Predicting indoor air temperatures by calibrating building thermal model with coupled airflow networks

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Abstract. Building models that can accurately predict hourly indoor air temperatures in free-running situations are key to understanding overheating conditions and the resilience of passive cooling strategies under a changing climate. To accurately predict indoor temperatures it is necessary to properly model pressure-driven infiltration and natural ventilation. This can be achieved by coupling a building thermal model to an airflow network model. In this paper, the development of coupled building thermal and airflow network models is described to calibrate building models using field measurements of indoor air temperature. Building models of three types of buildings were configured: long-term care building, primary school and multi-unit social housing. The building models were developed in Design Builder™ and exported for use in an EnergyPlus simulation package. From information obtained from building surveys, site visits and architecture drawings, building parameters and operation schedules were collected. The unknown parameters, which included envelope thermal properties, shading devices, internal heat gains, envelope air leakage, window and door openings, were then calibrated based on measured values of indoor temperature. Reasonable ranges in value of the unknown parameters were first retrieved from applicable building construction practice documents and building energy standards. Two rounds of calibration were conducted through parametric simulations using the Monte-Carlo sampling method. A sensitivity analysis was also conducted for ranking the importance of all building parameters. The values for indoor air temperature as obtained through simulation were compared with measurements and the RMSE (root mean square error) was calculated for all values. The parameter value combinations corresponding to the minimum RMSE were adopted for the building models. The calibration process ended when the value for RMSE was <1.5℃. Results showed that the detailed building model was capable of predicting room air temperatures with minimum error levels (0.56℃ ≤ RMSE ≤ 1.50 °C) within the limits of applicable building model calibration standards (MBE±10%, CVRMSE<20%).

Keywords. Indoor air temperature, building thermal model, airflow network, calibration, field measurement
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1. Introduction

Predicting indoor temperature accurately through building performance simulation is important to analyse the overheating situation of buildings in current and future projected climates. Previous studies mainly focused on the calibration of building energy performance [1]. A generalized and easily applied method is still needed to calibrate the indoor thermal performance. Before the calibration stage, the pre-modelling of buildings with proper consideration of natural ventilation and pressure-driven infiltration also significantly affect the accuracy of prediction results. Airflow networks [2], therefore, can be coupled to the building models to calculate air flows through cracks, doors, windows ducts, and other flow paths between zones.

In this study, three types of buildings are modelled through coupling with airflow network models and then calibrated based on the field measurements of indoor hourly air temperature. A framework of building calibration and validation is proposed, which can be applied to other building thermal simulation models.

2. Methodology

2.1 Workflow overview

Fig. 1 shows the procedure of building modelling and calibration. Through building survey, site visit and architecture plan, building parameters, operation schedules, and HVAC systems information are collected. Airflow network (AFN) is applied to the building models. There are unknown parameters to be calibrated based on the measured indoor hourly temperature. The subsections below will introduce the procedure in detail with three measured and modelled buildings.

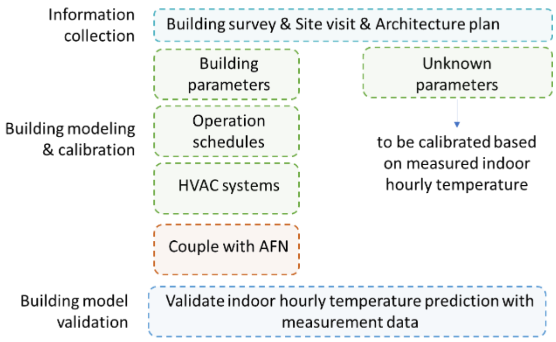


Fig. 1 - Workflow overview

2.2 Building measurement campaign

A building measurement campaign was conducted to monitor the indoor and outdoor thermal conditions of different types of buildings in Montreal, Canada [3]. The indoor temperature and relative humidity (RH) in selected spaces on different floors and orientations of 13 buildings (three primary schools, three hospitals and four residential buildings) were monitored continuously over the summer seasons from 2020 to 2021. On-site weather stations were placed on the roofs of buildings to gather local weather data, including air temperature, relative humidity, solar radiation, wind speed and direction, and precipitation. With the monitored indoor and outdoor conditions, the overheating issues of these buildings can be assessed during the monitored period. However, with climate change, the overheating conditions in future climate projections need to be predicted and possible mitigation strategies need to be investigated using calibrated building models.

2.3 Building modelling

Among the monitored buildings, three buildings including a long-term care building (LTCB), a primary school (PS), and a multi-unit social housing (SH) are modelled in Design Builder™ and exported for use in an EnergyPlus simulation package.

The monitored LTCB is an L-shaped building facing the northwest direction and is composed of five floors above the ground and below-grade basement floor. The total length and width of the building are 44m and 42m, respectively. The size of a typical private patient room in the building is 5.4m x 3.6m. The building was constructed in 1980 with exterior walls made of concrete and solid brick veneer cladding. There were no central cooling systems in the building. As for the mechanical ventilation system, five lounge spaces used a central system to provide fresh air.

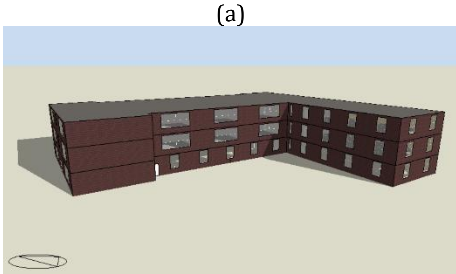
The PS building is a 3+1 story building originally built in 1930. The building was partially retrofitted six times including the extension in 1955, adding boiler room in 2008, masonry in 2009, plumbing in 2014, and new roof in 2015, sanitary blocks and foundations in 2019. The building can accommodate 396 students and 24 teaching staff. The total length and width of the building are 53m and 46m, respectively. The size of a typical private classroom in the building is 9.4m x 8.1m. The building was constructed with exterior walls made of concrete panels and solid brick veneer claddings. There were no cooling systems or mechanical ventilation system in the buildings. The classrooms were cooled by natural ventilation by opening windows and portable fans (in some classrooms).

The SH building is a three-story building built in 2008 and mainly occupied by older people. The total length and width of the building are 105m and 18.5m, respectively. The size of a typical unit in the building is 9.2m x 8.2m. The building is composed of 54 suites (dwelling units) with one bedroom. Each unit was occupied by one or two people. There were no cooling and mechanical ventilation system in the dwelling units. An activity room on the first floor is cooled by a rooftop unit.

Indoor sensors were installed in selected rooms in the above buildings to monitor the air temperature and relative humidity. In each building, all the sensors were installed in the same locations in each room, about 1.7-meter height near the corner. Outdoor weather stations were installed on the roof of the buildings to monitor the air temperature, relative humidity, wind speed, and solar radiation. The monitored data were collected during the summer 2020.

According to the information collected through building surveys, site visits and onsite measurement, the original building models were developed. The 3D models of the three buildings are shown in **Fig. 2**.

(a)



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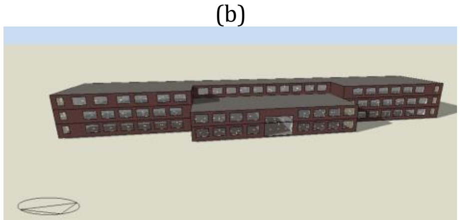


(c)

Fig. 2 - 3-D view of the as-simulated building models

The unknown building parameter values were calculated through building model calibration using the monitored temperature data. The ranges of the unknown parameter values were taken from related published literature and the national building code of Canada. **Tab. 1** summarizes the ranges of the unknown building parameters for building calibration of the LTCB. Unknown parameters and ranges of the primary school and social housing are also analysed in a similar way, the tables of which are not listed here due to the page's limitation.

Tab. 1 - Unknown parameters and ranges of the Long-term care building

Building Parameter		Range	Unit	References
Wall	U-Value	0.25-0.62	W/m²K	RDH (2017)
	Thermal mass	150-350	W/m²K	
Roof	U-Value	0.15-0.39	KJ/km²	
	Thermal mass	150-350	KJ/km²	
Window	U-Value	2.38-3.31	W/m²K	Double glazing with aluminum frame
	SHGC	0.3-0.7	/	
Shading	Slat angle	5-175	Deg	Blind shading parameter
	Solar reflectance	0.4-0.9	/	
Internal heat gain	Lighting power density	6.6-11.3	W/m²	NECB2017
	Equipment power density	2.5-10	W/m²	NECB2017
Infiltration	Air mass flow coefficient at reference crack condition	Walls: 0-0.0040 Roof: 0-0.0045	kg/s	RDH (2017)
Natural ventilation	Natural ventilation temperature set point	22-26	℃	Comfort range
	Window opening factor	0-0.1	/	Site visit
	Room door opening factor	0-1		
	Exterior doors opening factor	0.025	/	

2.4 *Airflow network (AFN)*

The airflow network models are applied to the building models. The buildings are treated as a collection of nodes representing thermal zones in the building and flow elements representing cracks, doors, ducts, and other flow paths between the zones. Conservation of mass flows between the zones generates simultaneous nonlinear equations, which can be solved to determine the resultant flow through the building.

Using an airflow network model to predict ventilation rates in a building allows the inclusion of external weather data in the calculation. The natural variability of the ventilation drivers such as wind speed and direction and thermal effects can be incorporated into the calculation, providing more realistic ventilation predictions than using a fixed ventilation rate based on open window area alone.

The airflow through each leakage component is assumed to follow the leakage relationship of a crack flow, which is characterized by the air mass flow coefficient (C) and exponent (n) as in **Eq. 1**.

$$\dot{m}_a = \dot{V}_a \times A \times \rho = C \cdot \Delta P^n \quad (1)$$

Where $\dot{m}_a$ is the maximum mass flow rate of each surface (kg/s), $\dot{V}_a$ is the maximum volume flow rate per area ($m^3/s/m^2$), A is the component surface area (m^2), ρ is air density (kg/m^3), ΔP pressure differential across the leakage component (Pa), n is the leakage exponent coefficient, defaulted to 0.65.

In the pre-modelling stage, the design infiltration rate for good airtightness of 0.4 ACH [4] for the whole building is set, and the DesignBuilder software automatically creates the leakage data of each exterior and interior surface. However, the infiltration rate is dynamic, affected by wind pressure and surface leakage characteristics. For old buildings (1980), the maximum leakage rate for the entire similar buildings was found to be 0.72 CFM/SF@75Pa = 3.66L/s/m2@75Pa, according to RDH (2017) [5]. For retrofit or new buildings, referring to ASHARE 90.1 [6], ABAA and NECB [4], the maximum air leakage for the entire building built after 2005 is 2.0L/s·m2@75Pa. Therefore, to make the leakage data closer to the actual situation, calculations of the maximum air mass flow coefficient for the exterior surfaces of the monitored rooms, assuming a uniform distribution over exterior building surfaces, are shown in **Tab. 2**.

Tab. 2 - Calculated air leakage data of the monitored natural ventilated rooms (using the Long-term care building as an example)

Surface	Air leakage limit @75Pa (L/s/m²)	Area (m2)	Air density (Reference condition) (kg/L)	n	C (max)
Roof	3.66	20.297	0.0012	0.7	0.0043
Wall_ North	3.66	13.095	0.0012	0.7	0.0028
Wall_ West	3.66	2.987	0.0012	0.7	0.00063
Wall_ South	3.66	18.893	0.0012	0.7	0.0040

In the airflow model, the exterior windows are opened when the indoor temperature is higher than the outdoor temperature and a given set point temperature (the natural ventilation setpoint temperature will be calibrated based on the monitored data). The thermal and ventilation conditions in the zones are affected by the window and door operations (the opening area percentage will be calibrated based on the monitored data), infiltration through the crack of roofs, walls, and partitions, as well as the air released through exhaust fans. The airflow path through the large horizontal openings is applied to the vertical stairway and elevator thermal zones.

2.5 Building calibration and validation

The building calibration process is composed of five steps: parametric simulation with all variables, the first-round calibration, sensitivity analysis, parametric simulation with the most important four variables, second round calibration, as shown in **Fig. 2.**

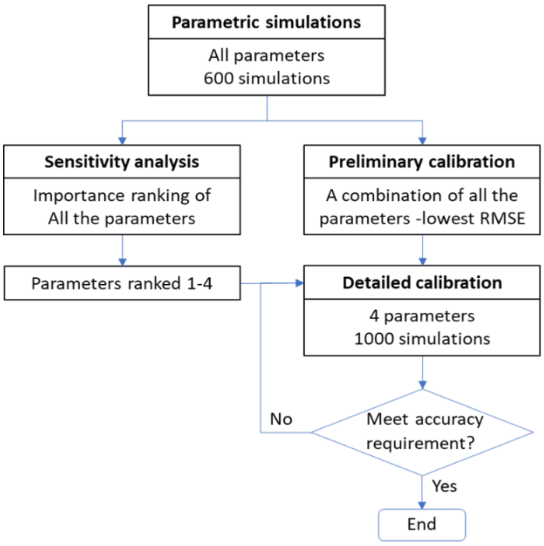


Fig. 3 - Building calibration procedure

In the first step, the unknown model parameters with their practical ranges are defined. The Hamiltonian Monte-Carlo (HMC) sampling method is used for 600 random samplings within each parameter range. HMC is a random sampling algorithm applicable when the model parameters are continuous rather than discrete and able to suppress random walk behaviour through a clever auxiliary variable scheme that transforms the problem of sampling from a target distribution into the problem of simulating Hamiltonian dynamics [7]. So 600 combinations of all the defined parameters are obtained, and then 600 parametric simulations are performed. The parametric simulations are realized with an R package named “eplusr”, which enables to use EnergyPlus directly in the R language. The input-output dataset can be used to do sensitivity analysis to identify the most important parameters of the building thermal model, as explained in the next paragraphs. The input-output dataset can also be used to do the first round calibration of all the defined parameters. In this round calibration, the simulated indoor air temperatures are compared with measurements, and the RMSE (root mean square error, **Eq. 2**) is calculated. The parameter combination corresponding to the minimum RMSE is adopted for the building model. In the second step, the most important four parameters (obtained from the sensitivity analysis) are further calibrated. HMC is again used for 1000 random samplings within each parameter range, resulting in 1000 combinations of all the defined parameters, and then 1000 parametric simulations are performed. The simulated indoor air temperature is compared with measurements, and the RMSEs are calculated. The parameter combination corresponding to the minimum RMSE is adopted for the building model. The calibration process stops when the RMSE reaches its low-level value of below 1.5℃. This low-level value is taken from the study of [8] about the error of predicting air temperatures in a naturally ventilated building. After calibration, validation is then done with the other set of measured data during the different periods for the calibration stage. All the above steps are realized and automated using a script developed in the R programing language.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{2}$$

Where y_i and $\hat{y}_i$ are the simulated and measured hourly temperatures, respectively, and n is the number of hours.

Typical building calibration metrics in existing standards [9] include: the coefficient of variance root mean square error (CVRMSE) and the mean bias error (MBE), as calculated in **Eq. 3** and **Eq. 4**, are used to evaluate the calibration and validation results, to check if the result errors meet the standard requirements. **Eq. 4** indicates that the positive value of MBE means the simulated data are in general higher than the measured data; the negative value of MBE means the simulated data are in general lower than the measured data. The threshold limits of the two metrics for hourly calibration are shown in **Tab. 1**.

$$CVRMSE(\%) = \frac{RMSE}{\sum_{i=1}^{n}\hat{y}_i/_n} \times 100\% \tag{3}$$

$$MBE\ (\%) = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{\sum_{i=1}^{n}\hat{y}_i} \times 100\% \tag{4}$$

Tab. 3 - Threshold limits of building calibration metrics in compliance with ASHRAE (2002), IPMVP (2003) and FEMP (2008)

Metrics	ASHRAE	IPMVP	FEMP
MBE [%]	±10	±5	±10
Cv(RMSE) [%]	30	20	30

Typically, there are six steps for implementing sensitivity analysis in building performance analysis: determine input variations; create building energy models; run energy models; collect simulation results; run sensitivity analysis; presentation of sensitivity analysis results. The first four steps have been finished after the first round of parametric simulation. So that the input-output dataset from the first round parametric simulations is collected to feed the sensitivity analysis to identify the most important parameters.

In this study, three different approaches are utilized to offer robust analysis results: SRC, t-value, and random forest variable importance. High SRC means more important of the variable. The t-value is the statistic used to test whether the coefficient of the corresponding variable is zero. The higher the absolute value of t, the more important is the corresponding variable. The conditional variable importance from the random forest applies to correlated inputs. If there is a large variation of the outputs unexplained (i.e., non-linear effects in the model), the conditional variable importance from the random forest can be used. The three approaches are integrated into one index called Sensitivity Value Index (SVI) [13] to avoid the potential inconsistency.

After calibration, the building models are validated with measured indoor temperature data (over different periods of time). For the LTCB, the monitored data were collected from July 14, 2020 to August 13, 2020. Therefore, the data from July 14 to July 28 were selected for model calibration so that all the parameters to be calibrated have significant effects on indoor temperature, and the data from July 29 to August 13 were selected for model validation. For the PS, the monitored data were collected from August 04, 2020 to September 30, 2020. Therefore, the data from August 26 to September 13 (school occupied) were used for the calibration and the data from September 14 to 30 were used for validation. For the SH, the monitored data were collected from May 01 to 26, 2021. However, from May 01 to 13, the outdoor temperature was from 5℃ to 20℃ and the simulated indoor temperature was lower than 22℃, which made natural ventilation not activated. Therefore, the data from May 14 to 20 were used for the calibration and the data from May 21-26 were used for the validation.

3. Results

3.1 Evaluation of calibration and validation results

Tab. 4(a) shows the evaluation criteria (RMSE, CvRMSE and MBE) of the calibration and validation results for each room and their spatial averages in LTCB. At a room level, the RMSE of the calibration and validation are from 0.56℃ to1.09℃, which are less than the 1.5℃ requirement (O'Donovan et al. 2019). The MBE is within ±1.2% and the CvRMSE is less than 3.65%, which are well within the requirement of standards (±5% and 20% as listed in **Tab. 3**). At a building level (calculated by averaging the data of the three rooms), the validation results show that the RMSE is 0.54℃, the MBE is 0.58% and the CvRMSE is 1.85%, which are all within the error limit requirements. **Tab. 4(b)** shows the evaluation criteria results of PS. At room level, the RMSE of the calibration and validation are from 0.63℃ to 0.78℃. The MBE is within ±1.39% and the CvRMSE is less than 3.19%. At the building level (calculated by average data of the two rooms), validation results show that the RMSE is 0.67℃, the MBE is -0.12% and the CvRMSE is 2.78%. The errors are all within the error limit requirements. **Tab. 4(c)** shows the evaluation criteria results of SH. At room level, the RMSE of the calibration and validation are from 0.56℃ to1.50℃. The MBE is within ±4.9% and the CvRMSE is less than 5.28. In building level (calculated by average data of the four rooms), validation results show that the RMSE is 0.71℃, the MBE is 0.47% and the CvRMSE is 2.55%, which are all within the error limit requirements. The positive MBE value means the simulated data are in general slightly higher than the measured data. The negative MBE value means the simulated data are in general slightly lower than the measured data.

Tab. 4 - Error metrics for the predictions of the hourly indoor air temperatures of monitored rooms in (a) LTCB (b) PS and (c) SH

(a)

Error metrics	Room 1		Room 2		Room 3		Room Average	
	Cal.	Val.	Cal.	Val.	Cal.	Val.	Cal.	Val.
RMSE (°C)	0.56	0.66	0.57	0.55	1.09	1.08	0.46	0.54
MBE (%)	0.25	0.90	-0.70	0.57	1.182	0.285	0.244	0.58
CvRMSE (%)	1.93	2.31	1.89	2.02	3.63	3.61	1.54	1.85

(b)

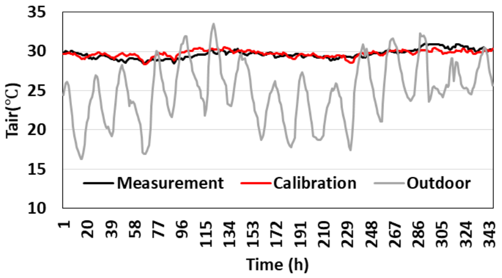
Error metrics	Room 1		Room 2		Room Average	
	Cal.	Val.	Cal.	Val.	Cal.	Val.
RMSE (°C)	0.73	0.7	0.63	0.78	0.63	0.67
MBE(%)	-0.82	1.17	-0.90	-1.39	-0.86	-0.12
CvRMSE(%)	2.57	3.12	2.22	3.19	2.21	2.78

(c)

Error metrics	Bedroom 1		Livroom 1		Bedroom 2		Livroom 2		Room average	
	Cal	Val	Cal	Val	Cal	Val	Cal	Val	Cal	Val
RMSE (°C)	0.63	1.05	0.56	0.91	1.49	0.77	1.21	1.50	0.59	0.71
MBE (%)	1.19	1.08	1.25	0.52	-4.90	-0.67	-3.72	0.99	-1.65	0.47
CvRMSE (%)	2.44	3.86	2.16	3.33	5.28	2.71	4.35	5.51	2.18	2.55

3.2 Comparison of the measured and simulated indoor temperature

Fig. 4 compares the measured and simulated indoor temperature (average values of the three monitored rooms of LTCB) after applying the calibrated parameter values during the calibration and validation periods. To analyse whether the simulated data can capture the peak indoor temperatures, the distribution of the measured and simulated hourly temperatures during the validation period are shown in **Fig. 5**. During the validation period, there are 11 hours when the measured temperature is above 30.4℃ (the last bin in **Fig. 5(a)**), and 8 hours when the simulated temperature is above 30.4℃ (the last bin in **Fig. 5(b)**). Therefore, the simulated data can capture 73% of the peak temperatures. Comparing the three bins of 29.8℃ to 30.4℃, the simulations overestimate the hours between 29.8℃ to 30.4℃ by 85 hours, but underestimate the temperature in the bins of 28.4℃ to 29.4℃ by 87 hours. This deviation might be because of occupant behaviour in adjusting window and door openings under different weather conditions to control nature ventilation, whereas in the simulation the opening factors of windows and doors are kept constant during the simulation period.



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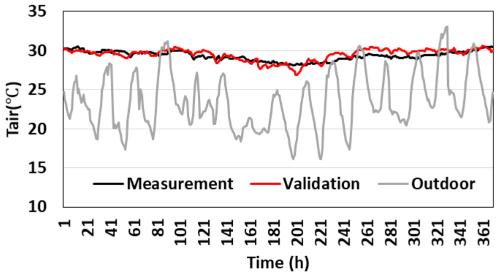
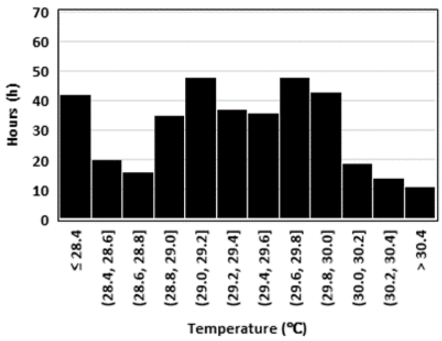


(b)

Fig. 4 - Comparison of the measured and simulated data (room averages of LTCB) during (a) calibration period and (b) validation period



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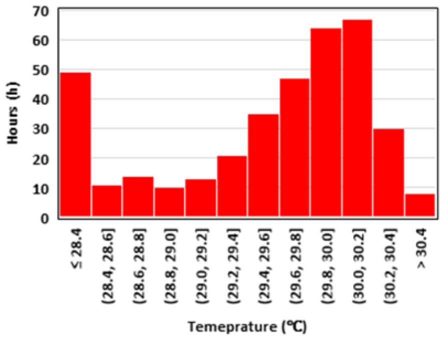
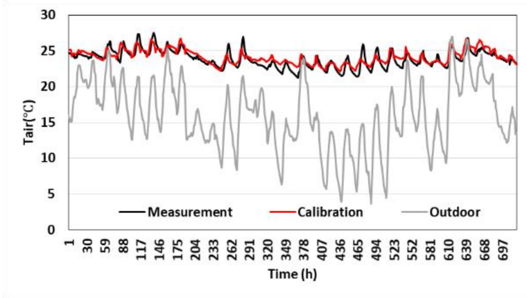


(b)

Fig. 5 - Distribution of average room data of LTCB during the validation period: (a) measured and (b) simulated temperatures

Fig. 6 shows a comparison between the measured and simulated data (average data of the two rooms in PS) after applying the calibrated parameter values, and the distribution of the measured and simulated hourly temperatures during the validation period is shown in **Fig. 7**. There are 26 hours when the measured temperature is above 31.2℃, and 42 hours when the simulated temperature is above 31.2℃. Therefore, the simulated data can capture 100% of the peak temperatures with a slight overestimation. The hours of the measured and simulated temperature above 28℃ are as well comparable: 514 hours versus 522 hours, respectively.



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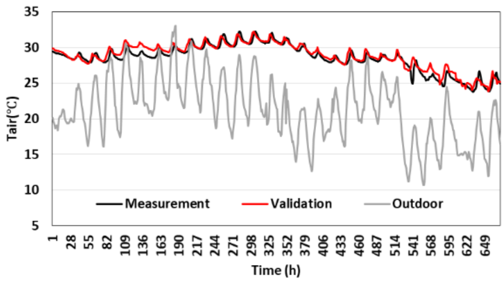
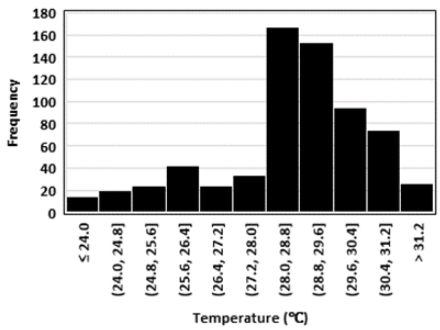


(b)

Fig. 6 - Comparison of the measured and simulated data (room averages of PS) during (a) calibration period and (b) validation period



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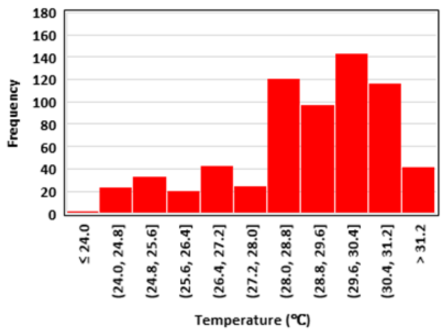
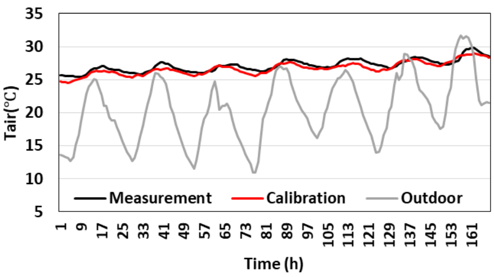


(b)

Fig. 7 - Distribution of average room data of PS during the validation period: (a) measured and (b) simulated temperatures

Fig. 8 shows the comparison of the measured and simulated data (average data of the four rooms in SH) after applying the calibrated parameters. The distribution of the measured and simulated hourly temperatures during the validation period is shown in Fig. 9. There are 10 hours when the measured temperature is above 30.0℃, and 8 hours when the simulated temperature is above 30.0℃. Therefore, the simulated data can capture 80% of the peak temperatures. The hours of the measured and simulated temperatures above 29℃ are comparable: 36 hours versus 41 hours, respectively.



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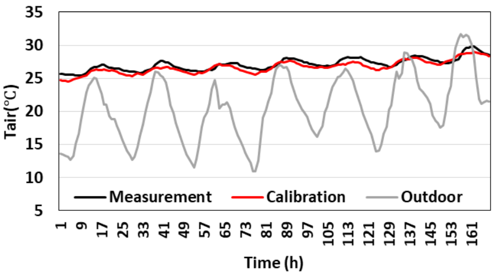
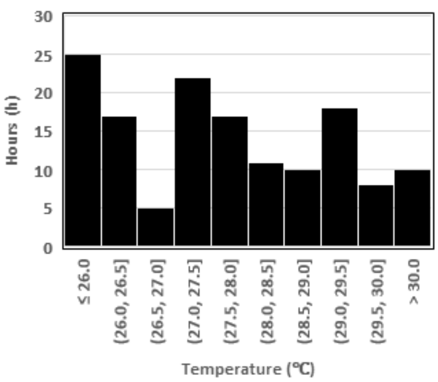
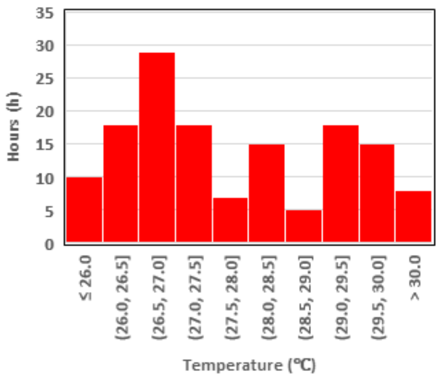


(b)

Fig. 8 - Comparison of the measured and simulated data (room averages of SH) during (a) calibration period and (b) validation period



(a)



(b)

Fig. 9 - Distribution of average room data of SH during the validation period: (a) measured and (b) simulated temperatures

3.3 Calibrated building parameter values

The calibrated values of the unknown parameters of the LTCB model are shown in **Tab. 5**. The tables for PS and SH are not listed here due to the pages limitation.

Tab. 5 Calibrated parameter values of LTCB

Object	Parameter	Unit	Final value
Wall	Wall U-Value	W/m^{2}K	**0.3**
Roof	Roof U-Value	W/m^{2}K	**0.25**
Wall	Wall thermal mass	KJ/km^2	**220**
Roof	roof thermal mass	KJ/km^2	**335**
Window	Window U-Value	W/m^{2}K	**2.72**
Window	Window SHGC	-	**0.37**
Interior blinds	Slat angle	Deg	**59**
	Solar reflectance		**0.6**
Equipment	Equipment power density	W/m^2	**2.93**
Lighting	Lighting power density	W/m^2	**9.94**
Air mass flow through cracks	Air mass flow coefficient at reference crack condition of walls and roof surfaces	kg/m·s	**0.0025**
		kg/m·s	**0.0012**
Natural ventilation control	Natural ventilation set point	℃	**26**
Interior room door opening factor	Width factor for door opening	%	**47**
Room window opening factor		%	**10**

4. Discussion

The mechanical ventilation systems are not considered in the three building models in this study. The calibration method is only demonstrated in the naturally ventilated buildings. Future studies can be conducted to apply the method to building models with mechanical cooling or ventilation systems.

5. Conclusion

This study developed building performance simulation models coupled with airflow networks. A two-round calibration framework was proposed to calibrate the building models based on measured hourly temperature data. The results showed that the detailed building model was capable of predicting room air temperatures with minimum error levels (0.56°C ≤ RMSE ≤ 1.50 °C) within the limits of applicable building model calibration standards (MBE±10%, CVRMSE<20%). As a future work, the calibrated building models will be used to implement and evaluate strategies to reduce overheating risk arising from extreme heat events of current and projected climates.

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