator was not exposed to the ground temperature, R4C3 was used by removing the floor branch from R5C3. Centralized multi-RC models characterized the heat flow between neighboring zones. R3C2_multi and R4C3_multi connected five single-zone RC models with a resistor R_{par} as the partitions (R1_partition). Further, R3C2_par and R4C3_par modeled the partitions with R2C1_partition (R_{pi}, R_{pe}, and C_{par}). In total, 6 RC model complexities were compared for the multi-zone case.

Another essential variable in the experiment design is the input data of RC models. All models took outdoor temperature T_{out} and global horizontal solar radiation Q_{solar} as external disturbances. The cooling power Q_{HVAC}

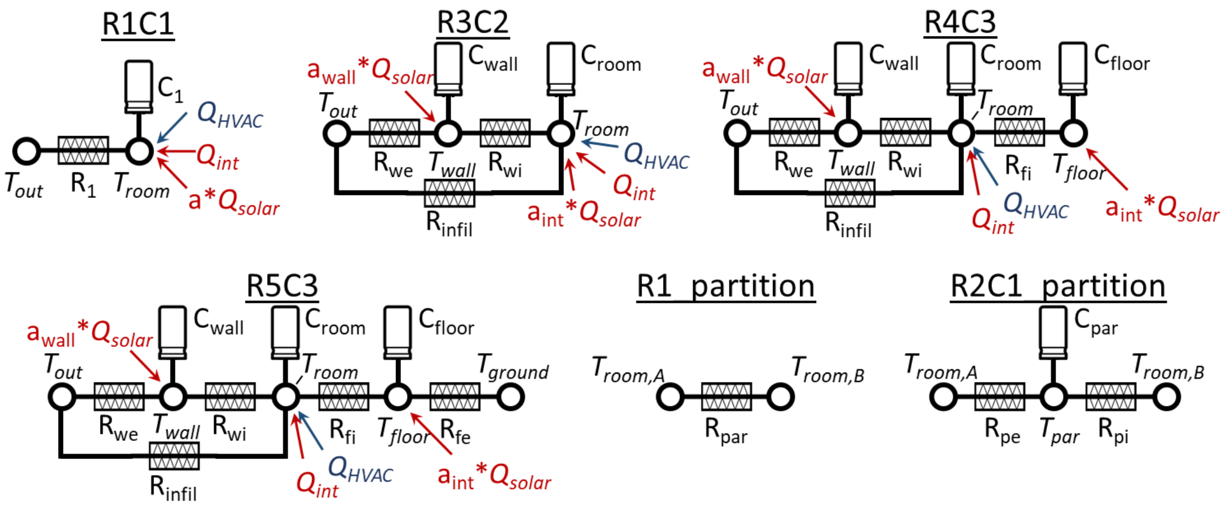

Figure 3: Structure of the RC models with the input of disturbances and control actions annotated by arrows.

was estimated with the supply airflow rate m_{flow}. For internal disturbances that model the internal heat gain (IHG), six data sources were tested: `none`, `schedule`, electricity consumption (`elec`), CO_2 ppm (`CO2`), `elec+CO`$_2$, and ideal measurement (`ideal`). More detailed measurements provide more information about IHG, yet is more costly to acquire in practice. `Schedule` referred to the standard schedule of offices [46] and the university administrative class schedule for the classroom. The load capacity Cap was multiplied to model IHG. `Elec` and `CO2` were outputs of the emulator. The coefficients a_{elec} and a_{CO2}, as well as the offset b, were applied to fit IHG. `Elec+CO`$_2$ was `elec` and `CO2` combined together, characterized by the three parameters a_{elec}, a_{CO2}, and b. These IHG-related parameters were also estimated through model identification. `Ideal` was the exact IHG measured from the emulators. Different combinations of RC model complexities and IHG inputs yield 18 alternative RC models for single-zone cases and 36 for the multi-zone case.

Temporal and operational factors were also considered when generating the training dataset. We conducted preliminary experiments to investigate how they affect the model identification as suggested in past studies [47, 24]. It appeared that time intervals smaller than 15 minutes were sufficient to capture the dynamics. Regarding the training data length, longer periods slightly reduced the error but drastically increased the computation time. Concisely, three days of training data with 15-minute intervals reached a balance between training error and computation time for the single-zone cases, whereas one-day data with 15-minute intervals best served the multi-zone case. Regarding the operation scheme, regular operation with a constant temperature setpoint of 24°C was sufficient for the single-zone cases. However, the multi-zone case desired operational data with time-varying setpoints to provide adequate excitation and represent the inter-zone dynamics. Consequently, these were adopted for training data generation in further experiments.

3. Single-zone simulation results

3.1. Identification and prediction

Figure 4 visualizes the RMSE results that evaluate the RC models' prediction accuracy. Each bar chart compares the RMSE of the 18 alternative RC models for the corresponding test case and operating conditions. The bars under specific testing conditions represent the average RMSE of the randomly-selected testing days.

It can be seen that RMSE was kept lower than 0.5°C in most cases for the office, which means these simplified RC structures were able to track the basic trend of the room dynamics. For the classroom, however, RMSE was overall larger, and the error of less accurate models frequently exceeded 1°C. The change of RMSE against different datasets was similar for the two cases: low for the training dataset, gradually increased as the testing conditions changed from 22°C to 24°C and 26°C. This indicates that the models had some extrapolation capability but were weakened when the external heat gain and cooling power are smaller.

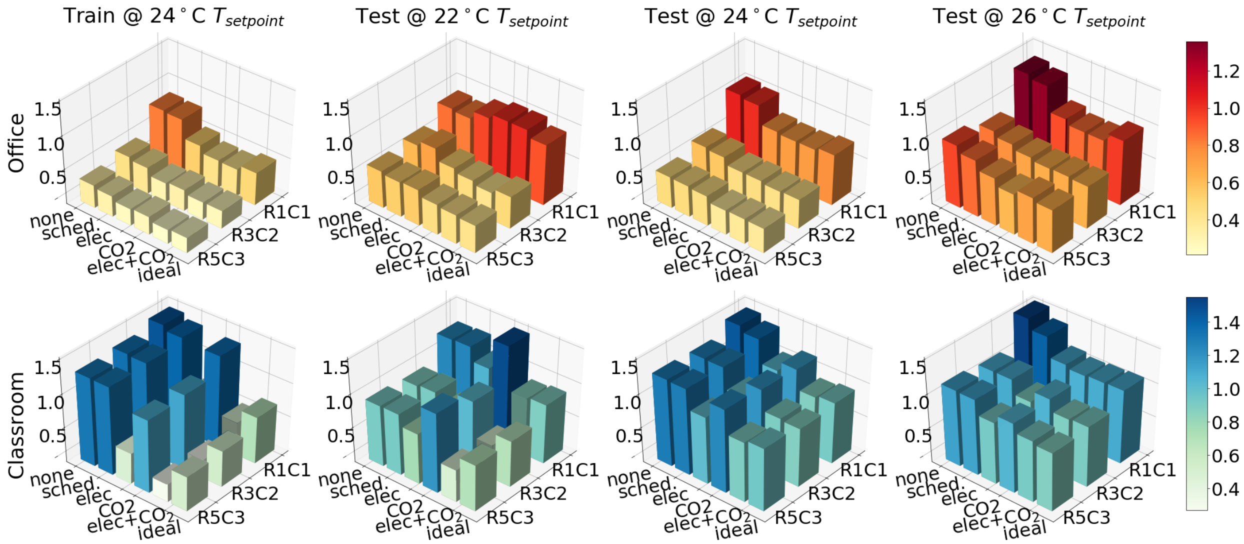

Figure 4: RMSE (°C) of different RC models for the single-zone office and classroom under training and the three testing conditions (X-axis is the 6 data sources for internal heat gain, Y-axis is the 3 model complexities, and Z-axis is the RMSE; darker colors and higher bars represent larger RMSE and worse performance).

In terms of comparing RC model structures, more complex models generally achieved lower training error. This is related to the stronger capability of fitting the data brought by the larger number of parameters. However, while `R1C1` resulted in the largest RMSE in all testing cases, `R3C2` and `R5C3` showed fluctuating testing RMSE of insignificant difference across the cases. This is because heat flow through the floor was relatively insignificant, and therefore was harder to capture than heat flow through the walls (ceiling included).

Figure 5 explains this phenomenon by comparing the disaggregated heat flow of the emulator and RC models. On this testing day, the prediction error of `R1C1` was mainly caused by the underestimation of cooling load in the afternoon. According to the second subplot, the order of heat flow intensity from the most to the least significant is wall, floor, internal heat gain (IHG), and infiltration. Comparing against the emulation data, it appears that neither `R3C2` nor `R5C3` correctly predicted the disaggregated heat flow. However, both models captured the aggregated heat flow and properly predicted the room temperature.

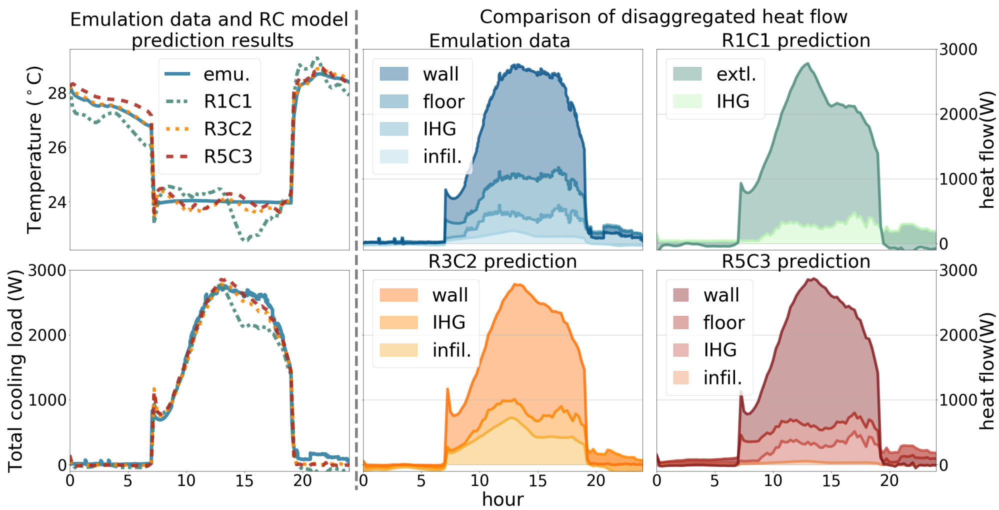

Figure 5: Prediction results of `R1C1_ideal`, `R3C2_ideal` and `R5C3_ideal` on a testing day of the single-zone office case.

Regarding the alternative IHG inputs, the office and classroom had different outcomes. Under the office internal disturbances, `elec`, `CO2`, and `elec+CO`$_2$ led to comparable RMSE results with `ideal`, better than `none` and `schedule`. Meanwhile, it is again worth noting that the reduction of RMSE is minor and that all inputs, if not integrated with `R1C1`, could contain the error within an acceptable range. In comparison, `none`, `schedule`, and `CO2` had difficulty fitting the training data and yielded larger testing RMSE for the classroom case. `elec` and `elec+CO`$_2$ achieved similarly good results as `ideal`.

Figure 6 plots the predicted internal heat gain of R5C3 models with alternative inputs, which agrees with the RMSE results. IHG served a more significant role and was harder to predict in the classroom, causing the larger RMSE. Since the number of occupants had a very high correlation with the plug load in the office, both `elec` and `CO2` followed the primary trend of IHG. Noticeably, `elec` missed several peaks created purely by occupants, and `CO2` was delayed and smoothed, serving as a low pass filter. As the occupants and electricity load were less coupled in the classroom, `elec` and `CO2` provided less accurate IHG prediction. Combining the previous two, `elec+CO`$_2$ got the highest accuracy in both cases. `Schedule` correctly modeled the rise in the daytime and the drop around noon of the office but failed to catch the minor variations and the baseload. For the classroom, `Schedule` could not capture the primary trend. Consequently, the identification underestimated the load capacity Cap to eliminate the influence, which also explains the amplified difference in RMSE.

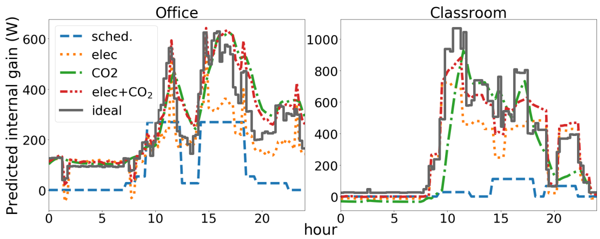

Figure 6: Predicted internal heat gain of `R5C3` models with different inputs for the two single-zone cases on a testing day.

3.2. Control experiment

The first typical MPC objective (Equation 2) balanced thermal comfort and energy consumption, referred to as the trade-off control task in the rest of this paper. Figure 7 plots one example of the resulting temperature profiles on a testing day, compared with the room temperature of baseline control (constant 24°C), the RC model's expected room temperature when doing optimization, and the comfort zone. Two benefits of MPC can be observed: 1) pre-cooling the zone according to the predicted thermal response so that the temperature is within the comfort zone at the beginning of each day, and 2) reducing cooling load by maintaining a higher temperature without violating the comfort constraint.

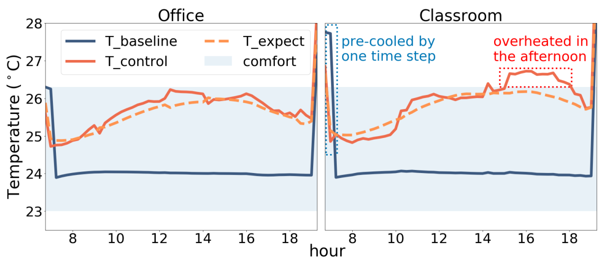

Figure 7: Temperature profiles of the trade-off control task with `R5C3_schedule` on a testing day for the single-zone office and classroom (T_{expect} is the room temperature expected by the RC model in optimization).

The control results were evaluated by the percentage of daily energy consumption compared with baseline control, the average PMV during operating hours, and the percentage of discomfort operating hours. All evaluation results are aggregated and visualized in figure 8. Comparing across the subplots first reveals that all `R3C2` and `R5C3` models produced mostly identical results, saving 10-15% of energy with the average PMV between 0.15-0.4. The office's energy-saving percentage was slightly larger than that of the classroom. On the contrary, `R1C1` models caused significant variances in the control performance. The risk of discomfort was substantially increased, making the lower average energy consumption not desirable.

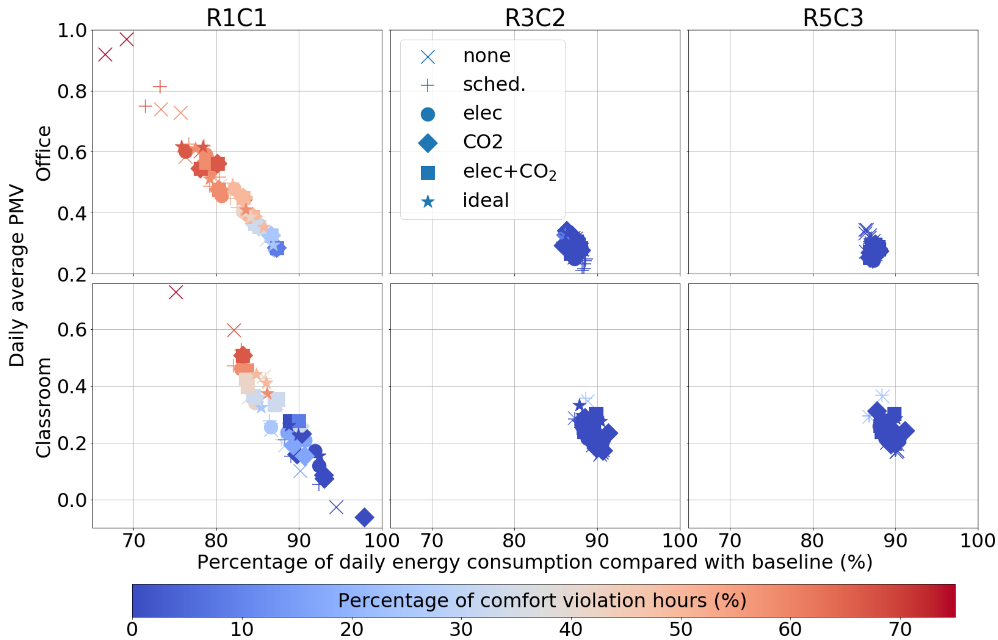

Figure 8: Control performance of the trade-off task for the single-zone office and classroom. Each scatter plot contains all daily evaluation results of the corresponding model structure and test case. The marker shapes represent the data source for internal heat gain input. X axis is the percentage of energy consumption compared with baseline control, Y axis is the average PMV during operating hours, and the color of points represents the percentage of operating hours when the comfort constraint ($PMV \in [-0.5, 0.5]$) is violated.

Looking at the marker shapes, most of the `R1C1` points with long discomfort hours had `none` and `schedule` as the input. Moreover, although the performance consistency among `R3C2` and `R5C3` models for the office was not affected by input types, a few testing days suffered minor discomfort hours with `none` and `schedule` in the classroom. The missing information of internal heat gain caused the error in predicting the room temperature and therefore the comfort violation. An example is highlighted in red in figure 7. When the cooling load was larger in the afternoon, the MPC optimizer attempted to balance the increase by pushing the room temperature closer to the upper bound of the thermal comfort constraint. This was when the requirements on the models' prediction accuracy became stricter. Coupled with the increased internal heat gain that was not captured by `schedule`, the temperature went beyond the comfort zone.

The second objective function (Equation 3) purely examined the control preciseness using alternative RC models, referred to as the setpoint-tracking control task in the rest of this paper. The violin plots in figure 9 describe the distribution of daily average setpoint deviations using different models. The main observations in the trade-off control results hold in this task, such as the large deviations for `R1C1` models and the stable performance among alternative model inputs in the office. Nevertheless, the classroom case had higher means and variances than the office, showing it was harder to control due to the more significant and variant disturbances. It is also shown that despite having close means, the variances of `R5C3` models were usually smaller than `R3C2`, indicating better robustness in controlling the temperature. In addition to the relatively bad performance of `none` and `schedule`, `CO2` also experienced larger deviations occasionally.

4. Multi-zone simulation results

4.1. Identification and prediction

The first and second row of figure 10 respectively shows RMSE against the average room temperature ($T_{ave} RMSE$) and the average of RMSE against the temperature of each room ($T_{zone} RMSE$). All models well contained the RMSE within 0.5°C with a few exceptions under 22°C $T_{setpoint}$ and varying $T_{setpoint}$. When the five zones were operated

Figure 9: Evaluation results of the setpoint-tracking control task for the single-zone office and classroom. Each violin plot shows the distribution of daily average temperature setpoint deviations of the corresponding RC model configuration, test case, and control setpoint. Note the y axis of R1C1 is an order of magnitude larger than the rest.

at the same temperature setpoint, the room temperature of different zones was essentially the same. Consequently, $T_{zone}RMSE$ was only slightly higher than $T_{ave}RMSE$. Therefore, the models were further tested with varying temperature setpoints. In this more stringent test, the single-RC models (R3C2 and R4C3) still achieved $T_{ave}RMSE$ close to the multi-zone RC models, but got significantly larger $T_{zone}RMSE$.

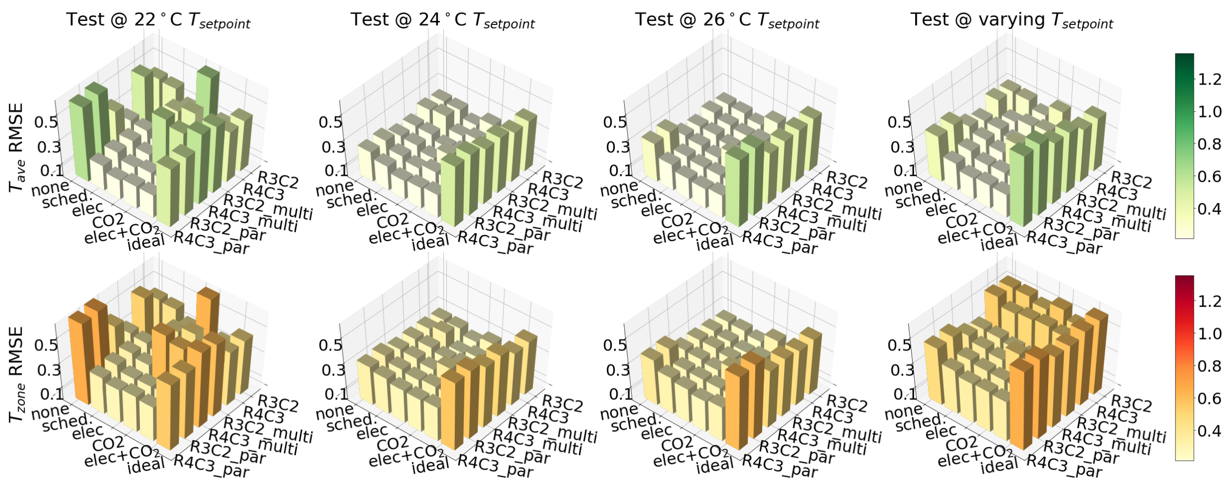

Figure 10: RMSE (°C) of different RC models for the multi-zone office under the four testing conditions ($T_{ave}RMSE$ is RMSE calculated against the average room temperature of five zones, and $T_{zone}RMSE$ is the average of RMSE calculated against the room temperature of each zone).

Among the multi-RC models, adding a capacitor for either the internal mass (R4C3) or the partitions (par) had no distinguishable impact on the RMSE results. Except that the most complex models without the occupant-related inputs (R3C2_par_none and R4C3_par_none) got larger errors than the simpler models. As for the IHG inputs, schedule, `elec`, `CO2`, and `elec+CO`$_2$ performed similarly, with the latter two sometimes extrapolated worse. Interestingly, RC models given the `ideal` measurement constantly observed the largest RMSE, which is further explored in section 5.3.

4.2. Control experiments

Figure 11 presents the trade-off control results on a testing day by `R4C3_ideal`, `R4C3_multi_ideal`, and `R4C3_par_ideal`. The benefit of pre-cooling and slightly warmer temperatures were similar to the single-zone cases. As the only control variable with single-RC models was the total cooling power, the supply air was proportionally distributed to the five zones according to the floor area. Understandably, the room temperature did not comply when the cooling load of each zone was subject to other factors. The first subplot of figure 11 serves as an illustration, where T_ctrl_East and T_ctrl_West went beyond the comfort zone respectively in the morning and afternoon because of the more intense solar heat gain. By contrast, `R4C3_multi_ideal` and `R4C3_par_ideal` supported more stable temperature control. Besides, the multi-RC models also maintained T_ctrl_Core higher than the other zones, knowing the core zone is more expensive to cool with its larger floor area.

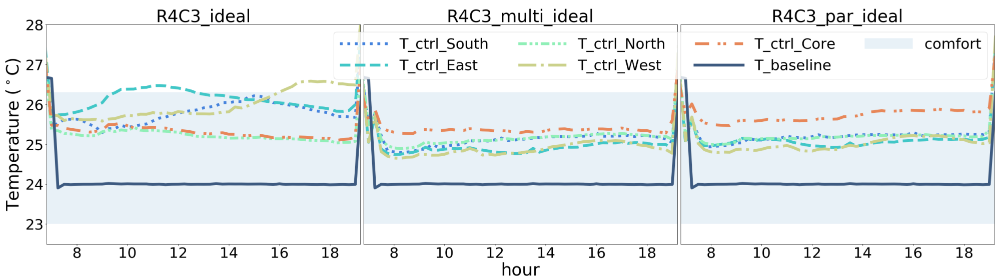

Figure 11: Temperature profiles of the five zones in the trade-off control task with `R4C3_ideal`, `R4C3_multi_ideal`, and `R4C3_par_ideal` on a testing day (room temperature of all zones were the same as the setpoint $T_{baseline}$).

Figure 12 summarizes the control evaluation results of all alternative models, where Y axis is the average PMV of all five zones. Unlike the single-zone cases, the multi-zone comfort compliance examination requires all zone temperatures to fall inside the comfort zone. Considering the aforementioned typical control behavior, it is not surprising to see the single-RC models frequently suffered a high percentage of discomfort hours. The multi-RC models achieved 10 to 25% energy saving with PMV varying between 0.1 and 0.2. A higher energy saving percentage was achieved with an even smaller average PMV than the single-zone office and classroom. The `R3C2` and `R4C3` results are basically the same, which means separated capacitors for internal mass and air did not improve the control performance. Meanwhile, adding the partition capacitor caused more diverse control performance and sometimes about 5% more energy saving. Multi-RC models with all IHG input types satisfied the thermal comfort during the experiments, implying no significant difference between each other in this control task.

The daily average deviations of each alternative model in the setpoint tracking control were consistent with 22, 24, and 26°C $T\_setpoint$ and therefore aggregated by zone in the violin plots in figure 13. The single-RC models were not included as their much worse performance can be inferred from the previous results. The temperature deviations of the four perimeter zones were always within 0.5°C. However, it is conspicuous that the core zone experienced higher means and variances than the other four. Without the partition capacitor, this setpoint deviation problem remained regardless of the type of IHG input. In comparison, the core zone deviation was much reduced given the partition capacitor in the model, together with proper IHG inputs. For those better models, the setpoint deviations of the perimeter zones were also further depressed. The `R4C3` models again showed no improvement from the `R3C2` ones, except that `schedule` improved the performance of `R4C3_par_schedule` but not `R3C2_par_schedule`. Lastly, models with the `ideal` input had marginal improvement compared with their peers.

5. Discussion

The experiment results guide control-oriented data curation and model development from three aspects:

- The practical decision of acquiring data points should be made considering their importance in the downstream control performance. Occupant-related data can be omitted in offices.

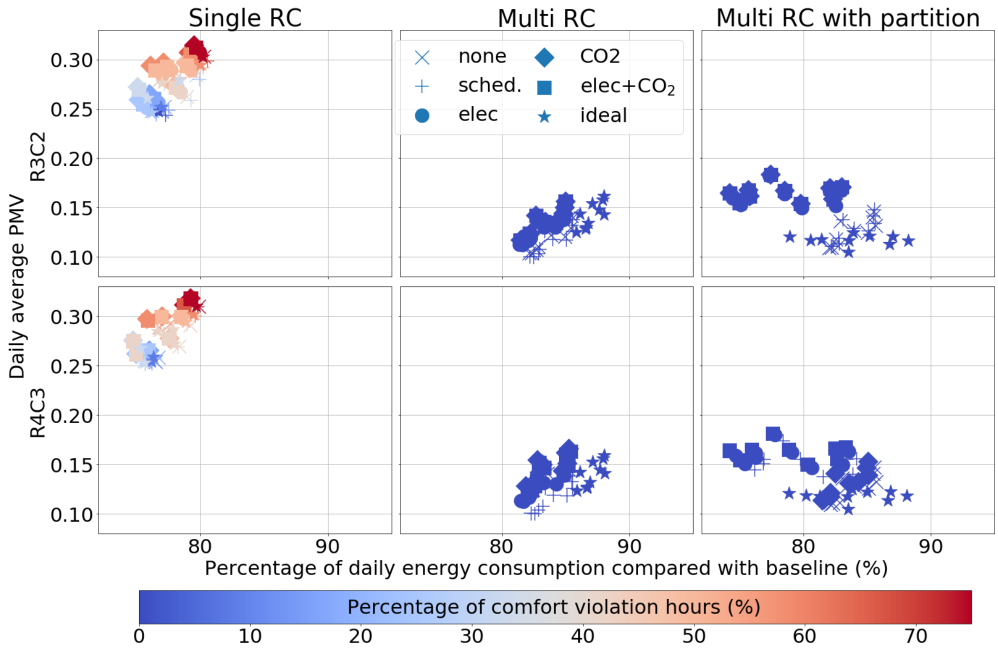

Figure 12: Control performance of the trade-off task for the multi-zone office. X axis is the percentage of energy consumption compared with baseline control, Y axis is the average PMV of the five zones during operating hours, and the color of points represent the percentage of hours when the comfort constraint ($PMV \in [-0.5, 0.5]$) is violated in any of the five zones.

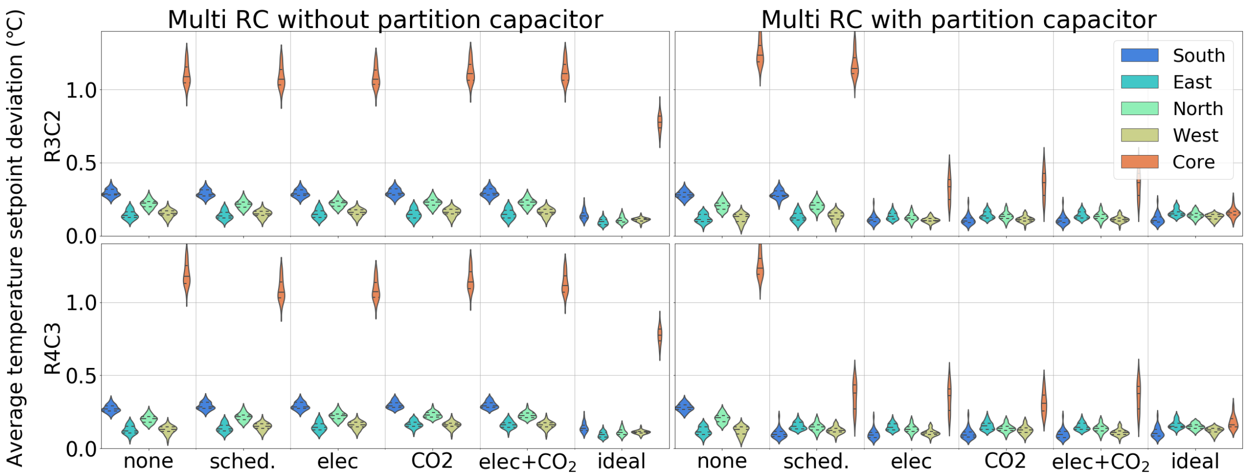

Figure 13: Multi-zone control results of the setpoint-tracking task. Each violin plot shows the distribution of average temperature setpoint deviations of one zone across the three testing conditions (22, 24, and 26°C $T\_setpoint$).

- The model adequacy should match the data informativeness to be properly identified for control. Critical components such as the partitioning capacitors are necessary.
- The effectiveness of identified models is to be carefully examined. Existing evaluation methods are not robust for multi-zone offices.

5.1. Occupant related data required for MPC

As occupants and electricity usage (equipment and lighting) are the two main sources of internal heat gain (IHG), their characteristics in the two building functions determine the importance of alternative data sources. As displayed in figure 2, the occupants' presence and usage patterns in an office are regular and correlated. Therefore, both `elec` and `CO2` achieved desirable performance, and `schedule` was not as good but reasonably close. For models with higher degrees of freedom, even `none` achieved comparable results. This is because the extra RC parameters partially compensated for the discrepancy in IHG prediction through the optimization-based identification, which explains why many past studies worked without any IHG input [12, 41, 29].

By contrast, the classroom had more diverse electricity usage patterns and no repetitive daily profiles. Thus, `elec` and `CO2` needed to be combined to better represent the internal heat gain. Moreover, since classrooms were commonly used for activities such as after-class discussion that is not included in the schedules, `schedule` provided limited useful information, performing as bad as `none`.

To sum up, more detailed occupant-related measurements led to better performance in most tested cases, with the amount of improvement liable to the actual IHG characteristics. In practice, the cost, reliability, and accuracy of data acquisition are of concern when installing sensors [48, 49]. Accordingly, it is crucial to select data sparsely to provide just sufficient information. Pragmatically, the traditional MPC problems could work in typical offices with any IHG inputs. Real-time measurements (`elec` and/or `CO2`) may improve the accuracy and robustness, especially for multi-zone buildings. For classrooms or other mixed-use buildings, it is advisable to include both `elec` and `CO2`.

In general, the dataset should be informative enough to be used for model identification and downstream applications. The data informativeness describes the overall amount of information about the building dynamics embedded in the dataset. As the internal heat gains can only be indirectly measured, the type of data sources is the main factor that affects the informativeness. Other forms of variations in data informativeness need to be explored in future research, including but not limited to the spatial and temporal resolution of data [50, 51], and the data generation schemes [52]. For example, air-based HVAC systems require higher time resolution than radiant systems to catch the faster thermal response [18], and the sensor placement needs to be carefully adjusted based on the room layouts to reflect the temperature distribution [53].

5.2. Matching model adequacy with data informativeness

To generalize the results across different case studies, a model's capability of fulfilling its purpose is jointly affected by its adequacy and the data informativeness. Compared with model complexity, model adequacy is a relative concept that assesses to what extent the model structure can represent the physical object. For example, the `R3C2` model is essentially adequate for the single-zone cases. Although the single `R4C3` is more complex, it is inadequate for the multi-zone case due to the absence of the inter-zone dynamics. It is important here to note the difference between adequacy and the degree of freedom. While the degree of freedom is up to the number of parameters to identify, not all parameters contribute to the adequacy. For instance, the IHG-related parameters provide extra degrees of freedom but do not improve the models' adequacy.

It has been advocated that the model adequacy and data informativeness should be carefully balanced when creating models [54, 18, 55]. Yet, the existing discussion is mostly based on qualitative analysis and expert experience. The experiments in this study serve as the first attempt to quantitatively manifest the interrelationship. The experiment results are aggregated together in figure 14. The X-axis is the average RMSE of each model under all testing conditions, and the Y-axis is the average setpoint deviation when applying MPC. Both axes are inverted to respectively represent more accurate prediction and stronger control capability. Each line denotes the performance change trajectory of a certain model structure, with the marker shapes showing IHG input types.

More informative data usually improves prediction but does not necessarily lead to better control. The `R1C1` models in the single-zone cases have low adequacy that can only capture the dominant dynamics. In this case, detailed IHG inputs helped describe the dynamics and enhanced the model, improving both prediction and control with strengthened physical representations. For the two more adequate model structures, feeding better data again got higher prediction accuracy. However, the control results barely changed, restricted by the portion of building dynamics that the model can explain. Another related mark is that `R3C2` and `R5C3` models with sufficiently informative data predicted with slightly larger error for the classroom due to the more uncertain disturbances. Meanwhile, the control capability, bounded by the level of adequacy, was about the same as that for the office. Regarding the single-RC models for the multi-zone office, the RMSE was mildly reduced with proper data, but the temperature deviations in control remained large. This is because the missing inter-zone dynamics cannot be accounted for by any additional data.

Both adequate model and informative data are needed to represent the building dynamics and achieve good control. This necessity is more prominent in the multi-zone office case. `R3C2_multi` and `R4C3_multi` (yellow lines) are more adequate than the single-RC models but were properly identified only with sufficient data. The IHG inputs other than `ideal` managed to reduce the prediction error but failed to reach better control. As illustrated in figure 15, the RC

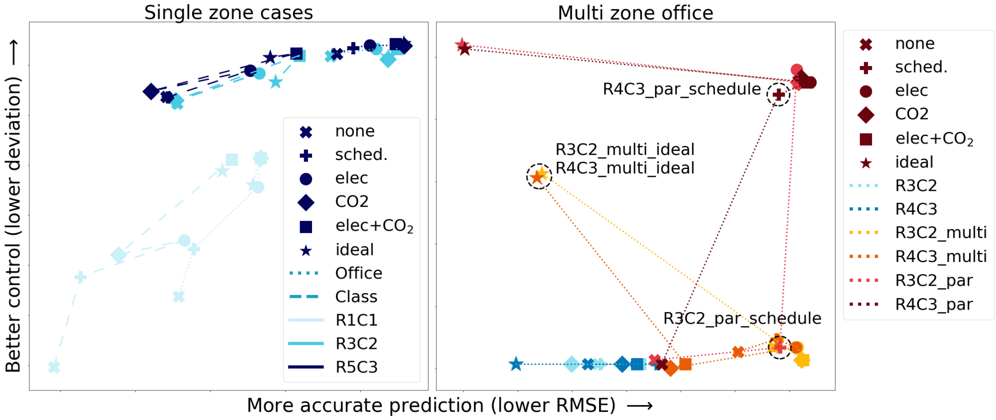

Figure 14: Aggregated experiment results to demonstrate the interrelationship between model adequacy and data informativeness with respect to prediction and control.

and IHG-related parameters were optimized to achieve lower prediction error, which did not correspond to the actual building dynamics and caused the problem in control. As for the `ideal` cases, the heat gain was injected without extra IHG-related parameters to tune. The model had the same adequacy but fewer degrees of freedom than those with other inputs. The input data thereby functioned as a form of constraint to the optimization that prevented sacrificing the dynamics for lower prediction error, resulting in better control.

More adequate model structures also constrained the optimization so that the physical dynamics were preserved in the identification results. Adding the partition capacitor (red lines) further improved the model adequacy. With this extra capacitor, the results were desirable given information from IHG inputs such as `elec` and `CO2`. The extra degrees of freedom now improved the prediction without losing the dynamics. Similarly, the more adequate `R4C3_par_schedule` got close prediction error but much better control than `R3C2_par_schedule`.

The big picture understanding of the interaction between data and models in the identification helps guide model creation in future applications. To begin with, the model must possess the minimum adequacy to capture the fundamental building dynamics. For example, the partitions are crucial for multi-zone models. Then, the decision should be made regarding the modeling purpose. If the only goal is low prediction error, more informative data coupled with higher degrees of freedom is usually desired. Typical practices to avoid overfitting are advisable [20, 52]. Should the control preciseness or building dynamics representation be of concern, the model adequacy becomes more critical and should be carefully decided.

For future research, the experiments are to be conducted under more diverse external disturbances other than the tropical climate of Singapore. Also, RC models were investigated in this study, considering that the model structure and prediction results are highly interpretable. It is to be proven that the conclusions would hold for other types of models. Towards the scalable application of MPC, more research is called for to quantitatively define model adequacy and data informativeness. Well-defined mathematical formulations could save the effort to pinpoint the balanced model adequacy and data informativeness in actual applications. Related concepts from other fields are to be adapted, such as the water resources model structural adequacy [56] and the sample entropy for time series data [57].

5.3. Towards control-informed model evaluation

RMSE is not a perfect indicator for the models' potential control performance, especially when the building dynamics get complicated. Linking figure 9 back to figure 4, the setpoint deviations in control aligned well with the RMSE results for the single-zone cases. In the multi-zone office case (figure 10 and 13), on the contrary, it is evident that the multi-RC models with `ideal` IHG input had larger RMSE than the others but performed better in tracking the setpoints. Figure 15 illustrates the reason with prediction and control results of `R3C2_par_schedule` and `R3C2_par_ideal` on a testing day. `R3C2_par_schedule` predicted the room temperatures closer to the setpoint (ground truth), yielding smaller RMSE. However, the partition capacitor C_{par} was significantly underestimated, and the five room temperatures displayed similar trends. Consequently, the core zone was continuously undercooled when applying the model for control. Whereas `R3C2_par_ideal` modeled the heterogeneous dynamics for each room instead of just fitting the temperature. While resulting in larger prediction errors, it achieved almost perfect setpoint tracking with the frequent state feedback in control. This particular case indicates that the more complicated multi-zone building dynamics demand stronger extrapolation capability of the models. Noting that absolute RMSE values were all small (mostly within 0.5°C), precise control was a more demanding task than achieving low RMSE.

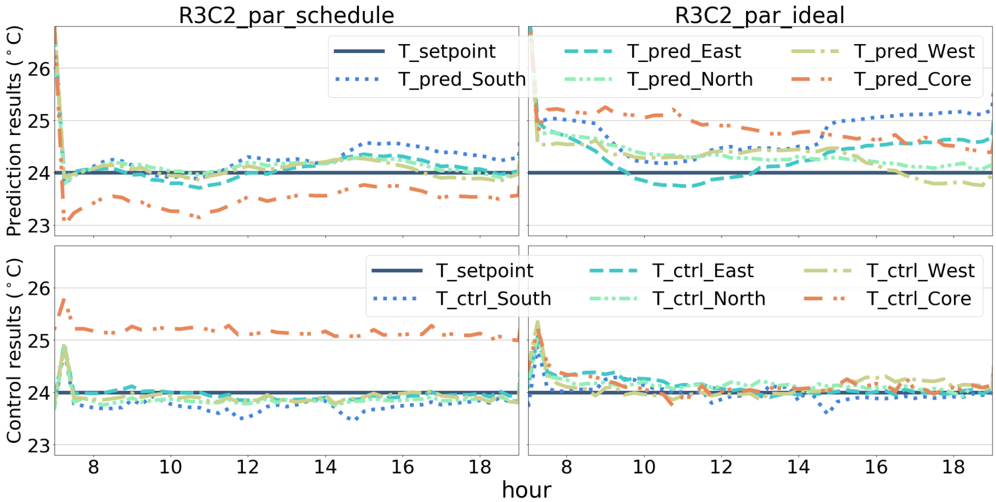

Figure 15: Prediction and setpoint tracking results of `R3C2_par_schedule` and `R3C2_par_ideal` on one testing day with 24°C $T_{setpoint}$.

The importance of control-oriented models being able to extrapolate has been widely acknowledged [47, 58]. We inspected current approaches' effectiveness in evaluating the models' extrapolation capability. The first potential path is to apply excitation signals rather than normal operation when collecting data for training and testing [20]. The dataset could contain more information about the system dynamics and therefore improve the model. In this study, the test with varying $T_{setpoint}$ (figure 10) successfully uncovered the deficiency of single-RC models but gave the same results regarding the `ideal` models. It might be arguable that a more aggressive test, such as varying temperature setpoints in a wider range, is needed. However, those experiments are expensive, if not infeasible, to conduct in practice, and the current test presented no tendency to yield better results.

Another typical method lies in examining the physical meaning of RC parameters to make sure the models are physically authentic [36]. Alas, this is a nonstandard and difficult procedure owing to the diversified ways to simplify the model structure and lump the RC parameters. Taking advantage of the high-fidelity emulator, we compared the disaggregated heat flow along with the parameter values. Related findings are twofold. Figure 5 demonstrates that RC models do not have to perfectly represent the building dynamics to obtain a good performance. Conversely, figure 15 reveals that well estimating the capacitors of the multi-RC models improved the control performance in the multi-zone office. To summarize, it is neither a rigid requirement nor an attainable goal for the RC models to exactly mirror the entire building dynamics. However, some critical components, such as the partitions in the multi-zone case, have to be correctly reflected.

Based on the above analysis and past studies, it is premature to define a threshold of prediction error that guarantees the control performance. Nor is it straightforward to justify the models' physical correctness. The insufficiency of existing model evaluation methods has started to draw attention recently [24]. The potential control performance needs to be informed before implementation to enable the scalable application. Thus, further investigation is needed to save the excessive experiments that ensure the models can be used for control.

6. Conclusion

This paper aims to address the interrelationships between data requirements, model quality, and control performance for MPC in buildings. Simulation-based experiments were conducted using high-fidelity emulation models integrated with real-world internal disturbances data. Case studies were designed to compare many combinations of IHG-related data sources and model complexities. The prediction and control performance of alternative models were tested under varied conditions in a single office, a single classroom, and five-zone offices.

The experiments first revealed that the importance of data changed across different test cases. Given the adequate model structure, comparable prediction and control results can be achieved in offices with or without the detailed measurements for internal heat gain. As the variability and impact of internal heat gain are more significant in classrooms, electricity consumption and CO_2 ppm were needed. More informative data helped model the building dynamics and resulted in more robust setpoint tracking for the five-zone office, which was not reflected in the RMSE. This discloses the imperfect match between prediction and control performance, calling for further investigation to identify more indicative metrics of model capability.

Last but not least, this is the first study that quantitatively articulates the complementary relationship between model adequacy and data informativeness. Disregarding the modeling purpose, a minimum level of adequacy is indispensable. Given sufficient data and proper identification, a higher degree of freedom is usually competent in improving prediction accuracy. More adequate models are desirable if the goal is to accurately represent the building dynamics for robust control. To advance the actual application of MPC, future research should be devoted to consolidating this theory of sparse data and parsimonious modeling.

CRediT authorship contribution statement

Sicheng Zhan: Conceptualization,Methodology,Data Curation,Formal analysis,Investigation,Visualization,Writing - Original Draft,Writing - Review & Editing. **Yue Lei:** Validation,Visualization,Writing - Review & Editing. **Yuan Jin:** Data Curation,Validation,Writing - Review & Editing. **Da Yan:** Writing - Review & Editing. **Adrian Chong:** Conceptualization,Supervision,Writing - Review & Editing.

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