www.itcon.org - Journal of Information Technology in Construction - ISSN 1874-4753

MULTI-STAGE CALIBRATION OF THE SIMULATION MODEL OF A SCHOOL BUILDING THROUGH SHORT-TERM MONITORING

SUBMITTED: November 2014
REVISED: December 2014
PUBLISHED: January 2015 at http://www.itcon.org/2015/10
GUEST EDITORS: Mahdavi A. & Martens B.

Paola Penna
Free University of Bolzano-Bozen, Italy;
paola.penna@natec.unibz.it

Francesca Cappelletti
University Iuav of Venice, Italy;
francesca.cappelletti@iuav.it

Andrea Gasparella
Free University of Bolzano-Bozen, Italy;
andrea.gasparella@unibz.it

Fahrang Tahmasebi
Vienna University of Technology, Vienna, Austria;
farhang.tahmasebi@tuwien.ac.at

Ardeshir Mahdavi
Vienna University of Technology, Vienna, Austria;
bpi@tuwien.ac.at

SUMMARY: *The increasing attention on the improvement of new and existing buildings' performance is emphasizing the importance of the reliability of the simulation models in predicting the complexity of the building behaviour and, consequently, in some advanced applications of building simulation, such as the optimization of the choice of different Energy Efficiency Measures (EEMs) or the adoption of model predictive control strategies. The reliability of the energy model does not depend only on the quality and details of the model itself, but also on the uncertainty related to many input values, such as the physical properties of materials and components, the information on the building management and occupation, and the boundary conditions considered for the simulation. Especially for the existing buildings, this kind of data is often missing or characterized by high uncertainty, and only very simplified behavioural models of occupancy are available. This could compromise the optimization process and undermine the potential of building simulation. In this context, the calibration of the simulation model by means of on-site monitoring is of crucial importance to increase the reliability of the predictions, and to take better decisions, even though this process can be time consuming. This work presents a multi-stage methodology to calibrate the building energy simulation by means of low-cost monitoring and short-term measurements. This approach is applied to a Primary School in the North-East of Italy, which has been monitored from December 2012 to April 2014. Four monitoring periods have been selected to calibrate different sets of variables at a time, while the validation has been carried out on two different periods. The results show that even if less than 8 weeks have been considered in the proposed calibration approach, the maximum error in the estimation of the temperature is less than ±0.5 in 77.3% of the timesteps in the validation period.*

KEYWORDS: *model calibration, energy simulation, optimization, monitoring*

REFERENCE: *Paola Penna, Francesca Cappelletti, Andrea Gasparella, Fahrang Tahmasebi, Ardeshir Mahdavi (2015). Multi-stage calibration of the simulation model of a school building through short-term monitoring. Journal of Information Technology in Construction (ITcon), Special Issue: ECPPM 2014, Vol. 20, pg. 132-145, http://www.itcon.org/2015/10*

COPYRIGHT: *© 2015 The authors. This is an open access article distributed under the terms of the Creative Commons Attribution 3.0 unported (http://creativecommons.org/licenses/by/3.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.*

1. INTRODUCTION

The building stock is responsible for a major fraction of the global energy demand. Currently buildings renovation represents a significant opportunity toward reducing buildings' energy use. To achieve this end, detailed simulation can be used as a tool not only to assess the energy performance of an existing building but also to optimize the choice of different Energy Efficiency Measures (EEMs) from an energetic and economic point of view or to compare different strategies of system control and building management. The dynamic simulation allows to create a detailed model of the building and to consider aspects that are normally neglected in simplified calculations. However, it requires significant input information that for existing buildings is often difficult to be provided with a sufficient level of reliability. Otherwise inaccurate building models could compromise the selection process of EEMs, thus preventing cost-optimal renovations. In order to use building energy performance models with any degree of confidence, it is necessary that the model closely represents the actual behaviour of the building under study (Coakley et al. 2014). This aim can be achieved through model calibration. Calibration process can be very useful to obtain more reliable predictions from the simulation even though authors have frequently underlined some issues to be solved (Carroll W.L. et al, 1993, Kaplan M. et al, 1990). In most of the cases the calibration of the simulation is "highly dependent on the personal judgment of the analyst doing the calibration" and it is based on a case-to-case approach without the implementation of a methodical way (Reddy, 2006). Respect to this issue monitored field data can be deployed to calibrate the simulation model in a systematic manner. The potential of using measured data to improve the results of the simulation has been already underlined by different authors (Reddy et al, 2007, Raftery et al, 2011). Otherwise the monitoring phase can be expensive and time-consuming. In this respect Liu and Liu (2012) propose short-monitoring of about two weeks with an hourly time-step in energy consumption data collection. The reliability of this approach has been also demonstrated by previous works (Soebarto 1997, Pedrini et al. 2002). Concerning the object of monitoring, some authors used energy consumption data to tune the model (Heo et al. 2012, Soebarto 1997, Pedrini et al. 2002, Liu and Liu 2012, Pan et al. 2007, Raftery et al. 2011), others deployed the zone air temperature alone (Tahmasebi and Mahdavi 2012, Tahmasebi et al. 2012, Taheri et al. 2013) or in combination with total solar radiation and energy consumption (Nassiopoulos et al. 2014). All of them used weather data collected by meteorological stations. Concerning the modality to process a calibration Coakley et al. (2014) distinguish between manual or automated calibrations: while the first ones rely on iterative pragmatic intervention by the analyst without the employment of any automated technique, the latter use a kind of automated (i.e., not user driven) process to assist or complete model calibration. In the automated approach the issue, related to the choice of the variables to calibrate and to the objective function to use for tuning, is assisted by mathematical and statistical methods. In this framework the optimization-based calibration approach, proposed in previous publications (Tahmasebi and Mahdavi 2012, Tahmasebi et al. 2012, Taheri et al. 2013), is an efficient manner to conduct the model calibration. The optimization process, through the adjustment of the input parameters of the simulation, is used to minimize the difference between the model output and the monitored data. The choice of the variables, that mostly influences the cost function, can be carried out by means of sensitivity analysis (Tahmasebi and Mahdavi, 2012). Concerning the assessment of the calibration performance, the difference between estimated and measured value can be calculated in different ways: in some papers the error was calculated as the simple percentage difference between the total calculated consumption and the collected data; other authors propose the use of standardised statistical indices such as the Mean Bias Error (MBE), the Root Mean Square Error (RMSE) or the Coefficient of Variation of the Root Mean Squared Deviations, CV(RMSE), that aggregates the individual time step errors into a single dimensionless number. Tahmasebi and Mahdavi (2012) propose a cost function that takes into account not only the CV(RMSD) but also the coefficient of determination, R^2, that provides a measure of the potential of the calibrated model in predicting the future outcomes.

In this paper a methodology to calibrate the building simulation model based on a low-cost monitoring and short-term measurements was tested and validated. The proposed calibration process has been applied to a real building, a Primary School in the North-East of Italy, in which the air temperature has been monitored from December 2012 to April 2014. A detailed simulation model has been set-up and calibrated using an optimization-based approach in order to minimize the difference between the temperature data collected and the ones predicted by the model. To achieve this aim four calibration periods have been considered according to different occupancy schedules (with or without occupants) and heating load (heating system switched on or switched off). Since different periods requires also a different number of inputs for simulation, it was possible to calibrate some simulation inputs during one period and some others during other periods, using an approach that can be defined as a progressive calibration.

2. METHODOLOGY

2.1 Monitoring of the case study

To test and validate the potential of the proposed calibration methodology in a realistic setting, a Primary School is selected as a case study (Fig. 1). The building was built in the ’50s and enlarged in the ’60s and is located in Schio (in the province of Vicenza), a municipality in North of Italy. The building has three-storeys: the basement, with canteen, gym and facilities rooms and two upper storeys with the classrooms. The monitoring of the building started in December 2012. A representative room in the first floor was selected and the difference between the room simulated and monitored data have been minimized in the calibration process (see Fig. 2). Data loggers and temperature sensors for radiators were installed in the selected room to store information on indoor air temperature, relative humidity and heat emitted by radiators. Data loggers were also installed in the adjacent rooms (Fig. 2) in order to get information on the boundary temperatures. All the indoor air temperature, relative humidity, and surface temperature of radiators’ supply and return pipes are logged at 5 min intervals. Hourly weather data collected by the weather station of the municipality of Malo, approximately 10 km far away from Schio, were used to create a real-year weather data file.

Since detailed occupancy recordings were not possible, users' interviews and surveys were conducted in order to describe presence and occupants’ behaviour in the simulation model. By means of school register book it was possible to define the activities schedule of the class and the student presence day by day. The staff of the school has been interviewed in order to get information on the activities done in the room, when the students used to leave the room for extra-activities (such gym, informatics or music), when the cleaning are carried out and how and when people use to open the windows and manage the shading devices.

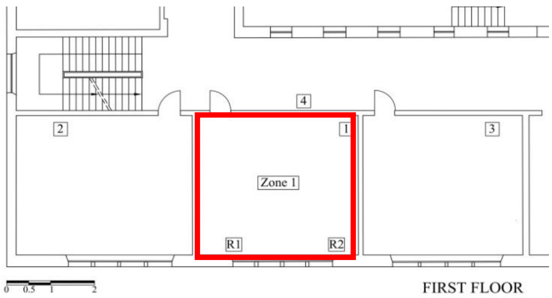

FIG. 1: (left) Case study: San Benedetto Primary School (Italy).

FIG. 2: (right) Selected room for monitoring (in square) and location of the sensors. Sensors 1-2-3-4 monitor Temperature and Relative Humidity, sensors R1-R2 log the surface temperature of radiators’ supply and return pipes.

2.2 Building model

The simulation code TRNSYS v.16 was used to model the building thermal performance. The thermo-physical model of the building was defined through the multi-zone building subroutine, Type 56. The building hydronic heating system is composed by two cast iron radiators that were modelled through the dynamic radiator model type TRNSYS subroutine 362 (Holst 2010).

Dynamic simulation allows a detailed representation of the buildings, but it requires a lot of input information. The required input data on the building can be grouped as follow: i) weather data and boundary conditions; ii) characteristics of the building envelope, furniture and appliances; iii) heating system characteristics; iv) occupants' presence and behaviour.

i) The hourly weather data collected by the weather station of Malo were interpolated to provide data consistent with a simulation time step of 10 minutes. The boundary conditions in the adjacent rooms recorded with a timestep of 5 minutes have been resampled to the 10 minute simulation timestep.

ii) A first assumption on the thermal properties of the building components was done according to on-site surveys and technical documentation. Walls, floor and ceiling are composed of a main material layer (brick for the walls and hollow concrete structure for floor and ceiling), covered with overlays on both sides,. The two-dimensional thermal coupling coefficient for thermal bridges at the intersections of floor and walls, as well as the windows and walls, were calculated in accordance with the EN ISO 10211:2007 (CEN 2007a) using Therm (LBNL 2013). The resulting values were considered in defining the effective thermal properties of building materials. The infiltration rate was fixed to 0.25 ACH according to the standard EN 12831:2003 (CEN 2003). The zone air capacitance is considered 10 times bigger than the default value (1.2 times the volume of the room) in order to consider the effect of the materials and furniture (McDowell 2003). The electric lights were considered switched on during the occupied period and the heat gains generated by their operation were set to 15 W m^{-2} (ASHRAE Handbook 2009). The monitored temperature of the corridor was used to estimate the air mass entering through the internal door by means of EN 15242:2007 (CEN 2007b).

iii) The first estimations of the radiator parameters were made according to the on-site surveys. With regard to the building heating system the monitoring data were used to identify: the heating system operation schedule, during weekdays and weekends in the working season, and the supply temperature, based on the outdoor air temperature for working and break seasons.

iv) The occupants presence and the schedule of the school activities were defined day-by-day based on the information obtained from the school register book. The internal gains due to the presence of people were defined according to the values proposed by ASHRAE (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 survey, users' interviews and some relevant literature a first assumption on those values 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 h^{-1} during occupied period based on simplified considerations (CEN 2007c).

2.3 Optimization-based calibration

The optimization-based approach (Tahmasebi et al. 2012a) is an automated process to assist the calibration of the simulation model. Setting the cost function as the minimization of the differences between model predictions and monitored data, the input of the simulation program are varied, within a specified range, in order to find the combination of values that is able to achieve this goal. The cost function was defined using two model evaluation statistics that can represent the cumulated differences between measured and simulated values for the indoor air temperature of the monitored zone.

The first indicator is the CV (RMSD), a dimensionless number that aggregates the time step errors over the runtime (Equation 1 and 2).

$$CV(RMSD) = \frac{RMSD}{\bar{m}} \cdot 100 \tag{1}$$

with

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n} (m_i - s_i)^2}{n}} \tag{2}$$

where m_i is the measured indoor air temperature; s_i is the simulated indoor air temperature; n is the number of the simulation time steps; m is the measured mean temperature.

The second indicator is the coefficient of determination, R^2, calculated according with the Equation 3. Coefficient of determination describes the proportion of the variance in measured data explained by the model (Moriasi et al. 2007). R^2 has a range from 0 to 1, where 1 indicates that the regression line perfectly fits the data. Therefore, R^2 value is to be maximized in the optimization process.

$$R2 = \left(\frac{n \sum m_i \cdot s_i - \sum m_i \cdot \sum s_i}{\sqrt{(n \sum m_i^2 - (\sum m_i)^2) \cdot (n \sum s_i^2 - (\sum s_i)^2)}} \right)^2 \quad (3)$$

The defined cost function f takes into account both the model evaluation statistics, with different weighted factors. In this analysis the minimization of CV(RMSD) was considered more important.

$$f = 0.7 \cdot CV\ (RMSD) + 0.3 \cdot (1 - R^2) \quad (4)$$

The optimization process has been carried out by means of the generic optimization tool GenOpt (LBNL 2012), that 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 generalizes pattern search with particle swarm optimization algorithm, which is one of the recommended optimization algorithms for problems, where the cost function cannot be simply and explicitly stated, but can be approximated numerically by a thermal building simulation program (Wetter 2010).

2.4 Calibration process

The aim of this work is to test and validate a methodology to calibrate the simulation without a comprehensive monitoring of the building system and based on short-term measurements. The proposed methodology can be defined as a progressive or multi-stage calibration. Firstly, the input variables to be calibrated have been listed and grouped in input sets dealing with a specific aspect of the building energy balance. Then, representative calibration periods of the year have been correspondingly identified in order to reduce the number of variables to calibrate at one time. As previously highlighted the required input data are: i) weather data and boundary conditions; ii) physical characteristics of the building envelope and infiltration; iii) heating system characteristics; iv) shading level and air change rate due to occupants' presence and behaviour. The weather data and the boundary conditions are considered reliable, because measured by the weather station, and therefore they are not involved in the calibration process. As concerns the three other sets of inputs, they have different impact in the energy balance in different periods of the year. In particular, their relevance and impact on the dynamic behaviour change depending on the occupants' presence (building occupied or not), on the occupants' behaviour according to the external environmental conditions (summer or winter) and on the type and operation mode of the air conditioning system. It is worth noting that, in the considered case, the school has only a heating system and no cooling system. Moreover it is not occupied during the summer months (mid of June to mid of September). To calibrate the three sets of input ii) to iv), four different representative periods of the year have been selected (Table1), considering occupied and non-occupied periods and active (winter) or passive (summer) operation modes. Each period is two weeks long, except for the Period 2, which is only eleven days long. Period 1 (non-occupied building, passive mode) is selected to calibrate the set i) building's physical properties and infiltration (1st calibration): in fact, the absence of occupants and the off-mode of the heating system limit the number of the variables to calibrate. Once defined the thermo-physical properties of the building, the monitored data from the Period 2 (unoccupied building, active heating) are used to calibrate the set iii) characteristics of the radiative heating system and the radiators' supply temperature as a function of the external temperature, which are being the only unknown variables affecting the dynamic behaviour of the model (2nd calibration and 3rd calibration). The so-calibrated values (1st and 3rd calibrated models) have been then used to calibrate the user interactions with the building (set iv). Since people tend to operate actively on the building in order to prevent discomfort conditions (Nicol 2002, Mahdavi 2011), it is reasonable to assume that they react differently in "summer" and "winter" conditions. For this reason in Period 3 (occupied building, passive mode) and in Period 4 (occupied building, active heating) the user behaviour has been modelled and calibrated separately. Fig. 3

outlines the calibration process. In the following sections, details on the above mentioned calibrations are provided.

TAB. 1. Monitoring periods used in the model calibration process

Periods	Start date	End date	Occupancy State	Operation mode
1	05.08.2013	18.08.2013	Non-occupied	Passive
2	24.12.2013	03.01.2014	Non-occupied	Active heating
3	03.05.2013	16.05.2013	Occupied	Passive
4	18.11.2013	01.12.2013	Occupied	Active heating

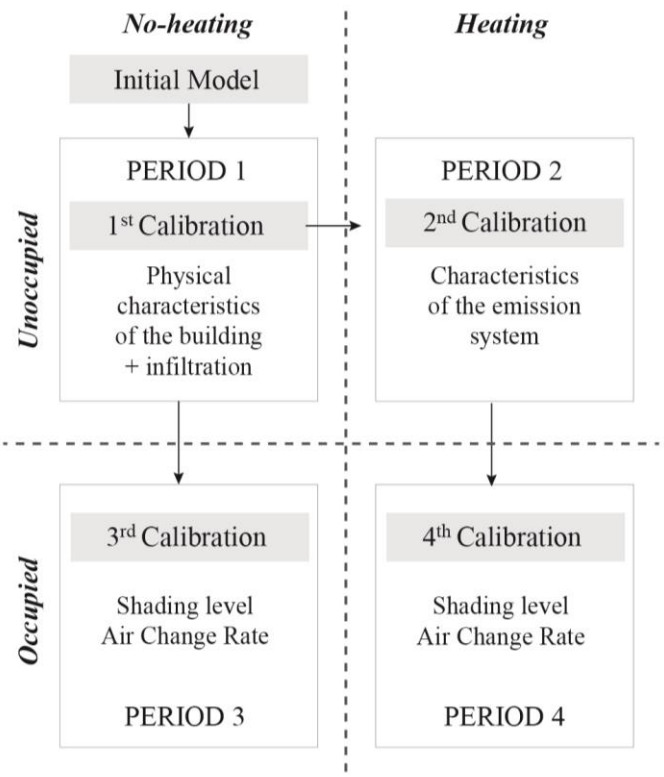

FIG. 3: Scheme of the Procedure of calibration

2.5 Calibration during Period 1

In the first calibration the values of ten building's thermophysical properties and of the infiltration rate were optimized. The selected period, from 5th to 18th August 2013,, was characterized by the absence of occupants and by the passive operation mode. According to the users interviews the blinds were considered closed. A variation range of approximately 20 % was allowed these parameters with respect to the first tentative value. The variables of the first calibration and their variability ranges are listed in Table 2. Not all the parameters can be considered independent: the thermal conductivity and the density of the components' dominant layer are related. To prevent the optimization process to lead to physically unrealistic combinations of these two variables, a simplified relationship between them was derived from information in the relevant literature (Gösele et al. 1996):

$$\lambda_{brick} = 0.0005 \cdot \rho_{brick} + 0.12 \quad (5)$$

$$\lambda_{concrete} = 0.0007 \cdot \rho_{concrete} + 0.2648 \quad (6)$$

where λ is the thermal conductivity of brick or concrete in [W m^{-1} K] and ρ is the density of brick or concrete in [kg m^{-3}].

The variation of the thermal properties of the building materials affects also the thermal bridges' impact. Three types of thermal bridges have been considered: the intermediate floor junction, the internal wall junction and the window intersection. Nine different linear thermal transmittances for each thermal bridge were calculated combining the lower, the mean and the higher values of thermal conductivity of the material layers. A polynomial regression was then obtained to calculate the variation of the linear thermal transmittance over the continuous variation of the thermal conductivity of the materials. The calibration of glazing properties was not performed in a continuous manner. A set of eleven glazings, with different thermal transmittance and the Solar Heat Gain Coefficient (SHGC) was created through Window 6.3 (LBNL 2013) and considered in the calibration.

TAB. 2: Input variables calibrated during the Period 1 (1st calibration).

Variables	Initial value	Range Value	Calibrated value
Ext. wall brick layer – λ [W.m^{-1}.K^{-1}]	0.8	[0.64; 0.96]	0.687
Ext. wall brick layer – Density [kg.m^{-3}]	1840	[1520; 2160]	1614
Ext. wall brick layer – Ext. Solar absorbtance	0.3	[0.24; 0.36]	0.336
Int. wall brick layer – λ [W.m^{-1}.K^{-1}]	0.8	[0.64; 0.96]	0.953
Int. wall brick layer – Density [kg.m^{-3}]	1840	[1520; 2160]	2268
Ceiling/Floor Hollow – λ [W.m^{-1}.K^{-1}]	0.606	[0.48; 0.73]	0.509
Ceiling/Floor Hollow – Density [kg.m^{-3}]	1244	[1070; 1417]	1105
Window frame – Conductance [W.m^{-2}K^{-1}]	5	[4; 6]	4.028
Windows* Transmittance [W.m^{-2}K^{-1}]	2.707	[1.569; 3.001]	1.569
Infiltration rate	0.25	[0.2; 0.3]	0.21
Zone air capacitance [kJ K^{-1}]	2771	[1385 – 4156]	4141

* the glazings were evaluated as a discrete variable

2.6 Calibrations during Period 2

The calibrated values of the material properties and of the infiltration rate obtained from the first calibration, were assumed as fixed in the second period of calibration, from 24th December 2013 to 3rd January 2014,when the heating system was operated in absence of occupants. The calibration of the characteristics of the radiative heating system was carried out in two steps. The model of the building hydronic heating system implemented in the dynamic radiator model type 362, calculates the return temperature and the heat emitted by radiators from the radiators' supply temperature, the mass flow rate and the indoor air temperature. In the first step (2nd calibration), the monitored radiators' supply temperature and the control function on the mass flow rate derived from measurements were assumed as input and the radiators characteristics, reported in Table 3, were calibrated. According to the measurements, the heating system operation schedule during weekdays and weekends in the working season were defined.

Once those heating system properties had been estimated, in the second step, the heating system operation schedule and the supply temperature were identified using the data collected in the same period. Then, the multiplying coefficient of the function that describes the radiators' supply temperature are calibrated (3rd calibration).

During the winter season, the hot water is circulated according to a schedule. In this case the supply water temperature is assumed as a function of the external one, according to the function:

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

$$\text{If } T_{ext}>10°C;\ T_{supply}=c \quad (11)$$

Where T_{ext} is the outdoor air temperature and *a, b, c* are the multiplying coefficients. The first tentative values for those parameters, obtained from a regression based on monitored data, are reported in Table 4.

Outside the scheduled heating time the heating system is switched on when the indoor temperature falls below 14°C. For this period, the supply temperature was set to:

$$T_{supply}=d \quad (12)$$

Where d was calculated as an average value equal to 22°C.

In the second step of the calibration (3rd calibration), a variation range of 20% were applied to the coefficient *a*, *b*, *c* and *d*, and these parameters were calibrated (Table 4).

TAB. 3. Input variables related to the radiators' characteristics calibrated during the Period 2 (2nd calibration).

Variables	Initial value	Range value	Calibrated value
Maximum water flow rate – [$kg.h^{-1}$]	150	[290; 210]	90
Nominal Power with ΔT=60 – [W]	2592	[1759; 6739]	2.7 1787
Radiator exponent	1.358	[1.28; 1.382]	1.378
Radiator Thermal Capacitance – [$kJ .K^{-1}$]	134.5	[100; 1340]	1164.2
Radiative fraction at nominal conditions	0.3	[0.2; 0.4]	0.49

TAB. 4. Input variables related to the radiators' supply temperature calibrated during the Period 2 (3rd calibration).

Variables	Initial value	Range value	Calibrated value
a	-1.108	[-1.33; -0.89]	-1.238
b	54.377	[43.5; 65.25]	48.077
c	43.136	[35.51; 51.76]	35.336
d	22	[17.6; 26.4]	20.7

2.8 Calibration during Period 3 and Period 4

The lack of detailed information on users' interaction during the occupied period have been solved by selecting two different periods to calibrate the user behaviour according to different seasons of the year. Period 3 (from 3rd to 16th May 2013), with occupants but without heating (passive mode), and Period 4 (from 18th November to 1st December 2013) with occupants and active heating mode. The number of occupants and the activities schedule were determined day-by-day based on the school register book, for this reason the internal gains due to the human presence were not involved into the calibration process. Object of the calibration is the human interaction with the building defined as variation of shading factor and air change rate. Since the environmental conditions inside and outside the building can affect the operational control devices operated by people (Mahdavi 2011), the calibration of these variables was performed twice, obtaining different values in Period 3 and 4. Table 5 summarizes the information on variables in the 4th and 5th calibrations.

TAB. 5. Input variables calibrated during the Period 3 and Period 4 (4th and 5th calibration).

Variables	Initial value	Range Value	Calibrated value
Shading level	0.68	[0 – 1]	
Period 3			0.33
Period 4			0.05
Air change rate	1.5	[0.7 – 3]	
Period 3			0.7
Period 4			0.7

3. RESULTS AND DISCUSSION

3.1 Calibration

The results of the calibration process are presented in Fig. 3 and the performance of the calibrated model synthesized in Table 6. In particular, Fig. 3 allows the comparison between the measured temperature profiles, the uncertainty range of the data logger and the calibrated model. The standardized statistical indices for the initial and the calibrated models in the four monitoring periods are presented in Table 6, where the calibrated model for a given phase has been tested as initial model during the following one.

During the first period (non-occupied building, passive mode) even though the thermal properties of the envelope components have been calibrated, the effect of this calibration is almost negligible especially for the first 7 days of the period. The calculated temperature is lower than the real one. This could be ascribed to the weather data used for the simulation, which have been collected in a rural area while the building is located in an urban district where the actual outdoor air temperature is probably higher than the one considered in the simulation. Almost all the calibrated variables are quite close to the initial values. The calibrated conductivities are about 15 % lower than the initial values, while the calibrated zone thermal capacitance is almost twice as large as the initial one. Concerning the standardized statistical indices, the calibration slightly improves the RMSD, which still lies outside the accuracy range of the measuring sensors (±0.35 °C). In general the calibrated model is slightly better than the first attempt model.

During the second period (non-occupied building, active heating mode) the calibration of the characteristics of the radiative heating system and especially the calibration of the regression model coefficients of radiator supply temperature is very effective in determining the improvement of the simulation. With the two-step calibration of the radiator the RMSD and the CV(RMSD) are highly decreased, while maintaining high R^2.

During the third period (occupied building, passive mode), the interaction between people and windows (shading factor and air change rate) has been calibrated starting from the previous results (actually after the 1st calibration, since the 2nd does not affect the performance in non-heating periods) leading to a good performance of the calibration obtained. During all the calibration period the estimated temperature is within the accuracy range of the sensors (±0.35 °C). In more detail, the RMSD of the calibrated simulation is 0.26, slightly lower than the RMSD of the 1st calibrated model, and the CV(RMSD) and R^2 are also better than in the 1st calibrated initial model.

Finally, during the fourth period (non-occupied building, active heating mode), once again the interaction between people and windows has been calibrated leading to a quite good performance in temperature prediction. The calibrated values show that the air change rate is the same as when the heating system is off, thus seems to demonstrate that the air change rate is much more related to the air quality perception than to people thermal conditions. On the contrary the shading factor is lower in autumn than in spring, probably because of the dependence of the shading control on the visual and thermal comfort sensation. Looking to the statistical indicators the 4th calibration model has a RMSD of 0.67 that is the highest of the models calibrated on the other periods, but it is a less than a half the initial error obtained after the 2nd Calibration. Looking at the temperature profile it can be seen that only during two days the calculated temperature does not match the measured one, thus worsening the overall calibration performance indicators: some unpredictable occupant behavior could be the reason of this difference.

TAB. 6: The evaluation statistics of the initial and calibrated models in the monitoring periods.

Period	RMSD	CV(RMSD)	R^2		Period	RMSD	CV(RMSD)	R^2
Period 1 1st Calibration					Period 2 2nd Calibration			
Initial Model	0.69	2.44	0.98		Initial Model (after 1st Calibration)	1.29	8.41	0.86
After 1st Calibration	0.54	1.92	0.99	>	After 2nd Calibration, 1st Step	0.39	2.56	0.97
					Initial Model (after 2nd Calibration, 1st Step)	0.56	3.63	0.96
					After 2nd Calibration, 2nd Step	0.17	1.07	0.98
	V					V		
Period 3 3rd Calibration					Period 4 4th Calibration			
Initial Model (after 1st Calibration)	0.32	1.53	0.94		Initial Model (after 2nd Calibration, 2nd Step)	1.44	7.60	0.84
After 3rd Calibration	0.26	1.24	0.95		After 4th Calibration	0.67	3.53	0.92

Some general consideration can be drawn. The calibration process presents a different effectiveness according to the period of the year used for calibrating even though in all the periods the initial model is improved by the optimization-based calibration. The calibration of the heating system (2nd period) gives as good results as the calibration of the occupancy interactions (3rd period) while combining the uncertainties of the two calibrations the simulation performance slightly decreases (4th period).

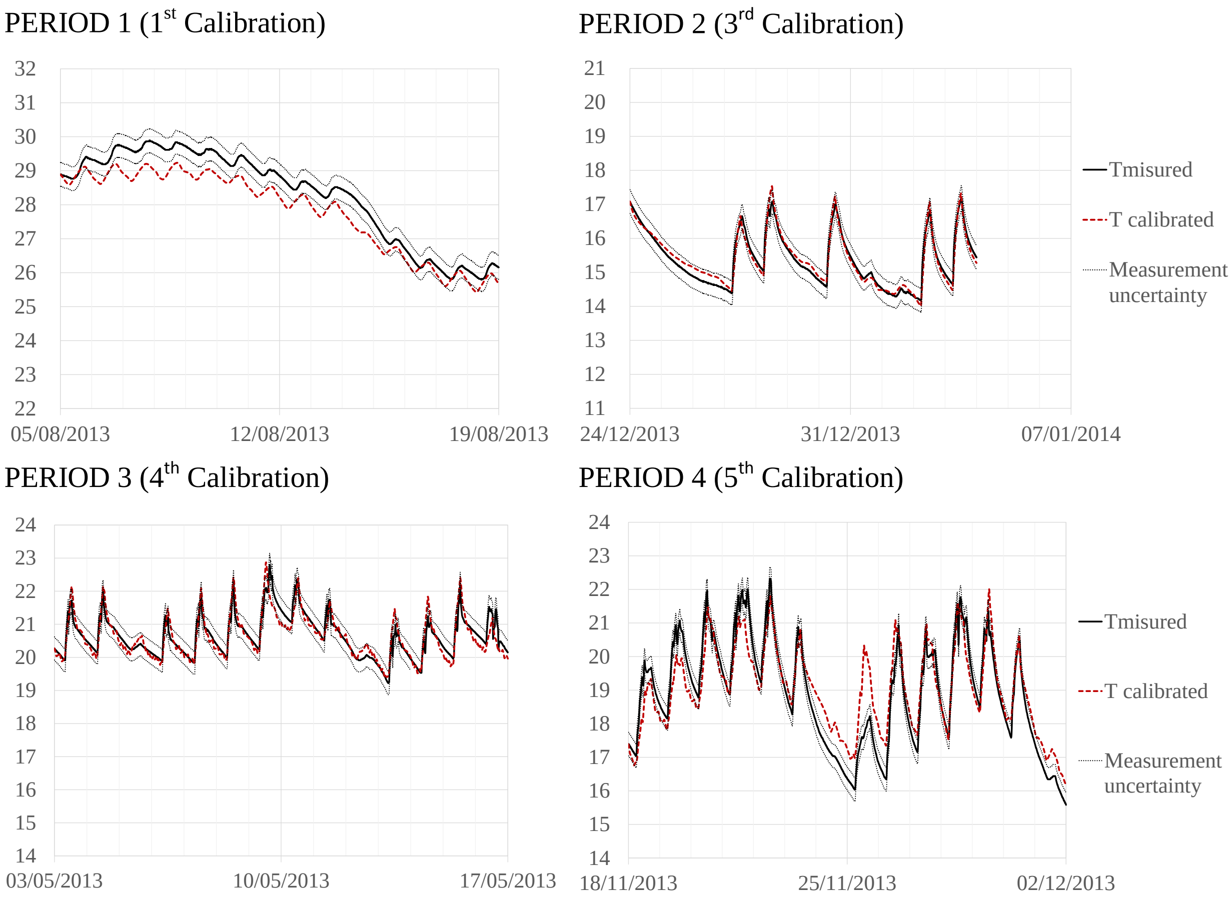

FIG. 3: Calibration of the Simulation Model in the four different Periods.

3.2 Validation

Two periods of validation have been selected in order to verify if the calibrated model is able to improve the prediction's reliability also in periods that are not involved into the calibration process. The calibrated model has been validated during 14 consecutive days in May and 14 consecutive days in December. Fig. 4 shows the trend of the measured and simulated zone air temperature. Comparing the initial simulation with the calibrated one it is possible to appreciate the advantages provided by the calibration process during the winter period, while during the spring time the calibration is not very effective in improving the correspondence between the model and the measurements. In particular, during winter time, with the calibration process, the RMSD and the CV(RMSD) have been halved while the coefficient of determination has been improved from 0.84 to 0.96. In May the validation results are not so different from the initial model results but they are still better: the RMSD changes from 0.49 to 0.41, the CV(RMSD) becomes 2.24 % and R^2 remains 0.91.

In Fig. 5 the cumulative distribution error between the simulated and measured temperature has been reported for the two validation periods. The differences between the predictions of the calibrated model and the real measurement are between -2.1 and 1.5, but for the 50% of the times the difference is approximately between -0.3 and 0.4. However the error obtained during the validation period is almost the same as the one obtained during the calibration period during the heating season while even if the error obtained during the spring validation period is twice as much as the calibration one it doesn't exceed much the sensor accuracy range. From the graph it is possible to see that the calibrated model tends to underestimate the indoor air temperature; that it is also visible in Fig. 4, especially for the winter period.

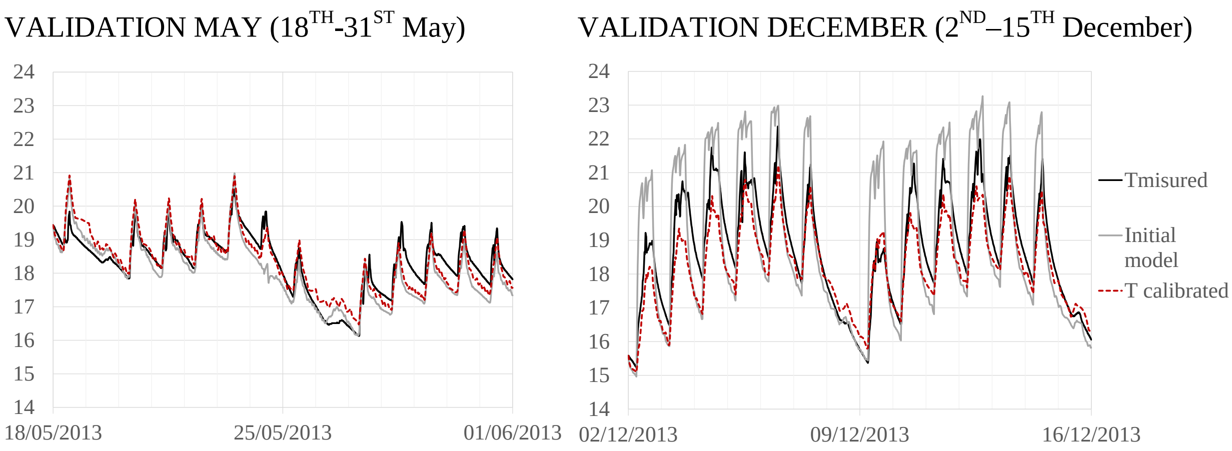

FIG. 4: Validation of the calibrated simulation model in two different periods.

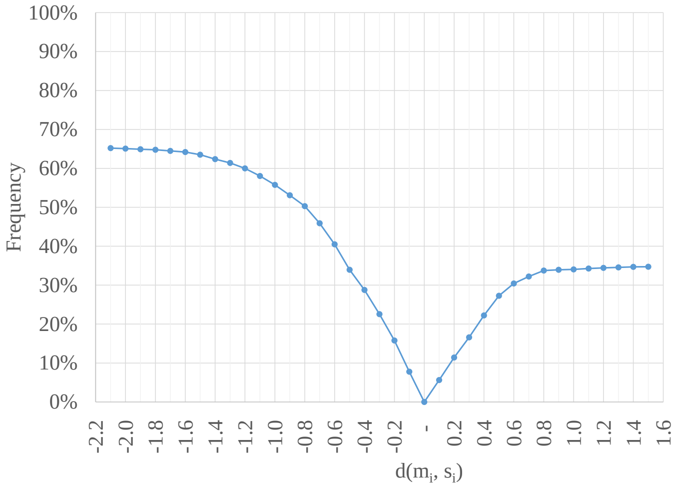

FIG. 5: Cumulative distribution error for the two validation periods.

4. CONCLUSION

In this work a methodology to deploy short-term monitored data for optimization-supported simulation model calibration was tested and validated on a case study. Different periods of the years were selected and used to calibrate different parameters of the simulation model. This way a progressive calibration has been performed in an order suitable to tune building physical properties, heating system characteristics and occupants interactions with windows and shading devices under different environmental conditions.

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 little discrepancies between simulation and real data, which however never exceed the temperature sensors accuracy also in the validation periods.

The main advantage of the calibration method proposed is the limitation of the amount of measurement to collect, not only concerning the room to be monitored in the building, thus reducing the number of sensors and consequently the costs, but also concerning the length of the monitoring itself (2/3 months).

Two main aspects have to be investigated yet: the robustness of the model on the long period (one or more years), and the application of the model to the whole building.

Concerning the first aspect a further development of this research will be the validation of the calibrated model over the whole academic year and over different years in order to assess the robustness of this calibrated model to predict representative performance and this way to confirm the efficacy of the multi-stage calibration implemented. In general, the robustness of the method should to be compared with that of more traditional and expensive (in terms of time and costs) approaches.

Moreover the procedure is going to be repeated for different classrooms in the same building. The verification of a reliable performance would then allow us to generalize the method which could be repeated in any building being of great advantage in several fields, such as the energy diagnosis of existing buildings, the definition of predictive control strategies, the identification of optimal retrofit options.

5. ACKNOWLEDGEMENTS

The research presented in this paper is supported by the scholarship "Ernst-Mach-Stipendien granted by OeAD – Austrian Agency for International Cooperation in Education & Research, financed by funds of the Austrian Federal Ministry of Science and Research (BMWF) and EU".

6. REFERENCES

ASHRAE. (2009). Handbook Fundamentals, Nonresidential cooling and heating load calculations, chapt. 18, p.18.1-18.62.

Carroll W.L. and Hitchcock R.J. (1993). Tuning simulated building descriptions to match actual utility data: methods and implementation. *ASHRAE Transaction 1993*;99:928–34.

CEN European Committee of Standardisation. (2003). EN 12831:2003, Method for calculation of design heat load.

CEN European Committee of Standardisation. (2007a). EN ISO 10211:2007, Thermal bridges in building construction, Heat flows and surfaces temperature – Detailed calculation.

CEN European Committee of Standardisation. (2007b). EN 15242:2007, Ventilation for buildings – Calculation methods for the determination of air flow rates in buildings including infiltration.

CEN European Committee of Standardisation. (2007c). EN 13779:2007, Ventilation for non-Residential building – Performance requirement for ventilation and room conditioning system.

Gösele K. and Schüle W. (1983). Schall, Wärme, Feuchte. *Bauverlag BV GmbH*, ISBN: 978-3762527329.

Heo Y., Choudhary R., Augenbroea G.A. (2012). Calibration of building energy models for retrofit analysis under uncertainty, *Energy and Buildings*, Vol. 47, 550–560.

Holst S. (2010). Dynamic radiator model with pipes (Type 162), *Bayerisches Zentrum für angewandte Energieforschung e.V.*, München, Germany

Kaplan M., Jones B., Jansen J. (1990). DOE-2.1 C model calibration with monitored end-use data. In: *Proc from ACEEE 1990 summer study energy efficient building*, vol. 10, 115–25.

LBNL (2013). THERM 6.3 and WINDOW 6.3, Laurence Berkeley National Laboratory: http://windows.lbl.gov/software/window/6/.

LBNL (2012). GenOpt user manual, Laurence Berkeley National Laboratory: http://SimulatioResearch.lbl.gov.

Liu G. and Liu M. (2012). A rapid calibration procedure and case study for simplified simulation models of commonly used HVAC systems, *Building and Environment*, Vol. 46, 409-420.

Mahdavi A., Mohammadi A., Kabir E. and Lambeva L. (2008a). Occupants' Operation of Lighting and Shading Systems in Office Buildings, *Journal of Building Performance Simulation 1(1):*57–65.

Mahdavi A. (2011). People in building performance simulation, in Hensen J.L.M. & Lamberts R., *Building performance simulation for design and operation* (2011), Spon Press, New York, USA, p.56-83.

McDowell T.P., Thornton J.W., Emmerich S., Walton G. (2003). Integration of Airflow and Energy Simulation Using CONTAM and TRNSYS, *ASHRAE Transactions*, Volume 109, Part , 2003.

Moriasi D. N., Arnold D. N., Van Liew M. W., Bingner R. L., Harmel R. D., Veith T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations, *Transactions of the ASABE, Vol. 50(3),* 885-900.

Nassiopoulos A., Kuate R., Bourquin F. (2014). Calibration of building thermal models using an optimal control approach, *Energy and Buildings,* Vol. 76, 81-91.

Nicol J.F., Humphreys M.A. (2002). Adaptive thermal comfort and sustainable thermal standards for buildings. *Energy and Buildings,* Vol. 34, 563-72.

Pedrini A., Westphal F. S., Lamberts R. (2002). A methodology for building energy modelling and calibration in warm climates, *Building and Environment,* Vol. 37, 903 – 912.

Raftery P., Keane M., O'Donnell J. (2011). Calibrating whole building energy models: An evidence-based methodology, *Energy and Buildings,* Vol. 43 , 2356-2364.

Reddy T. (2006). Literature review on calibration of building energy simulation programs: uses, problems, procedures, uncertainty and tools, *ASHRAE Transactions* 112 (2006): 226-240.

Reddy T., Maor I., and Panjapornpon C. (2007). Calibrating detailed building energy simulation programs with measured data-Part 1: general methodology, *HVAC&R Research,* Vol. 13, 221-241.

Saltelli A., Ratto M. and Andres T. (2011). Global Sensitivity Analysis – The Primer. John Wiley Sons Inc., ISBN: 978-0-470-05997-5.

Soebarto V. (1997). Calibration of hourly energy simulations using hourly monitored data and monthly utility records for two case study buildings, *Proceedings of the 4th international IBPSA conference. Prague, Czech Republic,* 411-419.

Taheri M., Tahmasebi F. and Mahdavi A. (2013). Two case studies in optimization-based thermal building performance model calibration, *CESBP2013, 2nd Central European Symposium on Building Physic,* Vienna, Austria, September, 9-11, 2013.

Tahmasebi F., and Mahdavi A. (2012a). Optimization-based simulation model calibration using sensitivity analysis, in: *Simulace Budov a Techniky Prostredi*, O. Sikula, J. Hirs (ed.), Ceska Technika - nakladatelstvi CVUT, 1 (2012), ISBN: 978-80-260-3392-9; Paper ID 71.

Tahmasebi F., Zach R., Schuss M., and Mahdavi A. (2012b). Simulation model calibration: An optimization-based approach, in: *BauSIM 2012* - Gebäudesimulation auf den Größenskalen Bauteil, Raum, Gebäude, Stadtquartier, C. Nytsch-Geusen et al. (ed.), IBPSA Germany-Austria, 1 (2012), Paper ID 170.

Tahmasebi F. and Mahdavi A. (2013). A two-staged simulation model calibration approach to virtual sensors for building performance data, *BS2013, 13th Conference of international building performance simulation association*, Chambéry, France, August, 26-28, 2013.

TRNSYS. (2014) TRNSYS 16 - Solar energy laboratory. A transient systems simulation program. http://sel.me.wisc.edu/trnsys.

Wetter M. (2001). GenOpt – A Generic Optimization Program, Seventh International IBPSA Conference Rio de Janeiro, Brazil, August 13-15, 2001.