UNCERTAINTY ANALYSIS IN BUILDING SIMULATION: A CASE STUDY IN LOW-INCOME DWELLINGS IN BRAZIL

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ABSTRACT

The main objective of this paper is to assess the uncertainty related to user behaviour in building simulation. Schedules for occupancy, household appliances and lighting, and windows and doors operation were obtained based on a sample of 16 low-income dwellings in Southern Brazil. Some analyses were performed, i.e., a sensitivity analysis to determine the most important parameters, and an uncertainty analysis based on factorial sampling. The main conclusion is that the user behaviour (schedules of occupancy and window operation) and the number of inhabitants generate considerable uncertainty in the simulations, and affect the statistical tests of means and individual values.

INTRODUCTION

The residential electricity consumption represented 23.6% of the total electricity consumption in Brazil in 2011 (Brasil, 2012), which is the second largest consumer behind the industrial sector. This fact justifies the need for energy efficiency researches on residential buildings using consolidated tools that can evaluate their thermal performance and energy consumption, i. e., the building simulation programmes.

Degelman (1999) states that in the last forty years the heat transfer mechanisms and other thermal processes became perfect on the building simulation programmes. However, the results are only accurate if the usage and operation of the building were predictable and regular (Kwok and Lee, 2011).

User behaviour is often disregarded on calibration studies, which leads to the inclusion of hypothetical values for the physical parameters (Ryan and Sanquist, 2012).

According to Mahdavi and Pröglhöf (2009), the occupancy and user behaviour have great impact on the building performance, but these are difficult to investigate analytically (Yu *et al*., 2011). The occupant changes the thermal environment by changing the set point temperatures of the air conditioning systems, opening windows or doors or to be absent at any given time; all this being something spontaneous and irregular (Ryan and Sanquist, 2012).

In general, the studies that propose models of user behaviour adopt "diversity profiles" that are hourly fractions of peak load, totalling a 24-hour profile (Page *et al*., 2008). Such profiles can be used for metabolism, equipment or lighting usage, and other routines related to their behaviour. However, they do not consider stochastic variations such as non-repeating profiles of the same day of the week, holiday periods and spontaneous alterations of behaviour. On that way, the behaviour of the occupant and the other internal gains are fixed by deterministic values (Saelens *et al*., 2011).

McLoughlin *et al*. (2012) conducted studies on the influence of occupancy on four parameters: energy consumption, maximum demand, load factor and time of use, taking into account socio-economic variables in approximately 4200 households in Ireland. Santin (2011) conducted studies in houses in the Netherlands, establishing routines for occupancy separated by type of occupant: seniors, families, single/couples and wealthier couples. The single/couples type is less related to the comfort temperature and space usage. Wealthier couples are less concerned with energy savings. Families need larger spaces and have more high-power appliances usage. Seniors are concerned about the thermal comfort and natural ventilation, and their homes usually have lower energy consumption.

Al-Mumin *et al*. (2003) studied the effect of the improvement of the user behaviour by means of computer simulation. Data on occupancy and electrical appliances schedules were collected from 30 students' residences of different culture and economic status from Kuwait. These data were compared with the default data of ENERWIN thermal simulation programme. The actual occupant behaviour led to 21% more energy consumption than the default data, which were based on the Western lifestyle.

Yu *et al*. (2011) proposed a method for improving the user behaviour on residential buildings in Japan. The method is based on end-use loads survey and helped to identify, on a base case residential building, which behaviour needs to be modified and improved.

Therefore, it can be concluded that more studies must be performed in order to analyse user behaviour effects on building simulation.

OBJECTIVE

The objective of this paper is to analyse the uncertainty related to user behaviour in the thermal performance of low-income dwellings in southern Brazil.

METHOD

The method is divided into: (1) data acquisition on user behaviour, (2) statistical data processing, (3) input data, (4) initial sensitivity analysis, (5) uncertainty analysis, (6) final sensitivity analysis and (7) output data.

Data Acquisition

The scope of the data acquisition includes (1) the amount of people in each room for each hour of the day, (2) the total time that each window or door are totally open, (3) the household appliances and lighting hourly usage; and all are separated by prolonged occupancy room and per day of the week.

The data were collected through structured research on a 16 low-income dwellings sample in Florianópolis, southern Brazil. The occupants were interviewed using two types of questionnaires: one about occupancy patterns of the rooms, windows and doors operations; and the other one regarding the household appliances and lighting usage patterns.

All electrical appliances were monitored for more than one week to determine the total electricity consumption and usage time, which leads to the average power calculation. The meter used was the PowerBall T8, from Northmeter manufacturer (www.northmeter.com). The light bulbs were characterized by the manufacturer power rating.

Data Processing

The nonparametric Wilcoxon rank sign test was performed with 80% confidence in order to assign confidence intervals to the collected data. Nonparametric tests are independent of adherence to known probability density functions.

The collected data were converted into hourly schedules, which represent the diversity profiles, as a fraction of peak loads. Thus, for the occupancy, the fraction refers to an hourly percentage of a maximum amount of people in each room. For the appliances and lighting, the fraction refers to an hourly percentage of the average installed power in each room.

For the determination of the average installed power in each room, the appliances were grouped, and usage schedules were assigned to each appliance. The data were weighted by both the average power of each appliance and their share on the total electricity consumption of each of the 16 dwellings.

The windows and doors operation are interpreted as availability schedules, with discrete values of 0 and 1 indicating that they are completely closed or open, respectively.

Input Data

The EnergyPlus v7.0 simulation programme was used for the thermal performance analysis. The base case is a low-income naturally ventilated house with 50.2 m², with two bedrooms, combined living room and kitchen, and bathroom, shown in Figure 1, along with the solar orientation settings varied in this paper.

The run period is from November to May, which is the hot period of the year. The mean of the daily minimal and maximum temperatures are 20.6°C and 26.8°C, respectively. The climate data is the Test Reference Year (TRY) file of Florianópolis. Slab programme was used in order to determine the ground temperatures, which depend on the internal temperatures of the rooms.

The internal loads and other schedules are results of this study, and are shown in the Results section.

Initial Sensitivity Analysis

The initial sensitivity analysis aims to determine which parameters most influence the Degree-hour for cooling in order to reduce the number of parameters analysed.

Table 2 shows the parameters and their values used on this analysis. A combined approach was performed through physical properties and user behaviour parameters. The screening sampling technique was applied, with one-parameter-at-a-time variation in the minimum and maximum levels, while the others were fixed on the average level (Saltelli *et al.*, 2000).

For the scheduled parameters, the levels indicate fractions of peak loads. For windows and doors availability schedules, the 0.50 value refers to half of the area opened.

The solar orientation was varied according to Figure 1. The set point control of openings operation refers to internal temperatures above which windows can be opened; the Off value indicates that the control is made according the availability schedules only.

To determine the influence of each parameter, the variance decomposition technique (Saltelli *et al.*, 2000) was performed with MiniTab 16 programme. The initial sensitivity analysis resulted in 152 runs.

Uncertainty Analysis

Table 3 shows the parameters varied in the uncertainty analysis. The user behaviour parameters were chosen from the results of the previous section, which are the occupancy schedules, window availability schedule and the number of inhabitants, in minimum, median and maximum levels from the 80% confidence interval. The factorial sampling was used (Furbringer and Roulet, 1995), with different configurations of physical parameters in two levels (average and variation), amounting 648 runs.

The thermal properties of the walls were considered together; the average level refers to a component with high thermal transmittance and low thermal capacity, and the variation level refers to a component with low thermal transmittance and high thermal capacity. The same was considered for the roof.

The simulations were separated into groups according to the five different physical parameters: (1) αwall, (2) εroof, (3) αroof, (4) Wall e (5) Roof; the two last ones contain the thermal transmittance and thermal capacity varied simultaneously. The analyses were performed for subgroups divided by each room and solar orientation, totalling 80 subgroups (considering five physical parameters, four rooms, and four solar orientations), each of which has two data distributions (average and variation).

For each subgroup, the 90% confidence intervals with Student's t-test for the mean and individual values were calculated, assuming the data are normally distributed. In other words, the interval represents a range containing 90% of the output data of each subgroup, and is not associated with the nonparametric confidence interval of the input data.

The differences between average and individual values were compared on each distribution of each subgroup, according to Equations 1 and 2.

$$\Delta avg = \frac{(\overline{x_i} - \overline{x_j})}{\overline{x_j}} \% \quad (1)$$

$$\Delta ind = \frac{U_i - L_g}{L_g} \% \quad (2)$$

Final Sensitivity Analysis

The variance decomposition (Saltelli *et al.*, 2000) was performed, regarding the results of the uncertainty analysis of the previous section, with MiniTab 16 programme. It represents the total variance due to each parameter and also the Error, which is the unexplained variance and third order effects. Thus, the parameters that caused larger variation were determined.

Output Data

The output data, i. e., the dependent variables, were the hourly operative temperatures of each prolonged occupancy room, which are the arithmetic average between the air temperature and the mean radiant temperature. Using these data, the Degree Hour (DH) for Cooling was obtained for each room considering a base temperature of 26°C. Such base temperature is independent from time or presence of occupants in the room; and represents the thermal performance for this study purposes. This limit is not associated with the set point temperatures of windows operation shown in Table 2.

RESULTS

Data Processing

Figure 4 shows the occupancy schedules for each prolonged occupancy room, with the 80% confidence interval. The abbreviation Linf means inferior limit, Lsup means superior limit, and when these two curves get close to each other, it indicates that more houses follow the same pattern, and the uncertainty is lower.

Figures 2 and 3 show the schedules of lighting and appliances as power fractions, for each room with 80% confidence interval, associated with the average power shown in Table 1.

In Figures 2 and 4, the median, in some cases, is equal to the minimum or the maximum limit. This is due to the lack of symmetry on the data. In other words, some of the values are so representative that they can be the median and one of the limits, simultaneously.

Table 5 shows the results for the doors and windows operation, with 80% confidence interval, as the total hours that the opening is half or totally open.

Initial Sensitivity Analysis

Figure 5 shows the ranking of the most influent parameters of the initial sensitivity analysis. As the data are extrapolated to the whole building, the interval (lower to upper) is due to the differences among each room. For the DH for Cooling, the most influent parameters were Solar orientation (Solar), thermal capacity of the walls (CtWall), windows availability schedule (OpWindow) and number of inhabitants (Inhab).

Although the one-parameter-at-a-time method has its limitations, the importance of the Ocup, OpWindow and Inhab parameters is noticed (schedules of occupancy, windows operation availability schedules, number of inhabitants). They were as influential on the DH for Cooling as the physical parameters and were chosen to be part of the uncertainty analysis.

Uncertainty Analysis

Figure 6 shows the results of the DH for Cooling, as an average in the whole building and in each group of physical parameter, along with subtitles information. The interval of the results refers only to user behaviour and number of inhabitants. Data are separated according to physical parameter and solar orientation (which had the greatest influences as shown in Figure 5) for better visualization. In Figure 6-a, for example, for αwall equal to 0.3 and solar orientation 1, the median DH for Cooling is 1600°Ch; there is 50% of probability that the data is between 1100°Ch and 1900°Ch, 25% above 1900 and 25% below 1100°Ch.

Referring to Figures 6-a and 6-c, the median of the data with high solar absorptance with the median of the data with low absorptance are distant enough in comparison with the other physical parameters (Wall, Roof and εroof). Thus, the variation of a high to a low absorptance (both walls and roof) has the capacity to reduce the DH for Cooling, regardless the solar orientation, user behaviour or number of inhabitants.

Solar orientations 2 and 4 (when the living room and kitchen have south and north facing walls, according to Figure 1) show the best results. This happens because there is cross natural ventilation in the rooms through the two opposite openings, as the predominant monthly wind direction is 20° azimuth for this run period (according to the TRY weather data).

Still based on Figure 6, the uncertainty of the user behaviour and the number of inhabitants is higher when the building has low thermal performance (high transmittances, low thermal capacities, high absorptances, and high long wave emissivity of the roof). The only case that is not clear is the solar absorptance of the walls, because its uncertainty in Figure 6 is generalized for the whole building. However, in each room, this parameter follows the same pattern as the others.

According to Eisenhower *et al.* (2011), high performance models are more robust to uncertainties. Thus, the confidence intervals were larger when the building had low thermal performance, characterized by high DH for Cooling.

Due to the impossibility to report all the calculated data of the differences between averages and individual values at 90% confidence in this paper, some comments were made.

In the variation of the wall and for the long wave emissivity of the roof, there was no success in reducing the DH for Cooling in average values, especially in the solar orientation 3, in all rooms, and in the kitchen, in all solar orientations. This explains the proximity between the medians of Figures 6-b and 6-d.

For all other physical parameters (Roof, solar absorptances of wall and solar absorptance of roof), there was success in reducing the DH for Cooling considering average values in all cases. However, the individual values assessment leads to different considerations. Analysing the $\Delta avg - \Delta ind$ value (difference between average and individual values from Equations 1 and 2) for the DH for Cooling:

a) 10.2 to 33.9% was obtained for the solar absorptance of the roof;

b) 12.0 to 34.4% was obtained for the solar absorptances of walls;

c) 38.8 to 84.2% was obtained for the roof type, which represents the largest range found.

In other words, there was a difference of 10.2 to 84.2% between averages and individual values. This indicates that the simulation reports that are based on only one deterministic simulation should consider up to 84.2% of error, at 90% confidence.

Figure 7 shows two examples of the probability distributions obtained in the uncertainty analysis, for just two subgroups among the eighty total subgroups of this analysis, to better understand the subheading a) to c). In Figure 7-a, no overlapping was found among distributions (average and variation, of Table 3). The difference between average values was 35.2% and between individual values was 23.2%, indicating high reliability for the solar absorptances of the walls. However, in Figure 7-b, the differences between average values is 41.1%, but due to uncertainty, the distributions overlap at 90% confidence, indicating poor reliability for the use of low solar absorptances in the roof, in this specific subgroup.

Final Sensitivity Analysis

Table 4 shows the ten most influent parameters on the DH for Cooling. The solar absorptances of walls and roof, roof component, and solar orientation together correspond from 79.9 to 89.1% of the total variance. The occupancy, windows availability schedules and number of inhabitants correspond from 3.9 to 9.5% of the total variance. As the ranges of user behaviour in this section are smaller than the ranges of the initial sensitivity analysis, they had little direct influence on the whole data analysis. The Error (third order effects) was more important than the user behaviour, in some cases (see Table 4). The largest second order effect is the solar absorptance of the walls together with solar orientation.

CONCLUSION

This study has shown the influence of the user behaviour on the thermal performance of low-income dwellings in southern Brazil, as well as their uncertainty due to variation of the physical parameters.

The occupancy and windows availability schedules (user behaviour), and number of inhabitants, represented little influence on the uncertainty analysis, when all data were analysed. However, by separating data by subgroups (by solar orientation and by physical parameters), they generate considerable uncertainty in the results and have influence in the hypothesis tests of differences between means and individual values. Thus, some not significant changes were found, at 90% confidence.

The importance of considering the user behaviour and number of inhabitants as a variable parameter was confirmed. They still generate uncertainty and affect the analyses in some cases. Only parameters that exert little influence can be frozen at any value within its range of variation (Saltelli *et al*., 2000).

About the limitations of this study, only one type of building was analysed, for one climate in Brazil, and only for the hot period of the year, due to limitation of space. The sensitivity analysis methods and sampling techniques were simple; other methods such as Morris Method (Morris, 1991) in the initial analysis and the Extended FAST (Saltelli and Bolado, 1998) in the final analysis will be applied in future works.

NOMENCLATURE

Δavg = Is the difference between average values with 90% confidence with the t-test;

x_i ; x_j = Is the average value from the ith and jth distribution in each subgroup;

Δind = Is the difference between individual values with 90% confidence, with the t-test;

U_l = Is the upper limit from the distribution with lower average value;

L_g = Is the lower limit from the distribution with the greater average value.

ACKNOWLEDGEMENT

The authors acknowledge the Funding of Studies and Projects (FINEP) and CNPq.

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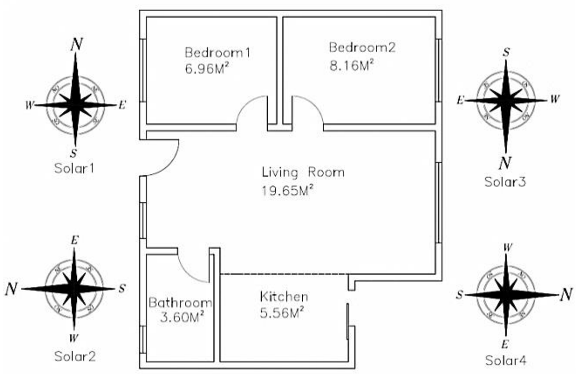


Figure 1 Floor plan of the house and Solar orientations

Table 1
Average installed power in each room.

Installed power	Kitchen	Living room	Bedroom
Appliances	942.8 W	90.2 W	160.6 W
Lighting	29.4 W	28.9 W	44.1 W

Table 2
Parameters varied in the initial sensitivity analysis.

Parameter	Identification	minimum	medium	maximum
Occupancy schedule	Ocup	0.0	0.5	1.0
Metabolic rate (W/person)	Met	81.0	103.5	126.0
Number of inhabitants	Inhab	0	3	7
Window operation schedule	OpWindow	0.0	0.5	1.0
Door operation schedule	OpDoor	0.0	0.5	1.0
Discharge coefficients of windows	Dc	0.4	0.6	0.8
Households appliances schedule	Equip	0.0	0.5	1.0
Lighting use schedule	Light	0.0	0.5	1.0
Radiant factor of the equipment	Fequip	0.1	0.4	0.8
Radiant factor of the luminaires	Flight	0.1	0.4	0.8
Roof solar absorptance	αroof	0.2	0.5	0.8
Roof thermal transmittance (W/m²K)	Uroof	0.68	2.99	4.11
Roof long wave emissivity (1)	εroof	0.1	0.9	0.9
Roof thermal capacity (kJ/m²K)	Ctroof	2.5	50.0	125.0
Walls solar absorptance	αwall	0.2	0.5	0.9
Walls thermal transmittance (W/m²K)	Uwall	1.05	2.25	3.82
Walls thermal capacity (kJ/m²K)	Ctwall	11.0	154.0	385.0
Infiltration rate (kg/s.m)	InfRate	0.00001	0.00100	0.00500
Site solar orientation	Solar	North, South, East and West		
Temperature control of window operation (2)	Setpoint	22	Off	24

Notes of Table 2: (1) The long wave emissivity of the roof was varied in just two values: 0.1 and 0.9, whereas for the average case, which the 0.9 value was maintained. (2) If the indoor air temperature is greater than 22°C or than 24°C (minimum and maximum case, respectively), and if the outside air temperature is lower than the indoor air, natural ventilation is allowed.

Table 3
Physical and user behaviour parameters varied in the uncertainty analysis and final sensitivity analysis.

User behaviour parameters	Identification	minimum	median	maximum
Occupancy schedule	Ocup	according to Figure 4 (1)		
Number of inhabitants (2)	Inhab	2	3	4
Window operation schedule	OpWindow	according to Table 5 (3)		
Physical Parameters	**Identification**	**average**		**variation**
Roof solar absorptance	αroof	0.8		0.2
Roof thermal transmittance (W/m²K)	Uroof	2.1		0.7
Roof long wave emissivity	εroof	0.9		0.1
Roof thermal capacity (kJ/m²K)	Ctroof	220.0		20.0
Walls solar absorptance	αwall	0.3		0.8
Walls thermal transmittance (W/m²K)	Uwall	2.3		0.9
Walls thermal capacity (kJ/m²K)	Ctwall	273.0		146.0

Notes of Table 3: (1) Schedules for occupancy determined for each room were used according to Figure 4. (2) The number of inhabitants varies from 1 to 2 people in the bedrooms and 2, 3 or 4 people in the whole house. (3) Window operation availability schedules were used according to Table 5.

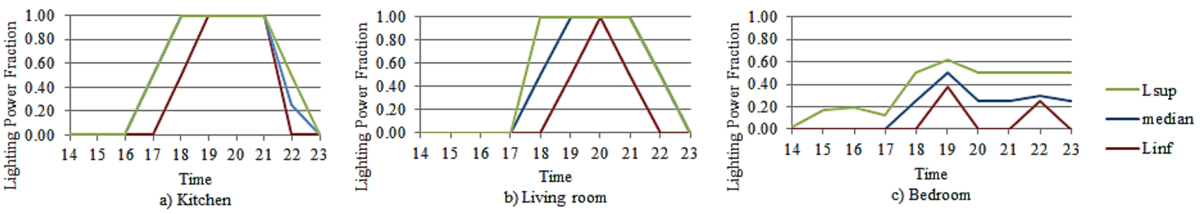


Figure 2 Lighting schedules for rooms with 80% confidence interval, as a power fraction.

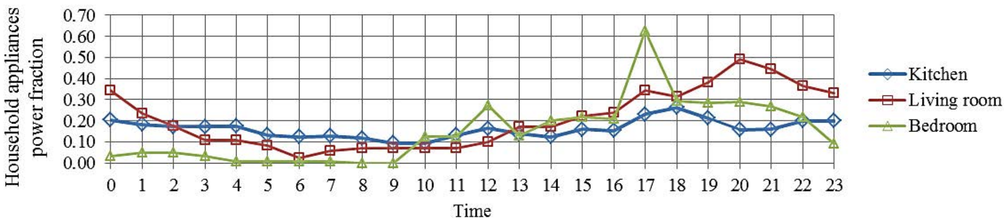


Figure 3 Household appliances schedules, as a power fraction.

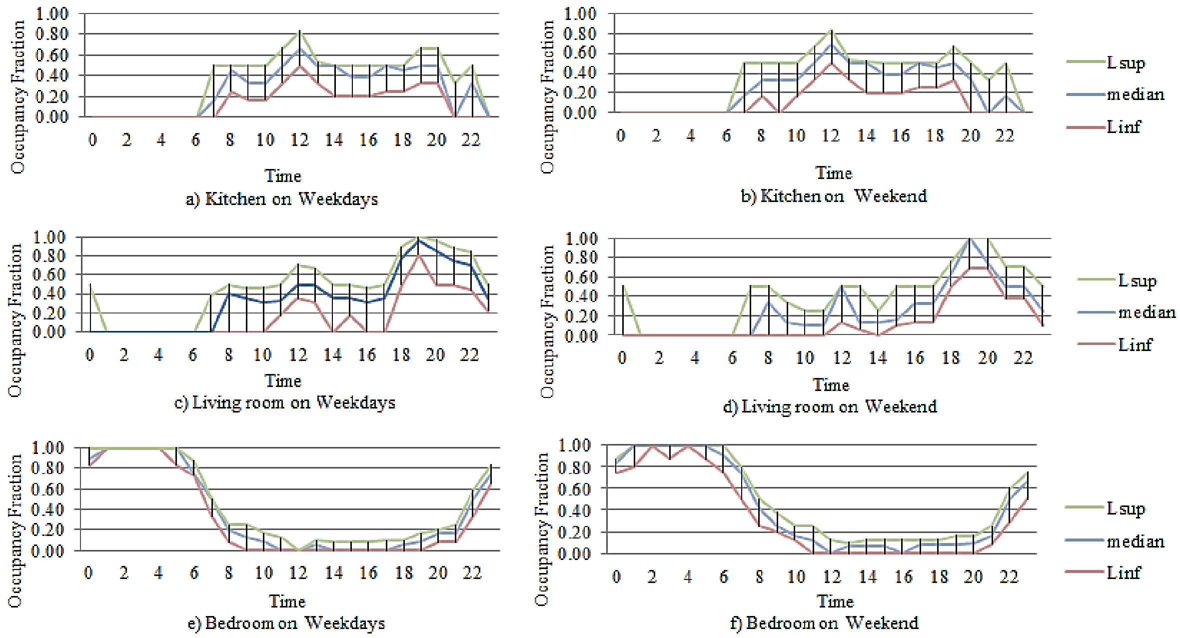


Figure 4 Occupancy schedules for rooms with 80% confidence interval, for weekdays and weekend.

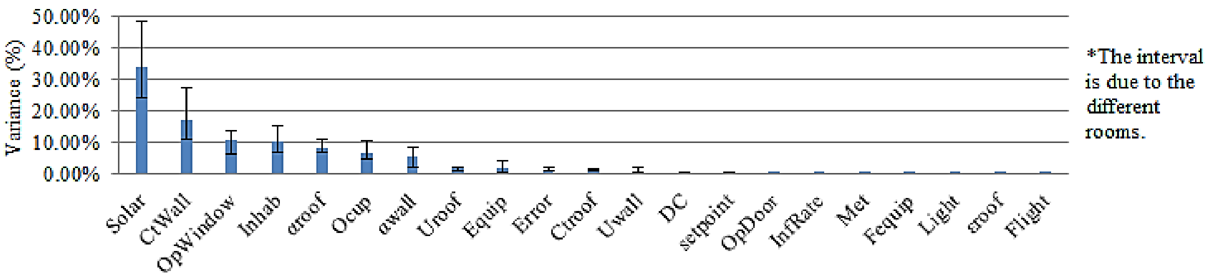


Figure 5 Most influent parameters in the initial sensitivity analysis, for the DH for Cooling.

Table 4
Ten most influent parameters in the final sensitivity analysis, for the DH for Cooling.

Rank	Bedroom1		Bedroom2		Kitchen		Living room	
	% variance	Factor	% variance	Factor	% variance	Factor	% variance	Factor
1	54.4%	αwall	49.7%	αwall	51.4%	αwall	43.4%	αwall
2	15.6%	Roof	16.0%	Solar	11.0%	Roof	16.6%	Roof
3	11.0%	αroof	12.7%	Roof	10.4%	αroof	14.2%	αroof
4	6.4%	Solar	10.6%	αroof	7.1%	Solar	11.0%	Solar
5	2.5%	Inhab	2.6%	Solar*αwall	3.9%	Ocup	2.9%	Wall
6	2.2%	Solar*αwall	1.9%	Inhab	2.9%	Wall	2.4%	Error
7	1.9%	Error	1.3%	Error	2.9%	Inhab	1.9%	Ocup
8	1.3%	Ocup	1.2%	OpWindow	2.7%	OpWindow	1.8%	OpWindow
9	1.3%	OpWindow	0.8%	εroof	2.3%	Error	1.5%	Inhab
10	1.1%	εroof	0.7%	Ocup	1.1%	Solar*αroof	1.4%	Solar*αroof

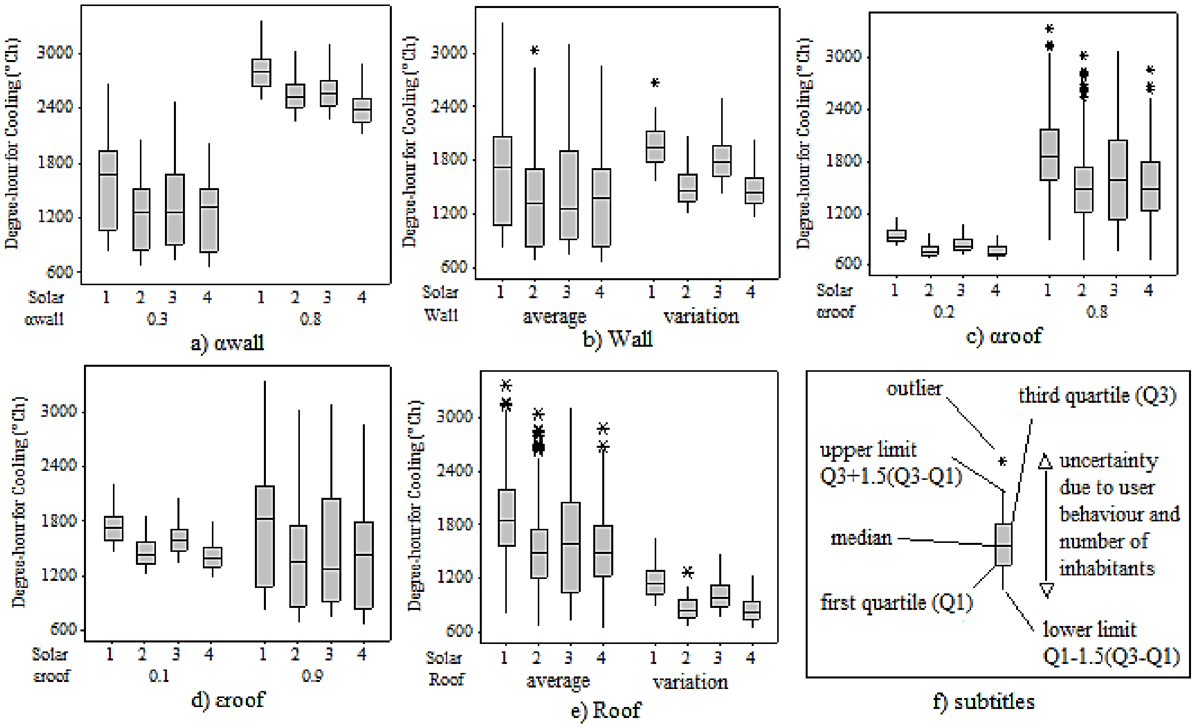
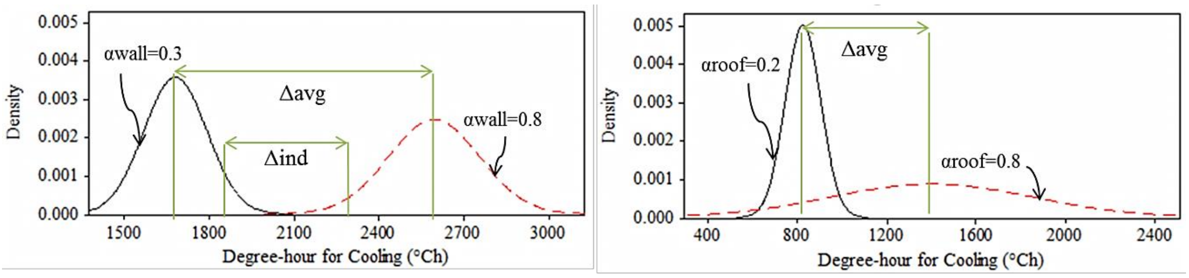


Figure 6 Uncertainty analysis for the DH for Cooling, corresponding to whole building average values.



a) b)

Figure 7 Comparison between average and individual values, in the subgroup a) and b): a) refers to the bedroom 2, solar orientation 1 and for the solar absorptance of the walls; b) refers to bedroom 1, solar orientation 3 and solar absorptance of the roof.

Table 5
Schedules of Doors and Windows operation in terms of time (hours per day) that they are half or entire open, with 80% nonparametric confidence interval.

Doors (hours per day)							**Windows (hours per day)**					
Zone	**Kitchen**		**Living room**		**Bedroom**		**Zone**	**Kitchen**		**Living room**		**Bedroom**	
Opening	**Half**	**Entire**	**Half**	**Entire**	**Half**	**Entire**	**Opening**	**Half**	**Entire**	**Half**	**Entire**	**Half**	**Entire**
lower	7	7	5	5	5	8	lower	5	10	3	6	4	9
median	6	10	5	8	6	11	median	5	11	6	9	5	10
upper	6	13	6	16	3	17	upper	3	13	7	11	6	11