RELIABILITY OF DYNAMIC SIMULATION MODELS FOR BUILDING ENERGY IN THE CONTEXT OF LOW-ENERGY BUILDINGS

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ABSTRACT

Within the framework of building energy simulation, empirical validation has been used for many decades. This paper presents a first step in the empirical validation of simulation tools in the context of low-energy buildings. We were interested in comparing results provided by two pieces of software for dynamic energy simulation Dymola and Pléiades+Comfie - to measurements from the experimental platform BESTLab built on the EDF site of the Renardières (France). Then a methodology was developed in order to identify the most influential parameters on simulations and to determine their influence on model predictions using sensitivity and uncertainty analyses.

INTRODUCTION

With 44% of the total energy consumption, the building sector is the first energy consumer in France and one of the most polluting with 25% of the total national CO2 emissions (e.g. ADEME, 2011). The building sector has to reduce its energy consumption in a context of global warming and fossil fuels rarefaction. Thus, the construction of low, passive and positive energy buildings should become a standard and simulation tools must be used to achieve such goals.

Reliable predictions are fundamental so as to be able to guarantee the building's energy performance. Even more so now that some generally accepted modeling assumptions for standard buildings may no longer be valid because of the increase in the building's performance. Moreover, a physical phenomenon previously neglected or inadequately considered for standard buildings could become preponderant for low-energy buildings and distort the simulation predictions should it not be reconsidered. Therefore, we must ensure that the physical models are able to represent the behavior of low-energy or very low-energy buildings just as the simulation results must reflect the uncertainty effects related to the design parameters, the solicitations and the building uses. In this context, many studies have been conducted over the years to compare simulation results to measurements taking their respective uncertainties into account, with local and global sensitivity analysis methods (e.g. Spitz, 2012, Mara et al., 2002).

This article presents a methodology developed as a first step of an empirical validation. To begin with, we provide a description of the chosen dynamic simulation tools for building energy. Then, we describe the experimental platform BESTLab and the studied test case. Finally, a methodology is set up with local and global sensitivity analysis methods to determine the most influential parameters on the predicted operative temperature while considering their respective uncertainties.

TOOLS

Two simulation tools were used for this study: one is rather used by researchers (Dymola) and the other one by design offices (Pléiades+Comfie).

Dymola is a commercial modeling and simulation environment developed by Dassault Systems and specialized in the resolution of dynamic and complex multi-physics systems for use within various applications such as automotive or robotics. As this environment uses the open Modelica® modeling language, besides standard libraries (e.g. Modelica), users are able to create their own model libraries for their specific simulation needs. In that way, EnerBAT, a department of EDF R&D, has developed its own library dedicated to dynamic simulation for building energy and related energy systems. This library was used for this study, restraining the test case model to a thermal model only (without hygrometry or pressure). The matrix system obtained was solved using the DASSL solver with a variable time step.

Pléiades+Comfie is a dynamic simulation tool for building energy developed by the Centre for Energy and Processes (CEP) of MINES ParisTech in collaboration with Izuba Energies. With this software it is possible to estimate comfort levels, heating and cooling needs (requirements) thanks to a multi-zone model. It consists in the reduction of a finite difference model using modal analysis in order to decrease computing time. The Comfie numerical model cannot be modified directly to model test cases since all the information on building components, environment, scenarios and weather are provided via the software interface Pléiades.

BESTLAB PLATFORM

The BESTLab platform was built in 2010 in the context of low-energy buildings. It aims to test innovative envelope components and building-integrated solar technologies. It is located at the Renardières site, at about 75 km southeast of Paris in a rural environment without any close obstacle on its Southern façade. In this section, BESTLab's physical features and modeling hypotheses are described.

Studied cell characteristics

- Envelope and geometry:

The test facility's goal is to compare different building technologies within several cells at the same time. For this purpose twelve independent cells were built in the same building and distributed on two floors. On each level the cells are disposed as follow: four South oriented cells, one to the East and one to the West (Figure 1).

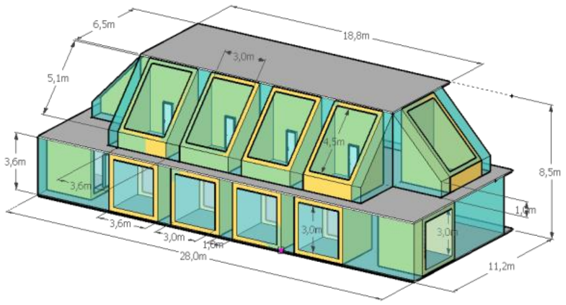

Figure 1: BESTLab platform

In each cell, only one wall (the test wall) is in contact with the outside. The others are over-insulated (U<0.1 W/m².K) and kept at a constant temperature through the contact they have with the thermal guard that is maintained at a certain temperature. Only the RDC_SUD2 (Figure 2) cell was taken into account. It is on the ground floor, South-facing and built with a low-emissivity double glazed window with a layer of argon.

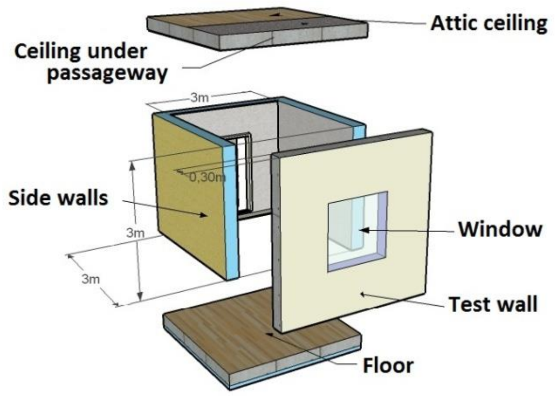

Figure 2: Description of the test cell studied

The setting of the window in retreat within the test wall (Figure 3) creates solar shading that must be taken into consideration when running simulations.

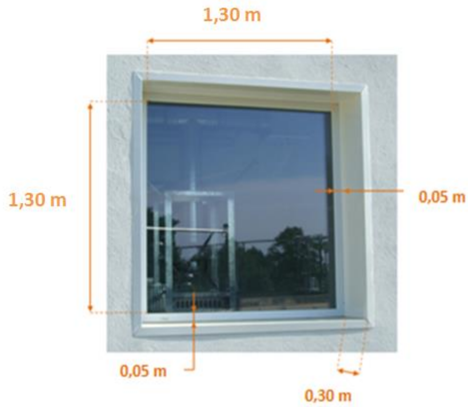

Figure 3: Window of ground floor test cell

- Infiltration:

Infiltration into the building's test cells was minimized during construction as has been confirmed by permeability measurements ($Q_{4PaSurf}$ coefficient is less than 0.5 m^3/h.m²). Therefore, it indicates a very good air tightness of the test cells. During the construction of the ETNA platform, adjoining the BESTLab facility, a study also showed that infiltration due to wind could be neglected (e.g; Barmaud, 1987).

Cells are not fitted with air vents, so that the cells' ventilation can be viewed as non-existent.

- Thermal bridges:

Limitation of thermal bridges was carefully investigated when designing and building the test facility. Nevertheless, thermal bridges can still be pointed out at a few singular points associated with the test wall which was designed to be replaceable, and with the floor slab which runs through the entire building.

On Dymola, thermal bridges are modeled using a single conductance between an indoor air node and the concrete floor. On Pleiades+Comfie, thermal bridges can model junctions between the outside façade and low and intermediate floors, window sills and doors. The values are chosen according to the thermal regulation values included in the software.

- HVAC system:

An air control unit with inertia of approximately 50 000 J/K is set up in the test cell (Figure 4). It aims at ensuring heating with an electrical resistance, cooling using an external cold battery and air temperature homogeneity by mixing. As it is impossible to create this air control unit on Pléiades+Comfie, its inertia is represented by the insertion of furniture with higher inertia (100 Wh/K) in the thermal zone that matches the test cell.

Figure 4: HVAC system

- Sensors and measurement uncertainties:

The cell is equipped with a lot of sensors, with data acquisition every minute. Measured variables and sensors used in this study are:

- Temperatures, measured using Pt100 sensors with an uncertainty of 0.1°C. They are located in near-wall air but also on external surfaces, internal surfaces and within the wall structure.
- Radiation temperature, measured using a black globe temperature sensor with an uncertainty of 0.5°C.
- Heating power and dissipated energy by the fan measured with a pulse counter, with an uncertainty of 0.1 Wh for the heating power and of 1 Wh for the dissipated energy.
- Cooling power measured using two water temperature Pt100 sensors, with an uncertainty of 0.1°C and an electromagnetic flow meter, with a precision of 0.5%.

Moreover, a weather station was built close to the test facility. It measures external parameters with a continuous acquisition system (every minute). Measurements used for this study and associated uncertainties are:

- Outside dry temperature measured using a Pt100 sensor with an uncertainty of 0.1°C.
- Global and diffuse solar radiations measured using two pyranometers with an uncertainty of 0.2% until an incidence of 40° then 3% for the global solar radiance and 0.2% for the diffuse solar radiance for an incidence of 80°.
- All data is given with a time step of 5 minutes on Dymola. This results from a compromise between the simulation duration and the accuracy to be reached, as the time step of the solver is variable. On Pléiades+Comfie, only the one-hour time step can be used. Moreover, temperatures, solar radiations, humidity, wind speed and powers are rounded up to the unit on this software, except for outside temperature rounded up to the tenth of degree.

COMPARISON BETWEEN MEASUREMENTS AND SIMULATIONS

Case study: Power step response

In this study, results obtained with Dymola and Pléiades+Comfie are compared with measurements coming from the RDC_SUD2 cell of the BESTLab platform over a period of 10 days in May 2011 (Figure 5).

Over this period, after a free evolution (1: test cell is only subject to outside climate variations without any internal power supply), the cell undergoes a cooling set point (2), and then a power step input (3). Lastly, another free evolution begins (4).

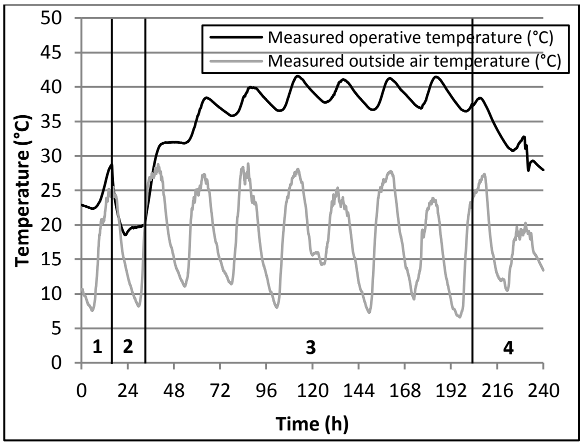

Figure 5: Experimental sequence

Various simplifying assumptions had to be made in addition to those mentioned before. The most important are:

- Wall surfaces are measured on the inside and the cell is simulated as a single thermal zone. On Pléiades+Comfie, a thermal zone is added behind every wall that is in contact with the thermal guard. Temperatures in these thermal zones are supposed constant and equal to 20°C, except for the thermal zone under the floor where the temperature measured in the middle of the floor is used. Thus, only half of the floor was modeled.
- Radiative and convective heat transfers are taken into account in a global constant coefficient which is different between both pieces of software. It depends on the angle and optical properties of the walls, in addition to wind exposure outside (e.g. Barnaud, 1987).
- The initialization of the dynamic simulation tool is different for each program. Initialization is an important step in an experimental validation since it strongly impacts the numerical results of the first day. On Dymola a steady state initialization is performed by using the first measurement values for each time varying input. This is

implemented through an initialization equation written in Modelica. On Pléiades+Comfie the first study day in terms of weather data is repeated from January to April with an initialization for the inside temperature at 23°C. Then, three full 10-day periods are simulated and only the last one is used to do the comparison.

Results

Both pieces of software calculate a zone temperature equivalent to an operative temperature (average of the mean radiant and ambient air temperatures). Figure 6 presents a comparison of the operative temperatures resulting from the simulations and from the measurements. An uncertainty margin equal to ±0.5°C is considered on the measured operative temperature. Figure 7 shows the results in terms of residue of operative temperature, calculated as:

(1)

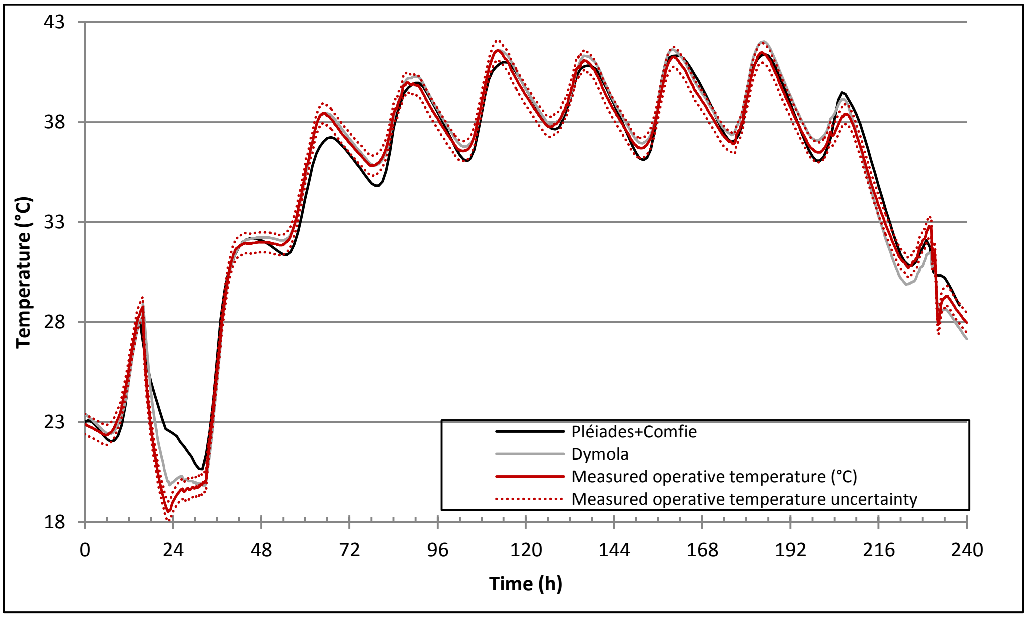

Figure 6: Operative temperature estimated vs. measurements.

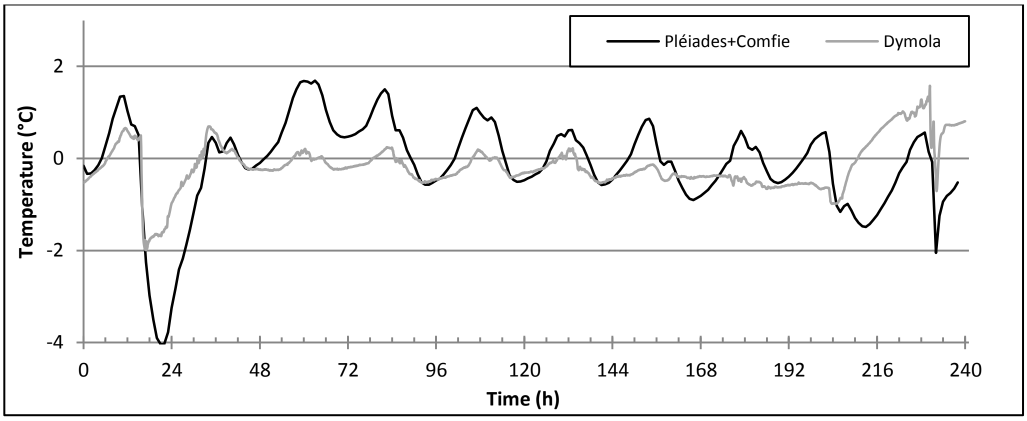

Figure 7: Residue of operative temperature

SENSITIVITY AND UNCERTAINTY ANALYSIS

Local sensitivity analysis

The local sensitivity analysis aims at determining the most influential input parameters on the simulation result which in this case is the operative temperature. As it classifies the impacts of parameters on the output, this method allows us to highly reduce the number of input parameters before applying a global sensitivity analysis with usually higher CPU time needs. The one-step-at-a-time method (OAT) is applied so that in each run only one input parameter value is changed by 5 percent around its nominal value. The local sensitivity index S_i for each parameter X_i is defined as:

$$(\,)\ \left(\frac{}{(\,)}\right)\frac{(\,)}{}\Bigg| \qquad (2)$$

Correlation analysis

After the local sensitivity analysis, a correlation analysis is performed in order to reduce the number of parameters by creating groups of parameters with similar effects. The degree of correlation $r_{i,\,j}$ between two parameters X_i and X_j is defined as:

$$\frac{-\sum \quad ( ) \qquad S(t)}{} \tag{3}$$

A coupling is made between the Dymola model and a program written in Python to perform the calculations needed and to post-treat the results.

Global sensitivity analysis

- Objectives

The first step was to select parameters that have a real influence on the operative temperature inside the experimental cell. It was performed by changing one parameter at a time around its nominal value. The global sensitivity analysis purpose is to examine changes of the result when all parameter values change over their uncertainty range. Therefore, this second analysis is more interesting than the first one. Furthermore, it is best suited for experimental validations when some parameters are well known.

- Simulation methodology

We used for these calculations Open TURNS, an open source platform developed by EDF, EADS and Phimeca and dedicated to uncertainty treatment by probabilistic methods (www.openturns.org). Open TURNS is usable as a Python module so that the coupling between Dymola and Python is kept, as for the local sensitivity analysis.

The global sensitivity of a given output T at time t to an input variable X_i (taken alone and not in interaction with any other inputs) is quantified by the following first-order Sobol index (Sobol, 2001):

$$( ) \quad \frac{(\; [\; ( ) \quad])}{(\; ( ))} \tag{4}$$

Where E[.] E[.|.] and Var[.] denote the mathematical expectation, the conditional mathematical expectation and the variance, respectively. Note that it is also possible to evaluate the influence of interactions between several input variables.

The Sobol indices can be estimated using a Monte Carlo approach, which relies upon a huge number of model evaluations, say 10^{-5}-10^{-6}. As this approach would be too time-consuming for our study case, we resort to an alternative method based on polynomial chaos expansions (Soize et al., 2004). In this setup, the model response $T(t)$ is expanded onto a specific basis made of orthogonal polynomials, namely the Polynomial Chaos (PC) basis. Then the Sobol indices are obtained analytically from the PC coefficients (Sudret, 2008). Hence the computational cost is focused on the estimation of the latter. The advantage of the PC approach over the "crude" Monte Carlo one is that the estimation of the PC coefficients often requires a relatively small number of model evaluations, say 100-1000.

The PC coefficients can be estimated by means of a set of model evaluations at random sets of input parameters (Monte Carlo sampling method). Nonetheless, as shown in Blatman et al. (2007), the convergence rate of estimation can be improved using the so-called quasi-Monte-Carlo sampling method (Morokoff et al., 1995). The efficiency of this scheme is due to the fact that it guarantees an excellent coverage of the variation domain of the input variables (space filling design).

Once the model has been evaluated at the design points, the PC coefficients are typically computed using a classical least squares approach. However, as done in Blatman et al. (2011), we prefer using a sparse least squares scheme, i.e. a method which automatically sets the insignificant coefficients to zero. Indeed, this method is known to be more robust and converges more rapidly than ordinary least squares. Precisely, the so-called Least Angle Regression (LAR) method was used (Efron et al., 2004).

The Open TURNS implementations of the quasi-Monte Carlo and LAR-based PC methods were used to solve the problem under consideration. 500 quasi-Monte Carlo samples were generated and the evolution versus time of the first-order Sobol indices (Saltelli et al., 2000) was determined for each parameter.

RESULTS, ANALYSIS AND DISCUSSION

Local sensitivity analysis

To carry out the local sensitivity analysis, most of the input parameters were considered, i.e. 193 parameters including: dimensional data (surfaces, material thicknesses, cell volume, dimensions of the solar shading) ; optical data (absorptivity and emissivity of walls, transmittance and absorptivity of double glazing, albedo of the environment) ; thermal characteristics of materials (conductivity, density, specific heat capacity) ; internal and external convective coefficients ; characteristics of the HVAC system (inertia and convective factor associated to the air mixing) ; thermal bridge conductance ; initialization of the cell air temperature.

Figure 8 represents the sensitivity indices of a few parameters as a function of time (Table 1 indicates the physical meanings of the X_i parameters). It shows different behaviours with influential parameters that consistently impact the output and others with strong temporal variations.

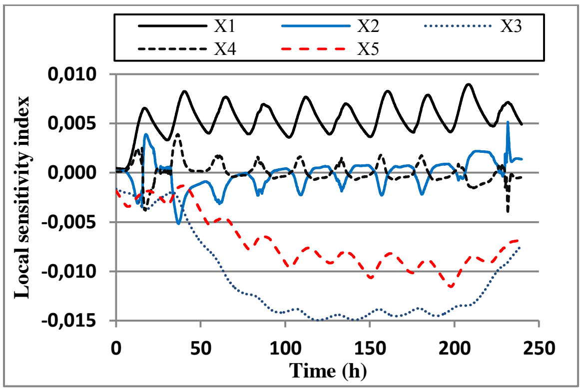

Figure 8: Local sensitivity indices versus time.

In order to keep parameters with a small mean value but a high variation in time, they were sorted from the most to the least influential by calculating their distance $S_{i,d}$ throughout the studied period (10 days). The distance is defined as a function of the mean $S_{i,m}$ and the standard deviation $S_{i,std}$ of the sensitivity indices $S_i(t)$:

$$S_{i,d} = \sqrt{S_{i,m}^2 + S_{i,std}^2} \tag{5}$$

In order to discard many parameters, we chose to retain the parameters with a distance greater than 0.002 which corresponds to a temperature variation of approximately 0.1°C. Consequently, 14 parameters were retained.

Then, on the plots of sensitivity indices as a function of time we checked if we had not dismissed some parameters with a strong instantaneous influence, i.e., if they have a sensitivity index greater than 0.1°C during the free evolution or the cooling period but not during the power step input and vice versa. Hence, 2 more parameters were selected.

Correlation analysis

A correlation analysis was carried out in order to remove correlated parameters which have the same effect on the output. When the degree of correlation $r_{i,j}$ between two parameters is higher than 0.99, they are supposed to be correlated and only the parameter with the highest distance is retained. 13 groups were found by using this method and the number of parameters previously selected was reduced to 13 (Bontemps et al., 2013).

Thus, among 193 parameters at the beginning of the study, 13 parameters (Table 1) remained as influential parameters on the operative temperature estimated by Dymola, using local sensitivity analysis.

Table 1
Parameters selected after local sensitivity analysis

X_1	Albedo	X_8	Test wall surface
X_2	HVAC system inertia	X_9	Window surface
X_3	Thermal bridge conductance	X_{10}	Floor surface
X_4	Convective factor associated to the HVAC system	X_{11}	Window frame overhang
X_5	Glazing thermal transmittance	X_{12}	Window width
X_6	Glazing direct transmittance	X_{13}	Window height
X_7	Glazing diffuse transmittance		

Global sensitivity analysis

The convergence of the various global sensitivity indices was considered to be attained with respect to the size of the quasi-Monte Carlo sample, as illustrated for instance in Figure 9 for input variable X_1.

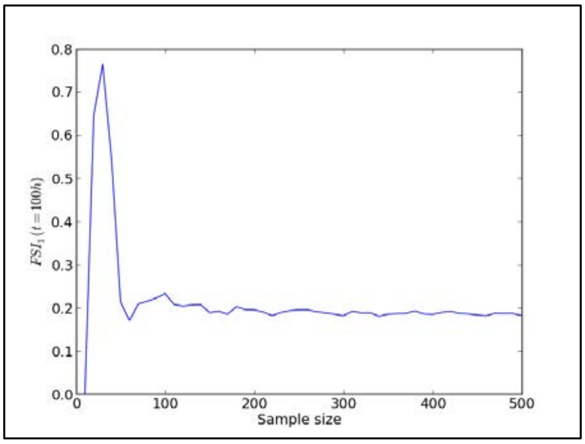

Figure 9: Convergence of the calculations with the sample size for parameter X_1 at time t=100h

Besides, Figure 10 shows the sum over all the parameters of the first-order Sobol indices versus time. Since this sum is very close to unity, it demonstrates that there is no interaction effect between the remaining parameters. Indeed, it is shown that the various indices (related not only to the input variables taken separately but also to interactions thereof) sum up to one (Sobol, 1993). Therefore, there was no need to compute higher order indices for the current study.

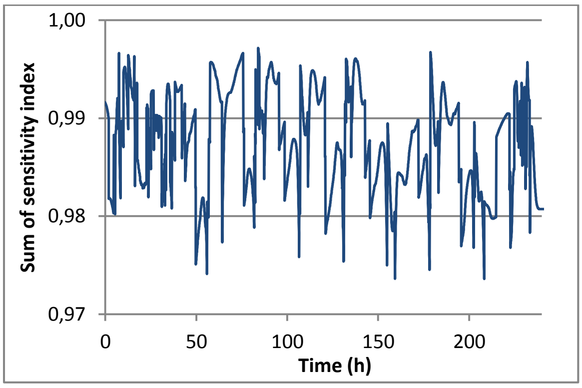

Figure 10: Sum over the parameters of the first-order Sobol index

Once the reliability of the calculations was verified, we could analyze the results. Firstly, the sensitivity indices are equal to zero during all the sequence for parameters X_8, X_9, X_{10}, X_{12} and X_{13}. It should seem surprising since they were selected from non-zero local sensitivity indices. This may be due to the sparse least squares scheme which forces all the low indices to zero.

Secondly, we observed in Table 2 the predominance of two parameters: the environment albedo and the thermal bridge conductance with respectively a mean sensitivity index of 40% and 50% and maximum values near 90%.

Table 2
Maximum value of first-order Sobol indices

X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_{11}
0.87	0.07	0.89	0.27	0.01	0.02	0.02	0.05

Based on these observations, Figure 11 indicates the evolution of the three most important first-order Sobol indices as a function of time. The main observation is that there is an inversion of the influence of the albedo and the thermal bridge conductance between the power step input period and the other experimental sequences. This indicates that in order to proceed to a better identification of thermal bridges due to construction design one should consider an experimental sequence with a power step response. In the same way, results showed that parameters of the HVAC system (inertia and convective factor) are influential in free-floating and cooling periods.

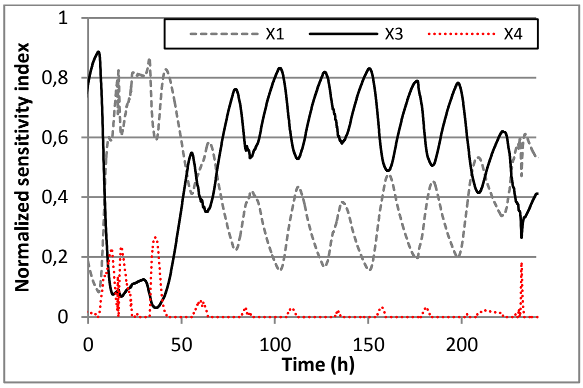

Figure 11: First-order Sobol indices versus time.

The influence of one parameter on the output can be seen by drawing scatter plots at selected times, i.e. a representation of the input-output sample in the (X_i,T) planes (Saltelli et al., 2000). Figure 12 indicates the evolution of operative temperature which increases with the thermal bridge conductance and it shows that the uncertainty on the output is around 2.9°C when the value of the thermal bridge conductance fluctuates between 3 and 4 W/K. Note that the experimental value is 37±0.5°C at that time and it matches with the uncertainty range of the temperature estimated with Dymola.

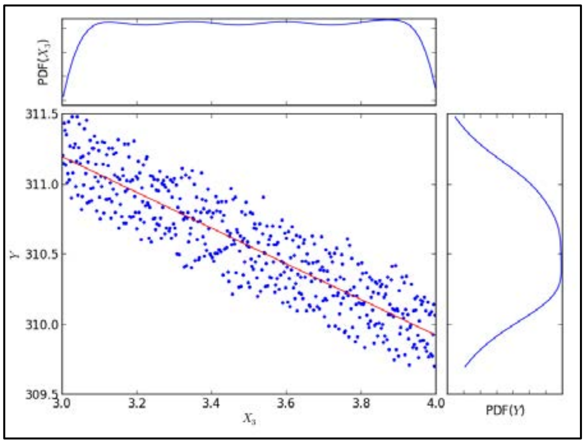

Figure 12: Scatter plot for parameter X_3 at t=100h

CONCLUSION

In this paper, a comparison between Pléiades+Comfie and Dymola demonstrates the capability of such pieces of software to represent the thermal behavior of experimental rooms. Nevertheless, modeling efforts were more important on Pléiades+Comfie since it is not a tool designed for such comparisons and some additional hypotheses had to be made.

In a first step, the problem was downsized by fixing 180 input parameters out of 193 to their nominal values. This was achieved using local sensitivity analysis. The influence of the 13 remaining parameters was analyzed in details by means of a global sensitivity analysis, which accounts for the variability of the variables over their whole variation domain. The global sensitivity analysis contributed to exclude from experimental comparison some well-known parameters such as surfaces or radiative properties.

First-order Sobol indices were evaluated over time and some parameters were then identified to be influential only for specific experimental sequences among the three boundary conditions applied in the test cell: free-floating, cooling set point and power step input. This point is important in order to better understand the physical phenomena modeled via the following parameters: thermal bridge conductance, albedo and convective factor associated to the HVAC system.

In particular, the albedo value will soon be measured with an albedometer near the BESTLab platform instead of using a guess value which remained constant in the model. The identification of structural defects modeled by thermal bridges will also be an important subject of study.

NOMENCLATURE

re	= residue
$y_{measure}$	= measured operative temperature, °C
$y_{simulation}$	= estimated operative temperature, °C
X	= input parameter
T	= operative temperature, °C
S	= local sensitivity index
FSI	= first-order global sensitivity index
r	= degree of correlation
N	= parameter number

Subscript and superscript

0	= nominal value
d	= distance
m	= mean
std	= standard deviation

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