A MULTI-STAGES APPROACH TO THE CALIBRATION OF A SCHOOL BUILDING'S SIMULATION MODEL

Paola Penna[1], Silvia Schmiedhofer[1], Francesca Cappelletti[2], Andrea Gasparella[1], Fahrang Tahmasebi[3], Ardeshir Mahdavi[3]
[1]Faculty of Science and Technology, Free University of Bozen-Bolzano, Italy
[2]Department of Design and Planning in Complex Environment, University IUAV of Venice, Italy
[2]Department of Building Physics and Building Ecology, University of Technology, Vienna, Austria

ABSTRACT

The calibration process is an important step to improve the reliability of the simulation model and to reduce the differences between simulated and measured building energy performance. This paper presents a methodology to calibrate a building simulation model by means of low–cost monitoring set-up and short term measurements. The proposed method can be defined as a multi-stage calibration. It is based on the assumption that input data affect the simulation results differently according to the considered period of the year. It seems thus possible to calibrate different sets of parameters in different reference periods, with the advantage of using shorter recording times when the calibration periods have been consistently selected.

INTRODUCTION

Dynamic simulation tools are widely used to predict the energy performance of buildings. Moreover, they are increasingly deployed in advanced applications, such as the optimization of energy efficiency measures or implementation of model predictive control. The benefits of using dynamic simulation strictly depend on the ability of the model to capture the dynamic behavior of the buildings, considering aspects that are normally neglected in simplified calculations. Needless to say, the effectiveness of building simulation depends on the reliability of the underlying models (Mahdavi, 2001). The inaccuracy of the energy model is frequently related to the uncertainty of the model parameters required by the simulation tools. This kind of data, especially for existing buildings, is often missing or characterized by high uncertainty. Thus, the calibration of the simulation model by means of on-site monitoring is a fundamental step to improve the predictive potential of the tool. Long-term and comprehensive monitoring can provide all the information necessary to calibrate the simulation model, but can be expensive in terms of time and budget. Moreover, the calibration is often driven by experience assumptions (Fabrizio & Monetti, 2015), instead of being approached systematically.

In this paper an optimization-based calibration by means of low-cost and short-term monitoring is proposed. The methodology is presented, tested, and validated on a real case study, namely a primary school building, located in the North of Italy.

METHODOLOGY

The aim of the work is to demonstrate the feasibility of calibration based on low budget monitoring setup, limited to part of the whole building and to short term measurements. To minimize the building portion to be analyzed, representative rooms have been selected in order to pursue the generality of the calibrated parameters to the whole building. To shorten the monitoring time, representative periods of the year have to be identified, in order to reduce the number of parameters to calibrate at each time. At each period the calibration process has been carried out in an automated manner using an optimization-based approach (Tahmesebi & Mahdavi 2012a, Tahmesebi et al., 2012b). The parameters' values that improve the model prediction have been determined by minimizing some metrics dealing with the difference between the measured and simulated indoor air temperature.

Building monitoring

To test and validate the multi-stage calibration approach in a realistic setting, a primary school, located in the North of Italy (Schio, in the province of Vicenza), has been monitored. The building, built in the 50's and enlarged in the '60s, has three storeys: the basement, with the facilities rooms, and two upper storeys with classrooms. Two representative classrooms (Room 1, R1, on the first floor and Room 2, R2, on the second floor) were selected for the surveys and equipped with sensors. The monitoring setup is composed of data loggers, to record indoor air temperature and relative humidity, and temperature probes. Data loggers were installed in the two rooms and also in the adjacent rooms, to detect the boundary temperatures. Temperature probes were installed on the supply and return pipes of each radiator, to get information on the emitted heat power. We logged the data at small time intervals (5 minutes), to catch the dynamic behavior of the building. In the school there is not air conditioning system, which simplified the summer operation monitoring. The monitoring of the building lasted from December 2012 until April 2014. On-site inspections were done to identify the building structure, furniture and appliances' presence.

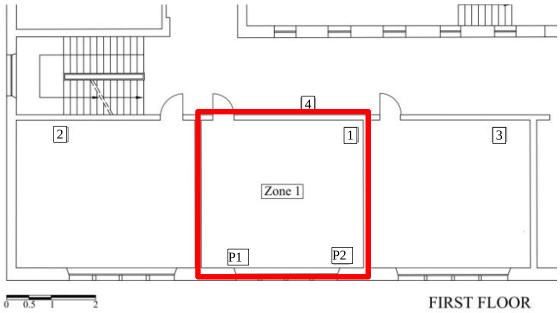

Figure 1 Selected room for monitoring, Sensors 1, 2, 3, 4 monitor T and RH, probes P1 and P2 the supply and return temperature of the radiators' pipes.

User's interviews allowed the definition of the occupancy profile and the users' interaction with the building. In particular, the activities schedule of the class and the student presence were based on day by day school register book. The school staff has been interviewed to obtain information on the activities and operations in periods when the students leave the room for special subjects (such as gym, informatics or music), or when the cleaning service is carried out, with special attention to the windows openings and shading devices control.

Building Simulation Model

The building simulation model has been defined by means of the simulation code TRNSYS v.16 (Solar Energy Laboratory, 2012). Dynamic simulation codes allow a detailed representation of the building, but they require several input information. To build the simulation model of the selected rooms, the following categories of data have to be considered:

i) weather data and boundary conditions; *ii)* physical characteristics of building envelope materials, furniture and appliances; *iii)* characteristics of heating or cooling system, in particular of the emission system; *iv)* occupants' presence and behavior have to be identified by means of users' interview.

Hourly weather data are supplied by a nearby weather station, located in Malo, approximately 10 km far from Schio. A 10-minute data series has been obtained by interpolation of the recordings. Consistently, the boundary conditions in the adjacent rooms, recorded with a time-step of 5 minutes, have been resampled to the 10 minute simulation time-step.

Tentative thermal properties of the building components, simulated by the multi-zone building subroutine Type 56, were estimated according to on-site inspections and technical documentation. Walls, floor and ceiling are considered as composed of a homogeneous massive layer (brick for the walls and hollow concrete structure for floor and ceiling), covered by a finishing plaster layer on both sides. Thermal bridges at the intersections of floor and walls, as well as windows and walls, have been accounted through linear thermal transmittance coefficients calculated in accordance with the EN ISO 10211:2007 (CEN, 2007a), using Therm (LBNL, 2013). The infiltration rate has been fixed to 0.25 ACH according to the standard EN 12831:2003 (CEN, 2003). The zone air capacitance is assumed 10 times larger than the default air value (1.2 times the volume of the room), to consider the effect of the thermal capacitance of materials and furniture (McDowell, 2003). The electric lights are considered switched on during the occupied period and the heat gains generated by their operation are estimated as 15 W m^{-2} according to the installed lights typology and ASHRAE Handbook (2009). The monitored temperature of the corridor was also used to estimate the coupling air flow rate entering through the internal door by means of EN 15242:2007 (CEN, 2007b).

The building hydronic heating system, composed by two iron cast radiators, has been modelled by means of the Type 362 (Holst, 2010). The radiators models' parameters were evaluated in the occcasion of on-site inspections. With regard to the building heating system, the monitoring data were used to identify the heating system operation schedule and the supply temperature.

The occupants presence and the schedule of the school activities were defined for each day based on the school register books. The internal gains due to the presence of people were defined according to ASHRAE Handbook (2009) for seated people (very light work). The users have been supposed to interact with the building affecting the shading factor and the air change rate. According to the inspections, to the users' interviews and some relevant literature, first guess on those quantities was defined. Concerning the shading factor, during occupied periods, the first trial value was set according to the façade orientation (Mahdavi et al. 2008), while during unoccupied periods the windows were considered completely shaded. The air change rate was set to 1.5 ACH during occupied period, based on simplified considerations (CEN, 2007c).

Multi-stage calibration

The proposed methodology uses only a few weeks of measurement to perform the calibration. The monitored periods have been carefully identified to reduce the interference of the different groups of input on the building energy balance. This allows to limit the number of parameters to calibrate at a time. Therefore, the method is defined as multi-stage calibration, because different sets of inputs are calibrated in different respective periods of time.

Even if the weather data could require to be adapted to local conditions through a model which could be calibrated, they were not modified. As concerns the three other sets of inputs, they have different impact in the energy balance depending on the periods of the year. In particular, their relevance and impact on the dynamic behavior change according to active (HVAC System operating) or passive operation mode (free floating) of the building and to occupants' presence (occupied or not).

The input *ii)* has been calibrated during period when the building is operated in a passive mode and is unoccupied (period 1). In this way, the heating and cooling system, as well as the human presence, do not interfere with the energy building's behavior. Once the calibrated values of input *ii)* have been fixed, recordings, from periods when the building is operated in an active mode (heating and cooling) and is unoccupied (period 2), are used to calibrate the characteristics of the heating system.

After defining the characteristics of the whole building system, the human presence and their interaction with the building have been calibrated. Since people tend to interact actively with the building in order to prevent discomfort conditions (Nicol, 2002, Mahdavi, 2011), it is reasonable to assume that they react differently according to the external environmental conditions. Therefore, two periods, a "summer" (period 3) and a "winter" one (period 4), were identified to calibrate the input *iv)*.

Optimization based approach

Using an optimization-based approach allows to avoid a "trial and error" calibration, automating the selection of the input values that improve the model reliability. Setting as objective function the minimization of the differences between measurements and simulation, the inputs of the simulation program are systematically varied, within a specified range, in order to find the combination of values that reduce those differences. To evaluate the goodness of fit between measured and simulated values for the indoor air temperature of the monitored zone, two statistical indicators are set. The first indicator is the coefficient of variance, CV (RMSD), a dimensionless number that aggregates the time step errors over the runtime. The second indicator is the coefficient of determination, R^2 (Moriasi et al., 2007). The cost function aggregates both the indicators, with different weighting factors (Penna et al., 2014, Penna et al., 2015). The first three days of the calibration period were not used in the calibration process. This allows to limit the influence of the initial transience in the model by using the first days of measurement as a warmup period.

GenOpt (LBNL, 2012) was used to carry out the optimization process, because it can be easily coupled with simulation tools. GenOpt can manage the repetitive process of varying the input variables, run the simulation and evaluate the cost function. The algorithm used to optimize the objective function is the hybrid generalized pattern search with particle swarm optimization algorithm (Wetter, 2010).

Calibration periods

According to the proposed multi-stage calibration approach, four periods were selected depending on heating load (passive or active heating mode) and occupancy schedule (with or without occupants) to calibrate the three different set of inputs for respective period of time.

Period 1, from 5th to 18th August 2013 (non-occupied building, passive mode), was selected to calibrate building's physical properties and infiltration (1st calibration). In the first calibration the values of ten building's thermophysical properties and of the infiltration rate were optimized. A variation range of approximately 20 % was allowed for these parameters with respect to the tentative value (Table 1). Thermal conductivity and density cannot be considered independent, therefore, a simplified relationship between them was used (Penna et al., 2015, Penna et al., 2014). The variation of the thermal properties of the building materials affects also the thermal bridges impact. The variation of the linear thermal transmittance over the variation of the thermal conductivity of the materials is considered by means of a polynomial regression, calculated according to Penna et al. (2015). A set of eleven glazing system, with different thermal transmittance and Solar Heat Gain Coefficient (SHGC) was created through Window 6.3 (LBNL, 2013) and considered as possible alternatives in the calibration.

Period 2 (non-occupied building, active mode) from 24th December 2013 to 3rd January 2014, was selected to calibrate the characteristics of the radiative heating system. The calibration process of the radiators is performed in two steps. Firstly, the parameters of the radiators (Table 2) are calibrated using as input the monitored radiators' supply temperature and the control function on the radiators' mass flow rate derived from measurements. Once defined those parameters, the heating system operation schedule and the radiators' supply temperature were defined using the data collected in the same period. Two operation modes of the radiators are identified: one standard, set during the working days, and a setback mode, during the holidays when the building is unoccupied for a long period. A climatic adjustment of the radiator supply temperature is assumed during the standard operation of the heating system.

$$\text{If} \quad T_{ext}<10°C; \; T_{supply}=a \cdot T_{ext}+b \qquad (1)$$

$$\text{If} \quad T_{ext}>10°C; \; T_{supply}=c \qquad (2)$$

where T_{ext} is the outdoor air temperature and *a*, *b*, *c* are the multiplying coefficients.

The heating system is assumed a setback temperature of 14.5°C during the unoccupied periods. Hence, the radiator supply temperature was set to:

$$T_{supply}=d \qquad (3)$$

where *d* was calculated as an average value.

Again the variability range was set to 20 % of the tentative value.

Period 3 (occupied building, passive mode), from 3rd to 16th May 2013, and Period 4 (occupied building, active heating), from 18th November to 1st December 2013, were selected to calibrate the user behaviour according to different seasons of the year. Since the number of occupants and activities schedule were determined day-by-day based on the school register book, they were not considered as input variables. Object of the calibration is the human interaction with the building, in this case, the variation of shading factor and air change rate by natural ventilation. This variables have been calibrated twice (4th and 5th calibration), to consider the influence of outdoor environmental conditions on the operational control devices operated by people.

RESULTS

Calibrated simulations

The parameters have been calibrated for Room 1 and 2 (Tables 1-4). Table 5 lists the standardized statistical indices for the four monitoring periods, before and after the calibration.

During the first period, the standardized statistical indices are improved by calibration, although the root mean square difference, RMSD still lies outside the accuracy range of the measuring sensors (±0.35 °C). In both rooms the simulated indoor air temperature is lower than the measured one.

Table 1- Calibrated building's physical properties and infiltration rate during Period 1

Variables	Initial attempt	Range Variability	Room 1	Room 2
Ext. wall brick layer λ $W\ m^{-1}\ K^{-1}$ Density $kg\ m^{-3}$ Solar absorptance	 0.8 1840 0.3	 [0.64; 0.96] [1250; 2160] [0.24; 0.36]	 0.7 1640 0.34	 0.651 540 0.34
Int. wall brick layer λ $W\ m^{-1}\ K^{-1}$ Density $kg\ m^{-3}$	 0.8 1840	 [0.64; 0.96] [1520; 2160]	 0.95 2140	 0.95 2140
Hollow slab λ $W\ m^{-1}\ K^{-1}$ Density $kg\ m^{-3}$	 0.606 1244	 [0.48; 0.73] [1070; 1417]	 0.51 1101	 0.51 1101
Hollow Ceiling λ $W\ m^{-1}\ K^{-1}$ Density $kg\ m^{-3}$ Solar absorptance	 0.606 1244 0.5	 [0.48; 0.73] [1070; 1417] [0.4; 0.6]	 - - -	 0.71 1387 0.58
Windows frame conduct. $W\ m^{-2}\ K^{-1}$	5	[4.00; 6.00]	4	4
Wind.* Transmit $W\ m^{-2}\ K^{-1}$	2.707	[1.57; 3.00]	1.57	1.57
Infiltration rate	0.25	[0.2; 0.3]	0.2	0.2
Airnode thermal capacitance	2771	[2217; 3325]	3321	3321

* the windows were evaluated as a discrete variable

This could be due to the weather data used for the simulation, since they have been collected in a rural area while the building is located in an urban district, the actual outdoor air temperature could have been higher than the considered one. Most of the values of the calibration parameters found for Room 2 are the same as the ones found for Room 1. Some difference can be seen in the thermal conductivity and density of the external wall brick layer. The values found for Room 2 are lower by around -7% compared to the ones found for room 1.The model of Room 2 presents higher RMSD compared to Room 1. The calibration of Room 2 seems to be more effective in improving the model reliability, in fact, the RMSD is reduced by 41 % compared to the initial model, while for the Room 1 the reduction is about 22 %.

In Period 2 the calibration shows its efficacy in reducing the differences between simulated and measured indoor air temperature, while maintaining high R^2. For Room 1, the RMSD is equal to the accuracy range of the data logger. For Room 2 the RMSD and CV(RMSD) are reduced by 37.5 % compared to the previous values. Concerning the calibration parameters found for Room 1 and 2, the main differences are related to the maximum water flow rate and to the nominal power of the radiators.

In periods 3 and 4, the interaction of people with windows (shading factor and air change rate) has been calibrated starting from the previous results (1st and 3rd calibrations). During period 3, in both rooms the calibration leads to good performance, moving the RMSD between measured and simulated indoor temperature within the accuracy range of the sensors (±0.35 °C).

Table 2- Calibrated characteristics of the hydronic heating system during Period 2

Variables	Initial attempt	Range variability	Room 1	Room 2
Maximum water flow rate – $kg\ h^{-1}$	150	[90; 210]	90	210
Nominal Power with ΔT=60 °C W	2592	[2073; 3110]	2082	2157
Radiator exponent	1.358	[1.28; 1.385]	1.358	1.358
Radiator Thermal Capacitance $kJ\ K^{-1}$	134.5	[100; 500]	484.5	484.5
Radiative fraction at nominal conditions	0.3	[0.2; 0.4]	0.4	0.4

Table 3- Calibrated multiplying coefficient of the radiators' supply temperature during Period 2

Variables	Ini R 1	Ini R 2	Range variability	R 1	R 2
a	-1.108	-0.95	[-1.33; -0.75]	-0.908	-0.785
b	54.377	50.207	[40.17;65.25]	42.38	44.21
c	43.136	39.76	[31.81;51.76]	33.14	39.76
d	22	22	[17.6; 27.192]	19.40	23.80

Table 4- Calibrated inputs regarding the user behaviour during Period 3 and 4

Variables	Initial attempt	Range variability	Room 1	Room 2
Period 3				
Shading level	0.68	[0; 1]	0.38	0.48
Air change rate	1.5	[0.7; 3.0]	0.80	0.70
Period 4				
Shading level	0.68	[0; 1]	0.08	0.08
Air change rate	1.5	[0.7; 3.0]	0.70	1.4

Table 5- Evaluation statistical indices of initial and calibrated models of Room 1(R1)and Room 2(R2).

	RMSD (°C)		CV(RMSD)		R^2	
	R 1	R 2	R 1	R 2	R 1	R 2
Period 1 Summer- not occupied						
Initial model	0.70	0.91	2.49	3.11	0.99	1.00
1st calibration	0.53	0.55	1.89	1.88	0.99	1.00
Period 2 Winter- not occupied						
Initial model (1st calibration)	1.58	1.54	10.3	10.2	0.91	0.88
2nd calibration	0.76	1.20	4.95	7.98	0.97	0.93
3rd calibration	0.34	0.75	2.21	4.95	0.94	0.89
Period 3 Summer- occupied						
Initial model (1st calibration)	0.35	0.44	1.69	2.10	0.92	0.85
4th calibration	0.24	0.33	1.17	1.59	0.93	0.90
Period 4 Winter -occupied						
Initial model (3rd calibration)	0.96	1.17	5.11	6.65	0.92	0.83
5st calibration	0.64	1.10	3.43	6.24	0.92	0.83

During period 4, the calibration process does not have as large benefits as in the previous period, especially for Room 2 where the RMSD and CV(RMSD) of the model decrease by only 22 %, and the CV(RMSD) remains about 6 %. Concerning the calibrated parameters in the two rooms, shading level is almost the same in the two rooms but it differs in one period from the other. The air change rate presents some differences between periods 3 and 4 room especially for room 2. These differences can be due to the different management of the windows by the users.

Long term data validation

To prove the robustness of the proposed calibration methodology, two different approaches have been compared and contrasted with long term measurements: the validation of the models through short term measurements in periods different than the calibration ones, and the use of the measurements of one room during calibration periods to validate the model of the second one.

Table 6- Weighted calibration RMSD and RMSD calculated on yearly based for room 1 and 2.

	$RMSD_{W}$ (°C)	$RMSD_{YEARLY}$ (°C)
Room 1		
Initial model I1	0.76	1.12
Calibrated model C1	0.37	0.62
Room 2		
Initial model I2	0.83	1.13
Calibrated model C2	0.58	0.84

Considering that the building has been monitored since December 2012 to April 2014, a period, from 12nd March to 31st December 2013, has been selected to validate the results. From this extended period, the days involved in the calibration and the ones during which the building was unoccupied (July and August) have been neglected. In particular, to assess the calibration robustness based on short term monitoring, a yearly equivalent weighted average RMSD has been evaluated. This has been calculated considering the RMSD of the calibration Periods 3 and 4 and the number of the days in the year expected in each of them, accordingly to the following equation:

$$RMSD_{w} = RMSD_3 \cdot n_3 + RMSD_4 \cdot n_4 \qquad (1)$$

$RMSD_3$ and $RMSD_4$ are the statistical indicator corresponding to the periods 3 and 4, and n_3 and n_4 are the number of the day in the considered year which can be attributed to each period respectively.

The weighted and yearly RMSD have been calculated for both rooms, for the initial (I1 and I2, after the number of the room) and for the calibrated models (C1 and C2) (Table 6).

In both rooms, the weighted RMSD of the initial and of calibrated model are lower than the yearly based RMSD. The reduction of the difference between simulation and measurements provided by calibration, calculated by the weighted RMDS, is around 50 % for Room 1 and 36 % for Room 2. Using the RMSD calculated respect to the yearly period, the reduction seems a bit lower of 40 % for Room 1 and 26 % for Room 2. According to these results, the calibration methodology based on short term period seems to be robust over an extended period, or, in different words, the selected periods seem to be representative of the whole year.

Short term data validation

Since long term monitoring data are not often available or collectable, the quality of the calibrated model has to be assessed differently using two validation periods, different from those in the calibration process. Fourteen consecutive days in “summer occupied” conditions (18th to 31st May 2013) and in “winter occupied” conditions (2nd to 15th of December) have been considered.

Table 7 reports the evaluation statistical indices for the two periods of validation. Comparing the initial simulations with the calibrated ones, it is possible to appreciate the improvement provided by the calibration process. As expected, the RMSD calculated during the validation periods are higher than the ones calculated in calibration periods 3 and 4 but it can be seen the same trend as during calibration: in winter the differences between measurement and simulation is larger than in summer period and the simulation model of room 2 presents the highest RMSD. In both validation periods, the simulation model of Room 2 tends to underestimate the indoor air temperature . Although the calibration of the input variables reduces the gap, it remains wider in Room 2 than in Room 1. In particular the RMSD and CV(RMSD), in Room 1, are almost half of the ones in Room 2, in both periods. For Room 1, in the "summer" validation period, the simulated air temperature is almost within the accurancy range of the sensor. In the "winter" validation period, the improvement of the model prediction is larger than in summer. In fact, in this period, the error of the initial model is more than twice than in May. For Room 2, the differences between simulation and measurements are greater and the benefits of the calibration are smaller than for Room 1.

To validate the reliability of the short term validation procedure, the RMSD values of Table 7 have been weighted over the year and compared to the yearly RMSD of Table 6.

The comparison (Table 8) allows observing that the short-term validation gives an error comparable with the yearly one. According to this comparison, short-term validation seems in quite good agreement with the yearly accuracy of the model, or, from a different perspective, the validation periods seems to be representative of the year.

Table 7- Evaluation statistical indices of the initial and calibrated models for Room 1 (R1) and 2 (R2).

	RMSD (°C)		**CV(RMSD)**		**R^2**	
	R 1	**R 2**	**R 1**	**R 2**	**R 1**	**R 2**
Summer occupied 18th -31st May						
Initial I	0.54	0.84	2.94	4.59	0.92	0.95
Calibrated C	0.36	0.60	1.98	3.28	0.92	0.97
Winter occupied 2nd -15th Dec.						
Initial I	1.24	1.48	6.63	8.45	0.86	0.77
Calibrated C	0.74	1.09	3.95	6.22	0.96	0.85

Table 8 - Weighted validation RMSD and RMSD calculated on yearly based for Room 1 and 2.

	$RMSD_{W}$ (°C)	**$RMSD_{YEARLY}$ (°C)**
Room 1		
Initial model I1	0.77	1.12
Calibrated model C1	0.48	0.62
Room 2		
Initial model I2	1.05	1.13
Calibrated model C2	0.76	0.84

Cross-validation

Finally, instead of using periods different from the calibration ones to validate the model, in order to further reduce the monitoring period required for calibration and validation, a cross validation approach has been adopted. In this kind of validation, the parameters calibrated for Room 1 (model C1) have been validated in Room 2 and vice versa during the calibration periods.

Table 9 reports the standardized statistical indices for the two calibrated model. Because of identical properties and characteristics of the two selected rooms, the calibrated parameters are expected to be the same.

The comparison of the calibrated models performance in both rooms shows a different impact according to the calibration period. In fact, during the "summer" periods, 1 and 3, the statistics of C1 in Room 2 and of C2 in Room 1, do not significantly differ from the calibrated models in the respective rooms. The RMSD and CV(RMSD) are slightly increased in both rooms and in both periods, while the R^2 almost remains the same. During the heating period using a model of a room in the other one, leads to worse performance. This is due to the large differences related to the characteristics of the heating system, in particular, to the higher values of water flow rate and nominal power of the radiators' of the calibrated model C2, which leads to an overestimation of the indoor temperature in Room 1 when the radiators are operated.

Especially in period 2 (heating mode no-occupancy), the performance indicators RMSD and CV(RMSD) in Room 1 with the model C2 are three times as much and in Room 2 with C1 are more than the double. Also the R^2 decreases, but less dramatically.

Even if still high, in period 4 those differences are not as evident as for period 2. In Room 1, the RMSD and CV(RMSD), are almost the double, while in Room 2 is a third higher than the respective model. The R^2 seems not to be not strongly affected.

Table 9- Evaluation statistical indices for the calibrated models C1 and C2 in room 2 and 1.

	RMSD (°C)		**CV(RMSD)**		**R^2**	
	R 1	**R 2**	**R 1**	**R 2**	**R 1**	**R 2**
Period 1						
C1	0.53	0.55	1.89	1.89	0.99	1.00
C2	0.53	0.55	1.89	1.88	0.99	1.00
Period 2						
C1	0.34	1.65	2.21	11.0	0.94	0.86
C2	1.06	0.75	6.91	4.95	0.91	0.89
Period 3						
C1	0.24	0.33	1.17	1.58	0.93	0.89
C2	0.25	0.33	1.19	1.59	0.93	0.90
Period 4						
C1	0.64	1.36	3.43	7.77	0.92	0.86
C2	0.98	1.10	5.20	6.24	0.90	0.83

The cumulative distribution error of the calibrated models C1 and C2 (Figures 1 and 2), which summarize the performance of the models during the considered four calibration periods, are useful to contrast their performance in the different rooms. The calibrated model C1 performs clearly better on the Room 1 compared to the Room 2, with an error considerably smaller, in the range from -2.6 to 2.1, with respect to the range from -2.8 to 3.3 in Room 2. Moreover, for 50 % of the time model C1 in room 1 has a narrow error range, from about -0.50 to 0.25, while in Room 2 it is from -2.8 to 0.55. Model C1 tends to underestimate the indoor air temperature in both rooms. The calibrated model C2 tends to underestimate the indoor temperature in Room 2, while in Room 1 the error is more balanced. The difference between the error range of the model in the two rooms ranges from -2.8 to 2.1 in Room 1 and from -4.4 to 2.5 in Room 2. For 50% of the time the performance of the model performs slightly better in Room 1, from -0.4 to 0.3, than in Room 2, from -0.7 to 0.35. Despite the difference in the temperature predicted by one model when used on the other room during the calibration periods 3 and 4, we have tried to compare the entity of this error, over the yearly occupied periods, by weighting the RMSD of periods 3 and 4, with the annual validation RMSD, and with the short-term validations (Table 10).

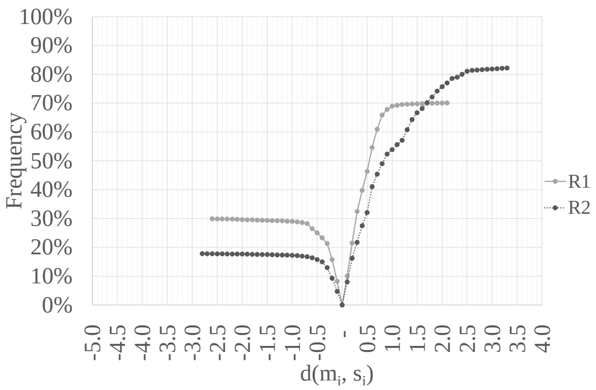

Figure 1- Cumulative distribution of the error of calibrated model C1 for the calibration periods.

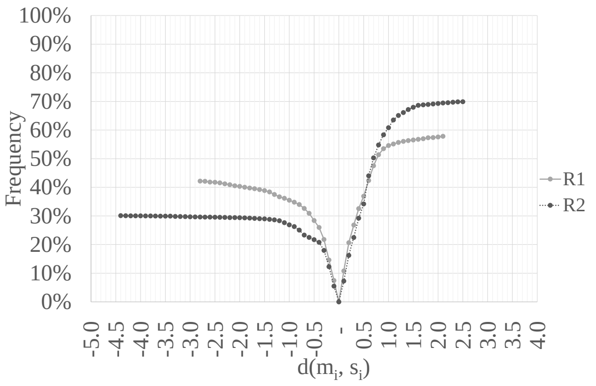

Figure 2- Cumulative distribution of the error of calibrated model C2 for the calibration periods.

Table 10- Weighted RMSD for cross-validated model C1 and C2 compared to long-term and short-term validations.

	RMSD $_W$ CROSS-VALIDATION	**RMSD** YEARLY	**RMSD $_W$** SHORT TERM
Model C1	0.67	0.62	0.48
Model C2	0.49	0.84	0.76

The entity of the error of the calibrated model changes considerably according to the validation method used. Cross-validation of C1 overestimates the yearly and the short-term errors. In contrast, cross-validation of C2 underestimates the yearly and the short-term validation. As a consequence the cross-validation does not seems to be suitable to replace the short term validation which, on the contrary is good in estimating the annual error. However it is possible to notice that model C2 applied on Room 1 (this is the meaning of cross-validation) gives an $RMSD_w$ very similar to the yearly and short-term error of model C1 applied on the same room, and vice versa model C1 applied on room 2 gives $RMSD_w$ similar to the yearly and short-term error of model C2 applied on room 2. In a similar way the comparison of cross-validation with short-term validation gives a good picture of how the two models work in the other room.

This could also be interesting when the aim is to identify which of the models is more useful to be used for both of the rooms, and possibly for most rooms in the building. In the considered case both calibrated models give in the other room an error of the same order as in the calibration room, but model C2 errors distribution profile (Figure 2) is more similar in the two rooms than the one of model C1 (Figure 1).

CONCLUSION

In this work a methodology based on low budget monitoring setup and short-term monitored data for optimization-supported simulation model calibration was tested and validated on a case study. The proposed multi-stage calibration methodology selects and uses different periods of the year to calibrate different parameters of the simulation model, such as building physics properties, heating system characteristics and occupant interaction with windows and shading devices. The calibration method has been applied on two different representative rooms of the building, to ensure the generalizability of the calibrated parameters to the whole thermal zone. Both rooms have been calibrated by means of the proposed multi-stage calibration approach and the models have been then validated in different periods of the year, which were not involved into the calibration. Results have demonstrated that the use of different periods to calibrate different parameters is a promising way to lead a calibration even though there are still some discrepancies between simulation and real data, especially during the winter period. The results proved that the calibrated models always improve the performances of the simulation model compared to the initial one. The robustness of results, obtained by means of short term monitoring, has been proved to be consistent with the one calculated over an extended period of almost one year. The short term data validation leads to an error close to the yearly based ones and both the models presents the same behavior in the short term period and in the extended one. Finally, a cross validation of the two calibrated model has been performed to check the performance of the calibrated models in the two different rooms. The cross validation presents larger discrepancies when compared to the long and short term validations so it seems that it is not a suitable strategy for short term validation. Otherwise the cross-validation highlights the possibility to extend the calibrated model to similar building zones, at least when similar orientation, occupancy schedules and internal gains are concerned. The main advantage of the calibration method proposed is the limitation of the amount of measurement to collect, not only concerned the number of rooms to be monitored, thus reducing the number of sensors to be installed and consequently the costs, but also concerning the length of monitoring itself.

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