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Uncertainty analysis of the computer model in building performance simulation

Arthur Santos Silva*, Enedir Ghisi

Federal University of Santa Catarina, Department of Civil Engineering, Laboratory of Energy Efficiency in Buildings, Florianópolis, SC 88040-900, Brazil

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ABSTRACT

A large number of studies in building performance simulation have analysed several types of uncertainties, i.e., physical, occupation, weather, algorithms; however, the modelling uncertainty is a poorly addressed topic. Thus, the objective of this paper is to analyse how the computer models can influence the results of heating and cooling energy consumption in a building. Three types of analyses were performed: (1) deterministic, (2) parameter variation and (3) parameter uncertainty. Fifteen computer models were created to represent the real building. Such models differ in relation to external geometry, grouping of internal zones and internal thermal mass. The simulations were performed using the EnergyPlus programme, for three climates in Brazil. The model represents the real building properly when the simulation run time was reduced, and the results were close to the base case. For the deterministic analysis, the modelling uncertainties ranged from −16.0% to 8.3% for energy consumption in Florianópolis climate. As for the cooling energy consumption, the uncertainty was lower, i.e., up to 7.4%. These uncertainties are relatively high, and should be accounted for in calibration or even in computer simulations.

1. Introduction

Building simulation is very useful to accurately determine the thermal performance and energy consumption of buildings, especially for improving buildings at the design stage [1]. However, the results predicted by the simulations are only valid if the model is properly calibrated [2].

Calibration means technical and operational adjustments of the computer model that represents the building. For this purpose, many techniques have been developed, which are based either on long or short term measurements of some building parameters. It is a laborious process, in which the user has to insert several input parameters in the simulation programme and, at the same time, collect responses from the actual building operation [3].

According to Heo et al. [1], the purpose of a calibration is not just to find the ideal combination of factors that generates results closer to measurements. Calibration should consider the uncertainties in the input parameters (at least in the most important ones), uncertainties in the measurement methods and in the theoretical conception of the algorithm used.

There is a topic that is poorly addressed in the literature in dealing with calibration analysis, which corresponds to the model itself used in the performance simulations. Such models should represent the physical behaviour of the building correctly [4]. High levels of detail may affect modelling time and the simulation steps [3]. However, large amounts of simplifications, without considering the thermal and physical phenomena involved, may lead to erroneous conclusions.

Calibration and uncertainty analysis techniques should be applied in computer models, since these models represent a simplification of reality. With these techniques, one can determine the level of imperfection of the models, before performing forecasting and decision making [5].

There are few studies that deal with the analysis of computer models. In this study the word "model" means the geometry characteristics and shape of the building. Such models do not need to represent a building as it is architecturally, but rather its thermal behaviour.

According to De Wit [6], the modelling uncertainties arise from commonly applied physical assumptions and simplifications in a computer model.

Some authors have proposed various methods of simplification, trying to reproduce the physical behaviour of a building in a few representative parameters [7].

Chlela et al. [8] proposed a method for designing buildings with low energy consumption through simulations using the statistical Design of Experiments approach. A meta-model was created for preliminary studies of prediction, optimization, sensitivity

* Corresponding author. Tel.: +55 48 3721 5184.
E-mail address: arthurssilva07@gmail.com (A.S. Silva).

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0378-7788/

analysis and interaction analysis in computer simulation of buildings. For the application, the authors have considered a three-floor commercial building for three different climates in France. Thirteen parameters were varied in two to five levels (depending on the method used), which were related to the envelope properties, like thermal transmittance and thermal capacity, thermal bridges, solar heat gain coefficient of the glass, percentage of openings in the facade, solar orientation, and different strategies of infiltration and natural ventilation. The simulations were performed using the SIMBAD programme. The effectiveness of different methods of Design of Experiments (which require different numbers of simulation runs) was evaluated by using the mean and standard deviation. The results showed that the meta-models are very useful and can replace the computer simulations, which are very laborious. The meta-models have shown good results for heating demand and the total energy consumption. However, less accurate results were obtained for the cooling demand. The more complex physical phenomena involved, the lower the accuracy of the meta-model.

De Wit [6] analysed modelling uncertainties in a case study of a three-storey office building, with heavy internal walls, double glazing, shading of windows and without a cooling system. The scenario conditions were assumed constant for elaboration of the modelling. Fourteen parameters were adopted, such as convection coefficients, wind reduction factor, pressure coefficient data, albedo, convective fraction of the internal loads and model used to calculate the internal and external convection. The authors used two programmes separately, the ESP-r and BFEP. For the sensitivity analysis the method of Morris [9] was used with the elementary effects at four levels of variation in all parameters. The variable analysed was the thermal comfort of the space. The parameters related to the deviation of external air temperature from the weather file value, the wind reduction factor, the database of wind pressure coefficients, and coefficients of internal heat transfer were the most influential parameters in the thermal comfort performance. As a conclusion, in order to reduce the uncertainty of some parameters, wind tunnel measurements for the pressure coefficients determination could be used. For reducing the temperature stratification uncertainty, CFD models could be used. The second order effects were considered to be unimportant.

Melo et al. [10] conducted a validation study of a simplified model for determining the energy performance of commercial buildings. The analysis involved the comparison of the code developed, which was based on multivariate linear regression, with the BESTEST applicable by ASHRAE Standard 140 [11] and the results of validated simulation programmes, in different typologies and climates. It was verified that the simplified model generally underestimates the energy consumption of the building, due to the difference between the typologies used in its design and conception.

Pan et al. [12] verified the use of simplified models for modelling of atrium in buildings. A glazed atrium shows complex heat transfer phenomena, which causes difficulty in calculating the heat load due to temperature stratification. They found that conventional models for energy analysis, with uniform internal temperature throughout the height of the atrium, without considering stratifications lead to large errors in the calculation of the thermal load. The authors developed three simplified models, differing by the number of nodes in which internal air temperatures are calculated. The three models divisions depend on the height of the atrium, which were compared with results of CFD models, in various heights.

Most of the studies assessed how the simulation results differ from results measured through calibration methods that include all types of parameters (physical, internal loads, usage and occupancy schedules, weather). However, one should also consider the simplifications in the same geometric model used, because they generate uncertainty that should be accounted for.

Table 1
Thermal properties of the construction components.

Variable	Walls and partitions	Roof	Floor
Thermal transmittance [W/m^2 K]	2.27	1.13	5.56
Thermal capacity [kJ/m^2 K]	146	2.18	129
Solar absorptance [–]	0.5	0.15	–
Long wave emissivity [–]	0.9	0.1	–

Table 2
Internal loads for each activity.

Activity	Equipment (W/m^2)	Lighting (W/m^2)	People (occupants/m^2)
Classroom	4.74	12.24	0.2034
Laboratory	8.73	12.24	0.1063
Reception	4.63	7.20	0.1122
Bathroom	1.56	6.00	0.2316
Corridor	1.83	8.52	0.1065
Office	10.49	14.28	0.0979
Computer cluster	27.81	12.24	0.2313

Thus, the objective of this paper is to analyse the uncertainties in the computer model in the cooling and heating energy consumption in a public building with complex geometry, through building performance simulation.

2. Method

The first part of this study refers to the description of the actual building and considerations about geometry, physical properties, usage, occupancy and internal loads. The second part refers to the general settings of the computer simulation, common to all models. The third part refers to three analyses performed successively, i.e., (1) deterministic analysis, (2) parameter variation analysis, with screening sampling technique, and (3) uncertainty analysis, with the Latin Hypercube sampling technique.

In all analyses, there is a base case model that represents a simulation model which contains the greatest amount of details possible, named model 1. Fig. 1 summarizes the method developed for this study.

2.1. Building description

The building model was based on the design of the Department of Architecture and Urbanism of the Federal University of Santa Catarina, shown in Fig. 2. The building is located in Florianópolis-SC, southern Brazil. It is an educational building, with 4800 m^2 of built area, distributed on three floors. The main facade faces North.

The floor plan of the building has the shape of an arch, which is complex in terms of modelling heat transfer phenomena, as each infinitesimal element of the facade has a slightly different solar orientation.

Table 1 shows the thermal properties of the construction components adopted in the study. The walls are of brickwork, with cement mortar, the floors are of concrete and the roof is metallic with PVC ceiling. The windows are 3 mm glass with a Solar Heat Gain Coefficient (SHGC) of 0.87. The metallic roof has low thermal capacity.

Table 2 shows the internal loads, which were defined for each thermal zone of the building. The internal loads of equipment and occupants density have been adopted according to ASHRAE Standard 90.1 [13]. For lighting loads, values 20% higher than required in the same standard were taken to avoid considering a high performance building model. The metabolic rate was set to 108 W/person, regardless of activity.

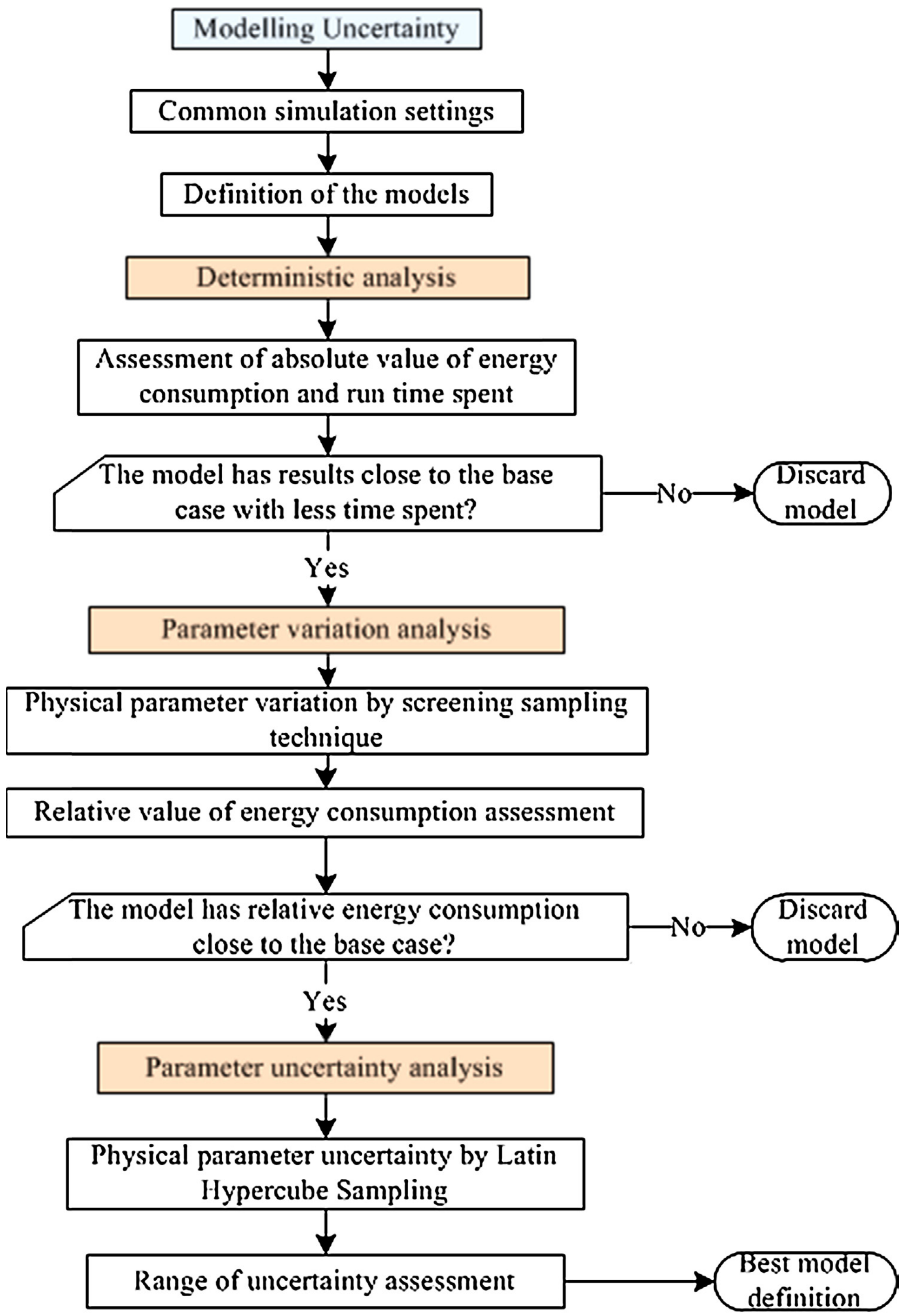


Fig. 1. Summary of the method.

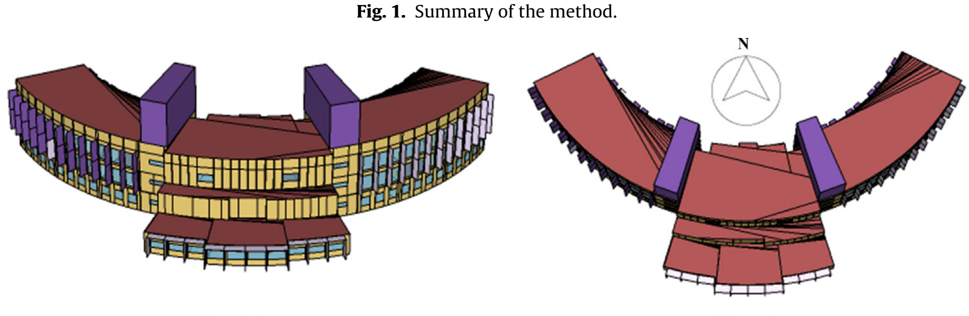


Fig. 2. Model 1 geometry, (a) showing the South facade, and (b) showing the top view of the building. Obs.: the colours are just illustrative. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of the article.)

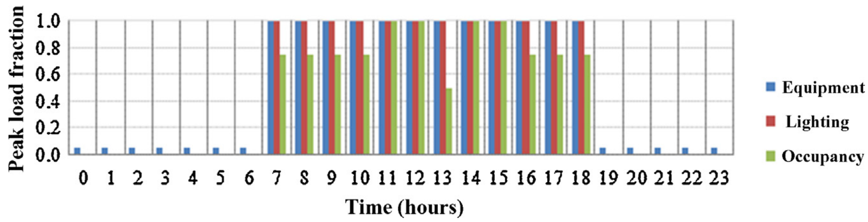


Fig. 3. Schedules for equipment usage, lighting and occupancy, in form of peak of load fraction.

In order to simplify the balance between the activities of equivalent thermal zones, the schedules were considered to be representative for the occupancy, lighting and equipment usage, and are shown in Fig. 3. These schedules indicate that the occupancy has a small variation on the working periods to a minimum of 50% of the peak load. For equipment and lighting, the peak is constant at 100% of the average power from 7 a.m. to 6 p.m. As for the unoccupied periods, a 5% equipment load was taken into account. Such figure can be much greater, as shown by Masoso and Grobler [14] and Pedrini et al. [15].

The radiant fraction of luminaires was taken as 0.72, and 0.50 for the equipment, according to the ASHRAE Handbook of Fundamentals [16].

2.2. Simulation settings

The EnergyPlus programme version 7.0 was used to perform the transient simulations. The weather file used is from the city of Florianópolis-SC (Southern Brazil) in TRY format, developed by [17].

As a comparative analysis, simulations using two other climates were carried out: Curitiba-PR (in southern Brazil) and Campo Grande-MS (in the mid-west Brazil). Both files were obtained from the Solar and Wind Energy Resource Assessment (SWERA) in TMY format. Fig. 4 shows the monthly outdoor dry bulb and wet bulb temperatures, and the relative humidity of the three cities analysed.

The minimum monthly outdoor dry bulb temperatures are 16.4 °C, 20.9 °C and 13.1 °C and the maximum monthly outdoor dry bulb temperatures are 24.2 °C, 25.8 °C and 20.9 °C for Florianópolis, Campo Grande and Curitiba, respectively. These temperatures characterize three very distinct climates. Ground temperature was considered according the monthly average obtained from each weather file. The ground reflectance was set as 0.20 for each month.

The building is artificially conditioned at constant set points of 20 °C for heating and 24 °C for cooling within a Package Terminal Heap Pump (PTHP) system. Heating is available only in the winter period (June to September), while cooling is available all year. Unconditioned areas were modelled as simplified natural ventilation with four air changes per hour (ac/h).

2.3. Simulation models definition

Fifteen simulation models were defined according to Fig. 5, differing in the:

(a) level of detail in internal zones;
(b) external geometry of the building;
(c) use of an equivalent internal thermal mass.

All these simplifications refer to common practices that might be adopted by computer tool users. The definition of all internal zones, the complex geometry and quantification of internal thermal mass of the partitions can be laborious, but it can generate uncertainties if not considered.

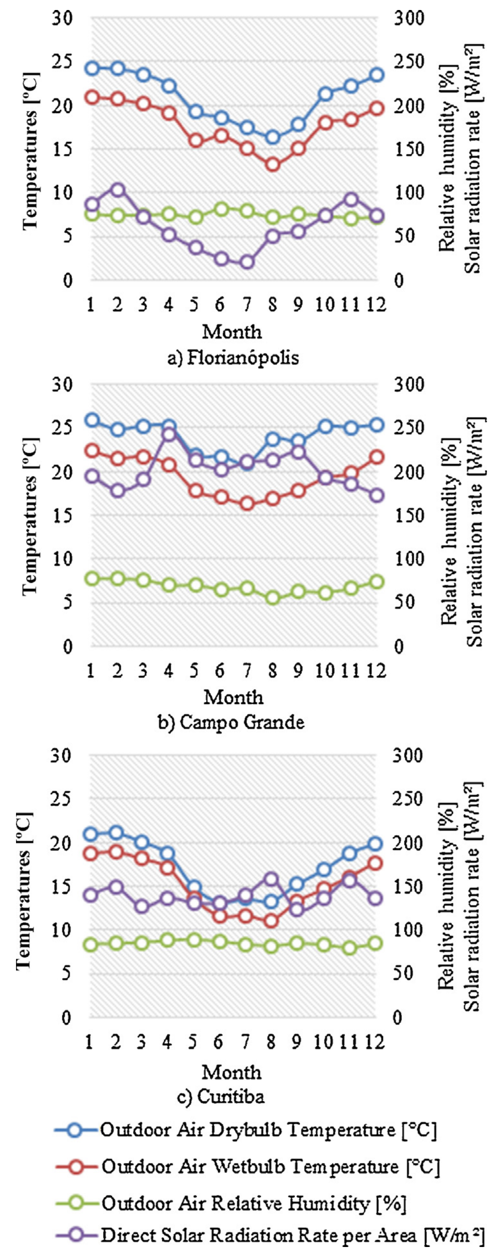


Fig. 4. Monthly average values for outdoor air dry bulb and wet bulb temperatures, relative humidity and direct solar radiation of Florianópolis, Campo Grande and Curitiba weather files.

The fifteen models were divided in three subgroups in order to address each of the three types of external geometry modelling, as follows:

Model 1 is the base case and represents the building with the best level of detail, by separating all thermal zones in accordance with the architectural design of the zones, definition of different internal loads in each zone, and external geometry in the form of an arch, with small elements of rectilinear walls facing slightly different solar orientations. Models 1–5 have no external geometry simplification.

Models 6–10 have the level 1 simplification of external geometry, in which the small linear elements are joined to form only one surface for each zone, i.e., in each zone there will be a wall thermal surface in contact with the outdoors, on the same solar orientation.

Models 11–15 have the level 2 simplification of the external geometry, in which each symmetrical part of the building is linearized in only one wall surface, and facing the same solar orientation.

In each subgroup, the internal zones were successively simplified by combining internal areas. For example, model 1 has no simplification of internal areas; model 2 has its internal zones grouped into conditioned or unconditioned areas; and model 4 has only one thermal zone per floor. Models 3 and 5 use an equivalent internal thermal mass.

Whenever the thermal zones are combined, the equivalent internal loads were calculated by weighting the internal load for the floor area of the zone.

When the partitions are removed and internal thermal zones are combined, there is a decrease of the computational effort to run the simulations. However, in these cases, there are less internal surfaces for heat exchange by radiation and convection, and there is more thermal mass for heat storage in the transient state. Models that include internal thermal mass equivalent to the partitions removed were created, with the same surface area for heat exchange and the same heat capacity. Such thermal mass only influences the model thermally.

2.4. Dependent variables

The dependent variables were the total heating and cooling energy consumption. As the external geometry in levels 1 and 2 was simplified, the floor plan area of model 1 is different from models 6–10 and from models 11–15. Therefore, the dependent variables were standardized per floor area, i.e., kWh/m^2 year.

Another variable analysed was the time spent for each simulation. The EnergyPlus programme records the elapsed time of each simulation. Thus, all simulations were performed on the same computer, with the same characteristics of random access memory and data processing capacity.

2.5. Deterministic analysis among models

This first analysis compares the results of a single simulation for each of the fifteen models, for heating and cooling energy consumption. The simulations were performed for the whole year of each weather file (Florianópolis, Campo Grande and Curitiba) and Eqs. (1)–(3) were used to determine the variation of consumption with heating, cooling and simulation time.

For this analysis, the thermal properties, simulation settings and models were set according to Sections 2.1–2.4. This deterministic analysis was performed to discard models that did not represent model 1 well. Thus, models whose simulation time was greater than in model 1 and energy consumption variation was greater than 10% were discarded.

$$\Delta Eheat_i = \frac{Eheat_i - Eheat_1}{Eheat_1} \times 100 \quad (1)$$

$$\Delta Ecoll_i = \frac{Ecool_i - Ecool_1}{Ecoll_1} \times 100 \quad (2)$$

$$\Delta T_i = \frac{T_i - T_1}{T_1} \times 100 \quad (3)$$

where i is the model number identification from Fig. 5, varying in 1–15 [non-dimensional]; $\Delta Eheat_i$ is the heating energy consumption variation for the ith model [%]; $\Delta Ecool_i$ is the cooling energy consumption variation for the ith model [%]; ΔT_i is the simulation time variation of the ith model [non-dimensional]; $Eheat_i$ is the heating energy consumption for the ith model [kWh/m^2 year]; $Ecool_i$ is the cooling energy consumption for the ith model [kWh/m^2 year]; $Eheat_1$ is the heating energy consumption of model 1 [kWh/m^2 year]; $Ecool_1$ is the cooling energy consumption for model 1 [kWh/m^2 year]; T_i is the simulation time spent for the ith model [min]; T_1 is the simulation time spent for model 1 [min].

2.6. Physical parameter variation analysis

With the results of the deterministic analysis, some models that showed little variation on the energy consumption and negative variation on time spent compared to model 1 were selected for the physical parameter variation analysis.

These selected models had the values of their physical parameters changed, in order to identify whether its behaviour is the same regardless of the configuration settings of the physical parameters. Table 3 summarizes the variation of physical parameters. For the screening sampling method, each parameter is varied individually, while the others are kept as a fixed value [18]. The parameters chosen are the ones that represent the energy efficiency of this type of building, according to [19], and are the same parameters included in the Brazilian regulations for energy efficiency of buildings [20–22]. It is noticed that, as the physical parameters were changed in this analysis, the settings of Section 2.1 regarding these parameters were also changed according to Table 3. The other settings of the simulations were the same as the deterministic analysis explained in Section 2.5.

The variation between the results at each value of variation (upper and lower) for each jth parameter according to Eqs. (4) and (5) was analysed. The difference in heating and cooling for each ith model with model 1 was calculated using Eqs. (6) and (7).

$$\Delta Eheat_i(P_j) = \frac{Eheat_i(P_{j,upper}) - Eheat_i(P_{j,lower})}{Eheat_i(P_{j,lower})} \times 100 \quad (4)$$

$$\Delta Ecool_i(P_j) = \frac{Ecool_i(P_{j,upper}) - Ecool_i(P_{j,lower})}{Ecool_i(P_{j,lower})} \times 100 \quad (5)$$

where i is the model number identification from Fig. 5, varying from 1–15 [non-dimensional]; j is the parameter number identification from Table 3, varying from 1–6 [non-dimensional]; $\Delta Eheat_i(P_j)$ is the heating energy consumption variation between upper and lower values of jth parameter for the ith model [%]; $\Delta Ecool_i(P_j)$ is the cooling energy consumption variation between upper and lower values of jth parameter for the ith model [%]; $Eheat_i(P_{j,lower})$ is the heating energy consumption with the lower value of the jth parameter for the ith model [kWh/m^2 year]; $Eheat_i(P_{j,upper})$ is the heating energy consumption with the upper value of the jth parameter for the ith model [kWh/m^2 year]; $Ecool_i(P_{j,lower})$ is the cooling energy consumption with the lower value of the jth parameter for the ith model [kWh/m^2 year]; $Ecool_i(P_{j,upper})$ is the cooling energy consumption with the upper value of the jth parameter for the ith model [kWh/m^2 year].

$$Diff\ Heat_i(P_j) = |\Delta Eheat_i(P_j) - \Delta Eheat_1(P_j)| \quad (6)$$

$$Diff\ Cool_i(P_j) = |\Delta Ecool_i(P_j) - \Delta Ecool_1(P_j)| \quad (7)$$

where $DiffHeat_i(P_j)$ is the heating energy consumption difference between the variation the jth parameter for the ith model and model 1 in absolute value [%]; $\Delta Eheat_i(P_j)$ is the heating energy consumption variation between upper and lower values of jth parameter for the ith model [%]; $\Delta Eheat_i(P_j)$ is the heating energy

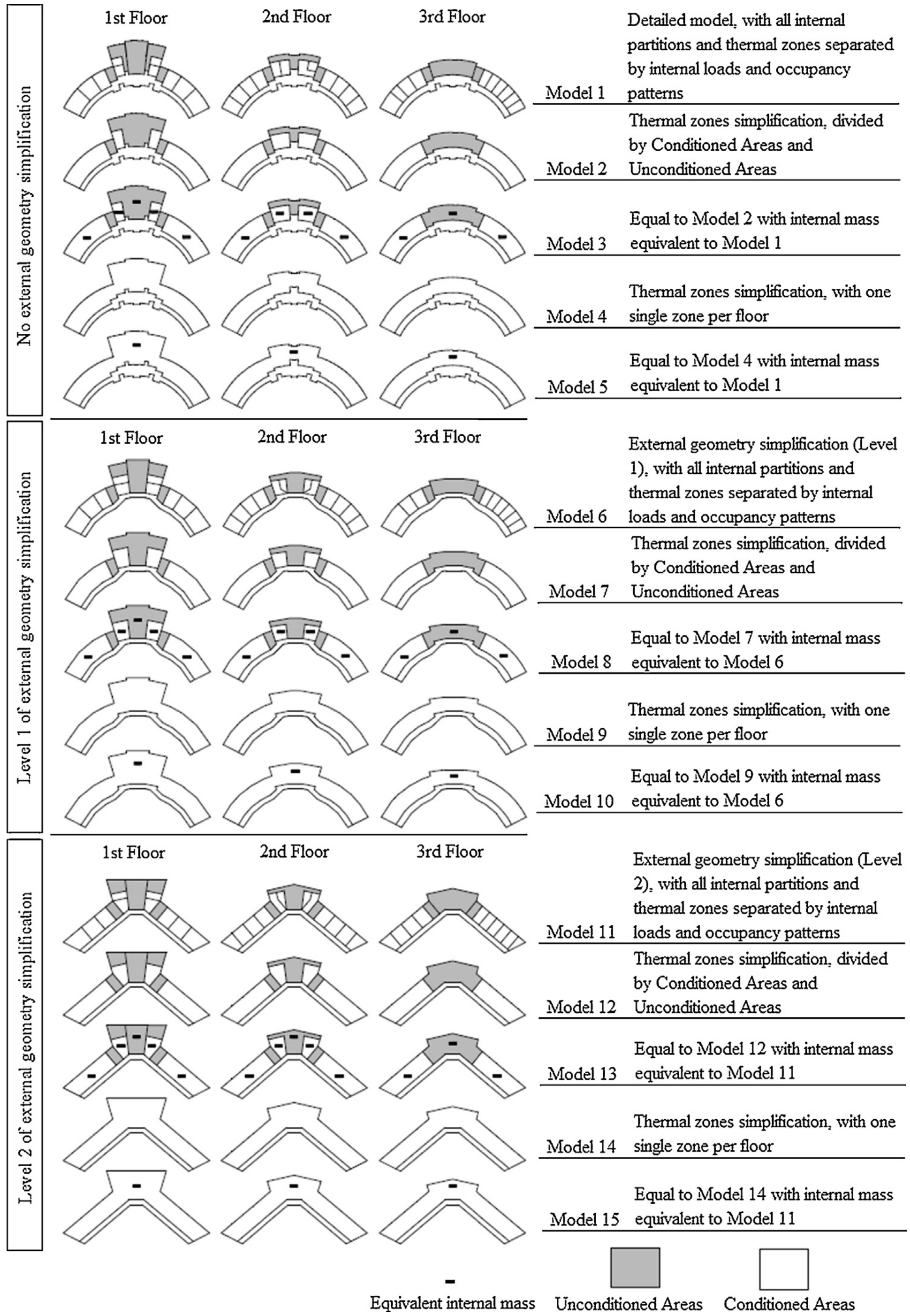


Fig. 5. Simulation models, showing the three floors and subtitles indication.

Table 3
Values for the physical parameters variation analysis.

j	Parameter	Unit	Lower	Fixed	Upper
1	α_{wall}	–	0.20	0.50	0.80
2	α_{roof}	–	0.10	0.50	0.90
3	ε_{roof}	–	0.10	0.10	0.90
4	U_{wall} and Ct_{wall}	[W/m^2 K] and [kJ/m^2 K]	0.93 and 122	2.48 and 121	2.48 and 121
5	U_{roof} and Ct_{roof}	[W/m^2 K] and [kJ/m^2 K]	1.16 and 2.18	2.18 and 3.23	2.18 and 3.23
6	SHGC	–	0.277	0.587	0.870

The thermal transmittance and thermal capacity of the walls were varied simultaneously; the same was performed for the roof. Thus, one parameter was set for the wall and another for the roof (both combining the transmittance and capacity). *j* is the parameter number identification.

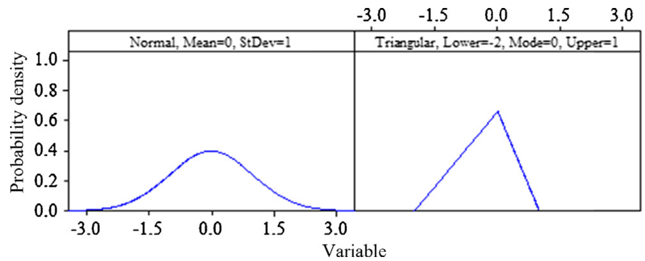


Fig. 6. Probability density functions (distributions) used in this paper.

consumption variation between upper and lower values of jth parameter for model 1 [%]; $DiffCool_i(P_j)$ is the cooling energy consumption difference between the variation the jth parameter for the ith model and model 1 in absolute value [%]; $\Delta Ecool_i(P_j)$ is the cooling energy consumption variation between upper and lower values of jth parameter for the ith model [%]; $\Delta Ecool_i(P_j)$ is the cooling energy consumption variation between upper and lower values of jth parameter for model 1 [%].

2.7. Physical parameter uncertainty analysis

The determination of uncertainty in parameters is a very complex task, which arises from the consideration of systematic uncertainties, related to methods and test conditions, and the random uncertainties between repetitions of experiments in the same test conditions. The uncertainty refers to the range of variation of a physical property, represented by a probability distribution.

Fig. 6 shows the probability distributions used in this work. The physical parameter uncertainty analysis complements the analysis of variation of parameters, with focus on the uncertainty of the physical parameters. The parameter uncertainties were propagated according to Table 4. Thus, two types of results were obtained in this analysis: (1) the modelling uncertainty achieved in comparison to model 1, when performing a physical uncertainty analysis; and (2) the actual physical uncertainty for each model.

The normal probability distribution was used for all parameters, except for the ground reflectance, for which the triangular distribution was used. The normal distribution is characterized by a mean and a standard deviation, and the triangular distribution is characterized by the mode, and lower and upper values.

For the layer thicknesses of the materials, a coefficient of variation of 10% was adopted, except for the metallic roof, with 5% variation.

The coefficient of variation of 19% for thermal conductivity, 19% for specific heat of cement and ceramic materials and 4% for the other materials were adopted according to [23]. These ranges include random and systematic uncertainties.

The density uncertainty of the materials was based on the Brazilian standard NBR 15220-2 [21] considering the normative uncertainty range as being 95% confidence interval in a normal distribution. With this interval, an equivalent standard deviation and coefficient of variation were calculated.

For the long wavelength emissivity of the materials, a standard deviation 0.02 was adopted; and for solar absorptance, a standard deviation 0.04 was adopted according to [23].

The albedo (ground reflectance) was taken as a triangular distribution from 0.13 to 0.26, with mode of 0.20 for a land without snow [24]. The ground temperature was taken based on the climate file, plus a standard deviation of 0.20 °C in a normal distribution.

The sampling method used was the Latin Hypercube (LHS), which was generated with the Simlab 2.2 programme. One hundred random runs were generated in accordance with probability density function of parameters shown in Table 4.

The Latin Hypercube Sampling method is a form of stratified sampling where the sample is forced to comply with the probability distribution of the variable analysed [25]. The probability function is divided into strata of equal probability, and the same number of points is taken from each interval [26].

Among the advantages of using this type of sampling, there is the independence of the number of parameters to the number of simulation runs, contributing to a lower computational effort. Thus, this specific sampling method has better coverage of the range of the parameter, in comparison with simple random sampling methods [27,28].

The variable analysed is the amplitude range, being the variation in results between the models for the same configuration as in Eqs. (1) and (2), and the deviation with 95% confidence according to Eq. (8):

$$S_{\alpha_i} = \frac{S_i \times t_{1-\alpha/2(n-1)}}{\bar{x}_I} \tag{8}$$

where S_{α_i} is the relative deviation with α significance, for the i distribution [non-dimensional]; S_i is the standard deviation of the distribution i [kWh/m^2 year]; $t_{1-\alpha/2(n-1)}$ is the inverse of the Student's distribution, for $1-\alpha/2$ confidence level and $n-1$ degree of freedom [non-dimensional]; $\bar{x}_I$ is the i distribution mean [kWh/m^2 year].

3. Results

3.1. Deterministic analysis

Table 5 shows the results of heating and cooling energy consumption, along with the elapsed time in the simulations for the climate of Florianópolis. It is clear that energy consumption for cooling represents the largest end-use of the building, as heating contributes to only 0.9% of total energy consumption with air conditioning for model 1. The heating represented 0.1% of the total energy consumption with air conditioning for Campo Grande climate, and 8.7% for Curitiba, both for model 1. Thus, the 10% criterion for discarding models was applied only to the cooling energy consumption.

Models 6, 8 and 13 have complied with the criterion (have reduced the simulation time, and reached results close to model 1 with 10% difference). Model 11 has a different behaviour in the cooling energy consumption among the other models.

Similar results were obtained for Campo Grande and Curitiba climates.

Models 2–5 have not reduced the simulation elapsed time, and the other models have not results close to model 1.

The existence of internal thermal mass always led to results closer to model 1 and increased the absolute value of consumption for cooling.

Models 4 and 5 showed greater variation compared to model 1, and, like models 2 and 3, increased the simulation elapsed time. In cases without external geometry simplification, the simplification of internal zones did not help to reduce the simulation time, making it actually more complex than model 1.

According to EnergyPlus [29], the thermal balance of the internal zones is basically due to internal loads, air exchange between zones, air exchanges with the external environment and convective heat transfer on surfaces. The most important part of the heat balance is heat transfer of the internal surfaces, as shown in Eq. (9). This heat transfer includes the conduction through the constructive components, convection with the air, absorption and reflection of short wavelength radiation and exchanges of long wavelength radiation, as follows:

$$q''_{LWX} + q''_{SW} + q''_{LWS} + q''_{ki} + q''_{sol} + q''_{conv} = 0 \tag{9}$$

Table 4
Values for the physical parameter uncertainty analysis.

Parameter	Unit	Mean	Standard deviation
Thickness of the brickwork (wall)	m	0.01340	0.00134
Thickness of the mortar inside face (wall)	m	0.0150	0.0015
Thickness of the mortar outside face (wall)	m	0.0250	0.0025
Density of the mortar (wall)	kg/m^3	1950.0	76.5
Density of the brickwork (wall)	kg/m^3	1772.0	51.0
Specific heat of the mortar (wall)	J/kg K	1000	190
Specific heat of the brickwork (wall)	J/kg K	920	175
Thermal conductivity of the mortar (wall)	W/m K	1.15	0.22
Thermal conductivity of the brickwork (wall)	W/m K	0.70	0.13
External solar absorptance (wall)	–	0.50	0.04
Thickness of the steel (roof)	m	0.0005	0.000025
Thickness of the PVC (ceiling)	m	0.008	0.0008
Density of the steel (roof)	kg/m^3	7800.0	25.5
Density of the PVC (ceiling)	kg/m^3	1300.0	51.0
Emissivity of the steel (roof)	–	0.10	0.02
Emissivity of the PVC (ceiling)	–	0.90	0.02
Specific heat of the steel (roof)	J/kg K	460	18
Specific heat of the PVC (ceiling)	J/kg K	960	38
Thermal conductivity of the steel (roof)	W/m K	55.00	4.95
Thermal conductivity of the PVC (ceiling)	W/m K	0.20	0.02
Solar absorptance (roof)	–	0.15	0.04
Thickness of the ceramic (floor)	m	0.0080	0.0008
Thickness of the concrete (floor)	m	0.08	0.01
Density of the ceramic (floor)	kg/m^3	1200.0	51.0
Density of the concrete (floor)	kg/m^3	2400.0	102.0
Specific heat of the ceramic (floor)	kJ/kg K	920	175
Specific heat of the concrete (floor)	kJ/kg K	1000	190
Thermal conductivity of the ceramic (floor)	W/m K	0.70	0.13
Thermal conductivity of the concrete (floor)	W/m K	1.75	0.33
Thermal conductivity of the glass (window)	W/m K	0.90	0.06
Ground temperatures (January)	°C	24.17	0.20
Ground temperatures (February)	°C	24.44	0.20
Ground temperatures (March)	°C	23.83	0.20
Ground temperatures (April)	°C	22.93	0.20
Ground temperatures (May)	°C	20.61	0.20
Ground temperatures (June)	°C	18.85	0.20
Ground temperatures (July)	°C	17.69	0.20
Ground temperatures (August)	°C	17.37	0.20
Ground temperatures (September)	°C	18.04	0.20
Ground temperatures (October)	°C	19.44	0.20
Ground temperatures (November)	°C	21.30	0.20
Ground temperatures (December)	°C	22.99	0.20
Ground reflectance	–	0.13–0.20–0.26	

All parameters have normal distribution, except the ground reflectance, which has a triangular distribution.

Table 5
Results of the energy consumption and time of simulation of the deterministic analysis for the Florianópolis weather file.

External geometry	Model	Heating [kWh/m²year]	Cooling [kWh/m²year]	Time [minutes]	Δheating [%]	Δcooling [%]	Δtime [%]
	Model 1	0.70	75.56	19.8	-	-	-
No simplification	Model 2	0.64	71.99	27.6	-7.8	-4.7	39.5
	Model 3	0.67	74.75	24.9	-3.2	-1.1	26.1
	Model 4	1.21	41.57	175.2	73.3	-45.0	786.4
	Model 5	1.37	43.41	180.3	95.9	-42.5	812.0
Level 1 simplification	Model 6	0.66	73.39	6.2	-4.8	-2.9	-68.9
	Model 7	0.57	70.67	5.0	-18.0	-6.5	-74.5
	Model 8	0.60	73.92	5.1	-14.5	-2.2	-74.4
	Model 9	0.96	44.88	4.8	37.8	-40.6	-75.7
	Model 10	1.07	46.91	5.5	53.1	-37.9	-72.1
Level 2 simplification	Model 11	0.60	82.74	4.8	-14.5	9.5	-75.5
	Model 12	0.57	69.69	3.1	-18.7	-7.8	-84.2
	Model 13	0.56	71.49	3.2	-20.4	-5.4	-84.0
	Model 14	0.51	61.62	2.3	-27.0	-18.4	-88.1
	Model 15	0.56	66.18	2.4	-19.3	-12.4	-87.8

where q''_{LWX} is the net long wavelength radiant exchange flux between zone surfaces [W]; q''_{SW} is the net short wavelength radiation flux to the surfaces due to the lighting [W]; q''_{LWS} is the long wavelength radiation flux from the zone equipment [W]; q''_{ki} is the conduction flux through the walls [W]; q''_{sol} is the transmitted solar radiation flux absorbed by the surfaces [W]; q''_{conv} is the convective heat flux to the zone air.

For radiation heat transfer, EnergyPlus considers the air as being transparent to long wavelength radiation due to the small size of the zones and disregarding the existence of significant amounts of water vapour. This consideration makes possible the separation of heat transfer by convection and radiation.

The programme considers a simplified way to calculate the View Factor according to the ScriptF model, which depends only on the total area that each surface sees (except its own area) and a direct view factor, which for a certain Surface 1 represents the ratio of the seen area of Surface 2 by the total area of Surface 1. Thus, the heat exchange is performed according to Eq. (10).

$$q_{i,j} = A_i \sigma F_{i,j} (R_i^4 - T_j^4) \tag{10}$$

where $q_{i,j}$ is the radiant heat flux between surface i and j [W]; A_i is the area of the surface I [m^2]; $F_{i,j}$ is the ScriptF view factor between surfaces i and j; T_i is the temperature of the surface i [Kelvin]; T_j is the temperature of the surface j [Kelvin]; σ is the Stefan–Boltzmann constant of 5.67×10^{-8} [W/m^2 K^4].

As for models 2–5, the grouping of multiple zones in one thermal zone generates a large increase of factorial combinations between numerous surfaces for the calculation of ScriptF. This fact overloaded the simulation and generated more surfaces for the calculation of air convection procedure.

However, in the case of models with simplified external geometry (models 6–15) the effect is the opposite: as the geometry is rectilinear, there are no small wall surfaces for heat transfer in each zone. In these cases, the simulation time decreased as the grouping of internal zones continued. The first model with level 1 of external geometry simplification (model 6) has a reduction in simulation elapsed time of 69% for Florianópolis.

3.2. Parameter variation analysis

Models 6, 8, 10, 13 and 15 were chosen for the parameter variation analysis. Models 6, 8 and 13 were chosen because they comply with the adopted criterion; models 10 and 15 were only chosen as a comparative analysis.

Fig. 7 shows the results of energy consumption difference between parameters values of each model with model 1, according to Eqs. (6) and (7).

It is apparent that models 6 and 8 always have differences of less than 3% compared to model 1. This indicates that the behaviour of these computer models is similar to model 1, regardless of the value of the physical parameters. This result shows that simplified computer models (e.g. models 6 and 8) are useful to simulate some energy-efficient strategies, as they can represent well the case of model 1 with sufficient accuracy.

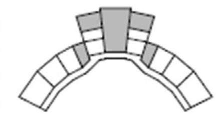
The simplification assumption of model 6 was only the linearization of the external wall, by maintaining the interior of the building the same as model 1. With the proximity of the results, it could be proved that the arch shape could be simplified in linear shape, without losing significant accuracy. Model 8 has internal thermal mass instead of internal partitions, by separating the conditioned of the unconditioned areas, proving that this strategy could be correctly used as an effective solution to saving simulation time and having good results.

Models 10, 13 and 15 have major differences; besides, the absolute values of energy consumption are very different from model 1, as shown in Table 5. In model 10, the energy consumption difference with cooling by reducing solar absorptance of walls and roof is overestimated. The cooling energy consumption variation of model 10 was overestimated in 11.8% for the solar absorptance of walls, and in 13.1% for the solar absorptance of the roof when compared to model 1.

This indicates some problems in the use of simplified computer models of a single zone to indicate an idea of energy consumption in absolute values and also in terms of variation. The inaccuracy is high.

For the other climates, the same trend was observed, in which models 10, 13 and 15 showed the worst correlation to model 1 results.

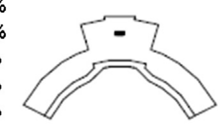
Model 6

Parameter (*Pj*)	*DiffHeat*	*DiffCool*	1st floor plan
$\Delta\alpha$wall	0.8%	0.0%	
$\Delta\alpha$roof	0.1%	0.8%	
$\Delta\varepsilon$roof	0.4%	0.8%	
ΔU&Ctwall	1.0%	0.1%	
ΔU&Ctroof	0.2%	0.1%	
ΔSHGC	1.2%	0.2%	

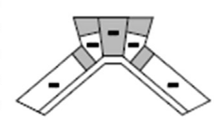
Model 8

Parameter (*Pj*)	*DiffHeat*	*DiffCool*	1st floor plan
$\Delta\alpha$wall	3.0%	2.0%	
$\Delta\alpha$roof	2.4%	1.5%	
$\Delta\varepsilon$roof	2.9%	0.7%	
ΔU&Ctwall	1.0%	0.1%	
ΔU&Ctroof	1.1%	0.3%	
ΔSHGC	1.0%	0.9%	

Model 10

Parameter (*Pj*)	*DiffHeat*	*DiffCool*	1st floor plan
$\Delta\alpha$wall	3.3%	11.8%	
$\Delta\alpha$roof	6.6%	13.1%	
$\Delta\varepsilon$roof	8.6%	4.7%	
ΔU&Ctwall	2.0%	0.1%	
ΔU&Ctroof	1.2%	1.9%	
ΔSHGC	3.3%	0.8%	

Model 13

Parameter (*Pj*)	*DiffHeat*	*DiffCool*	1st floor plan
$\Delta\alpha$wall	4.2%	3.3%	
$\Delta\alpha$roof	1.1%	0.8%	
$\Delta\varepsilon$roof	0.7%	0.3%	
ΔU&Ctwall	1.2%	3.7%	
ΔU&Ctroof	0.5%	0.1%	
ΔSHGC	2.3%	0.9%	

Model 15

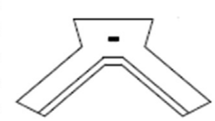
Parameter (*Pj*)	*DiffHeat*	*DiffCool*	1st floor plan
$\Delta\alpha$wall	1.4%	5.6%	
$\Delta\alpha$roof	0.6%	4.3%	
$\Delta\varepsilon$roof	2.3%	1.7%	
ΔU&Ctwall	3.5%	4.0%	
ΔU&Ctroof	5.9%	0.3%	
ΔSHGC	3.7%	2.9%	

Fig. 7. Results of the parameter variation analysis for Florianópolis.

3.3. Parameter uncertainty analysis

Models 6 and 8 were chosen for the uncertainty analysis, because they have reduced the simulation time spent, passed the deterministic analysis, and passed the parameter variation analysis. The difference between them is related to the internal zones division. Model 6 has all zones separated while model 8 is divided in conditioned and unconditioned zones only.

Fig. 8 shows the results of 100 simulations with Latin Hypercube Sampling for the cooling energy consumption for Florianópolis, Curitiba and Campo Grande climates. Fig. 9 shows the same data for the heating energy consumption. For model 1, the simulation process took 33.0 h; for model 6, it took 20.5 h; and for model 8, 8.4 h (using the same computer).

Table 6 summarizes the modelling uncertainties reached in this work, which must be considered when model 6 or 8 is chosen to represent model 1. The uncertainties were separated by each type of analysis.

For Florianópolis, the difference between individual simulations with heating consumption ranged from −16.7% to −6.8%; for Campo Grande the difference ranged from −24.3% to 34.6% and for Curitiba, from −16.3% to −7.8%. The cooling energy consumption differences were smaller, being from −4.2% to 1.5% for Florianópolis, from −3.6% to 2.4% for Campo Grande, and from −7.4% to 2.9% for Curitiba. All these percentage differences originate only from the modelling uncertainties between model 1 and model 8, when comparing the same set of physical parameters. The differences in consumption with heating for Campo Grande had higher amplitudes, but the heating itself is not representative on the energy end-uses for this climate.

An example might be suggested for the interpretation of Table 6. For an analysis of parameter variation in Florianópolis using model 8 to represent model 1, any energy consumption variation value should be accounted with −2.3% to 2.0% of uncertainty. If the result of this analysis comes to a saving of 10 kWh/m^2 year with the decrease of solar absorptance of the roof, for example, the confidence interval of 95% would be 9.8–10.2 kWh/m^2/year.

The first analysis type (deterministic analysis) has the largest uncertainties involved, reaching 33.5% for heating consumption in Campo Grande with 95% confidence. The parameter variation uncertainties reached their extreme on the cooling consumption in Curitiba, with −11.1% of uncertainty. In the uncertainty analysis, any relative deviation should consider up to 4.5% in the case of heating consumption in Campo Grande for model 8.

3.4. Physical uncertainties of each model

The uncertainty values presented in Table 6 could be high or low, depending on the case study. However, in an attempt to discover the magnitude of uncertainties, the modelling uncertainties were compared to the actual physical uncertainties.

Table 7 shows the relative deviation with 95% confidence in the physical uncertainties. The physical uncertainties are similar to the modelling uncertainties for the deterministic analysis. However, the modelling uncertainties are lower than the physical uncertainties for the parameter variation and uncertainty analysis, both in heating and in cooling.

For example, the extreme modelling uncertainty for Florianópolis climate is −7.9% when choosing model 6 to represent model 1,

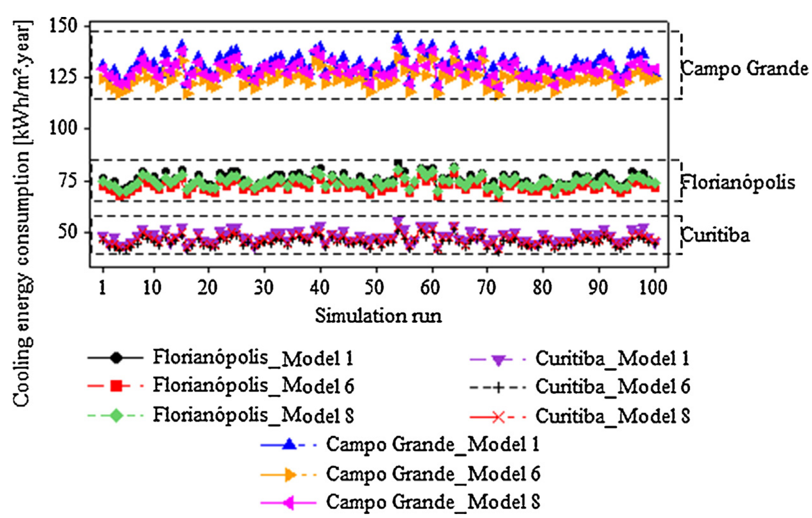


Fig. 8. Results for the uncertainties in cooling energy consumption for models 1, 6 and 8, for the three cities analysed.

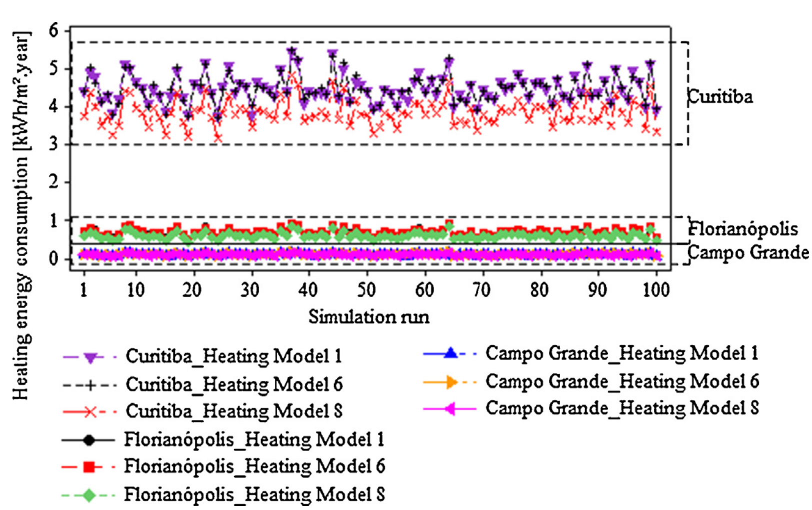


Fig. 9. Results for the uncertainties in heating energy consumption for models 1, 6 and 8, for the three cities analysed.

Table 6
Modelling uncertainties that should be included when model 6 or 8 is chosen to represent model 1, with 95% confidence.

Analysis type	Climate (weather file)	Model	Heating consumption		Cooling consumption	
			Minimum	Maximum	Minimum	Maximum
Comparison of a deterministic value of simulation	Florianópolis	Model 6	−4.00%	8.30%	−7.90%	−1.50%
		Model 8	−16.70%	−6.80%	−5.00%	0.70%
	Campo Grande	Model 6	−14.30%	48.00%	−8.00%	−2.00%
		Model 8	−25.00%	33.50%	−4.40%	1.30%
	Curitiba	Model 6	−4.10%	6.10%	−11.10%	−0.50%
		Model 8	−17.00%	−8.50%	−8.10%	2.10%
Determining the potential energy savings with a physical parameter variation	Florianópolis	Model 6	−1.20%	1.00%	−0.80%	0.80%
		Model 8	−3.00%	3.30%	−2.30%	2.00%
	Campo Grande	Model 6	−2.20%	1.70%	−0.80%	0.60%
		Model 8	−1.40%	6.60%	−2.10%	2.70%
	Curitiba	Model 6	−1.00%	1.00%	−0.50%	0.60%
		Model 8	−3.20%	5.30%	−4.00%	2.80%
Determining the uncertainty due to physical parameters	Florianópolis	Model 6	−0.60%	0.60%	−0.80%	0.80%
		Model 8	−0.90%	0.90%	−0.90%	0.90%
	Campo Grande	Model 6	−1.00%	1.00%	−0.80%	0.80%
		Model 8	−4.50%	4.50%	−0.80%	0.80%
	Curitiba	Model 6	−0.20%	0.20%	−1.80%	1.80%
		Model 8	−1.40%	1.40%	−1.90%	1.90%

Table 7
Physical uncertainty represented by the relative deviation with 95% confidence.

Climate (weather file)	Model	Relative deviation with 95% confidence	
		Heating	Cooling
Florianópolis	Model 1	26.0%	7.5%
	Model 6	26.7%	6.7%
	Model 8	27.0%	6.6%
Campo Grande	Model 1	54.8%	7.3%
	Model 6	53.8%	6.5%
	Model 8	50.4%	6.4%
Curitiba	Model 1	16.4%	12.0%
	Model 6	16.7%	10.2%
	Model 8	17.8%	10.1%

in a deterministic analysis. The physical uncertainty is ±7.5% for model 1. In this case, one should consider the greater uncertainty.

The physical uncertainties were greater for heating energy consumption. For the climate where heating end-use represents the least value (Campo Grande), the uncertainty is higher. This indicates that, when the absolute value of the energy consumption is low, the physical uncertainty related to it is high.

4. Conclusions

This study examined the accuracy of the results of energy consumption due to simplifications in a computer model for a building of educational use and complex geometry.

The simplification of the external geometry of the building most influenced the simulation time. A 74.4% reduction in time spent was found for model 8, compared to the time spent for model 1.

Models that had simplifications only in internal zones, keeping the outside walls in small thermal surfaces in arch shape, have increased simulation time compared to model 1. This fact could be explained by the algorithms of radiation heat transfer of EnergyPlus, that overloaded the iterations on the simulation runs. The existence of an internal thermal mass always increased the results of cooling energy consumption, as they come closer to model 1 results in all cases.

After the three proposed analysis, models 6 and 8 were good simplified models. They have closer results to model 1 in the deterministic, parameters variation and uncertainty analyses. As the physical uncertainties could be greater than the modelling uncertainties in some cases, one could choose model 8, instead of model 6, as it is the easiest modelling type in few internal zones, facilitating future uncertainty and sensitivity analyses with large number of runs.

These models are suitable to represent a complex building (as model 1) for computer analysis purposes like energy consumption determination, thermal performance or meta-modelling approaches for regulations, standards or certifications. However, it should be considered at least the physical uncertainties in the simulations, which were relatively higher than the modelling uncertainties, with 95% confidence.

These achieved results are valid for the building type adopted in this work, along with all configurations of the parameters as internal loads, geometry and simulation settings. However, some findings could be set to different buildings to analyse the consequences, i.e., the simplification strategies of models 6 and 8 could be applied to another building to verify whether the results would be close or similar.

The method developed for this study, including the selection of models, dependent variables and the three types of analyses, is well suited to be applied to other studies, cases and buildings.

Additional studies need to be performed with different strategies of external geometry simplifications, different internal zones simplifications, and different building thermal components. The ideal simplified model would be the one that resulted in a low simulation time and closer results to the base case model.

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