Exploring the possibility of calibrating a whole-building model from the short-term monitoring of selected reference rooms

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Abstract

Accurate simulation models of existing buildings provide a reliable picture of building and system behaviour, useful for diagnostic purposes, for designing retrofit interventions or improving the control strategies. Reliable building models can be obtained through monitoring and calibration, aiming at minimizing the discrepancy between predicted and actual performance by fine-tuning the values of the simulation parameters. Analytical calibration methods may become a complex and time expensive process, especially when a large number of parameters has to be estimated as in the case of the largest buildings. In addition, overfitting issues can undermine the reliability of the calibration process.

This work explores the possibility of carrying out a model calibration based on low-cost and short-term measurements in order to avoid overfitting issues. In particular, the proposed approach is based on the selection of representative spaces in the buildings, and the identification of multiple monitoring periods during which only a subset of building parameters needs to be calibrated at a time. This calibration approach is extended to the entire building in a multi-stage and multi-level approach.

Key Innovations

The method presented in this work has two main advantages that represent its main innovation:

- It uses the measurements inside a small portion of a building (i.e. 9 rooms out of 24) to calibrate the whole building, lowering the monitoring costs.
- It uses short monitoring periods to calibrate different sets of building parameters separately, reducing the number of parameters to be optimized each time, thus improving the calibration process.

Practical Implications

The described approach allows the definition of an accurate calibrated model for evaluating the effectiveness of energy retrofitting strategies both in design phase and after the interventions. Moreover, this method accelerates the calibration process and improves its accuracy.

Introduction

Over the recent decades, an increasing amount of works focused on the application of building simulation procedures for the optimization and application of predictive methods for building system control in existing buildings (Tahmasebi and Mahdavi, 2013) or for retrofitting strategies. In order to obtain a reliable representation of the building and energy systems behaviour, accurate simulation models for energy diagnoses of buildings are required and generally, expensive and long-term monitoring of some building performance variables (e.g. energy consumption, air temperature, etc.) are needed. A calibration process, by changing uncertain building parameters until the output matches measured values is often adopted to improve the model. However, when the complexity of the building is high, the number of descriptive parameters is typically too high to rely on a calibration method based on an iterative manual procedure and it requires a time-consuming trial-and-error process (Yang et al., 2015). Moreover, it potentially leads to results which are still far from reflecting the real building data, due to compensation effects as highlighted by Coakley et al. (2014). To make the process easier, the calibration can be divided into different steps in order to limit the number of model parameters to calibrate at each step, considering their different impact in different reference periods. In addition, the monitoring phase can be less expensive by choosing a small representative portion of building to monitor and calibrate the values of some specific quantities to be extended to the whole-building model. This method allows to calibrate fewer parameters when considering the model of the entire building and reduces the possibility of overfitting. This paper explores the potential of calibrating a whole-building simulation model by means of a multi-stage and multi-level approach based on an automated process. The calibration has been applied to a case study, namely a school building located in the North-East of Italy, monitored from December 2012 to April 2014. The result is a multi-level calibration implemented by means of the automated discrepancy minimization of the temperatures measured during short-term periods and the simulated temperatures.

Methods

Calibration method

The calibration method proposed in this paper is based on the monitoring of the air temperature and the relative humidity of a portion of a building such as one or two reference rooms along with all their surrounding rooms (i.e. monitored zones) in order to provide the required boundary conditions. The calibration phase is split into two main levels: (i) the calibration of a limited portion of

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the building (i.e. partial-building calibration) and (ii) the afterwards calibration of the whole-building model (i.e. whole-building calibration). Since the first level considers only a portion of the building, the calibration is set on the indoor conditions (i.e the indoor air temperature and relative humidity), while the building energy consumptions are considered for the annual validation whole-building calibrated model. According to this method, a model of the reference rooms needs to be set-up and calibrated. To avoid compensation effects during the automated calibration process, the unknown building parameters are separated into subsets and the partial-building model is progressively calibrated during different periods of the year. These periods are selected to be representative of different seasons and building operation modes in relation to human presence (occupied/unoccupied) and HVAC system operation (on/off). In each period, different sets of building parameters are consequently calibrated (e.g.: physical characteristics of the building envelope and infiltration, heating system characteristics, shading level and ventilation rate due to occupants' presence and behavior). Then, the already calibrated parameters are used to the following periods and to the whole-building model, while the remaining unknown quantities are calibrated for the entire building, considering again the different periods already defined. The result of this approach is a multi-stage multi-level calibration of whole-building model. The simulation output to calibrate is the indoor air temperature trend in the reference rooms in the first level and the air temperature of all the monitored rooms in the second level.

The calibration process is performed following an optimization-based approach simultaneously minimizing the differences between the simulated and monitored indoor air temperatures of the selected reference rooms in the partial-building calibration and of all the monitored rooms in the whole-building model calibration. Among the calibration performance indexes reviewed in Coakley et al. (2014), for representing the cumulative differences between measured and simulated air temperatures, we selected the Coefficient of Variation of the Root Mean Square Difference CV(RMSD) (Equation 1 and 2), widely used in the literature (Attia et al. 2020).

$$CV_{\mathrm{j}}(RMSD_J) = \frac{RMSD_J}{\overline{m}_j} \tag{1}$$

$$RMSD_{\mathrm{J}} = \sqrt{\frac{\sum_{i=1}^{n}\left(m_{ij} - s_{ij}\right)^2}{n}} \tag{2}$$

where $\boldsymbol{m_{ij}}$ is the measured indoor air temperature; $\boldsymbol{s_{ij}}$ is the simulated indoor air temperature; $\boldsymbol{n}$ is the number of the simulation time steps and $\overline{m}_j$ is the measured mean temperature; i is the time step index and j is the number of monitored rooms utilized for the calibration process. In addition, in order to avoid overfitting issues, the cost function of the optimization-based calibration is defined combining the CV(RMSD) with the regression coefficient R^2, since the latter adds complementary information about the quality of the model. The determination coefficient R^2 (Equation 3) is used for describing the proportion of the variance in measured data according with the model (Moriasi et al., 2007):

$$R^2{}_{\mathrm{J}} = \left(\frac{\mathrm{n}\sum_{\mathrm{i}} \mathrm{m_{ij}s_{ij}} - \sum_{\mathrm{i}} \mathrm{m_{ij}s_{ij}}}{\sqrt{\left(\mathrm{n}\sum_{\mathrm{i}} \mathrm{m^2{}_{ij}} - \left(\sum_{\mathrm{i}} \mathrm{m_{ij}}\right)^2\right) * \left(\mathrm{n}\sum_{\mathrm{i}} \mathrm{s^2{}_{ij}} - \left(\sum_{\mathrm{i}} \mathrm{s_{ij}}\right)^2\right)}}\right)^2 \tag{3}$$

For calibration purpose, different weighting factors have been assigned to the statistical indexes (Tahmasebi et al., 2012; Tahmasebi et al., 2013) with the aim to prioritise the minimizing of the CV (RMSD. Hence a value of 0.7 for the CV(RMSD) weighting factor and a value of 0.3 for R^2. For each monitored zone, the cost functions f_j are defined (Equation 4) and the overall cost function f_{tot} is calculated as their summation (Equation 5).

$$f_{\mathrm{j}} = 0.7CV_j(RMSD_j) + 0.3(1 - R_j{}^2) \tag{4}$$

The overall cost function f_{tot} is calculated as their summation (Equation 5).

$$f_{\mathrm{tot}} = \sum_j f_j \tag{5}$$

In order to test and illustrate the abovementioned calibration method, a school building has been calibrated and presented in this work as case study. In particular, the focus is on the implementation of the entire calibration method, from the partial model to the entire building, considering only the passive performance. The calibration is conducted on two periods, the first one with unoccupied building, and the second one with the building regularly occupied. Moreover, two levels are considered in the first period, starting from two representative classrooms and extending the calibration to the whole-building. The calibrated parameters have been used in the second period. In order to test their effectiveness, the calibrated models have been validated in other periods with the same characteristics, respectively unoccupied and building with the system off.

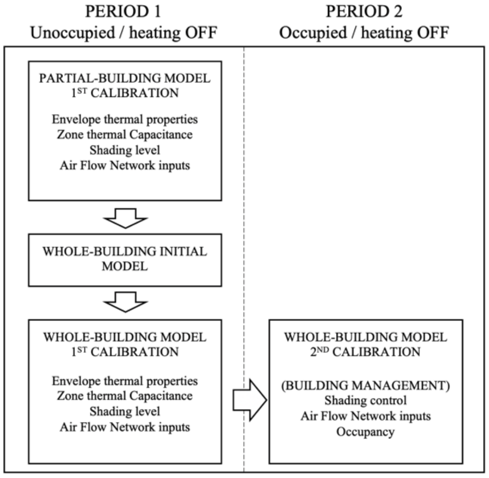

Figure 1: Scheme of the applied calibration procedure: from partial-building to the whole-building calibration. Period 1 (non-occupied building, passive mode) and Period 2 (occupied building, passive mode).

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Monitoring of the case study

The case study selected for testing the proposed method is a primary school located in Schio, a municipality in the North-East of Italy (Fig. 2). The building complex was realised at the beginning of the 1950s and considerably extended by the middle of the 1960s. The building has three stories: the basement and two upper floors, where the classrooms are located. Two overlying classrooms, R1 and R2, located respectively on the first and second floor of the school, have been chosen as the reference rooms (Fig. 3) and used for testing the first level of the calibration in Period 1. For this reason, measuring instruments were located in the reference rooms and in all the adjacent spaces, having different uses: the canteen located in the basement level (B1), two ground floor classrooms (B2 and B3), the library and a classroom located at the first floor (B5 and B6) and the corridors, B4 and B7, located respectively on the ground floor and on the first floor. which comprise. As a result, the indoor air temperature of 9 rooms have been monitored (Fig. 3). The measurement setup includes data loggers (HOBO® U-12 and U-13) to measure indoor air temperature (accuracy ±0.35°C), relative humidity (accuracy ±2.5%) and supply and return radiator pipe temperatures at small intervals (10 minutes). In the first level of this approach, also explored in Penna et al. (2015a) and Penna et al. (2015b), i.e. the partial-building calibration (or two-zone calibration), the monitored temperatures of the spaces adjacent to the reference rooms are used as boundary conditions for the model of the two reference classrooms. Afterwards, in the second level, the so called whole-building calibration (or multi-zone calibration), all the 9 monitored zones are used as reference in the calibration process. Regarding the outdoor conditions, the weather data file has been implemented through the hourly weather recordings from the weather station of the municipality of Malo (10 km far away from school site) The recordings refer to school year 2013-2014.

Figure 2: Case study: San Benedetto Primary School (Italy)

Partial-building model simulation and calibration in Period 1

The dynamic simulation model of the entire school building has been implemented with the simulation code TRNSYS v.18. The 3D geometry model of the building has been described using the TRNSYS plugin and Google Sketch-up v.8, while the building thermo-physical characteristics have been set in TRNBuild. The model of the building has been defined through the multi-zone building subroutine Type 56, using Simulation Studio. The ground temperature profile has been modelled with the subroutine Type 77.

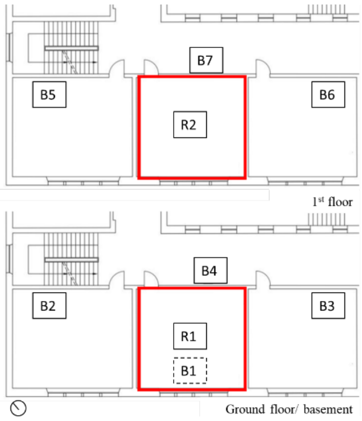

Fig. 3 – Sensors inside the 9 monitored rooms. Letters R and B before sensor numbering indicate respectively Reference room and Boundary room.

The Air Flow Network has been implemented with the tool TRNFLOW, the integration of the multizone air flow model COMIS (Conjunction of Multizone Infiltration Specialists) into the thermal building module of TRNSYS, Type 56-TRNflow. A simulation time-step of 10 minutes has been selected. The first selected period for the calibration process, from 5th to 19th August, is characterize by the absence of occupants while the system is off. In the partial-building model calibration, several buildings' thermophysical properties, the windows thermal and solar transmittance and the shading coefficient have been calibrated. In addition, in order to consider the air coupling between the control rooms, the convective airflows between the stories and to assess the airtightness of the building, three parameters related to the Air Flow Network (AFN) have been calibrated, namely the crack area of the window, the crack area of the door and the wind velocity exponent profile. For all these quantities, tentative values were set and a variability ranges defined. These and the calibrated value after the partial-building calibration are listed in Table 1. As concerns the parameters related to the AFN the variation ranges were defined according to the TRNFLOW manual.

Whole-building model simulation, calibration in Period 1

Calibrated parameters from the partial-building model were then used in the model of the entire school building. In detail, calibrated values of the thermal properties of the envelope (i) and parameters related to the AFN (ii) obtained from the two-zone calibration were extended to all the similar thermal zones in order to construct the whole-building multi-zone initial model. The multi-zone model requires a certain number of further parameter to be calibrated, namely the single-glazed windows thermal and solar transmittance, additional parameters related to the AFN (i.e. the crack value of the single-glazed window and the pressure drops of the stairwells), the thickness of the ground floor hollow slab and the shading coefficients

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of the boundary rooms. The variability ranges and the calibrated value of the whole-building calibration are listed in Table 2. For all these quantities, tentative values were set in order to build the whole-building initial model (Table 2) and were calibrated further. For the parameters related to the AFN the variation ranges were defined according to the TRNFLOW manual. The calibration was validated by simulating the building model in the period 20th August–1st September (unoccupied building, passive mode).

Table 1: Building parameters calibrated in the partial-building model in the Period 1 (from 5th to 19th August).

Parameters	**Initial value**	**Range value**	**Calibrated value**
External Wall Brick			
• Conductivity λ [kJ/h m K]	2.5	[2-7]	6.75
• Density ρ [kg/m^3]	1500	[1000-2000]	1450
• External Solar Absorptance	0.3	[0.24-0.36]	0.32
Internal Wall Brick			
• Conductivity λ [kJ/h m K]	2.5	[2-7]	6
• Density ρ [kg/m^3]	1500	[1000-2000]	1350
Internal Hollow Slab			
• Conductivity λ [kJ/h m K]	2.5	[1.53-2.84]	2.3
• Density ρ [kg/m^3]	1417	[1070-1417]	1350
Roof Hollow Slab			
• Conductivity λ [kJ/h m K]	2.5	[2-7]	3.2
• Density ρ [kg/m^3]	1500	[1000-2000]	1850
• External Solar Absorptance	0.3	0.4-0.6	0.56
Window 1			
• Frame Transmittance [kJ/(h m^2 K)]	18	[14.4-21.6]	21.6
• Window *	11	[4-14]	13
- glazing U-value [kJ/(h m^2 K)]	6.6	[5.7-11.2]	6.0
- glazing g-value [%]	67.1	[65.9-67.3]	67.2
Shading coefficients			
• Room R1	0	[0-1]	0.75
• Room R2	0	[0-1]	0.35
Air Flow Network			
• Window 1 crack area [kg/s at 1Pascal]	0.000006	[0.000001-0.0012]	0.000564
• Door crack area [kg/s at 1Pascal]	0.0013	[0.0013-0.0024]	0.00184
• Wind velocity exp. profile	0.3	[0.15-0.4]	0.2
Air node thermal capacitance R1	6000	[477-9540]	6201
Air node thermal capacitance R2	6000	[477-9540]	4054

* *Windows were evaluated as discrete parameters.*

Table 2: Building parameters calibrated in the whole-building model in the Period 1 (from 5th to 19th August).

Parameters	**Initial value**	**Range value**	**Calibrated value**
Basement floor			
Hollow slab			
• *Slab thickness [m]*	0.5	[0.4-0.5]	0.4
Window 2			
• Frame Transmittance [kJ /(m^2 K)]	7	[5.6-8.4]	7.2
• Window *	1	[1-3]	2
- glazing U-value [kJ/(h m^2 K)]	20.5	[20.2-20.5]	20.2
- glazing g-value [%]	85.5	[82.7-85.5]	82.7
Air Flow Network			
• Window 2 crack area	0.000006	[0.000001-0.0012]	0.001
• Discharge coeff. stairs 1	1	[0-1]	0.8
• Discharge coeff. stairs 2	1	[0-1]	0.2
Shading coefficients			
• Room B1	0.45	[0.25-0.75]	0.58
• Room B2	0	[0-1]	0.9
• Room B3	0	[0-1]	0.7
• Room B5	0	[0-1]	0.8
• Room B6	0.25	[0.25-0.75]	0.48
Air node thermal capacitance B1	2000	[420-8406]	1681
Air node thermal capacitance corr. T4	4000	[890-17804]	11129
Air node thermal capacitance B4	2000	[477-9540]	4531
Air node thermal capacitance B7	2000	[477-9540]	4054
Air node thermal capacitance room T6	2000	[890-17806]	6677

* *Windows were evaluated as discrete parameters.*

Whole-building model simulation and calibration in Period 2

The parameters of the whole-building model calibrated in Period 1 (unoccupied building/system off) was used for constructing the whole-building model in Period 2 (occupied building/system off), from 3rd to 17th of May. This period has been selected in order to calibrate building parameters related to the user behaviour, such as window opening and shading operation during the occupation period. In order to consider students' interaction with the windows, (i.e. windows opening), a logistic regression model have been used. The windows status (open or closed) is due to either random events (students or teacher interaction with the window during lessons) or scheduled

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events as the opening of the windows during break-time or cleaning time and the closing during the night. While an opening or closing schedule was set for the scheduled events, a logistic regression model had to be implemented for the period of occupation in which students are also present and attending the lessons. Using the logistic regression model, it is possible to obtain the probability for each classroom of finding at least an open window or all closed windows given a set of parameters. In this model we have chosen to use only one variable, the internal temperature, since as highlighted by Stazi et al. (2017) it is the best predictor for both opening and closing probability in classrooms. Below is reported the equation to calculate according to the regression model the probability of finding at least one window open.

$$p = \frac{exp^{(\beta_0+\beta_1*x)}}{1+exp^{(\beta_0+\beta_1*x)}}) \qquad (7)$$

In equation 7 the coefficients β_0 and β_1, are constants estimated by the regression analysis through maximum likelihood estimation and x is the environmental parameter, namely the indoor air temperature.

Table 3: Building Parameters calibrated in the whole-building model during the Period 2 (from 3rd to 17th May).

Parameters	Lower limit	Upper limit	Calibrated value
Logistic regression			
• Probability threshold (opening)	0.8	[0.6-0.95]	0.68
• Probability threshold (closing)	0.8	[0.6-0.95]	0.6
• Regression param. β_0	-19	[-21/-18]	-20.75
• Regression param. β_1	0.922	[0.85-0.99]	0.86
Air Flow Network			
• Wind velocity coeff.	1	[0.2-1]	0.25
• Discharge coeff. window 2	0.6	[0.01-1]	0.01
• Discharge coeff. door	0.8	[0.01-1]	0.23
Shading coefficients			
• Basement	0.5	[0-1]	0.21
• Basement (east)	0.5	[0-1]	0.65
• Basement (west)	0.5	[0-1]	0.61
• Ground floor (east)	0.5	[0-1]	0.57
• Ground floor (west)	0.5	[0-1]	0.68
• First floor (east)	0.5	[0-1]	0.51
• First floor (west)	0.5	[0-1]	0.5
• Room R1	0.5	[0-1]	0.87
• Room R2	0.5	[0-1]	0.87
• Room B2	0.5	[0-1]	0.6
• Room B1	0.5	[0-1]	0.42
• Room B5	0.5	[0-1]	0.59

Given the need to calibrate the regression model as well, it was necessary to transform the model from probabilistic to deterministic. This was done by imposing two parameters that determine the probability threshold beyond which the windows status is changed to open or closed.

$$p > T_{open} \qquad (8)$$

$$(1-p) > T_{closed} \qquad (9)$$

Moreover, additional parameters related to the AFN have been considered in the model, i.e. wind velocity coefficient and the discharge coefficients of the windows, and calibrated. For all these quantities, tentative values were set and the variation ranges were defined according to the TRNFLOW manual for the parameters related to the AFN, according to Stazi et al. (2017) for the parameters related to the logistic regression model, 0.2-1 for the shading. The variability ranges and the calibrated value of the 2nd whole-building calibration are listed in Table 3. In order to take into account building occupancy, people are considered at school from Monday to Friday from 8 a.m. to 1 p.m. and Saturday from 8 a.m. to 12 a.m. The number of people in the two control rooms (R1 and R2) was derived from the register books; while in the other classroom was calculated by multiplying the surface area of the classrooms with the concentration rate obtained from the two control rooms (0.38 people per square metre). The library was considered occupied by one person during the occupancy period and in the canteen the occupancy was considered during lunch time and the number students were calculated using the concentration rate 0.6 people per square metre as suggested by the Italian standard UNI 10339.

Table 4: Comparison of the Statistical indices of Reference Room1 (R1) and 2 (R2) in Period 1 (from 5th to 19th August).

Model type	RMSD [°C]		CV(RMSD) [%]		R^2	
	R1	R2	R1	R2	R1	R2
Partial-building calibration	0.09	0.18	0.32	0.6	1	0.99
Whole-building initial model	0.66	0.38	2.33	1.28	0.98	0.99
Whole-building 1st Calibration	0.11	0.18	0.4	0.6	1	0.99
Whole-building 1st Validation	0.3	0.18	1.21	0.72	0.99	0.99

Results

Whole-building initial model and calibration model in Period 1

Tables 4 and 5 report the standardized statistical indices RMSE, CV(RMSE) and R^2 of the partial-building calibrated model, the initial whole-building model, the whole-building calibrated model and the whole-building validated model in Period 1. Comparing the results of the whole-building initial model and those of the partial-building calibrated model, it can be noticed that the air temperature of the two reference rooms is less accurately predicted by the whole-building model. The statistical indices of the two reference rooms (R1 and R2) are worse in the initial whole-building model: RMSD=+86%, CV(RMSD) = +86 %, R^2 = +2% for R1 and RMSD =+53 %, CV(RMSD) = +53 %, with the same R^2 = 0.99 for R2. But, focusing on the results of the whole-building calibration it can be seen that the calibration significantly enhanced the whole-building model and the statistical indices are very similar to those of the partial-building calibration: RMSD=0.11°C, CV(RMSD) = 0.4 %, R^2 = 0.99 for R1 and RMSD =0.18°C, CV(RMSD) = 0.6%, R^2 = 0.99 for R^2. Looking at the average values of the statistical indices calculated in all 9 monitored zones, the whole-building calibration leads to good improvements of the initial model ($RMSD_{avrg}$ = -80 %, $CV(RMSD)_{avrg}$ = -67 % with the same R^2_{avrg}=+1%). During the first validation period, the statistical indices of the control rooms are consistent with the calibrated model with a slightly worse value of the CV(RMSD) of R^2. Figure 4 shows that simulated temperatures are within the range of ±0.35 °C from the measured values for almost all the time both in the calibration and in the validation period.

Table 5: Overview of the Statistical indices of the whole-building model during Period 1 (from 5th to 19th August).

Thermal zone		**RMSD [°C]**			**CV(RMSD) [%]**			**R^2**		
		Initial Model	1st Calibration	1st Validation	Initial Model	1st Calibration	1st Validation	Initial Model	1st Calibration	1st Validation
Basement	**B1**	0.85	0.25	0.65	3.31	0.99	2.81	0.94	0.96	0.88
Ground floor	**R1**	0.66	0.11	0.3	2.33	0.4	1.21	0.98	1	0.99
	B2	1.22	0.19	0.36	4.39	0.66	1.49	0.97	1	0.99
	B3	0.92	0.18	0.43	3.21	0.62	1.73	0.97	1	0.98
	B4	0.81	0.34	0.32	2.88	1.2	1.32	0.99	0.99	0.98
1st floor	**R2**	1.28	0.18	0.18	1.28	0.6	0.72	0.99	0.99	0.99
	B5	3.06	0.3	0.39	3.06	1.05	1.58	0.98	0.99	0.96
	B6	1.27	0.31	0.22	1.27	1.03	0.88	0.98	0.98	0.99
	B7	0.94	0.28	0.36	0.94	0.95	1.45	0.99	0.99	0.96
Average of the 9 zones		1.22	0.24	0.36	2.52	0.83	1.47	0.98	0.99	0.97

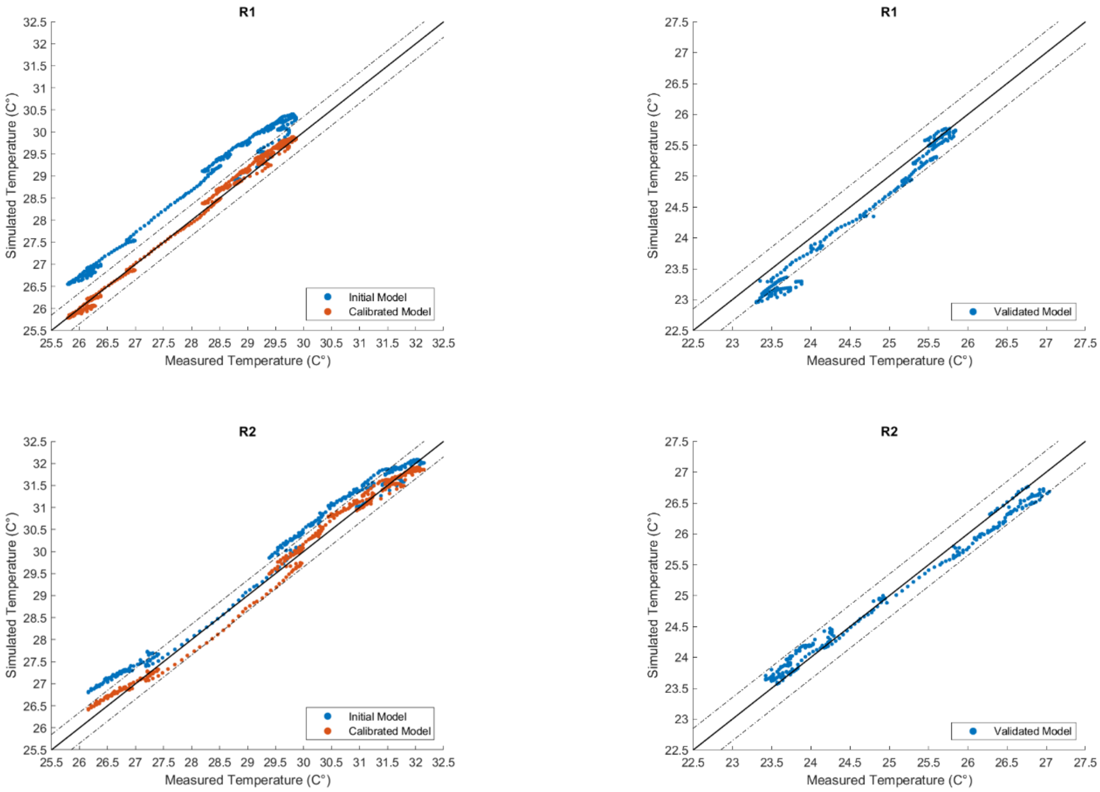

Fig. 4 – Comparison of the initial model, calibrated model and validated model in Period 1 (unoccupied-passive mode): measured vs simulated temperature of room R1 (top) and R2 (bottom) at the same time-step.

Whole-building initial model and calibration model in Period 2

Table 6 reports the standardized statistical indices RMSE, CV(RMSE) and R^2 of the initial whole-building model, the whole-building calibrated model and the whole-building validated model in Period 2. Comparing the statistical indices of R1 and R2 obtained with the whole-building initial model and those obtained with the whole-building calibrated model, it can be noticed that the calibration leads to a fair improvement of the initial model, with RMSD= -59%, CV(RMSD) = -59 %, R^2 = +58% for R1 and RMSD = -39 %, CV(RMSD) = -38%, R^2 = +39% for R2). Globally, looking at the average values of the statistical indices calculated in all 9 monitored zones, the whole-building calibration leads to fair improvements of the initial model ($RMSD_{avrg}$ = -27%, $CV(RMSD)_{avrg}$ = -27% and R^2_{avrg}= +39%). During the validation period (from 18th to 31st May), the statistical indices of the control rooms are worse than those of the calibrated model in terms of RMSD and CV(RMSD) with a slight improvement in terms of R^2.

Table 6: Overview of the Statistical indices of the whole-building model during Period 2 (from 3rd to 17th May).

Whole-building model										
Thermal zone		**RMSD [°C]**			**CV(RMSD) [%]**			**R^2**		
		Initial Model	2nd Calibration	2nd Validation	Initial Model	2nd Calibration	2nd Validation	Initial Model	2nd Calibration	2nd Validation
Basement	**B1**	1.03	0.95	1.53	5.45	5.07	8.73	0.55	0.44	0.28
Ground floor	**R1**	0.69	0.28	0.53	3.34	1.37	2.88	0.33	0.78	0.82
	B2	0.6	0.37	0.53	3.04	1.87	3.07	0.41	0.56	0.89
	B3	0.7	0.33	0.4	3.38	1.59	2.15	0.25	0.68	0.83
	B4	0.58	0.56	0.83	2.91	2.77	4.68	0.69	0.76	0.93
1st floor	**R2**	0.59	0.36	0.5	2.8	1.72	2.71	0.45	0.74	0.85
	B5	0.49	0.39	0.53	2.44	1.94	3.09	0.55	0.70	0.93
	B6	0.42	0.29	0.51	2.04	1.38	2.82	0.53	0.78	0.84
	B7	0.66	0.67	0.92	3.2	3.29	5.14	0.57	0.60	0.83
Average of the 9 zones		**0.64**	**0.47**	**0.7**	**3.18**	**2.33**	**3.92**	**0.48**	**0.67**	**0.80**

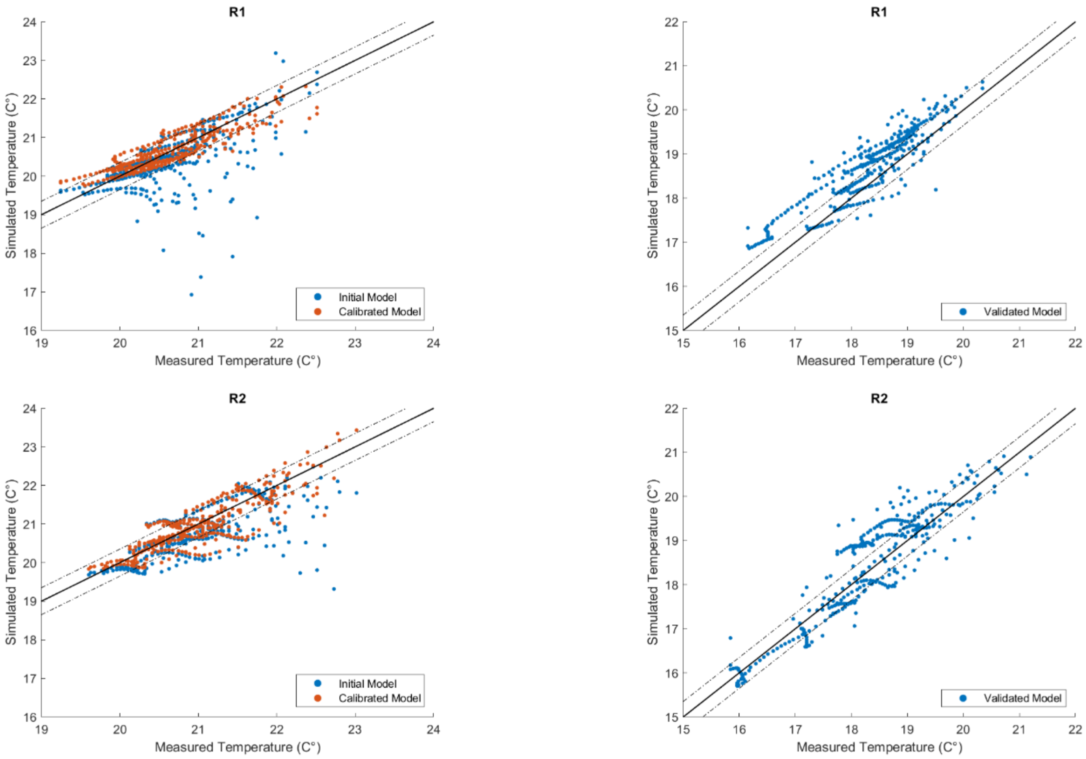

Fig. 5 – Comparison of the initial model, calibrated model and validated model in Period 2 (occupied-passive mode): measured vs simulated temperature of room R1(top) and R2 (bottom) at the same time-step.

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Conclusion

In this paper a calibration methodology based on a multi-stage multi-level approach has been presented. The calibration phase is split into two main levels: (i) the calibration of a small part of the building (i.e. partial-building calibration) and (ii) the subsequent calibration of the whole-building model (i.e. whole-building calibration). The main advantages of this method are that it enables (i) to extend the calibrated building parameters in the calibration of a partial-building model to the entire building in order to build the whole-building initial model in the same period and (ii) to use the measurements inside a small portion of a building during short periods (i.e.: short-term measurements in 9 rooms) to calibrate the whole building, avoiding any additional monitoring costs. This method was tested and validated in a real school building. The application of this approach to the case study highlights that the partial-building model calibrated in Period 1 (non-occupied building, passive mode) is a reliable approximations of the whole-building model in the same period. However, the subsequent calibration of the additional building parameters of the whole-building model can further enhance the prediction of the temperature trend in the whole-building model in the same period, as shown by the statistical indices. Results from the Period 2 (occupied building, passive mode) show that the presence of people inside a building augments the complexity of a calibration because of the lack of knowledge about occupant behavior, namely the opening and closing of windows and doors especially in the corridors, in the canteen and in the library. This leads to a reduction in convective air exchanges and air change rates within the building, affecting the temperature of the classrooms, resulting in an overestimation of the internal temperatures compared to the measured ones.

Further developments

A further development of this work will be to use the calibrated models in Period 1 in order to calibrate the building operation during the heating period, considering two more periods respectively an unoccupied one with active heating and an occupied one with active heating. Moreover, the validation of the model towards air humidity and energy consumption will be a further step of the work.

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