On the influence of several parameters in energy model calibration: the case of a historical building

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Abstract

The aim of this work is to investigate the extent to which several different variables (e.g. climate conditions, infiltration rates and envelope characteristics) could affect the calibration process and, consequently, the reliability of the simulation outcomes. In this regard, in this paper the calibration phases of a dynamic hourly energy model for an existing building are presented. The test case is a historical construction built at the end of the nineteenth century in northern Italy. The building, originally designed for tobacco processing, has a massive envelope and it has no HVAC system. Therefore, the simulation model is calibrated using the actual air and wall surface temperature as control variables. Finally, a sensitivity analysis is carried out in order to assess the incidence of different inputs in building thermal behaviour and to identify which parameters have to be refined with the aim of optimizing the model calibration.

1. Introduction

Energy simulation represents a useful tool to describe building actual behaviour; hence it is used not only in the design process but also in the post occupancy analysis with the purpose of evaluating the actual energy efficiency of a building. In fact, the recast Energy Performance Building Directive (*EPBD 2010/31/EU*) highlights that residential and commercial buildings account for more than one third of total annual energy consumption. Since significant energy savings can be achieved through energy conservation measures (ECM) for existing building stock, the importance of refurbishment has been growing. Consequently, simulations have been applied to existing constructions to assess their energy performance and to define effective ECM. However, the large number of required parameters affects the reliability of a simulation and significant discrepancies between predicted and real data could occur. For this reason, model calibration with monitored data is often appropriate in order to refine models and to develop more realistic energy-behaviour simulations.

In this regard, a new European standard is going to be developed by CEN Technical Committee 89 (Working Group 14) and it will provide for calibration strategies and measurements post processing procedures for building energy models. Currently, three standards define general criteria and tolerance ranges for model calibration:

- International Performance Measurement and Verification Protocol (IPMVP 2012),
- Measurement and Verification (M&V Guidelines 2008);
- ASHRAE Guideline 14/2002: Measure of energy and demand savings.

However, none of these protocols establish an operative methodology to calibrate building models. In the literature, several studies face the model calibration issues using actual energy consumption either from in situ measurements during the calibration period (e.g. Raftery et al. 2011; Norford et al. 1994) or from the analysis of monthly utility bills (e.g. Yoon et al. 2009). Only a few works adopt the internal temperature as a calibration goal (e.g. Tian et al. 2009). In fact, in this approach the monitoring data could be affected by a series of uncertainties and interactions with the indoor environment, such as occupant behaviour, internal gain and building equipment. Besides, the measurement of several variables can be an

expensive and time consuming activity. However, the model calibration using temperature as a control variable is the only viable procedure when no operating HVAC are present in a building. Taking into account these considerations, an issue closely related to calibration activity becomes the sensitivity analysis (SA) of the model to the input data. This calculation technique is applied for the evaluation of building thermal response according to a given perturbation of inputs in order to assess the parameter influence on the building energy performance. Hence the results of the sensitivity analysis reveal the strategy to refine a building simulation model (e.g. Lam et al, 1996).

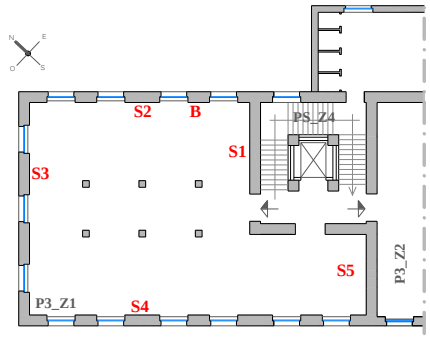
This paper aims firstly to define a suitable calibration procedure of an existing building model using temperatures as control variables. Secondly, starting from the model calibrated against the experimental data, a sensitivity analysis is carried out with the aim of investigating the extent to which several parameters affect the energy model. The purpose of this investigation is to discover which parameters, if experimentally measured, can improve the model calibration.

2. Case study

The case study is a historical manufacturing facility built in Rovereto in northern Italy. The overall surface of the construction is 3650 m^2 and it has four levels and one basement. The envelope has a high thermal mass with a homogeneous ratio of the glazing over an opaque surface, which is equal to 0.3.

Since the building has no HVAC system, the internal temperatures have been monitored in order to calibrate the simulation model. In particular, both the surface and air temperatures have been collected every 10 minutes in the control thermal zone (i.e. P3_Z1) that is placed on the 4th floor next to the roof (Figure 1). The measurement campaign was carried out from March to June 2012.

In Figure 1 the instrument position is shown: the heat flux meter (HFM) apparatus (two HFM and two thermo-resistance pt100) is installed in B, while the points from S1 to S5 indicate the thermistors employed for the surface temperature recording.



S1: Thermistor 1 **S2**: Thermistor 2 **S3**: Thermistor 3
S4: Thermistor 4 **B**: Thermo-resistance + HFM

Fig. 1 – Control thermal zone

3. The calibration procedure

Model calibration is an iterative process which, through the assessment of a series of simulations with different inputs, aims to reduce the discrepancies between simulated and actual building energy behaviour.

The main steps of a calibration procedure are as follows:

- Simulation plan: aim of calibration, availability of data and validation criteria;
- data gathering: input and calibration parameters have to be collected
- simulation runs
- comparison between predicted and actual values

If the results of the validation indices are in agreement with the tolerance range, the model is correctly calibrated, otherwise the model has to be revised in order to reach the calibration target. Inputs have to be refined according to the source hierarchy, which must be defined for each case study as a function of the accuracy and the reliability of the data source. Further, a sensitivity analysis can be carried out to investigate the most influent inputs and refine them.

3.1 Model calibration criteria

The calibration protocols employ some validation indices to quantify the calibration of the model. Then, the calibration indices have to consider both the gap between actual and predicted values and their correlation.

Defining M the monitored data, S the simulation outcomes and N the number of data, the following indices are applied:

Mean Bias Error MBE

$$MBE = \frac{\sum_{i=1}^{n}(S_i - M_i)}{N} \quad (1)$$

MBE provides for a general gap between predicted and actual values. This index can give a misleading indication due to the sign error compensation.

Root Mean Square Error RMSE

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - M_i)^2}{N}} \quad (2)$$

It overcomes MBE weakness, since it considers the absolute error values.

Pearson's Index r

$$r = \frac{\sum(S_i \cdot M_i) - \sum(M_i) \cdot \sum\left({S_i}/{N}\right)}{\sqrt{\left(\sum(M_i^2) - \frac{\sum(M_i^2)}{N}\right) \cdot \left(\sum(S_i^2) - \frac{\sum(S_i^2)}{N}\right)}} \quad (3)$$

It represents a measure of the correlation between two variables. The Pearson´s index ranges from −1 to 1, where a negative value means an opposite correlation.

3.2 Building model input

The calibration procedure aims to optimize the model and to reduce the discrepancies between predicted and real values. In order to reach this target a set of simulations is defined. In particular, due to the building characteristics, three variables are assumed as main inputs of the energy model:

- weather data;
- air-change rates;
- thermo-physical properties of the envelope.

Since weather variables (temperature, solar radiation, relative humidity and wind speed) are the external solicitation and the main cause of heat losses/gains, they play an important role in the building energy model. Consequently a reliable dataset is necessary to assess a correct energy simulation.

Regarding the case study, three different sets of data were available.

The first source of data is the Test Reference Year (TRY), which reports hourly standard values for weather variables defined according to EN 15927-4. This standard defines a method to develop a reference year starting from long period measurements (at least ten years). In a recent study (Baggio et. al, 2010), the TRY for the Italian provinces are developed and the TRY are now provided by Thermo-technical Italian Committee (C.T.I.). The other two datasets are collected by a meteorological station in Rovereto close to the building location but on two different sides of the valley: Meteo Trentino (45.88° N, 11.05° E) and IASMA (45.89° N, 11.65° E). Figure 2 and Figure 3 show respectively the temperature and the solar radiation trends for the three datasets over three days (i.e. March 17th - 19th) which represent both sunny and cloudy conditions. Despite the different exposure, Meteo Trentino and IASMA show consistent trends for every day while, obviously, the TRY presents significant discrepancies, especially during the second day.

The second analysed variable is the air change rate, in fact, since the building has no HVAC system, natural ventilation is considered. In particular the effect of infiltration is taken into account since it represents the only source of ventilation.

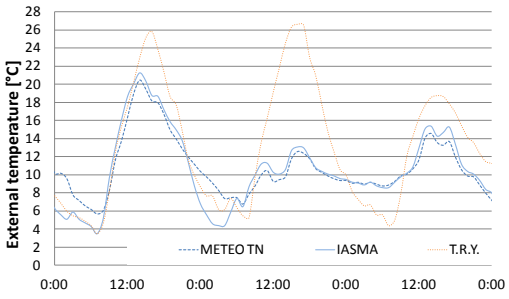


Fig. 2 – External temperature (March 17th - 19th)

Table 1 shows the different air change rates applied in the calculation. The standard values (0.3 and 0.5 ach) are adopted even if they are used for global natural ventilation because the envelope presents numerous cracks and leakages. EN 15242 and the ASHRAE Handbook define standard methods to estimate the infiltration air-change rates, according to envelope features and to local weather data (temperature and wind speed).

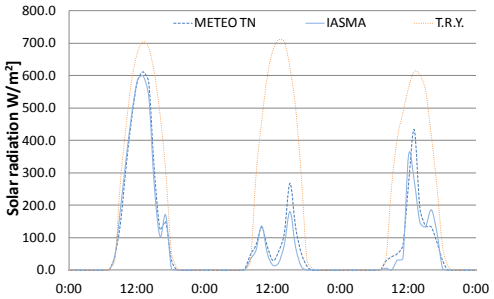


Fig. 3 – Solar radiation (March 17th - 19th)

Code	Air-change rate [h-1]	Standard source
0.3	0.3	UNI/TS 11300-1
0.5	0.5	-
EN	variable	UNI EN 15242: 2008
ASH	variable	ASHRAE Handbook

Table 1 – Air change rates

Finally, the thermo-physical properties of the envelope are evaluated both through standard and experimental analysis. The external wall in zone P3_Z1 is 65 cm thick, it has a high thermal mass and it is built of bricks and sand. Therefore, according to UNI TS 11300-1, the reference structure CO-01 is chosen. Moreover an experimental analysis was carried out conforming to ISO 9869; two couples of HFM and thermo-resistance pt100 were positioned on internal and external surfaces in order to measure surface temperatures, inward and outward heat fluxes. The measurements were carried out over 70 days (March 2nd - May 10th) in order to obtain stable results. The monitored data were post processed with the average method described in standard ISO 9869. The values of conductance for standard and experimental method are reported in Table 2.

Λ [W m-2 K-1]	
Standard approach (STD)	**Experimental approach (MS)**
1.372	1.552

Table 2- Thermal conductance

Starting from the different sources of input data, a series of simulations was carried out with the TRNSYS software. A code identifies each model and it describes which kind of parameter is applied in the analysis. Table 3 shows the set of simulations and it explains which inputs have been implemented.

4. Results of Model Calibration

After the run of the simulation set shown in Table 3, the discrepancies between simulated and real values are evaluated in terms of MBE, RMSE and Pearson's index, for the hourly temperature measured during the monitoring period (March 2nd - June 26th).

The indices give information both for air (air) and for the envelope surfaces (S1 - S2 - S3 - S4 - S5) temperature in the control thermal zone P3_Z1.

MBE in Figure 4 highlights a general underestimation of the predicted temperature with respect to actual data. Moreover, the results of TRY simulations present high discrepancies; in fact MBE generally ranges from 0.05°C to 0.8°C for positive values and between − 0.05 to − 1.4 for negative ones, except for TRY results, whose MBE account for −0.8°C −3.4°C. Obviously, the end of the TRY, and consequently of its calculation procedure, is to be representative of the average weather conditions of the location. For this reason, the TRY does not lend itself to an accurate punctual assessment as it is instead the model calibration. Considering MBE error compensation, this index is not exhaustive to evaluate the reliability of simulations.

RMSE overcomes this problem, because it reveals

the absolute discrepancies between real and simulated values. In this case RMSE indices confirm the previous considerations: in fact TRY simulations have RMSE values next to 4°C (5°C for S2 temperature surface), while the other simulations carried out with real weather datasets range from 1°C to 1.7°C (Figure 5). The other parameters (thermo-physical properties of external walls and air change rates) do not significantly affect the RMSE values.

Input data		IAS_03_STD	TN_03_STD	TRY_03_STD	IAS_05_STD	TN_05_STD	TRY_05_STD	IAS_EN_STD	TN_EN_STD	TRY_EN_STD	IAS_ASH_STD	TN_ASH_STD	TRY_ASH_STD
Weather data	IASMA	x			x			x			x		
	MeteoTn		x			x			x			x	
	TRY			x			x			x			x
Air change rates	0.3	x	x	x									
	0.5				x	x	x						
	EN ISO 15242:2008							x	x	x			
	ASHRAE										x	x	x
Envelope properties	Standard	x	x	x	x	x	x	x	x	x	x	x	x
	Measured												
Input data		**IAS_03_MS**	**TN_03_MS**	**TRY_03_MS**	**IAS_05_MS**	**TN_05_MS**	**TRY_05_MS**	**IAS_EN_MS**	**TN_EN_MS**	**TRY_EN_MS**	**IAS_ASH_MS**	**TN_ASH_MS**	**TRY_ASH_MS**
Weather data	IASMA	x			x			x			x		
	MeteoTn		x			x			x			x	
	TRY			x			x			x			x
Air change rates	0.3	x	x	x									
	0.5				x	x	x						
	EN ISO 15242:2008							x	x	x			
	ASHRAE										x	x	x
Envelope properties	Standard												
	Measured	x	x	x	x	x	x	x	x	x	x	x	x

Table 3 - Set of simulations

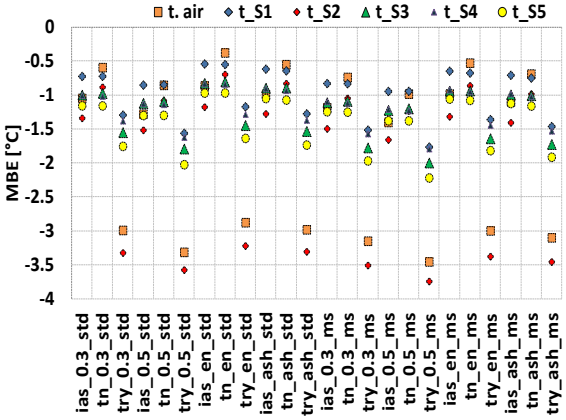


Fig. 4 – Mean Bias Error

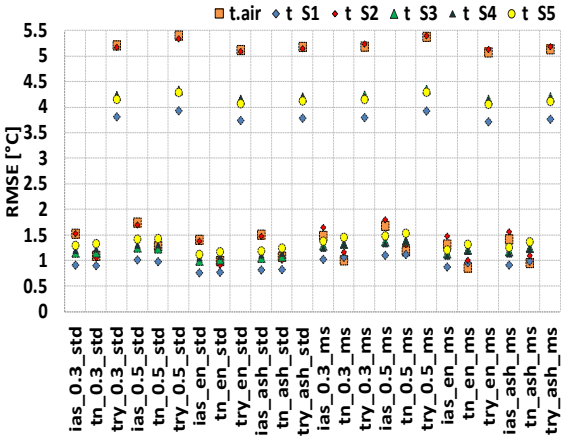


Fig. 5 – Root Mean Square Error

Nevertheless, error indices give information about the global gap between actual and predicted temperature and, in order to understand the reliability of building simulations, it is necessary to evaluate the hourly temperature trends in the control thermal zone, comparing the monitored values and the simulation results.

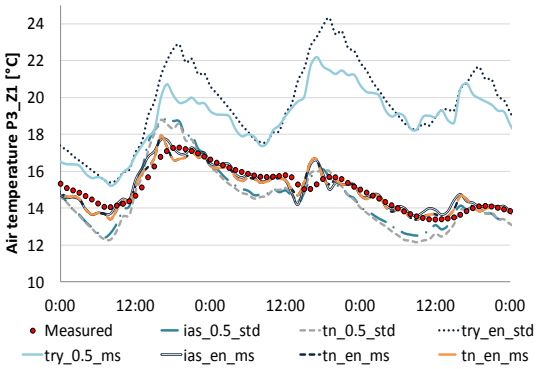


Fig. 6 – Air temperature - April 23rd - 24th

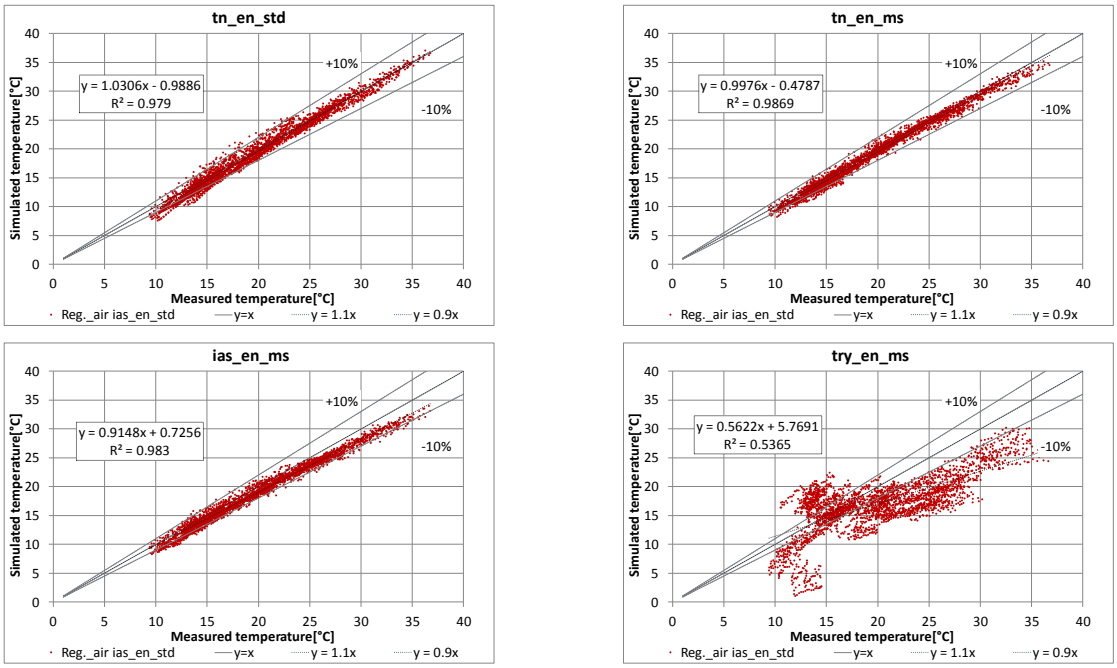


Fig. 7 – Regression analysis t. air P3_Z1 - measured and predicted values

ias_03_std	tn_03_std	try_03_std	ias_03_ms	tn_03_ms	try_03_ms
0.982	0.988	0.711	0.988	0.990	0.742
ias_05_std	**tn_05_std**	**try_05_std**	**ias_05_ms**	**tn_05_ms**	**try_05_ms**
0.979	0.987	0.711	0.988	0.991	0.742
ias_en_std	**tn_en_std**	**try_en_std**	**ias_en_ms**	**tn_en_ms**	**try_en_ms**
0.982	0.989	0.715	0.989	0.992	0.746
ias_ash_std	**tn_ash_std**	**try_ash_std**	**ias_ash_ms**	**tn_ash_ms**	**try_ash_ms**
0.981	0.988	0.715	0.989	0.991	0.746

Table 4 – Pearson's Index for air temperature

In Figure 6 some representative air temperature trends are reported for three days of the calibration period (April 21st-23rd). TRY simulations are featured by different thermal behaviours of the zone, according to the different weather conditions of the standard dataset. The other simulations have more reliable trends, but the models with standard thermo-physical properties reproduce positive and negative temperature peaks higher than real ones, probably caused by the different thermal capacitance of the walls.

Pearson's indices (Table 4) confirm the previous considerations; in fact weather data strongly affect the model results while the other parameters cause slight variations in *r*: air-change rates determine negligible differences, and measured thermo-physical properties increase the correlation between real and predicted values.

Finally, in order to identify the most reliable simulation for internal air temperature, also a regression analysis between measured and simulated temperature is developed. The simulations with air change rates computed by means of EN 15242 are reported in Figure7.

It clearly appears that simulations with standard weather data have low R^2 values, and a significant spread of results, which indicates low correlation between the two variables. The models with real datasets have regression indices close to 1 and a more regular distribution across the regression line; in fact most of the values are include in the tolerance interval of ±10%. In particular, the simulation tn_ash_ms could be considered the most reliable simulation which is obtained applying the calibration procedure.Nevertheless, some discrepancies between predicted and real temperature still affect the model, therefore, in order to refine the model, deeper analysis are necessary. Hence a sensitivity analysis is carried out in order to identify the parameters with an high impact on the model results.

5. Sensitivity analysis

The sensitivity analysis aims to evaluate the influence of input data on the dependent variables which, in the case of building simulations, represent the energy behaviour of constructions. Since in the test case there are no energy systems, the dependent variables are related to the air temperature of the control thermal zone (i.e. P3_Z1). In particular, since the final goal of the energy model will be the system sizing and the evaluation of energy demand, four different indexes are herein adopted and investigated from January 1st to September 30th.

- Minimum temperature (t_{min})
- Maximum temperature (t_{max})
- Zone Heating Degree Hour (HDH_{18})
- Zone Cooling Degree Hour (CDH_{26})

Heating and Cooling Zone Degree Hour indicate the sum of hourly difference between internal set point temperature (i.e. 18°C for heating and 26°C for cooling) and the simulated values for P3_Z1 thermal zone; they are evaluated with the following equations and to a certain extent they are proportional to the heating and cooling demand, as well as minimum and maximum temperature are closely related to the required size of energy system.

$$HDH_{18} = \sum_{i=1}^{n}\left(\vartheta_{i,H,set} - \vartheta_{i,H,sim}\right) \quad (4)$$

$$CDH_{26} = \sum_{i=1}^{n}\left(\vartheta_{i,C,sim} - \vartheta_{i,C,set}\right) \quad (5)$$

In this work, a sensitivity analysis has been carried out with a local external approach using two different procedures, i.e. differential sensitivity analysis and factorial method, with the aim of evaluating which parameters have to be refined in order to improve the model results, according to the limited resources in terms of experimental analysis.

5.1 Differential sensitivity analysis

The Differential Sensitivity Analysis (DSA) works by perturbing an input data around the mean value while all the other parameters remain fixed. For each perturbed value the numerical simulation is carried out and the model response is calculated. Due to its robustness and simplicity, the DSA is the most diffused method for a local uncertainty evaluation. The effects of an uncertain parameter are estimated by comparing the results of these simulations against those with unperturbed inputs. Consequently, a sensitivity index of the model prediction to the uncertain parameter is defined as:

$$s = \frac{\Delta O}{\Delta I} \quad (6)$$

where O is the model output and I is the perturbed input (the other parameters influencing the output are held fixed). Since the absolute sensitivity index depends on the magnitude of parameter perturbation, a direct comparison between different variable influences is not possible. In order to overcome this aspect, a percentage sensitivity index is defined as

$$s_{\%} = \frac{{}^{\Delta O}/_{O_{un}}}{{}^{\Delta I}/_{I_{un}}} \quad (7)$$

where O_{un} is the model output with unperturbed input and I_{un} is the unperturbed input.

For the analysed building, the following inputs are perturbed applying a ±10% variation to the original value of:

- Infiltration air change rates (Q_{4Pa})
- Roof thermal transmittance (U_{roof})
- Wall thermal transmittance (U_{wall})
- Intermediate Floor thermal transmittance (U_{floor})
- Roof thermal capacitance (κ_{roof})
- Wall thermal capacitance (κ_{wall})
- Floor thermal capacitance (κ_{floor})
- g-value for glazing systems (g-value)

In Figure 8 the computed $s_{\%}$ for HDH_{18} and CDH_{26} are reported for each case analysed. Note that for CDH_{26}, g-value and roof thermal transmittance are the most influent parameters. Besides, for these variables, the indices have a positive sign which indicates a direct correlation. The greater the input values the higher the CDH_{26} and, consequently, the cooling demand. The other indices are negative but the magnitudes of sensitivity index are close to zero and therefore they indicate an inverse correlation. The graphs highlight the role of thermal capacitance both of the wall and roof in smoothing over the cooling demand. It is also interesting to note the negative correlation between

CDH_{26} and the wall thermal transmittance. This means that for the test case the night heat losses prevail on the inward heat losses.

Similarly, the graph shows the percentage sensitivity indexes for HDH_{18}. Figure 8 highlights again the role of g-value in the building energy demand. It should be emphasized that a direct comparison between the percentage sensitivity index of CDH_{26} and HDH_{18} is not possible. In fact, the low value of CDH_{26} for unperturbed input stresses the magnitude of the percentage sensitivity index. In order to understand if each input affects

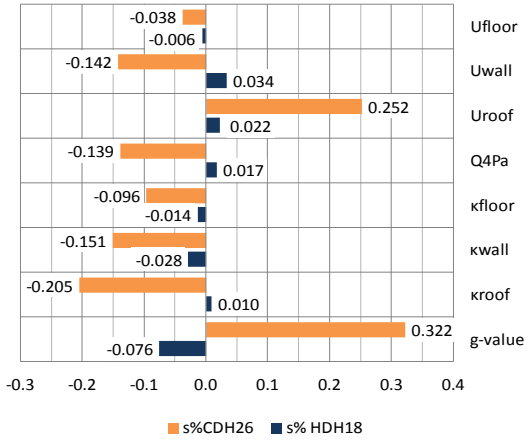


Fig. 8 – $s_{\%}$ for Cooling and Heating Degree Hour

	HDH_{18}	CDH_{26}	$s(HDH_{18})$	$s(CDH_{26})$	
Base	26316.8	8568.2			
U_f	26301.6	8535.5	-211.6	-98.6	°C h [W/(m² K)]$^{-1}$
U_w	26405.5	8446.5	733.9	-1005.6	°C h [W/(m² K)]$^{-1}$
U_r	26375.4	8783.9	453.7	1670.5	°C h [W/(m² K)]$^{-1}$
Q_{4Pa}	26362.5	8449.3	76.1	-197.9	°C h (m³/h)$^{-1}$
κ_f	26362.5	8449.3	-7.5	-17.3	°C h[kJ / (m² K)]$^{-1}$
κ_w	26241.9	8438.7	-11.5	-19.9	°C h[kJ / (m² K)]$^{-1}$
κ_r	26342.1	8392.1	3.0	-21.2	°C h[kJ / (m² K)]$^{-1}$
g	26118.1	8843.9	-2450.4	3401.5	°C h

Table 5 – Sensitivity index (s) for HDH_{18} and CDH_{26}

more deeply HDH_{18} or CDH_{26}, the dimensional index s has to be adopted (Table 5).

In Figure 9 percentage sensitivity indices for minimum and maximum air temperatures are reported for each perturbed input.

The graph shows that thermal capacitance of the envelope strongly affects both minimum and maximum temperature. Lower magnitude is registered for the other parameters and in particular is interesting to note the low effects of g-values on CDH_{26} with respect to envelope capacitance.

Even in this case, in order to define if a single input causes higher differences for t_{min} than for t_{max}, the sensitivity analysis has to be integrated by s index (Table6).

The main weakness of differential analysis is the assumption of perfect independency among all parameters. Consequently, the combined effects can be estimated by a superposition only in case of a linear problem. With the aim of overcoming this issue, the Factorial Method (FM) is also applied in this work. This analysis allows to investigate the extent to which input data have a synergic effect on the simulation results.

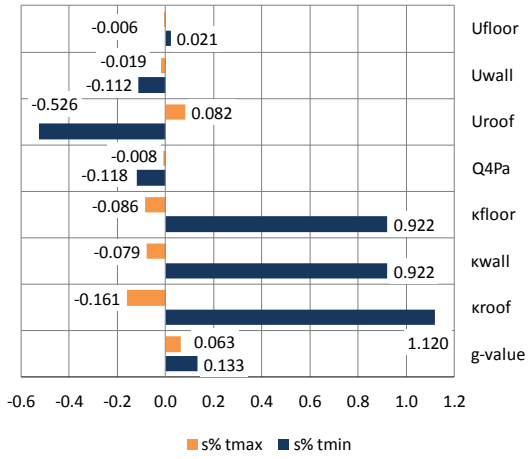


Fig. 9 – $s_{\%}$ for minimum and maximum air temperatures

	t_{max} [°C]	t_{min} [°C]	$s(t_{max})$	$s(t_{min})$	
Base	36.270	-2.710			
U_{floor}	36.250	-2.702	-0.132	0.037	°C/[W/(m²°C)]
U_{wall}	36.250	-2.702	-0.563	-0.25	°C/[W/(m²°C)]
U_{roof}	36.568	-2.851	2.303	-1.102	°C/[W/(m²°C)]
Q_{4Pa}	36.241	-2.740	-0.048	-0.053	°C/(m³/h)
κ_{floor}	35.959	-2.458	-0.065	0.052	°C/[kJ/(m²°C)]
κ_{wall}	35.984	-2.458	-0.044	0.038	°C/[kJ/(m²°C)]
κ_{roof}	35.685	-2.405	-0.070	0.037	°C/[kJ/(m²°C)]
g-value	36.500	-2.672	2.829	0.443	°C

Table 6 – Sensitivity index (s) for t_{min} and t_{max}

5.2 Factorial analysis

The FM is a further development of the DSA approach, which includes the interactions between parameters and permits the estimation of the high order effects. In this procedure three parameters

are perturbed simultaneously around their mean values: wall thermal capacity, floor thermal capacity and g-value for glazing surfaces.
In this case two different perturbation levels are considered: +5% and -5%. The drawback of this technique is the number of simulations required that is factorially related to the number of inputs.
The implementation of the factorial method is essentially the same as for the differential method. The main difference is that multiple parameters are perturbed simultaneously in the same simulation process. Consequently, the possible synergistic effects of variable perturbations can be observed. The factorial design scheme is developed according to three-variables analysis (e.g. MacDonald 2002 and Prada 2012).
The first order effects of each variable perturbation can be determined by combining the simulation results as reported in the following equations:

$$F_{kf} = \frac{(Z_2+Z_4+Z_6+Z_8)-(Z_1+Z_3+Z_5+Z_7)}{4} \quad (8)$$

$$F_{kw} = \frac{(Z_3+Z_4+Z_7+Z_8)-(Z_1+Z_2+Z_5+Z_6)}{4} \quad (9)$$

$$F_{g} = \frac{(Z_5+Z_6+Z_7+Z_8)-(Z_1+Z_2+Z_3+Z_4)}{4} \quad (10)$$

Similarly, the high order effects are given using the signs founded by multiplying the sign of the individual variable state (e.g. MacDonald 2002) and the indices are determined as:

$$F_{kf-kw} = \frac{(Z_1+Z_4+Z_5+Z_8)-(Z_2+Z_3+Z_6+Z_7)}{4} \quad (11)$$

$$F_{kf-g} = \frac{(Z_1+Z_3+Z_6+Z_8)-(Z_2+Z_4+Z_5+Z_7)}{4} \quad (12)$$

$$F_{kw-g} = \frac{(Z_1+Z_2+Z_7+Z_8)-(Z_3+Z_4+Z_5+Z_7)}{4} \quad (13)$$

$$F_{kw\,kf\,g} = \frac{(Z_2+Z_3+Z_5+Z_8)-(Z_1+Z_4+Z_6+Z_7)}{4} \quad (14)$$

In order to compare the results both for degree hour indices and for internal peak temperatures, also the relative factorial factors are used; these indices are calculated by dividing the results of the previous equations for the unperturbed output. The indices reported in Table 7-8 are consistent with the results of differential analysis.
Regarding first order, the factorial method confirms that HDH_{18} and CDH_{26} are less affected by thermal capacitance of floor, whose index is of an order of magnitude lower than $F_{\kappa wall}$ and $F_{g\text{-}value}$ (both the absolute and the relative ones). The results of factorial analysis show weak second order effects and the link between variables has generally a negative sign, which means that there is not a synergic effect. Therefore the assumption of perfect independent variables of the DSA approach has been proved.

	CDH_{26} [Ch]	HDH_{18} [Ch]	t_{max} [°C]	t_{min} [°C]
$F_{\kappa f}$	-32.87	-24.58	-0.055	0.060
$F_{\kappa w}$	-258.62	-110.72	-0.525	0.495
F_{g}	612.88	-444.06	0.500	0.085
$F_{\kappa f-\kappa w}$	3.52	1.97	0.000	0.000
$F_{\kappa f-g}$	-0.10	-0.06	-0.005	0.000
$F_{\kappa w-g}$	-5.66	-3.59	-0.015	0.005
$F_{\kappa w\,kf\,g}$	0.12	-0.69	0.000	0.000

Table 7- Factorial analyses - dimensional indices

	CDH_{26}	HDH_{18}	t_{max}	t_{min}
$F_{\kappa f}$	-0.0038	-0.0009	-0.0015	0.0221
$F_{\kappa w}$	-0.0302	-0.0042	-0.0145	0.1827
F_{g}	0.0715	-0.0169	0.0138	0.0314
$F_{\kappa f-\kappa w}$	0.0004	0.0001	0.0000	0.0000
$F_{\kappa f-g}$	0.0000	0.0000	-0.0001	0.0000
$F_{\kappa w-g}$	-0.0007	-0.0001	-0.0004	0.0018
$F_{\kappa w\,kf\,g}$	0.0000	0.0000	0.0000	0.0000

Table 8- Factorial analyses - relative indices

6. Conclusion

The thermal behaviour of a historical building without HVAC system is investigated, therefore a calibration procedure using the internal temperature measured in a control thermal zone is developed.
MBE and RMSE, and Pearson's index with regression analysis are employed to assess the errors and the correlation between predicted and real temperature. With these indexes, the set of main parameters that ensure the best prediction of air and surface temperature compared against actual data has been determined.
Nevertheless there are still some discrepancies between predicted and real temperature so, in order to understand the most influent parameters, a sensitivity analysis has been carried out.

The sensitivity analysis highlights that the necessity to improve the knowledge of input data depends on the final goal of the energy model. In fact, if the model is to be used for energy system sizing, the reliable estimation of the thermal capacitance of the envelope will assume a key role. On the other hand, for the consistent calculation of the building energy performance the estimation of the glazing solar transmittance and of the roof thermal transmittance becomes more important.

In particular g-value for glazing system and roof thermo-physical properties affects both summer and winter energy demand; and thermal capacitance of the roof significantly influences the temperature peaks. Finally, the Factorial Method confirms the negligibility of the high order effect of the input data analysed. Consequently these parameters have not a synergic effect in the model predictions.

Further investigations are necessary and, according to the aim of the optimization, different parameters have to be refined, according to the results of the sensitivity analysis.

7. Nomenclature

Symbols

CDH_{26}	Cooling degree hours base on 26°C
F	Sensitivity index for factorial method
HDH_{18}	Heating degree hours base on 18°C
k	Specific heat capacitance [J m^{-2} K^{-1}]
n	Number of Simulation Steps (hours)
s	Sensitivity Index (DSA)
R^2	Regression Index
U	Thermal transmittance [W m^{-2} K^{-1}]
Z_j	Model response of the j-th simulation

Greek symbols

Λ	Thermal Conductance [W m^{-2} K^{-1}]
θ	Dry bulb temperature [K]

Subscripts

C	Cooling
f	Floor
H	Heating
I	Internal
r	Roof
sim	Simulated
set	Setpoint
w	wall

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