Optimization-based calibration of a school building based on short-term monitoring data

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ABSTRACT: The dynamic energy simulation can be used as a tool to assess the energy performance of an existing building and to optimize the choice of different Energy Efficiency Measures (EEMs) from an energetic and economic point of view. However, it requires significant input information. Especially for the existing buildings, this kind of data is often lacking or characterized by high uncertainty. Inaccurate behavioral models of buildings could compromise the selection process of EEMs. In this context, monitored field data can be deployed to calibrate the simulation model, to obtain more reliable predictions, and to make better decisions. The aim of this work is to validate a methodology to calibrate the simulation based on short term measurements. Subject of the study is a real building, a Primary School in the Italian municipality of Schio (VI), which has been monitored since December 2012.

1 INTRODUCTION

The building stock is responsible for a major fraction of the global energy demand. Currently the thermal retrofit of existing buildings represents a significant opportunity toward reducing buildings' energy use. Toward this end, dynamic energy simulation can be used as a tool to assess the energy performance of an existing building and to optimize the choice of different Energy Efficiency Measures (EEMs) from an energetic and economic point of view. 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. Especially for existing buildings, this kind of data is often lacking or characterized by high uncertainty. Inaccurate behavioral models of buildings could compromise the selection process of EEMs. Calibration can help to obtain more reliable predictions from the simulation. In most of the cases the calibration process is "highly dependent on the personal judgment of the analyst doing the calibration" (Reddy, 2006). But this case-to-case approach is not conducted in a methodical way. In this context, 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 model has been already underlined by different authors (Reddy et al. 2007, Raftery et al. 2011). The optimization-based calibration approach, proposed in previous publications (Tahmasebi et al. 2013, 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 model, is used to minimize the difference between the model output and the monitored data.

In this paper a methodology to calibrate the building performance simulation models based on short term measurements was tested and validated. The proposed calibration process was applied to a real building, a Primary School, which has been monitored starting December 2012.

2 METHODOLOGY

2.1 *Case study*

The building selected for this study is a Primary school located in Schio (VI), a municipality in North of Italy, built in the '50s and enlarged in the '60s. The building has three-storeys: the basement, with canteen, gym and facilities rooms and two upper storeys with the classrooms. A representative room in the first floor was selected for monitoring and used as a reference to minimize the difference between simulations and monitored data (see Figure 1).

2.2 *Monitored data*

The monitoring of the building started in December 2012. Indoor air temperature, relative humidity, and surface temperature of radiators' supply and return pipes are logged at 5 min intervals.

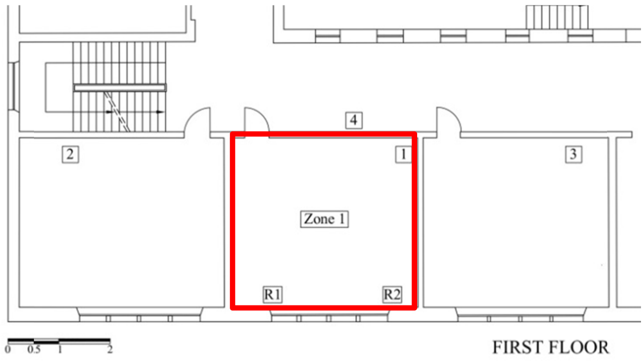

Figure 1. Selected room for monitoring (in square). Location of the sensors, 1-2-3-4 monitor the Temperature and RH, sensors R1-R2 log the heat emitted by radiators.

Data Loggers were also installed in the adjacent rooms (Figure 1) in order to get information on the boundary conditions. Since detailed occupancy monitoring was not possible, users' interviews and surveys were conducted in order to represent occupancy presence and behavior in the simulation model. Hourly weather data collected by the weather station of the municipality of Malo (VI), approximately 10km far from Schio, were used to create a real-year weather data file.

2.3 *Building model*

The simulation software package TRNSYS v.16 was used to model the building thermal performance. The initial model was defined according to on-site surveys and technical documentation on the thermal properties of the building components. The thermal bridges at the intersections of floor and walls, as well as the windows and walls were calculated in accordance with the UNI EN 10211:2008 using Therm (LBNL, 2013). The resulting values were considered in defining the effective thermal properties of building materials.

The infiltration rate was fixed equal to 0.25 h-1 according to the standard UNI EN 12831:2006. The number of occupants and their schedule 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 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). According to the surveys and users' interviews the windows were considered completely shaded during unoccupied periods. For the occupied periods, the initial value for shading level was defined according to the façade orientation (Mahdavi et al. 2008). The monitored temperatures of the adjacent spaces were incorporated into the input stream and given as boundary condition of the monitoring zone. The monitored temperature of the corridor was used to characterize the air mass entering through the internal door.

The dynamic radiator model type 362 (Holst, 2010) was used to model the building hydronic heating system. This model calculates the return temperature and the heat emitted by radiators based on the radiators' supply temperature and the indoor air temperature as input. With regard to the building heating system the monitoring data were used to identify a) the heating system operation schedule during weekdays and weekends in the working season; b) the supply temperature based on the outdoor air temperature for working and break seasons.

The supply temperature for winter working season, when the system is on, was derived from the monitored data, as follows:

$$\text{If } T_{ext}<10°C \qquad T_{supply}=-1.108\cdot T_{ext}+54.377 \tag{1}$$

$$\text{If } T_{ext}>10°C \qquad T_{supply}=43.136 \tag{2}$$

For the winter break season, it was derived from the monitored data that the heating system is operating if the indoor temperature is below 14°C. For this period, the supply temperature was set to 22°C as the average of monitored values.

When the heating system is off, the supply temperature was calculated via Equation 3, which takes into account the heating system inertia:

$$T_{\sup ply} = A \cdot e^{(-a \cdot (t_n - t_0))} + b \tag{3}$$

Where A is the supply temperature of the radiator before switching the system off, t_n is the current time, and t_0 is the time of switching the system off. The coefficient a and the constant b were set to 0.3087 and 13.872 accordingly based on the monitored data, using the least square method.

2.4 *Optimization-based calibration*

The optimization-based approach (Tahmasebi et al. 2012a) allows calibrating the simulation models in an automated way. The objective function is set to minimize the differences between model predictions and monitored data, and to achieve this goal the input variables of the model are systematically varied, within a specified range. In this work the differences between measured and simulated values for the indoor air temperature of the monitored zone were calculated and accumulated. The optimization process was executed through the generic optimization tool GenOpt (LBNL, 2012). GenOpt can be easily coupled with simulation tools such as TRNSYS that is deployed to model the building. 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).

In order to address the cost function, two model evaluation statistics were used. The first indicator is the CV(RMSD), a dimensionless number, that aggregates the time step errors over the runtime (Equation 4 and 5).

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n} (m_i - s_i)^2}{n}} \tag{4}$$

$$CV(RMSD) = \frac{RMSD}{\overline{m}} \cdot 100 \tag{5}$$

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 other indicator used is the "coefficient of determination" denoted by 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.

$$R2 = \left(\frac{n\sum m_i \cdot s_i - \sum m_i \cdot \sum s_i}{\sqrt{(n\sum m_i^2 - (\sum m_i)^2) \cdot (n\sum s_i^2 - (\sum s_i)^2)}} \right)^2 \tag{6}$$

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 (Equation 4).

$$f = 0.7 \cdot CV(RMSD) + 0.3 \cdot (1 - R^2) \tag{7}$$

To efficiently manage the repetitive process of varying the input variables, run the simulation and evaluate the cost function, the calculation of f was integrated in the simulation application.

2.5 *Calibration process*

The model calibration and testing process involved four monitoring periods, including occupied and non-occupied periods during summer (passive operation mode) and winter (active heating with a hydronic system). Each period is two weeks long; except for the Period 2 that is eleven days long. Table 1 summarizes data on the periods used in the model calibration process.

Figure 2 illustrates the calibration process. As the absence of occupants and the heating system in the first period limits the number of unknown parameters, the building's physical properties were calibrated based on the monitored data from this period (1st calibration). The monitored data from the second period were then used to calibrate the characteristics of the radiative heating system (2nd calibration). The resulting calibrated models (1st and 2nd calibrated models) were then used to calibrate the user behavior in "summer" and "winter" conditions using the data from the third and fourth periods. In the following sections, details on the above mentioned calibrations are presented.

Table 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

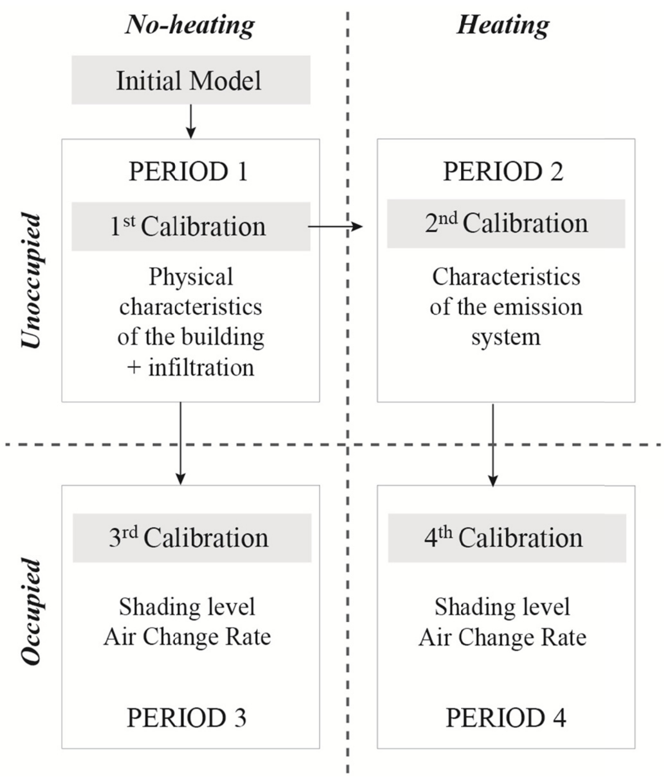

Figure 2. Scheme of the Procedure of calibration.

2.6 *First Calibration*

In the first calibration the building's physical properties were subjected to optimization. The variables of the first calibration and their variation ranges are reported in Table 2. The 10 input parameters were selected via heuristically-based consideration. A variation range of 20% was applied to these parameters. Not all the variables reported in Table 2 can be considered independent: the thermal conductivity and the density of the components' dominant layer are related. To prevent the optimization process to arrive at physically unrealistic combinations of these two variables, a simplified relationship between them was derived from information in the relevant literature (Gösele et al. 1996):

$$\lambda_{brick} = 0.0005 \cdot \rho_{brick} + 0.12 \quad (8)$$

$$\lambda_{concrete} = 0.0007 \cdot \rho_{concrete} + 0.2648 \quad (9)$$

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 involved also the variation of the thermal bridges effect. Considering the lower, the mean and the higher value of thermal conductivity of the two materials composing a thermal bridge, nine combinations were calculated to define the different linear thermal transmittance of each thermal bridge. From these configurations a polynomial regression was used to calculate the variation of the linear thermal transmittance according to the variation of the thermal conductivity of the two layers.

The calibration of windows thermal properties was not performed in a continuous manner. A set of eleven windows, with different thermal transmittance and the Solar Heat Gain Coefficient (SHGC) was created through Window 6.3 (LBNL, 2013).

2.7 *Second Calibration*

The calibrated values of the building's physical properties were used for the second period of calibration. The monitored data of the second period was used to calibrate the characteristics of the radiative heating system. The variables and their variation range are reported in Table 3.

2.8 *Third and Fourth Calibration*

Considering the lack of information on users' interaction in the occupied period, the shading level and the air change rate (representing the occupants' interaction with windows) were subjected to calibration in the third and fourth periods. The calibration of these variables was performed separately in periods 3 and 4, because the environmental conditions inside and outside the building can affect the operational control devises operated by people (Mahdavi, 2011). Table 4 summarizes the information on variables in the 3rd and 4th calibrations.

Table 2. The calibration variables in the first calibration period.

Variables	Initial value	Range Value	Calibrated value
Ext. wall brick layer – λ [$W.m^{-1}.K^{-1}$]	0.8	[0.64- 0.96]	0.833
Ext. wall brick layer – Density [$kg.m^{-3}$]	1906	[1520 - 2160]	2268
Ext. wall brick layer – Ext. Solar absorbtance	0.3	[0.24- 0.36]	0.359
Int. wall brick layer – λ [$W.m^{-1}.K^{-1}$]	0.8	[0.64- 0.96]	0.833
Int. wall brick layer – Density [$kg.m^{-3}$]	1906	[1520 - 2160]	2268
Ceiling/Floor Hollow – λ [$W.m^{-1}.K^{-1}$]	0.606	[0.48 - 0.73]	0.492
Ceiling/Floor Hollow – Density [$kg.m^{-3}$]	1244	[1070 - 1417]	1081
Window frame – Conductance [$W.m^{-2}K^{-1}$]	5	[4 – 6]	4.2
Windows* Transmittance [$W.m^{-2}K^{-1}$]	2.707	[1.569- 3.001]	1.569
Infiltration rate	0.25	[0.2 – 0.3]	0.2

* the windows were evaluated as a discrete variable

Table 3. The calibration variables in the second calibration period.

Variables	Initial value	Range value	Calibrated value
Maximum water flow rate – [$kg.h^{-1}$]	300	[200- 400]	200
Nominal Power with ΔT=60 – [W]	5184	[3629- 6739]	3787
Radiator exponent	1.358	[1.28- 1.382]	1.345
Radiator Thermal Capacitance – [$kJ .K^{-1}$]	269	[188 - 350]	294
Radiative fraction at nominal conditions	0.3	[0.2 – 0.4]	0.2

Table 4. The calibration variables in the second calibration period.

Variables	Initial value	Range Value	Calibrated value
Shading level	0.68	[0 – 1]	
Period 3			0.24
Period 4			0.01
Air change rate	1.5	[0.7 – 3]	
Period 3			1.7
Period 4			0.9

3 RESULTS AND DISCUSSION

The evaluation statistics for the initial and the calibrated models in four monitoring periods are presented in Table 5.

Table 5. The evaluation statistics of the initial and calibrated models in the monitoring periods.

Periods & models	RMSD	CV(RMSD)	R^2
Period 1			
Initial Model	0.73	2.59	0.96
1st Calibrated Model	0.60	2.11	0.97
Period 2			
Initial Model	1.07	6.92	0.75
1st Calibrated Model	0.99	6.40	0.74
2nd Calibrated Model	0.50	3.25	0.88
Period 3			
1st Calibrated Model	0.48	2.34	0.77
3rd Calibrated Model	0.46	2.23	0.76
Period 4			
2nd Calibrated Model	0.90	4.76	0.78
4th Calibrated Model	0.75	3.96	0.80

As shown in Table 5, comparing the initial and calibrated models, the evaluation statistics values show an improvement of the model predictions. The calibration process presents a different effectiveness according to the period of the year. For some periods the performance of the model predictions are slightly improved: in Period 1 the CV(RMSD) was reduced from 2.59% to 2.11% and in Period 3 from 0.48 to 0.46. Moreover, for the Period 3 the improvement of the CV(RMSD) leads to a moderate reduction of the "coefficient of determination".

In "winter" conditions (periods 2 and 4) the non-calibrated models perform significantly better than the non-calibrated ones. In Period 2 the CV(RMSD) of the calibrated model has been reduced from 6.40 to 3.25 and the R^2 has been increased from 0.74 to 0.88.

4 CONCLUSION

In this work a methodology to deploy short-term monitored data toward optimization-supported simulation model calibration was tested and validated on a case study. Different periods of the years was selected and used to calibrate different aspects of the simulation model. Step by step calibrations were performed in a logical order to adjust building physical properties, heating system properties and occupants interactions with windows and shading devices in different environmental conditions.

Further development of this research will be the exploration of retrofits options through the use of the fully calibrated model. A multi-objective optimization of retrofit strategies can help to identify the most promising options in view of energy use, cost, and thermal comfort.

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