OPTMIZATION-BASED CALIBRATION FOR DYNAMIC BUILDING SIMULATION MODELS: A CASE STUDY

Valentina Monetti [1], Elisabeth Davin [2], Enrico Fabrizio [3], Philippe André [2], Marco Filippi[1]

[1]DENERG, Politecnico di Torino, Torino, Italia
[2]Building Energy Monitoring and Simulation, Université de Liege, Arlon, Belgium
[3]DISAFA, University of Torino, Grugliasco (TO), Italia

ABSTRACT

This study presents an original methodology for calibrating building energy models based on monitored data. An optimization-based approach was applied to a monitored test building coupling the building simulation program EnergyPlus with the optimization software GenOpt. An objective function was set to minimize the difference between the simulated and the monitored energy consumption at the hour time scale, varying the building model parameters selected at the beginning as the most influencing. After calibration, the observed heating energy consumption of the case study matched closely the monitored data, the model accuracy was verified according to the MBE and the Cv(RMSE) limit set by the ASHRAE guideline 14.

INTRODUCTION

To date, building simulation application in post-construction stages has been growing with a view of optimizing the building real operation and reducing its energy consumption. The performance gap often observed between the building energy performance predicted at the design stage and the real measured performance has thus paved the way for buildings real monitoring and operation diagnostic activities. In this kind of scenario, the process of fine-tuning the building model input data, for making simulated building energy consumption match with real monitored consumption, has spread out under the name of Calibration.

Many applications of calibration can be currently listed (Claridge, 2011): first, accompanied by energy audits for determining the potential savings from proposed retrofit measures or from changing building operational strategies (“what-if” analysis); second, in commissioning activities of existing buildings; third, for fault detection and diagnostics activities. Notwithstanding these recent applications, still no universal and consensus calibration guidelines have been presented yet. Statistical indices, such as the Mean Bias Error (MBE) and the Coefficient of variation of the Root Mean Square Error (Cv(RMSE)) are used for validating a calibrated model, as a measure of the goodness-of-fit of the building energy model (ASHRAE, 2002). However a formal and recognized methodology still lacks.

From a literature review carried out by the authors (Fabrizio et al, 2015), it emerged that, even though new applications of calibration are being performed, trial-errors approaches still remain the most frequently employed (Bertagnolio et al, 2012; Ferrara et al., 2014, Mihai et al, 2013; Monetti et al, 2015; Parker et al, 2012). However, among the recent calibration applications, other methods, beyond the trial-error approach, have began to emerge. For instance, the use of automated methods to fine-tune the models and improve their accuracy, is of growing interest (Fontanella et al., 2012; Liu et al., 2015; Penna et al, 2014; O’Neill et al. 2013).

Uncertainties are often overlooked in calibration studies, whilst uncertainty and sensitivity analyses should be integrated as necessary components of the calibration process of a building model. To this regard, a Bayesian calibration of normative energy models was performed by (Heo et al, 2013) for accounting uncertainties, by means of the Morris method, during the retrofitting of existing buildings.

This paper wants to apply calibration to detailed building energy models and provides some guidelines to architectural experts to integrate calibrated building simulation in post-construction design stages, in order to achieve more reliable results. Calibration studies are often performed on simplified building models, while the applications on detailed models are less frequent. This study presents a methodology for the calibration of detail dynamic building energy models based on monitored data. An optimization-based approach was chosen and applied to a test building, based on the coupling of the EnergyPlus simulation software with the GenOpt optimization program. A short monitoring period of one month, during the winter season, was investigated for hourly calibration based on the building space heating demand.

METHODOLOGY

Most of the techniques used for calibration, generally considers simplified building models (e.g. normative quasi-steady models). Given this, the main objective of this study was to reach a higher degree of detail by using detailed building models created with building simulation programs and investigated in a dynamic state. The calibration of detailed dynamic building energy models, based on hour time step, was thus investigated within this study. The hereby proposed methodology builds on an optimization-based calibration of building energy models based on monitored data, similarly to (Fontanella et al., 2012, Tahmasebi et al., 2013). The process of optimization was devoted at finding the parameters optimal values for a better matching of the simulated energy consumption with the building measured energy consumption.

Depending on the input data availability, 4 different calibration levels can be distinguished (Reddy, 2006): from a level 1 based on as-built data and a more level 4-5 based on audit information, inspection and monitoring. To this regard, a calibration level 4 was performed on a test building based on the use of data from short monitoring. A four-step methodology, based on the coupling of the dynamic building simulation program EnergyPlus with the optimization software GenOpt, was defined, as depicted in Figure 1.

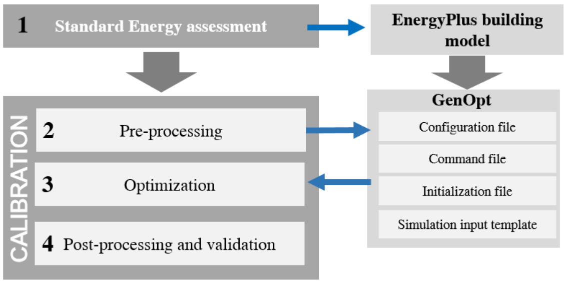

Figure 1 Four-step methodology for calibration.

Step 1 regards the building standard energy assessment by means of a dynamic building simulation. From step 2 to 4, calibration is performed. During pre-processing, data are collected and processed for optimization. Both meteorological and measured data are necessary at this stage for calibration. As pictured in Figure 1, four different files are prepared to be used in the optimization stage. The initialization file specifies the files location, while the configuration file sets the configuration of the simulation program. The simulation input template file is a copy of the energy model read by GenOpt for identifying the parameters to be tuned. Finally, the command file specifies all the parameters to be altered in the energy model, their variation constraints and the algorithm selected to perform the optimization.

Given the high level of uncertainty usually accompanying dynamic building simulation, the inclusion of uncertainty and sensitivity analyses was closely considered by studying different possible approaches for implementing them within the calibration process. However, due to the large computational time for running the simulation with detailed dynamic models, uncertainty and sensitivity analyses were not run by the authors. Usually, most of sensitivity and uncertainty analyses are carried out using simplified and normative energy models based on the Standard ISO 13790:2008 (complied in Matlab, Excel or other simplified simulation program). In literature, few applications of these kind of analyses on detailed dynamic building energy models can be found due to the high simulation time and the difficulty of coupling building simulation programs with tools running sensitivity and uncertainty analysis. For this reason, based on a detailed literature review, a set of parameters, referred as the most influencing the building energy consumption was defined. They were gathered into four main categories (site, building envelope, operation, building system).

During Step 3, the optimization-based calibration is performed: the building model parameters are altered, based on constraints, until the optimization problem is solved. The optimization is defined, within the initialization file, through a specific error-minimizing objective function (1) aimed at reducing the difference between measured and simulated data in each thermal zone.

$$\begin{gathered}\text{Function} = \text{minimize} \\ [(\text{Abs\_(climatic room)}\ (S-M)) + \\ (\text{Abs\_buffer}\ (S-M)) + (\text{Abs\_office}\ (S-M)) + \\ (\text{Abs\_(office 1st floor)}\ (S-M))]\end{gathered} \quad (1)$$

The optimization process stops when the minimum difference is found, that means that simulated heating energy consumption of the case study matches closely the monitored data. A hybrid generalized pattern search algorithm with particle swarm optimization was used as generally recommended algorithm for problems where the cost function cannot be simply and explicitly stated, but it can be approximated numerically by a thermal building simulation program (Wetter, 2000). Different optimization runs were performed to find the “best estimates” for calibration, varying at each run different parameters in the energy model (e.g. internal gains, building envelope features, etc). First, a series of runs was performed varying time dependent parameters (equipment, infiltration and ground temperature). Then, building envelope related parameters were also included in the optimization process.

Finally, Step 4 post-processes the optimization outputs for validating the calibrated building model based on its accuracy. The statistical indices Mean Bias Error (MBE), the Root Mean Square Error (RMSE) and the Coefficient of Variation of the RMSE (Cv(RMSE)) are calculated and verified to be consistent with the ASHRAE guideline 14 limits (ASHRAE, 2002), respectively ±10% and 30% on hourly basis. The consideration of both indices allows preventing any calibration error due to errors compensation. MBE is used to measure how closely the simulated data corresponds to the monitored ones. It is an overall measure of how biased are the data. MBE is calculated (2) as the total sum of the difference between measured energy consumptions and simulated ones at the calculation time intervals (e.g. month) of the considered period. The difference is then divided by the sum of the measured energy consumptions. Where M is the measured energy data point during the time interval and S is the simulated energy data point during the same time interval.

$$MBE\ (\%) = \frac{\sum_{Period}(S-M)_{Interval}}{\sum_{Period} M_{Interval}} \times 100\% \ (2)$$

The Root Mean Squared Error (RMSE) is a measure of the sample deviation of the differences between the measured values and the values predicted by the model. The Cv(RMSE) is the Coefficient of Variation of RMSE and is calculated as the RMSD normalized to the mean of the observed values. This is a normalized measure of the variability between measured and simulated data and a measure of the goodness-of-fit of the model. It indicates the overall uncertainty in the prediction of the building energy consumption, reflecting the errors size and the amount of scatter.

$$Cv(RMSE_{Period}) = \frac{RMSE_{Period}}{A_{Period}} \times 100\ (3)$$

$$RMSE_{Period} = \sqrt{\frac{\sum(S-M)^2_{Interval}}{N_{Interval}}}\ (4)$$

$$A_{Period} = \frac{\sum_{Period} M_{Interval}}{N_{Interval}}\ (5)$$

Where $N_{Interval}$ is the number of time intervals considered for the monitored period.

CASE STUDY

Building description

The case study is a test building monitored and located in the Environment Campus of the University of Liege in Arlon, Belgium. The building was selected for the availability of monitored data and also for the affordable time estimation both for modeling and simulating, considering the small and manageable dimensions (total gross floor area of 162 m^2). As test building, the case study is built around a climatic room, surrounded by a buffer area, as pictured in Figure 2. On each side of the climatic room two main zones can be identified: a two storeys office area on the north-east side of the building, including a small service area on the ground floor, and a technical equipment on the south-east side. The climatic room upper border faces an unconditioned attic. The building has an all wooden structure and envelope. Windows are equipped with exterior wooden blinds that were shut during monitoring. During monitoring, the office areas, the climatic room and the buffer zone were conditioned by means of electric resistances with a constant heating set point of 20°C.

Energy model

The building energy model was created within the EnergyPlus simulation program. The model defined at this stage is “uncalibrated” and based on the design data and standard boundary conditions. The modeling process performed for the energy assessment of the case study in standard conditions corresponds to stage 1 of the methodology.

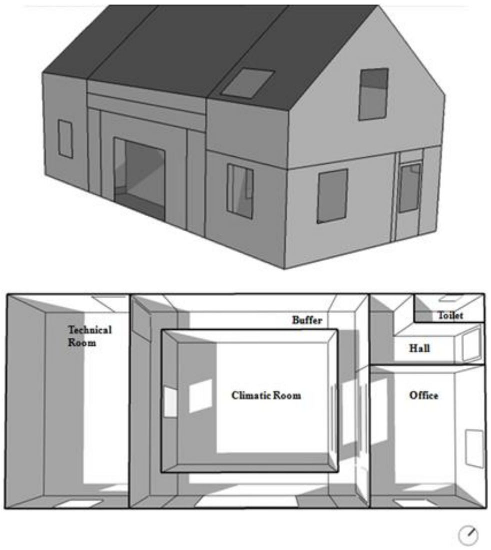

Figure 2 3d view and ground floor of the case study.

With regard to the geometry, given the small building size, a detailed modeling was pursued: a thermal zone was defined for each room (seven thermal zones in total). Four zones were modeled as conditioned ones (climatic room, office, buffer and upper-floor office), while the remaining three were not conditioned (technical room, attic, toilet). The building envelope components were characterized according to the as-built technical documentation. For higher accuracy in the simulations the building surrounding urban context was also modeled.

Moreover, given the small extension of the building and its direct contact with the ground, the ground heat transfer was assessed with the Slab auxiliary program of EnergyPlus for calculating the core and perimeter surface of the ground floor slab temperature.The temperature of ground floor slab surface was also subjected to tuning during the calibration process.

As the building is only used for experimental activities, the occupancy rate was set to zero; the power installed for the two computers in the office and for the attic server was set respectively to 230 W (based on a literature review), and to 120 W (based on measurements). The infiltration air flow rate was taken into consideration within the building energy model by using the EnergyPlus AirflowNetwork model for natural infiltration. The airflow rate was set to 0.43 ACH in some zones on the basis of a blower door test measurement and to 0.5 ACH in the remaining zones. The building dedicated outdoor air system was not operating during monitoring, therefore mechanical ventilation was not modelled. As described previously, four rooms of the building were heated by means of electric resistances. The real heating system of the building was thus not operating in order to simplify the measurement of the heating rate and to have a better accuracy of the measure. In order to provide a fair representation of theis heating system, an EnergyPlus ideal load system was modelled in order to assess the building space heating energy consumption.

The building model was simulated before calibration, to evaluate how far the simulated model performance was from the real building one. The simulation results of the "uncalibrated" energy model are reported in Table 1. On one hand, at the whole building level, simulation results appear to be accetable and close to measured data: the calibration indices are also verified for hourly calibration. On the other hand, looking at the results for each single zone, major disagreements are observed and the indices are not verified. Given this, considering the building small extent, a thermal zone calibration should be performed.

Table 1 Measured and simulated energy consumption of the case study (before calibration).

	ENERGY CONSUMPTIONS		**CALIBRATION INDICES [%]**	
	Simulated [kWh/m^2]	**Measured [kWh/m^2]**	**MBE**	**Cv(RMSE)**
Climatic Room	4.6	1.0	352	8696
Office	4.7	5.9	- 20	490
Buffer	16.7	18.9	- 11	286
Office (1st floor)	10.6	11.4	- 7	177
Whole building	36.6	37.2	- 0.7	17

CALIBRATION

Data for a short-term monitoring period, from the 8th of February to the 5th of March, was used during the calibration process. According to step 2 "Pre-processing", metered meteorological data, was retrieved from the university campus weather station and processed for creating the real weather file of Arlon, where the case study is located. Other data from monitoring (e.g. indoor ambient temperature, heating energy consumption) was retrieved from ambient sensors located in the case study rooms.

A set of the parameters considered as the most influent on the building energy consumption, was defined based on a detailed literature review (Fabrizio et al., 2015). Table 2 lists the parameters tuned during the optimization-based calibration process. For each parameter, a constraint domain, with a lower and an upper bound, was set. Only the materials of the main exterior building envelope components were selected. The materials thickness was taken into account for tuning as the building envelope components were altered with respect to the construction technical documentation and therefore a level of uncertainty in the material proprieties definition had to be accounted during simulation. For the material properties parameters, the variation constraints were always set to 25%, with the exception of the materials thickness variation set to 10%. For instance, the installed power in the attic room was set to 120W based on on-spot measurements, while the computers power was set to 140W as initial value, with a lower bound of 80W and an upper bound of 230W, based on a literature review. Table 3 reports an extract of the parameters subjected to optimization.

Table 2 List of the parameters altered during optimization.

SITE	**BUILDING ENVELOPE**	**INTERNAL GAINS**	**VENTILA-TION**
Ground temp. [°C]	Material conductivity [W/mK]	Equipment Installed Power [W]	Infiltration [ACH]
	Material Density [kg/ m3]	Equipment Radiative fraction [-]	
	Material Specific Heat [J/kg K]		
	Thickness [m]		

Table 3 Extract of the equipment related parameters altered during optimization.

POWER [W]	**INITIAL VALUE**	**MIN**	**MAX**	**VARIA-TION RANGE**
Technical room	100	75	125	25%
Office	140	80	230	based on literature review
Attic	120	120	120	constant
RADIATIVE FRACTION [-]	**INITIAL VALUE**	**MIN**	**MAX**	**VARIA-TION RANGE**
Technical room	0.5	0.375	0.625	25%
Office	0.5	0.375	0.625	25%
Attic	0.5	0.375	0.625	25%

During stage 3, the calibration was performed based on the optimization function. GenOpt was run, coupled with EnergyPlus, for optimizing the influencing parameters to match the simulated heating energy consumption with measured consumption. Different calibration runs were performed. Although one calibration run should be considered sufficient to tune input data of the building model, the process of calibration is a highly undetermined problem that brings to a non-unique solution (Carroll et al., 1999). For this reason, it was decided to perform multiple calibration runs. For each run, GenOpt reached the minimum of the objective function approximately after 1500-1600 EnergyPlus simulations. Two main sets of optimization runs were defined and overall eleven calibration runs, distinguished into two main sets, were conducted. In the first set of runs (Calibration run 1 to 6) only time dependent parameters were altered and subjected to optimization. Then, in the second set of runs (Calibration run 7 to 11), materials related parameters were included in the optimization process. The ground temperature was also included into the set of parameters to be tuned as given the building small dimension and the direct contact of the building ground floor slab with the ground.

During stage 4, the output of the calibration process were post-processed. In order to evaluate the model accuracy, the statistical indices MBE and the Cv(RMSE) were calculated, as in compliance with the ASHRAE Guidelines 14 (ASHRAE, 2002).

RESULTS

Figure 4 reports the time series plot of the simulations data (uncalibrated and calibrated model) and the measured data as regards the heating rate of the office room on the ground floor. As it can noted, large disagreements are observed from measured to uncalibrated data. A similar trend, with slight differences on the top and bottom peak, can indeed be observed comparing measured and calibrated data.
For each calibration run, the statistical indices were calculated and verified in each conditioned thermal zone, based on the heating building energy consumption. The MBE and the Cv(RMSE) variation is reported in Figure 5 and in Figure 6, respectively.

In the first set of runs, the MBE is always consistent with the ± 10% threshold limit recommended by the ASHRAE guidelines for hourly calibration, while Cv (RMSE) is dramatically out of the threshold limit. To this regard, considering both statistical indices is important to observe that, noted that Cv(RMSE) does not fall within the allowed limits, MBE may be verified only due to compensations errors. On the other hand, in the second set of runs, the Cv (RMSE) significantly improved, especially in the last three runs (calibration runs 9 to 11) with the inclusion of non-time dependent variables, such as material proprieties, that allow considering the decaying of the building envelope. Similar considerations can be made with regard to the MBE. In general, looking the indices trends in Figure 5, soften variations are observed for both the office zones. Except for the first runs, where higher values are recorded, after calibration run 4 there aren't strong variations in the indices trends for the buffer zones. On the contrary, the strongest disagreements are met for the climatic room.

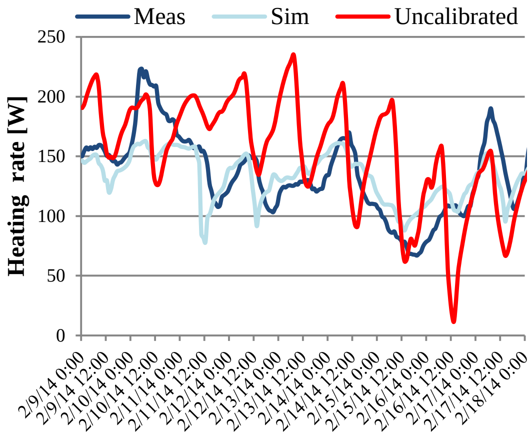

Figure 4 Comparison of the simulated and measured space heating rate of the office room.

In particular the Cv (RMSE) trends record high peek in the first runs of both set of calibration runs. Table 4 reports the MBE and Cv (RMSE) values, before calibration and in the calibration runs 5 (1st stage) and 11 (2nd stage), the last runs of the first and the second set of runs.

Table 4 MBE and Cv (RMSE) before and after calibration (run 5 and 11).

		UNCALIBRATED MODEL	RUN 5	RUN 11
MBE	Climatic Room	352	0.58	0.17
	Office	-20	1.66	-0.11
	Office (1st floor)	-7	6.82	0.14
	Buffer	-11	-8.75	-0.01
CV(RMSE)	Climatic Room	8696	14.34	20.40
	Office	490	53.01	3.51
	Office (1st floor)	177	74.94	1.54
	Buffer	286	54.85	0.19

Finally, in Table 5 an extract of the parameters subjected to the optimization process are listed. For each parameter the initial value (uncalibrated model), the defined constraints (minimum and maximum value of the parameter) and the final optimal (calibrated) value are reported. The reported values belong to the Calibration run 11, that correspond to the calibrated model with the "best estimates".
In general, with regard to the variation of the parameters during optimization, the parameters that reported the most constant trend, are those related to the building envelope. Light deviations are hence observed during the optimization process, from the starting value to the simulated and optimal values. On the contrary, the most unstable parameters are those related to the internal gains and ventilation rates, which achieved larger variations within the constraint threshold during optimization. It can be noted that smaller variations are observed during optimization for the density of the "OSB panel 12mm" and the conductivity of the slab mortar, on the left side of Figure 7.

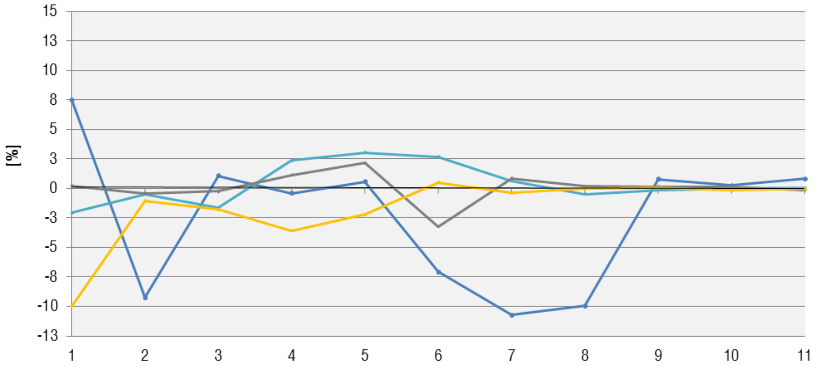

Figure 5 MBE variation during calibration runs.

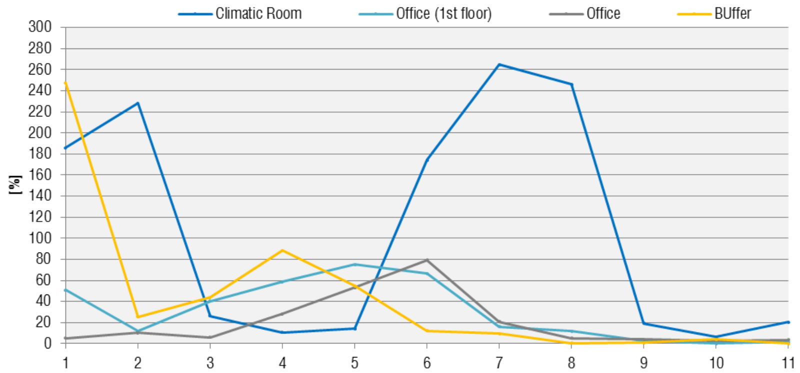

Figure 6 Cv (RMSE) variation during calibration runs.

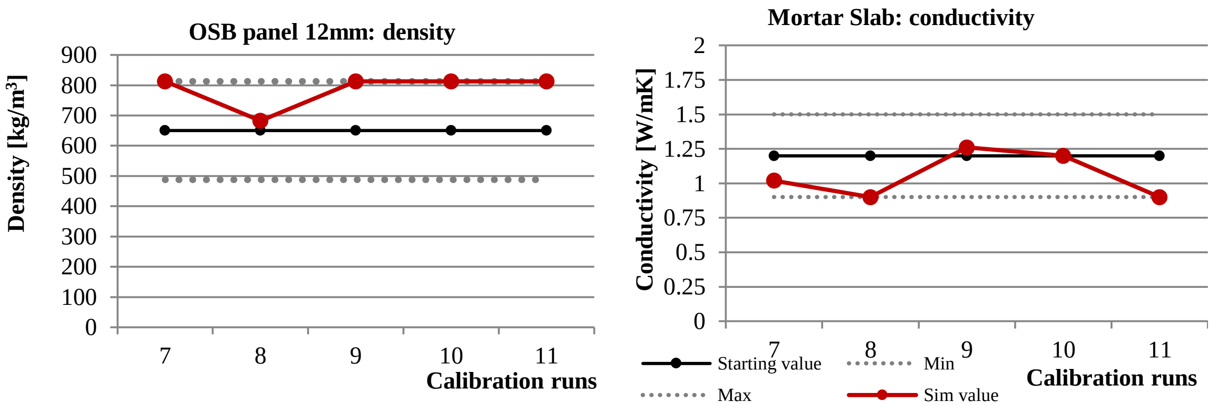

Figure 7 Variation of the material parameters during the optimization process (calibration runs 7 to 11).

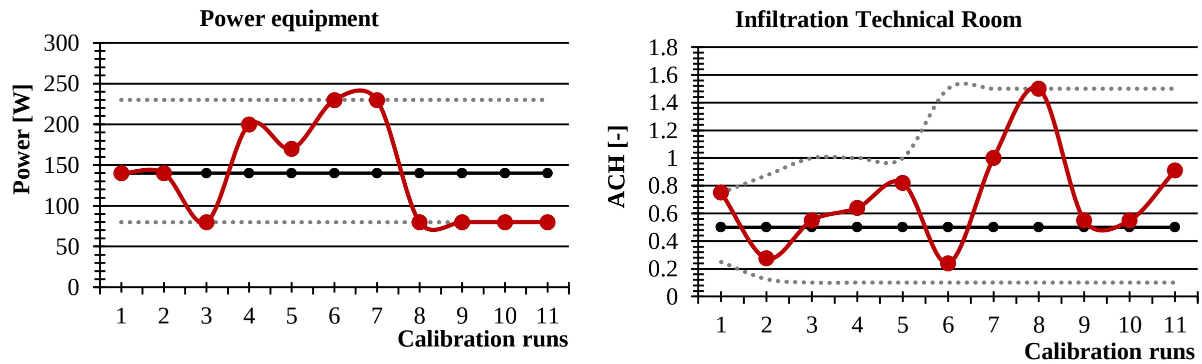

Figure 8 Variation of the office power equipment and the technical room infiltration rate during optimization.

Table 5 Extract of the building model parameters altered during optimization.

INPUT: INFLUENCING PARAMETERS					
	Starting value	**Min**	**Max**	**Variation range**	**Simulation value**
BUILDING ENVELOPE					
Material: Conductivity [W/ mK]					
Extruded Polystyrene	0.03	0.023	0.038	25%	0.0255
Mortar Slab	1.2	0.900	1.500	25%	0.9
OSB Panel 12mm	0.13	0.098	0.163	25%	0.1652
Osb Panel 18mm	0.13	0.098	0.163	25%	0.0975
Reinforced concrete	2.2	1.650	2.750	25%	2.75
Rockwool 89mm	0.04	0.030	0.050	25%	0.05
Rockwool 140mm	0.04	0.030	0.050	25%	0.05
Rockwool 150mm	0.04	0.030	0.050	25%	0.05
Material: Thickness [m]					
Extruded Polystyrene	0.08	0.072	0.088	10%	0.088
Mortar Slab	0.1	0.09	0.11	10%	0.009
OSB Panel 12mm	0.012	0.0108	0.0132	10%	0.011
OSB Panel 18mm	0.018	0.0162	0.0198	10%	0.019
Reinforced concrete	0.14	0.126	0.154	10%	0.14
Rockwool 89mm	0.15	0.135	0.165	10%	0.080
Rockwool 140mm	0.14	0.126	0.154	10%	0.134
Rockwool 150mm	0.089	0.0801	0.0979	10%	0.135
GAINS: Equipment: Power [W]					
Technical room	100	75	125	25%	75
Office	140	80	230	based on literature review	80
Attic	120	120	120.00	In situ measurement	120
VENTILATION: Infiltration [ACH]					
Technical room	0.5	0.125	1	-	0.91
Buffer Zone	0.43	0.1	0.75	-	0.75
Climatic Room	0.43	0.1	0.75	-	0.11
Office	0.43	0.1	1	-	0.28
Office 1st floor	0.43	0.1	1	-	0.46
Attic	0.5	0.1	1	-	0.19

Indeed, it can also be observed that for the installed power of the office computers and the infiltration rate of technical room, the tuning final value significantly varies during the calibration runs, as pictured in Figure 8. For instance, the initial value associated to the computers installed power in the office (office equipment) was set to 140 W and during optimization, its value varied from 80W to 240 W. In particular, while the computer power achieved the same final value from run 8 to 11, the infiltration rate still assumed different values. The variation of the materials thermal properties is thus milder than other parameters, that means they hold a smaller influence on the optimization process.

CONCLUSION

As acknowledged, calibration mostly depends on users' experience and assumptions. Given this, the user's role is thus of high relevance during the process. User's skills and knowledge are essential for performing calibration, having a direct impact on the building model accuracy and the calibration running time. To this regard, the use of an automated method can help non-expert users into the carrying out of a calibration process, preventing for manually tuning each parameter, dealing with tedious and unmanageable calibration timings and improving on traditional trial and errors methods. Of course the use of automated methods cannot disregard a deep knowledge of the building physics phenomena and replace an accurate user's experience on the domain.

Optimization-based methods belong to the category of automated methods. They are little by little becoming more common in calibration applications. Within this study, an optimization-based calibration was conducted on a test building for a short-term monitoring period. The method was applied to a detailed dynamic building energy model rather than to a simplified building model. This automated approach was preferred to a manual approach for the possibility of including a higher number of parameters and changing simultaneously more than one parameters.

The validation of the building model accuracy was based on the hourly threshold limits of the MBE and Cv (RMSE) statistical indices.

Further improvements can be made to refine the calibration process: statistical indices may be integrated in the optimization objective function and additional variables such as the indoor ambient temperature can be employed for calibration beyond the building energy consumption. The methodology should also be tested on more complex buildings and for a longer monitoring period.

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