Multi-level Identification Performance for RC-based Control-oriented Model of the UK Office Archetype

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Abstract

Resistance-capacitance-based grey-box models are widely adopted as one of the modelling solutions in model-predictive controls. These models have been evaluated to determine the optimal level of complexity in standardised cases. However, further evaluations are needed to draw more universal conclusions across diverse scenarios, modelling approaches, and operational conditions.

In this study, a series of grey-box models were identified by MPCPy based on a British office model, followed by a parametric analysis on model format, modelling details, training data volume, and validation periods. The R2C2 model yielded the most accurate predictions with less deviations, and more accurate estimations were observed in multi-zone models. Additionally, it is suggested to consider direct normal irradiance as a modelling input in multi-zone models, and adaptive re-calibrations are recommended when significant changes in solar radiations occur.

Highlights

- Evaluates identification accuracy in a parametric analysis on modelling levels, model orders, and model inputs;
- Contributes to understanding the grey-box model performance under weekly-based occupancy patterns;
- Highlights recommendations for developing multi-zone grey-box models in UK;
- Discusses data-training periods and adaptive re-calibration scheme for control-oriented models.

Introduction

As a data-driven approach, model-based predictive control (MPC) was progressively developed and applied to buildings and HVAC systems, but there are few real-world case studies demonstrating successful solutions for building control and operations (Drgoňa et al., 2020; Yao and Shekhar, 2021; Blum et al., 2022). One of the bottlenecks in MPC implementation is the absence of generalised yet effective solutions for developing and identifying the control-oriented model in MPC. According to Rockett and Hathway (2017), obtaining an appropriate model for MPC was estimated to take up 70% of time during its implementation, hence diminishing the benefits of model predictive control. Meanwhile, developing such an accurate control-oriented model also has positive effects on the reduction of deviations between the measurements in real buildings and estimated predictions from control-oriented models.

Numerous simulation-based and real-world case studies revealed their modelling solutions for the control-oriented models in MPC, which can be classified into three types of models: the white-box model, grey-box model, and black-box model. The grey-box model is a combination of the white-box and black-box models. It requires less predetermined information, such as building parameters, than the white-box model and can calibrate parameters in simplified models with a smaller dataset than the black-box approach. RC models are informative because they present the model structures of building envelopes and HVAC systems and the algorithms of basic thermodynamics in the resistance-capacitance (RC) format. Nonetheless, RC models were incapable of performing precise calculations in nonuniform heat convection, such as buoyancy effects and air exchange between the indoor and outdoor environments (Li et al., 2021).

With the convenience of a concise and relatively accurate format, grey-box models, especially the resistance-capacitance (RC) models, are preferred by researchers and engineers to be selected as the control-oriented model in buildings. An organised approach presented in Candanedo et al. (2022) proposed several RC-based control-oriented models for Canadian archetypes that provide generalised and affordable models to estimate control effects at the building and district levels. A multi-level modelling approach covering the development of both single-zone and multi-zone models was demonstrated in the article, with the advantages of flexibility and convenience in benchmarking. Harb et al. (2016) developed several RC models to identify the demands of both residential and office buildings located in central Europe, getting accurate models within acceptable levels.

Inaccurate identification has a negative influence on developing a comparable model for improving the performance of model-predictive control. Several studies have been undertaken recently to examine the effect of modelling structures and parameters on the identification accuracy of the grey-box model. For instance, Arroyo et al. (2020) compared the modelling outcome of single-zone and multi-zone grey-box models in a 7-zone residential building with a hydronic heating system, where the performance of the single-zone model is comparable to that of the centralised multi-zone model. Blum et al. (2019) investigated the impact of model structures, data length, and identification algorithms on identification accuracy in standardised single-zone models, BESTEST Case 600 and 900, and indicated that the values and quality of the training data have significant impacts on model accuracy. In these studies, the accuracy of the model identification procedure was measured by the differences between the measured and estimated values. Yet, the energy performance of archetypes varies greatly due to their dimensions, envelopes, weathers, occupant levels, and setpoints, resulting in different control consequences. There are still emerging needs for further investigations on (1) performance validations of these reduced-order models in different buildings and realistic operation conditions, and (2) finding optimal identification-related parameters when identifying grey-box models in different modelling levels. These investigations are necessary steps to enhance the accuracy of the control-oriented models, and improve its adaptability for a wider range of buildings.

This research, therefore, proposes an initial solution for the development of the control-oriented model for UK office buildings with the fan-coil unit (FCU) system, identified by the values of electricity and indoor temperature which were simulated from a white-box emulator for the British office archetype. A parametric analysis of different modelling levels (single-zone or multi-zone model), the number of model orders, the types of radiation inputs, training data lengths, and validation periods will be conducted, in order to assess their impacts on the accuracy of model identification in the proposed control-oriented model. The parametric results will provide guidelines for developing control-oriented models for office buildings by analysing the best-performing RC model. Meanwhile, different validation results will also be examined over extended control periods for a discussion on the recalibration scheme.

Methods

Building information

Archetypal buildings represent a large scale of buildings and provide a good abstraction of building parameters and layout according to a national-level dataset, as compared to existing studies that target specific buildings. Models developed on the basis of

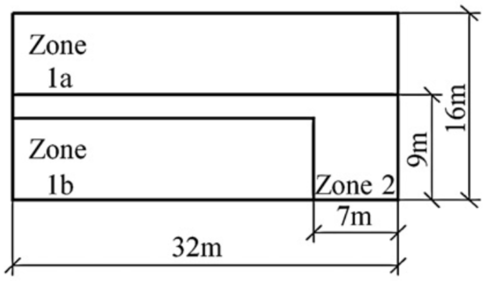

Figure 1: Floor plan of the selected model (Type 2-CS in Korolija et al. (2013)), representing for most popular office buildings in the UK

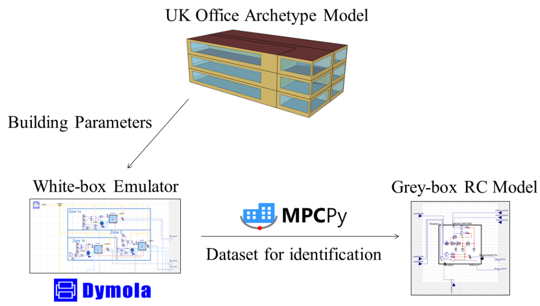

Figure 2: Model development and identification workflow for control-oriented models of office buildings.

an archetype model are capable of predicting typical conditions of building demands and energy usage at a larger scale and saving the model development time in the evaluations (Candanedo et al., 2022). In the research, a 3-zone office building with a fan-coil unit system developed by Korolija et al. (2013) is chosen to represent a typical floor of office buildings in the UK. The floor plan is depicted in Figure 1 since it is the most common layout in UK office buildings. Zone 1a and 1b are marked as the office area, while zone 2 is the connected space with fewer occupants. Latest best-practice U-values and weekly-based occupancy patterns from UK National Calculation Methodology were applied as the modelling parameters in the white-box model. The total heating capacity of three fan coils is 83.1kW, which is sufficient to meet the building's peak heating requirements. The heating setpoint is set to 21°C during working hours (7:00 - 19:00) on weekdays, with a setback temperature of 12°C for the remainder of the time. Typical Meteorological Year (TMY) weather data from London Gatwick was selected as the design scenarios in both models.

Model development

Figure 2 demonstrates the workflow for developing two types of Modelica models described in this paper. The white-box model, which represents the virtual building, was developed Modelica Buildings Library version 8.1.0 according to the building parameters and occupant patterns derived from UK office archetypes. In order to reduce model complexity and improve scalability, the white-box model only modelled building envelopes and secondary

HVAC system within a single floor, without considering the thermal transmissions from the roof and ground. Building envelope were modelled by the detailed zone models, *ThermalZones.Detailed.MixedAir* component, and then they were connected to the *Fluid.HeatExchangers.HeaterCooler_u* components for simulating the fan coil unit. Meanwhile, in line with the grey-box model, energy consumptions caused by outdoor air were added into FCU for the calculation of the heating input power in each zone. According to ASHRAE (2018), these energy consumptions can still be calculated individually at the later stage if the outdoor air flowrate and supply air temperature are held constant.

Meanwhile, as the control-oriented models, RC-based grey-box models were identified by the measurements and inputs of the white-box model. A total of twelve grey-box model implementations were developed in order to justify the best implementation for the grey-box model, with parameterization in the level of modelling details including two modelling levels, three types of modelling order, and two sets of modelling input.

Three model orders presented in Figure 3, namely the R2C2, R4C3, and R6R4 models, were considered since they were recognised as common RC model layouts in Li et al. (2021). The R2C2 model consisted of two thermal resistances for external wall r_w and internal wall r_i, and two capacitances for zone air c_z and internal wall c_i. In the meantime, the model took account for the heating power from FCU Q_{fcu} [W], convective internal gains Q_{con} [W], and radiative internal gains Q_{rad} [W]. Indoor temperature T_i was affected by several weather disturbances, including the outdoor dry-bulb air temperature T_{out} [°C] and horizontal solar radiation which was the product of global horizontal irradiance Q_{glo} [W/m^2], absorption coefficient α, and the area of external wall A_w [m^2]. Compared to the R2C2 model, internal wall capacitances, c_i, and thermal resistance caused by infiltration, r_{inf}, were added to the R4C3 model; fan-coil component's resistance r_e and capacitances c_e were further added to the R6C4 model. Since direct sunlight has a substantial impact on the solar gain for UK buildings, two sets of weather-related modelling inputs will be compared to determine underlying benefits of including direct normal solar radiations in the grey-box model, which can be calculated from the product of the direct normal irradiance Q_{dir} [W/m^2], transmittance of solar gains through windows g, and the area of window glazing A_g [m^2]. Two modelling levels including single-zone and multi-zone model were compared, and the development of the multi-zone models was based on hierarchical modelling in Modelica. In other words, the multi-zone models were developed from a combination of three single-zone models with the aforementioned model structures and were linked by internal wall resistance.

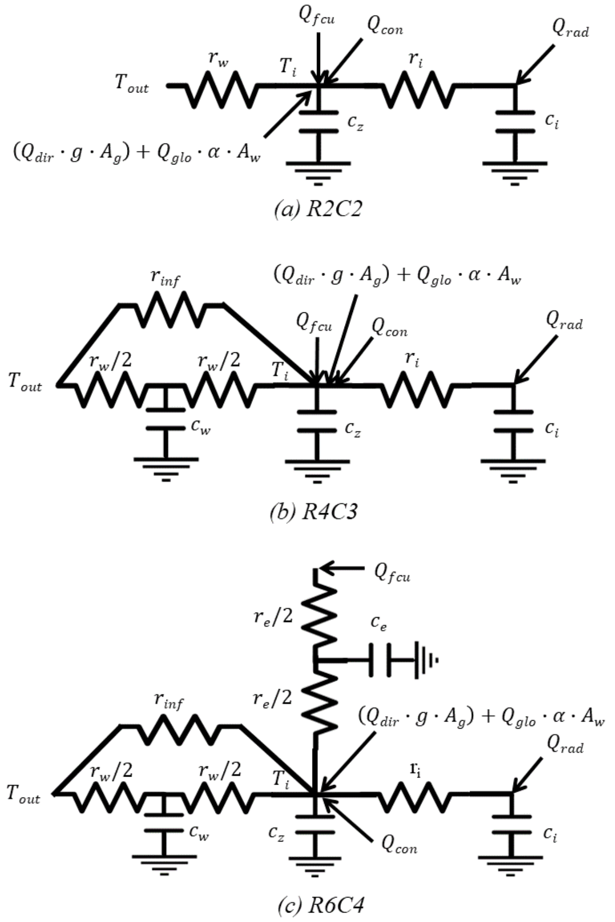

Figure 3: Three grey-box implementations tested for single-zone simplified FCU system: (a) R2C2 model (b) R4C3 model (c) R6C4 model. Contents in brackets are the additional modelling inputs to be tested.

Model identification

Parameter estimation was solved in Python using the open-source MPCPy package (Blum and Wetter, 2017) by using JModelica optimisation. With the help of the CasADI toolbox (Andersson et al., 2019) in the back end and the MA57 solver (HSL, 2013), MPCPy has capabilities to transfer Modelica models into a high-level dynamic optimisation problem. Identification of estimated values can be illustrated by an objective function, shown in Equation 1.

$$\min_{\theta_i} J = \int_{t_0}^{t_1} \left| T_{i,est} - T_{i,mea} \right| \, \mathrm{d}t \qquad (1)$$

The equation seeks a list of properly estimated parameters θ_i (listed in Table 1) in the grey-box model, while minimising the deviations between the indoor air temperature predictions $T_{i,est}$ [°C] and measurements $T_{i,mea}$ [°C] from the starting time t_0 to the ending time t_1 [s] of training periods. In other words, grey-box models in the format of Figure 3 were trained by the white-box data over a 30-minute interval, including the data from heating power input (Q_{fcu}), internal gains (Q_{con} and Q_{rad}), weather data (T_{out}, Q_{glo} and Q_{dir}), building parameters (A_w and A_g), and indoor temperature (T_i). Each parameter in Table 1 were then estimated within a reasonable, predetermined boundary by using the Latin Hypercube Sampling method (Blum and Wetter, 2017; Blum et al., 2019) with 10 iterations. The maximum solver steps were limited to 2,000 steps and 300 seconds per iteration to ensure optimisation convergent when using the largest training set.

Table 1: Boundaries of estimated parameters in the grey-box model identification

Variable name	Minimum	Maximum	Unit
r_w	1×10^{-5}	0.01	K/W
r_i	1×10^{-6}	0.01	K/W
r_{inf}	1×10^{-5}	0.01	K/W
r_e	1×10^{-6}	0.01	K/W
α	0	5	1
g	0	5	1
c_w	10^6	5×10^{10}	J/K
c_i	10^6	10^{10}	J/K
c_z	10^6	10^{10}	J/K
c_e	1000	10^7	J/K

Different training periods (ranging from 1 to 7 days) were tested in the parametric analysis to further evaluate the impact of dataset size and modelling parameters. Therefore, a total of 84 testing cases were executed in the Ubuntu 18.04 operating system, and multiprocessing was implemented by the Python built-in multiprocessing module to accelerate the simulations. The accuracy of the model identification procedure was defined as the Coefficient of Variation of Root Mean Square Error (CV[RMSE]) and the Normalised Mean Bias Error (NMBE), which evaluates hourly deviations of indoor air temperature between estimations and measurements during the training period in the current week and the validation period in the following week. CV(RMSE) and NMBE are defined in Equation 2 and 3 where the $\bar{T_{i,mea}}$ denotes the average of measured indoor temperature [°C] (since $T_{i,mea} > 0$), and n is the number of hours in the testing period. NMBE could inform biase direction of errors, while CV(RMSE) could quantify the level of deviations. As highlighted in ASHRAE Guideline 14 ASHRAE (2014), these two statistical indicators are common indices used in building calibration, and hourly temperature deviations within 20% for CV(RMSE) and ±10% for NMBE would be acceptable in model validation studies (Jain et al., 2020).

$$\text{CV(RMSE)} = \sqrt{\frac{\sum_1^n (T_{i,est} - T_{i,mea})^2}{n}} \times \frac{100}{\bar{T_{i,mea}}} [\%] \tag{2}$$

$$\text{NMBE} = \frac{\sum_1^n (T_{i,est} - T_{i,mea})}{n} \times \frac{100}{\bar{T_{i,mea}}} [\%] \tag{3}$$

Measurements used for training were derived from the peak weekly heating load over the year beginning on January 22^{th} and ending on January 28^{th}, and the flowing one-week period beginning on January 29^{th} and ending on February 4^{th} was considered as the validation period. Meanwhile, the identification results were further validated over the following three extended periods for discussing the recalibration scheme.

Results

General identification results

Since the CV(RMSE) and NMBE can indicate the deviation between the estimated values and actual values, these two indicators demonstrate the level of training accuracy during the training periods, whereas during the validation periods, the validation CV(RMSE) and NMBE indicate the accuracy of model prediction under the grey-box model in comparison to the "real" measurements. Consequently, both values are displayed in Figure 4 in the group of training data length. The majority of training CV(RMSE) values are found to be less than 5%, and NMBE are within ±1%. This training data demonstrates that the grey-box model was adequately trained by the optimisation algorithm described above and that model mismatches were minimised during the training periods. In the validation results, however, CV(RMSE) and NMBE values were significantly higher after only using 1-day training data, because weather conditions on a single day could be biased and the number of estimation steps is limited. For grey-box models trained with two- to seven-day's data, CV(RMSE) remains below 7%. To pursue lower computational costs, the optimal number of training days therefore is 2 to 3 days (96 - 144 estimation steps). Further extending the training period to 6-7 days was not hugely detrimental to the identification accuracy, and in fact, the deviations in six training days were smaller than 4-day training data because the grey model was exposed to the weekend's free-floating condition.

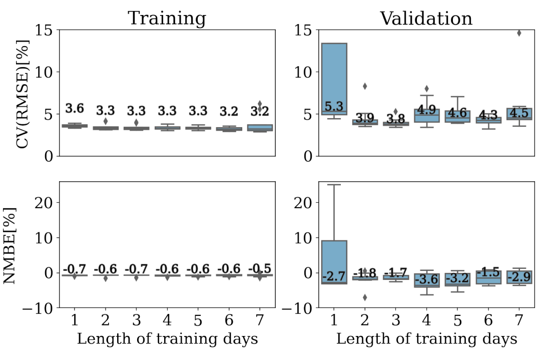

Figure 4: CV(RMSE) and NMBE during the training and validation periods, grouped by training day length.

The high CV(RMSE) and NMBE observed in the

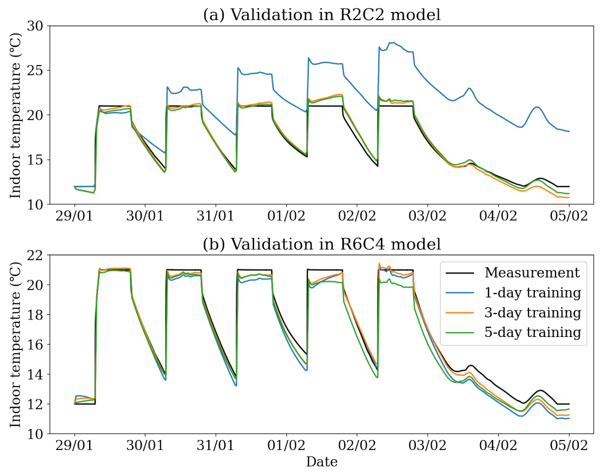

Figure 5: Predicted indoor temperature values in (a) R2C2 model (b) R6C4 model compared to the measurements

R2C2 model based on one-training-day data was further determined through a comprehensive analysis. The validation results of indoor temperature recorded in the single-zone R2C2 and R6C4 models are illustrated in Figure 5, along with results from a longer training day. Significant deviations were observed in the single-zone R2C2 model transferring to high NMBE values up to 25% in 1-day training results. However, the deviation decreased rapidly with longer training data. It could be determined that insufficient training steps led to an overestimation of both solar absorption and capacitance variables in the model. In contrast, the R6C4 model with a higher level of detail performed reasonably accurate identification with one day of training data, but more deviations occurred with longer training periods, indicating overfitting.

Optimisation on model structures

Further optimisations on the development of control-oriented models were emphasised on the modelling methods, after choosing the data from 2 to 7 training days to eliminate the potential inaccurate results. A comparison of different modelling methods, i.e., the single-zone case versus the multi-zone case, was demonstrated in Figure 6. The median CV(RMSE) from multi-zone modelling methods were lower than the ones from the single-zone model, with the help of more detailed models. However, more multi-zone cases had inaccurate predictions (NMBE<-5%) in zone 1b with a wider distribution. These negative NMBE values would cause over-sizing of heating demands and ultimately affect system operations. To explore the causes of this phenomenon, Figure 7 illustrates indoor temperature predictions from different zones in a multi-zone R6C4 model, compared to the measurement in zone 1a. Notably, some variations in south-oriented zones (zone 1b and 2) were both found in the weekday's occupied hours and the weekend's free-floating hours. It indicated some modifications

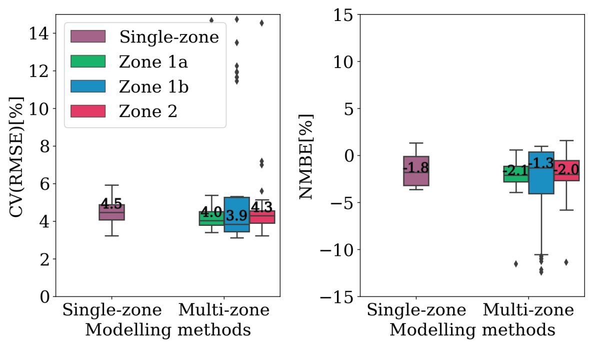

Figure 6: Comparison of CV(RMSE) and NMBE in single-zone model against multi-zone model, sorted by zones

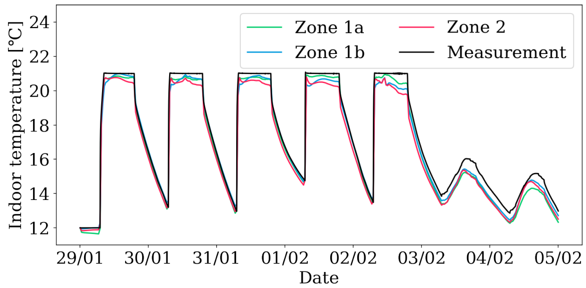

Figure 7: Predicted indoor temperature values from all zones in a multi-zone R6C4 model compared to measurements in zone 1a

in the multi-zone model could be done to minimise the observed temperature mismatch.

According to the pilot simulation, the addition of direct normal irradiance data could improve the accuracy of estimating solar gains. Figure 8 demonstrates the compared results from identified models with different irradiance input variables, categorised by the modelling levels discussed in the previous paragraph. Adding additional irradiance input to single-zone models did not produce significant differences in CV(RMSE) and NMBE, as the median values for both groups were approximately at 4.5% and -1.8% respectively. Conversely, considerable improvements were made in multi-zone control-oriented models, with a lower CV(RMSE) value at 4.0% and NMBE value being closer to 0. These changes in radiation types narrowed the CV(RMSE) distribution in zone 1b significantly because direct normal irradiance, an additional external data source for training, is useful for accurately estimating solar gains in south-facing zones. Thus, a multi-zone model should consider direct solar irradiance in the model identification, especially in the south-facing zones located in the northern hemisphere at high latitudes.

Furthermore, the model complexity of control-oriented control is one of the most crucial aspects in the identification of the model. As demonstrated in Figure 9, an analysis of suitable model order was conducted in a single-zone model trained without di-

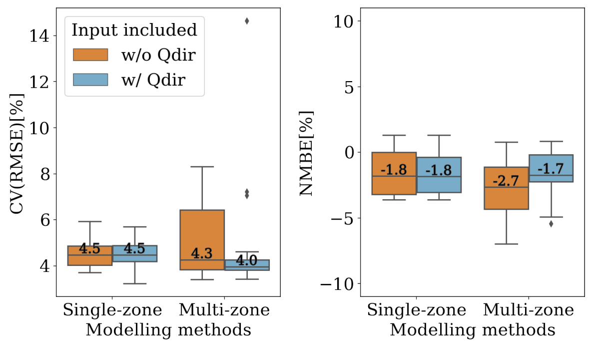

Figure 8: Comparison of CV(RMSE) and NMBE in models with or without direct normal irradiance (Q_{dir}) as input variables in the training

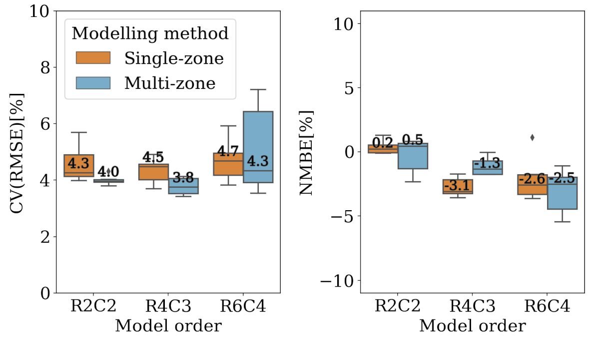

Figure 9: Comparison of CV(RMSE) and NMBE in different model orders in the parametric analysis

rect irradiation and a multi-zone model trained with direct irradiation, based on the recommendation of adding external data sources and selecting proper modelling methods. Single-zone cases showed similar distributions among these three types of models. The R2C2 model had a lower median CV(RMSE) value (4.3%) and small NMBE (0.2%). As for multi-zone models, the R4C3 model had the optimal structure with the lowest CV(RMSE) at 3.8% among all three model orders, but the R2C2 model had a similar CV(RMSE) distribution with NMBE value closing to 0 (median value at 0.5%). Hence, the final result demonstrated that the R2C2 model is generally recommended in the single-zone model , and both the R2C2 and R4C3 model are recommended in the multi-zone model as the control-oriented model for the UK office archetype.

Validation on the extended weeks

Considering that the control-oriented models are simplified models whose performance would be affected by input values, an additional validation was conducted to further validate the robustness of the model based on the recommended model orders and model structure. The validation week was extended from the following first week (starting from Jan 29th) to the fourth week (starting from February 19th) after the training week. Condensed but deviated results were identified in those extended weeks, indicated by Figure 10. With a median CV(RMSE) of 4.1%

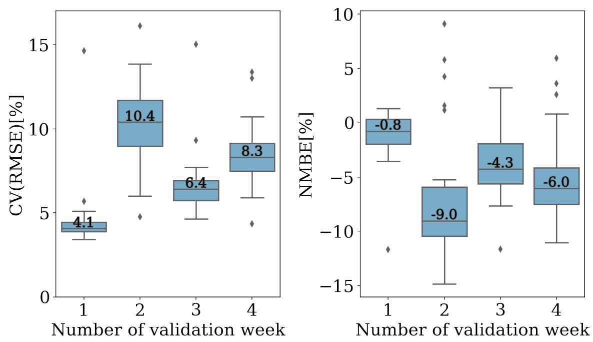

Figure 10: Validation results in the extended validation periods

and NMBE of -0.8% in the original validation week, temperature prediction performed worse in the next three weeks. The deviations in the 2nd and 4th week exceeded the acceptable range, with the highest deviated values occurring in the second week median (CV(RMSE) at 10.4% and NMBE at -9.0%. Significantly, validation CV(RMSE) and NMBE values were related to the conditions in the training periods, as influenced by weather fluctuations in this case. Table 2 showed the average values of CV(RMSE) and NMBE, outdoor temperature T_{out}, global horizontal irradiance $I_{glo,hor}$, and direct normal irradiance $I_{dir,nor}$ in the training week and the extended validation weeks to illustrate their internal relationships. Due to comparable values in outdoor temperature and solar radiation, validation week 1, which is the original validation week, produced the most accurate predictions compared to the other three validation weeks. This demonstrated that the initial validation week was an appropriate choice for validating the identification and performance of the control-oriented model developed for the UK office archetype. Nonetheless, beginning in the second week, both horizontal and normal irradiance increased by at least one and ten times, respectively, in comparison to the training week. The lack of training in high-radiation scenarios compromised the accuracy of the identification.

Table 2: CV(RMSE), NMBE, outdoor temperature (T_{out}) and solar irradiance ($I_{glo,hor}$, $I_{dir,nor}$) values of the training week and four proceeding weeks

Evaluation weeks	**CV (RMSE)** [%]	**NMBE** [%]	$\mathbf{T}_{out}$ [°C]	$\mathbf{I}_{glo,hor}$ $[W/m^2]$	$\mathbf{I}_{dir,nor}$ $[W/m^2]$
Training	3.5	-0.8	3.1	21.9	4.4
Validation 1	4.6	-1.4	3.7	24.2	4.9
Validation 2	10.3	-6.9	4.3	62.4	98.6
Validation 3	6.7	-3.7	2.4	48.8	37.2
Validation 4	8.4	-4.9	2.0	50.2	59.5

Discussion

Recommendations for control-oriented model development

The training and validation of the proposed RC control-oriented models yielded reasonably accurate results, as training CV(RMSE) was less than 5%, with NMBE within ±1%. Meanwhile, the marjority of validation CV(RMSE) was less than 7%, indicating good identification results. While an optimal level of modelling details, model structure, and the training dataset size could further enhance the accuracy of the grey-box model, recommendations for RC control-oriented model can be drawn from this identification.

Firstly, the identification of the single-zone model was significantly different from that of the multi-zone model. Relating to the results from Figure 6 and Figure 9, the multi-zone model appeared to be a more accurate model, with its R4C3 model yielding the lowest identification CV(RMSE) among all models. It matched the outcomes of other model identifications study (Arroyo et al., 2020). In fact, multi-zone models were a higher-order model with nine capacitances as opposed to three capacitances in the single-zone model. Moreover, additional measurements in each zone are helpful to identify the grey-box model and minimise the temperature deviation. Therefore, it is difficult to justify the optimal model structure between the single-zone model and the multi-zone model, but the multi-zone model has more potential to calibrate as an accurate model. It should be dependent on the model complexity, computational costs, and the objectives of the control-oriented model during the model development process. For example, a multi-zone RC model could indicate zone-level peak demands, reducing the possibility of under- or oversizing in each zone. In addition, the multi-zone model should be modified to adapt to weather changes, such as capturing direct solar radiation.

Secondly, the size of training data and the complexity of model structure have a combined influence on model identification accuracy. For instance, optimal model structures can vary based on the size of the dataset and the level of model detail. Under one-day training data, the single-zone lower-order model (R2C2) had some biased predictions, while this did not occur in the detailed, multi-zone models. Similarly, by observing the impact of training lengths on CV(RMSE) and NMBE from Figure 4, it is possible to avoid under- and over-fitting by using two to three days of data for control-oriented models. In fact, good estimations can be yielded from a multi-zone model with only one day of training data. Therefore, a more detailed grey-box model, such as a higher-order model or a multi-zone model, can have a shorter training period.

Thirdly, as shown in Figure 9, there are more negative NMBE values in higher-order model, resulted by the oversizing of capacitances. Moreover, the estimations from R6C4 models with the capacitances of fan-coil unit were not as accurate as those from the other two model forms. As the system delay of the fan-coil unit system was minimal, it was determined that there were no significant differences between identifying the energy performance of secondary HVAC systems and directly identifying energy demands in buildings.

Validation results and re-calibration scheme

From this identification testing, it was found that selecting proper validation periods for the control-oriented model is very important, given the fact that the external weather conditions would highly influence the estimation of RC parameters in the control-oriented model. In our case, the results from Table 2 indicated that certain weather indices, including outdoor temperature and solar radiation level in the validation periods, should be matched with the training periods to ensure the most accurate identification of control-oriented models. However, several validation methods, such as time-series split cross-validation and blocked cross-validation, could be used for evaluating the robustness of the model.

Moreover, the fluctuating validation results from Figure 10 suggested that periodic re-estimation of grey-box parameters is needed, in line with the conclusion from Blum et al. (2019). An adaptive re-calibrations scheme could be considered in the operation of the control-oriented model, in response to changes in weather variables. New parameter estimation for the grey-box model could be issued when there were noticeable changes in solar irradiance, concerning the fact that London is located within mild weather zones and significant temperature changes would not happen in a week's time.

Conclusion

Overall, this paper investigated the optimal modelling level, model input and structures, and training dataset size for control-oriented models in a British office archetype with the fan-coil unit system. The development pathway of the control-oriented model was proven to be a valid approach, including generating a Modelica-based white-box model used for collecting the measurements and developing an RC-based grey-box model for parameter estimations. Based on the parametric analysis, several guidelines for developing control-oriented models of office buildings were summarised in this study. Single-zone R2C2 model yielded the most accurate predictions, with a lower median CV(RMSE) value at 4.3% and smaller NMBE at 0.2% More accurate estimations were observed in multi-zone models than single-zone models. A combination of R4C3 zone models adding direct normal irradiance as the external input was recommended, which yielded the lowest median hourly CV(RMSE) at 3.8% against the measurements. Based on a list of identification results, the length of training days can be as low as two to three days, but a more simplified model should be trained under a longer training period since the optimal training data size and model structure are highly associated with each other. This modelling guideline overall facilitates the development of the control-oriented models of British office buildings and improves their identification accuracy.

A consequent discussion was drawn based on the validity of the identification results, evaluated over the extended validation periods. Higher deviated indoor temperature predictions were found as there were significant weather changes during validation periods. Therefore, it is recommended that an adaptive recalibration approach should be adopted for UK buildings, depending on significant changes in solar radiation values.

However, this study did not investigate the effect of various other factors such as internal loads, operation time and climate zones. Future works can be focused on (1) expanding the evaluation under the full-year condition with different load profiles; (2) investigating the effects of external disturbances on model identification to generate a fully adaptive calibration scheme. These future works, along with this paper, will be helpful for developing a robust model-based predictive control at the building and district levels.

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