Finding patterns of occupant behaviour in actual data for thermal performance simulation: a case study in low-income houses

Identificação do padrão de comportamento de moradores em dados reais para simulações de desempenho térmico: estudo de caso em habitações de interesse social

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Abstract

The way residents occupy and operate houses influences the energy consumption. The objective of this paper is to find patterns of occupant behaviour in actual data for thermal performance simulation. Data on occupancy of rooms and operation of doors and windows were obtained through a database created by means of application of questionnaires in low-income houses located in Florianópolis, southern Brazil. The reference profiles were obtained using cluster analysis, hierarchical and non-hierarchical techniques combined. Such profiles were submitted to computer simulations. The results showed significant variability within the clusters regarding the occupancy and operation of doors and windows. It was possible to verify the impact that different profiles have on the performance of the house, either due to occupancy or heat losses and gains from air changes through doors and windows. The combination of these effects resulted in some profiles that were highly vulnerable to external temperature conditions, while others were able to maintain the internal temperatures more constant. It was possible to verify that the use of reference profiles based on actual data lead to more reliable performance indicators.

Keywords: Occupant reference profile. Cluster analysis. Computer simulation. Occupant behaviour. Occupancy. Social housing.

Resumo

A forma como os moradores ocupam e operam as casas influencia o consumo de energia. O objetivo deste trabalho é encontrar padrões de comportamento dos moradores em dados reais para fins de simulação do desempenho térmico. Dados sobre ocupação de cômodos e funcionamento de portas e janelas foram obtidos por meio de um banco de dados criado por meio da aplicação de questionários em habitações de interesse social localizadas em Florianópolis. Os perfis de referência foram obtidos por meio de análise de agrupamento, com técnicas hierárquicas e não hierárquicas combinadas. Tais perfis foram submetidos a simulações computacionais. Os resultados mostraram variabilidade significativa entre os grupos quanto à ocupação e operação de portas e janelas. Foi possível verificar o impacto que diferentes perfis têm no desempenho da casa, seja pela ocupação ou pelas perdas de calor e ganhos com as trocas de ar através de portas e janelas. A combinação desses efeitos resultou em alguns perfis altamente vulneráveis às condições de temperatura externa, enquanto outros foram capazes de manter as temperaturas internas mais constantes. Foi possível verificar que a utilização de perfis de referência baseados em dados reais leva a indicadores de desempenho mais confiáveis.

Palavras-chave*: Perfil de referência dos ocupantes. Análise de agrupamento. Simulação computacional. Comportamento dos usuários. Ocupação. Habitação social.*

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Introduction

According to the National Energy Balance (Brazil, 2022), buildings account for approximately 50% of energy consumption in Brazil, of which 26.4% corresponds to the residential buildings. Thus, alternatives aimed at improving their energy efficiency, such as the use of more efficient appliances, the adoption of envelopes with high thermal performance and the use of natural lighting, may result in a reduction of energy consumption (Silva; Ghisi, 2021; Costa; Alvarez; Martinho, 2021; Hazboun; Carvalho; Pedrini, 2023). In order to infer the effectiveness of adopting such measures, there is a need to perform computer simulations, which allow for estimating the impact of strategies before adopting them. By performing simulations, it is possible to obtain relevant data regarding the use and performance of buildings. However, to achieve reliable results and conclusions, input data must be consistent and reliable. Silva, Almeida and Ghisi (2017) point out that the uncertainties regarding the results of simulations are high when adopting parameters that do not correspond to what actually happens in the building. D'Oca and Hong (2014) suggest that differences between the energy consumption obtained through simulations and actual energy consumption are the result of assumptions not based on practice. Mo *et al.* (2019) corroborate with this point of view, stating that engineers have realized a significant difference between the building's designed performance and actual performance, which is defined by Haldi *et al.* (2017) as performance gap. Thus, when the objective of the study is to understand the real energy consumption in the building, all the main influence factors must be investigated in order to be consistent with what happens in the buildings under study. Causone *et al.* (2019) argue that occupant behaviour is one of the most relevant sources of uncertainty in building energy modelling. Understanding the relationship between occupant behaviour and the energy consumption of a building is one of the most effective ways to identify the difference between the energy consumption predicted by simulations and the actual one (Ciappina; Urbano; Giglio, 2022; Mo *et al.*, 2019; Fabi *et al.*, 2012; An; Yan; Hong, 2018).

Occupancy is one of the main factors to understand the operation and energy consumption of a building due to the variability of human behaviour (Bonte; Thellier; Lartigue, 2014; Papakostas; Sotiropoulos, 2008). Page *et al.* (2008) state that being in the building is the primary condition for interaction between user and building and that, therefore, occupancy is, in some ways, the basis for all other models. Occupancy has passive and active effects: as passive effects there are heat changes and demand for cooling, and as active effects there are the use of appliances and the operation of controlled devices. Therefore, by understanding the occupancy pattern, one can infer about trends on the energy consumption in buildings (Causone *et al.*, 2019; Mitra *et al.*, 2020).

However, the variability of occupant behaviour is not always taken into account in thermal and energy performance studies, causing inconsistencies between simulation results and reality (Bonte; Thellier; Lartigue, 2014; Buttitta *et al.*, 2019; Happle; Fonseca; Schlueter, 2018). For Chen *et al.* (2015), the lack of understanding about occupant behaviour in buildings is an obstacle to improving energy efficiency. Silva and Ghisi (2014) state that the uncertainties in the simulation results arise from the uncertainties related to the input data, such as the number of occupants in a particular room and occupancy in the building as a whole. In this sense, Mo *et al.* (2019) claim that accurate modelling of occupant behaviour can provide great support on building performance simulation to achieve more reliable computer-aided design of buildings. Thus, when using real occupancy data in simulations, one can obtain a better understanding of the operation of the building, as well as conclusions coherent with reality.

Several studies have shown the importance of finding occupancy patterns in buildings. Based on data from a national survey, Aerts *et al.* (2014) identified seven occupancy models for houses. The authors created a probabilistic model capable of reproducing the sequences of occupancy in a very similar way to the real sequences of occupancy. For the authors, occupancy patterns are of great value, since they incorporate the high variability of the behaviour of occupants without the need of applying simulation performance as something so complicated (Aerts *et al.*, 2014). In a study conducted by Erickson, Carreira-Perpifian and Cerpa (2014), an occupancy model was developed based on data extracted from sensors. The sensors were installed at border points (windows and doors) to set the air-conditioning system. Initially, in the building studied, the air-conditioners did not consider the degree of occupancy in the room, and, for many times, operated at maximum power, even when there were few occupants in the room. To overcome this problem, the authors proposed integration between the air-conditioning system and the occupancy model to reduce energy consumption. The simulations indicated that, using occupancy models proposed and taking comfort standards proposed by ASHRAE (2010) into account, the annual energy consumption reduction in the building reached 42% on average. Causone *et al.* (2019) proposed a novel procedure based on machine-learning algorithm to obtain five types of uses, described by occupant-related input schedules from electricity recordings of smart meters, in Italy. The schedules obtained were used to simulate the impact of different profiles on the energy need for space heating. The results from the simulation were compared to actual data, showing a variation range of 8% by changing occupancy schedules.

Windows pattern operation is another important research topic regarding performance of buildings (Hawila; Diallo; Collignan, 2023; Liu *et al.*, 2022). Pan *et al.* (2019) state that modelling windows opening behaviour is essential for building performance simulation, due to the significant impact of the opening operation effects on indoor environment and, consequently, on its energy consumption. As for the effects of the operation of windows in the energy consumption of Brazilian residential buildings, Sorgato, Melo and Lamberts (2016) concluded that the operation of windows is an important alternative for the maintenance of thermal comfort in buildings. As Brazil is a country with abundant winds, the operation of the windows can provide thermally comfortable rooms without the use of air-conditioning systems. The authors concluded that occupant behaviour about the operation of windows is a factor that needs to be considered when energy performance analyses are being conducted. Wang and Greenberg (2015), Moghadam *et al.* (2015) and Mo *et al.* (2019) agree with such a conclusion, stating that the occupant behaviour regarding opening and closing of windows has an important impact on the energy consumption in buildings.

The studies conducted by Haldi and Robinson (2009) as well as Andersen *et al.* (2013) proved that the development of computer models based on actual characteristics of occupant behaviour led to results that were closer to reality when analyses of thermal and energy performance were carried out. Both studies obtained data by monitoring opening and closing of doors and windows. In addition, Andersen *et al.* (2013) also showed the need to develop more than one model to represent occupant behaviour adequately in terms of opening and closing windows in simulations. The authors identified a great variation in the behaviour of individuals leading to differences of up to 300% in energy consumption, even in identical buildings. The authors proposed four occupant reference models to apply in simulations, stating that the models would have the ability to increase the validity of the output data significantly. Andersen, Fabi and Corgnati (2016) corroborate this claim. In their study, actual energy consumption from five flats in Denmark was compared with simulation results using models for windows operation and heating system operation for the same five flats. The authors concluded that applying only one occupant behaviour model to several buildings is not an effective practice because this will generate inconsistent results.

The studies cited above demonstrate the strong trend in the development of reference profiles, based on actual data, to be used as input data in thermal and energy simulations of buildings. For the development of such profiles, in addition to obtaining the actual data in field surveys, it is necessary to apply some data mining techniques capable of finding the recurring patterns of behaviour within the sample (Lian *et al.*, 2023; Khani *et al.*, 2021; Zhou *et al.*, 2021).

A technique easy to use that could be applied to this problem is the clusters analysis. Such an analysis aims to group a specific set of individuals into clusters whose characteristics are similar, to obtain high internal homogeneity and high heterogeneity between groups (Hair *et al.*, 2009; Bussab; Miazaki; Andrade, 1990). This technique is capable of grouping individuals whose characteristics are very similar and therefore could be summarised in a single model that would represent them.

For the formation of clusters, it is necessary to define a partition algorithm and a distance measure. The partitioning algorithm defines the set of rules that will determine how each individual will be assigned to one cluster or another. The distance measure is responsible for calculating the differences between individuals, determining how similar or divergent they are (Hair *et al.*, 2009; Schaefer; Ghisi, 2016; Kaufman; Rousseeuw, 2005).

Cluster analysis has already been used in other studies to determine occupant behaviour profiles. Yu *et al.* (2011) applied cluster analysis in a database obtained from measurements in residential buildings in order to identify different patterns of use. They concluded that the method assists in better modelling of occupant behaviour in numerical simulations, which leads to more adequate results in terms of proposing measures to reduce energy consumption in buildings. Aerts *et al.* (2014) also applied cluster analysis to identify different patterns of occupant behaviour. They found seven different occupant profiles. Balvedi *et al.* (2018) analysed the influence of occupant behaviour on the performance of multifamily residential buildings. They simulated three different profiles obtained from cluster analysis and found variations greater than 130% in terms of degree-hours. An, Yan and Hong (2018) employed cluster analysis to analyse the air-conditioning use pattern in a residential building district in China. They obtained four representative air-conditioning use patterns schedules for bedrooms and dining rooms and three for living rooms from actual data. Authors found a large variation in the total cooling energy consumption (up to 140 kWh/m^2) among all households, even for the same district, climatic conditions and envelope performance. According to the authors, this load diversity was mainly caused by occupant behaviour.

Since both occupancy and operation of doors and windows in buildings have a significant impact on their energy consumption, one can notice the importance of using input data based on actual data when thermal and energy performance simulations are performed. In addition, given the variability of occupant behaviour, the use of different profiles is necessary to obtain more reliable performance indicators. For this reason, the objective of this paper is to find patterns of occupant behaviour in actual data for thermal performance simulation purposes. The technique used to obtain such occupant reference profile was cluster analysis, taking into account the studies of Aerts *et al.* (2014) and Schaefer and Ghisi (2016).

To achieve this goal, a case study was conducted considering a sample of low-income houses in the greater Florianópolis region, southern Brazil. The reason for which this object of study was chosen refers to the fact that:

(a) it is a relevant population in terms of the number of houses, i.e. quite representative;

(b) an increase in predictable demand for the future, considering the large existing deficit added to the progressive increase in housing policies in Brazil; and

(c) the lack of data for this population group.

This last fact, in particular, shows the importance of obtaining and publishing data about this specific group, because usually what is done in simulations is to use data from other population groups, which may result in conclusions that are inconsistent with reality, because their habits and behaviours at home, as well as their routine, differ from other groups of the population (for example, external door opening schedules). Additionally, the climate in southern Brazil differs from the other regions, because it presents two very characteristic seasons: hot summer and cold winter. Therefore, the behaviour of the occupant, especially with regard to the use of openings, should be considered for the different seasons.

Another important consideration to be made about this population group is the method for obtaining data, and there is a need to apply a simple and accessible method. For example, getting the data from monitoring, through sensors, proved to be ineffective. Monitoring is not well accepted by the population, the reasons among which one can mention the feeling that they are being watched, the interference of trafficking, fear of handling or spoiling equipment, theft of equipment, among others. Thus, it was necessary to develop an effective but also simple method for data collection, with a more practical and objective approach, so that the residents themselves could understand and read what was being raised, improving the acceptability to participate in the study and provide the required data. Such a method may be applied in other areas where monitoring and access is hampered.

Method

The method applied in this research consists of three steps:

(a) obtaining occupant behaviour data;

(b) determining occupant reference profiles; and

(c) analysing the thermal performance in houses by using such occupant reference profiles.

Occupant behaviour data were obtained from the application of questionnaires. The data collected were organised and submitted to cluster analysis. From the clusters formed, it was possible to obtain models to represent different profiles of users. Then such reference profiles were simulated. The simulation results were compared in order to verify the influence of the different schedules of occupancy and operation of doors and windows on the thermal performance of the house.

Actual occupant behaviour data

Data used in this study were obtained from an existing database created during the research "Rational Use of Water and Energy Efficiency in Low-income Housing”" (Ghisi *et al.*, 2015). Data on occupancy schedules, number of occupants per room and patterns of operation of doors and windows in houses in Florianópolis were collected based on 98 questionnaires.

Data were organised in a spreadsheet and recorded on an hourly basis, for each hour of the day, resulting in 24 intervals. Data on the occupancy of the rooms were recorded as binary data, in which 1 represented the occupied room and 0, the unoccupied room. Likewise, 1 represented an open window and 0, a closed one. Only information regarding the living room, the main and secondary bedroom was recorded. Data were obtained for weekdays and weekends.

In order to simplify the database for the next step, it was decided to rearrange the hourly data by grouping them into three-hour intervals, i.e. from 0:00 to 2:59, from 3:00 to 5:59, from 6:00 to 8:59, from 9:00 to 11:59, from 12:00 to 14:59, from 15:00 to 17:59, from 18:00 to 20:59 and, then, from 21:00 to 23:59. This process resulted in a database composed of 144 variables: 48 variables related to the schedule of occupancy and opening of doors and windows of each room.

From the initial amount of cases, it was necessary to select those that were obtained from houses with the same boundary conditions (e.g., number of rooms and fabric), in order to establish an equivalent measure of comparison. In addition, cases with incomplete or invalid data were excluded from the sample, resulting in a final sample containing 16 complete and consistent cases.

As the data organising process was complete, the cluster analysis step was performed.

Reference profiles

The technique used for cluster analysis was based on the study developed by Schaefer and Ghisi (2016), in which hierarchical and non-hierarchical cluster techniques were combined. The hierarchical technique was used to define the number of clusters to be formed, while the non-hierarchical technique was used for the final formation of clusters.

The Square Euclidean Distance (Bussab; Miazaki; Andrade, 1990) was defined as the similarity measure used in the hierarchical analysis, and the Ward Method (Hair *et al.*, 2009) was defined as the partition algorithm. The formation of clusters using the hierarchical technique allowed the formation of a dendrogram. For each new cluster, the distance between the grouped objects was recalculated, indicating the similarity between the objects that were in the cluster formed. The shorter the distance, the greater the similarity between the objects. The evolution of this distance was used to the dendrogram partitioning decisions and to the definition of the number of clusters to be formed.

As the optimal number of clusters with the hierarchical procedure was determined, the non-hierarchical procedure was followed, adopting the k-means algorithm (Schaefer; Ghisi, 2016). Seed points were determined for the number of clusters defined in the hierarchical method.

For determining the reference profile of each cluster, a comparison was made between the distance of each element within the cluster and its centroid (multivariate mean of the clustering values). The reference profile of each cluster was selected as the element closest to the centroid. Each reference profile was defined according to the number of occupants, the occupancy pattern and the operation of doors and windows of living rooms and bedrooms.

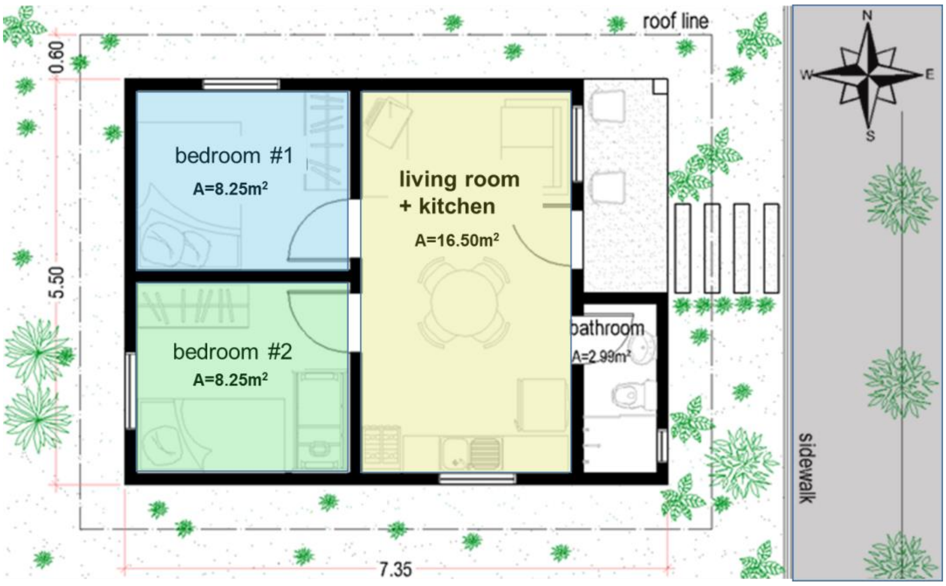
Thermal performance of reference profiles

Computer simulations were performed using the computer programme EnergyPlus, version 8.6 (DEPARTMENTO OF ENERGY, 2019). They were configured using the input data regarding the operation of doors and windows and the occupancy of the rooms, referring to each reference profile obtained in the cluster analysis. All other simulation parameters were kept constant, so that, when simulating the building using data of each reference profile, the difference caused by different schedules of occupancy and operation of doors and windows prevailed. The climate considered in the simulations was the test reference year of Florianópolis (TRY), available at the LabEEE website (LABEEE, 2019).

The house adopted was one of the reference models obtained by Schaefer and Ghisi (2016), which is the representation of an existent house. It is a low-income single-family house, which has two bedrooms, a combined living room and kitchen, and a bathroom. The total floor-plan area of the model is 36.00m². The bedrooms and the combined living room and kitchen have, respectively, 8.25m^2 and 16.50m². The floor plan of the model is shown in Figure 1.

The house was configured as naturally ventilated through the Airflow network object. The construction systems that composed the envelope are shown in Table 1, as well as their thermophysical properties (PROJETEEE, 2019). The internal loads were configured as shown in Table 2. The metabolic rates were obtained from ASHRAE (2010), considering a mean skin area equal to 1.80m^2. The light and equipment powers were adopted as presented by Schaefer and Ghisi (2016), as well as the operating schedules. The bathroom was not configured in the simulations.

Figure 1 - **Floor plan of the house reference model used in the simulations**



Source: based on Schaefer and Ghisi (2016).

Table 1 - **Characterisation of the construction systems of the envelope**

Construction system	Composition	Thermal transmittance (W/(m²K))	Thermal capacity (kJ/(m²K))	Absorptance of the outer layer (%)	Solar factor
Walls	Mortar on the external layer (2.5cm) Ceramic brick (9x14x24cm) Mortar on the internal layer (2.5cm)	2.39	152.00	50	-
Roof	Ceramic tile (1cm) Concrete slab (10cm) Wooden lining (2cm)	2.05	238.00	60	-
Floor	Concrete slab (10cm) Subfloor (2cm) Ceramic tile	3.40	293.80	-	-
Windows	Clear single glazing (3mm)	5.70	-	-	0.87

Table 2 - Configuration of internal loads

Thermal zone	Metabolic rate (W/m²)	Lighting power (W)	Equipment power (W)
Living room + kitchen	153	100	1644
Bedroom #1	81	60	120
Bedroom #2	81	60	120

The occupancy schedules were configured in Energyplus according to the number of occupants and the frequency of occupation in each room, for each reference profile found in the previous step. The schedules of operation of doors and windows were also adopted according to the results obtained through the reference profiles, in the cluster analysis step.

Different output variables were obtained from the computer simulations, in order to verify the influence that the different patterns of occupancy and operation of doors and windows have on the thermal performance of the house. For each variable, data were obtained separately for each room.

In order to quantify the influence of occupancy in each room, EnergyPlus provided the internal heat gains due to the occupancy. This variable represents the heat transferred to the environment by the users, exerting certain activity (represented by the metabolic rate). The influence of the different operations of doors and windows was analysed by means of two variables: the air changes between the room and the external environment, and the sensible heat losses and gains through infiltration. Finally, to analyse the combined impact of occupancy and operation of doors and windows on the thermal performance of the house, thermal loads and heating and cooling degree-hours were obtained. The thermal loads were obtained directly from the simulations, while the degree-hours were calculated based on the operative temperature of each room and external dry bulb temperature, both provided by EnergyPlus.

For the calculation of the degree-hours, the minimum and maximum comfort temperature limits were obtained based on the equations recommended by ASHRAE (2010). The equations used consider that the comfort temperature is a function of the average monthly dry bulb temperature, as can be observed in Equations 1 and 2. The degree-hours were calculated as the sum of the differences between the room operative temperature and the comfort limits set for cooling and heating.

$$T_{o\,max} = 0.31 \times T_{mean} + 2.3 \quad \text{Eq. 1}$$

$$T_{o\,min} = 0.31 \times T_{mean} + 14.3 \quad \text{Eq. 2}$$

Where:

T_{mean} is the dry bulb mean monthly outdoor temperature (ºC);

$T_{o\,max}$ is the temperature below which 80% of occupants feel thermally comfortable (ºC); and

$T_{o\,min}$ is the temperature above which 80% of occupants feel thermally comfortable (ºC).

Results and discussion

In this section, results obtained through the cluster analyses and the occupant reference profiles found for each cluster are presented. Then, the results on the performance of each occupant reference profile, obtained from the computer simulations, are shown.

Determining reference profiles

Formation of clusters

The first application of the hierarchical clustering method resulted in five clusters. However, one of the clusters consisted of only one element. As the objective of this research is to determine representative profiles of occupants, clusters with only one element may not contribute to this goal. They may represent very particular cases in the sample and are therefore not relevant to the final product. Therefore, the cluster with one element was excluded, and a new analysis was performed.

Figure 2 shows the dendrogram obtained from the hierarchical cluster analysis. Based on this type of graph, it is possible to infer about the ideal number of clusters to be formed. The number of clusters is defined by applying a stop rule line (a line that crosses the graph horizontally) at a time when there is a relatively significant increase in the level of similarity when two clusters are joined. In the case of the dendrogram shown in Figure 2, this line was drawn at the height corresponding to the level of similarity equal to 500, resulting in the division of the sample into four distinct clusters.

Then, the non-hierarchical technique was applied and the final definition of clusters was obtained as shown in Table 3.

When comparing the results obtained through the hierarchical and non-hierarchical cluster methods, it can be observed that the clusters formed by each method are not the same. The difference between the results happens due to the grouping sequence used in each of the methods. In the hierarchical method, two clusters are attached at each step. Hence, once an element is assigned to a particular cluster in the process, it never goes undone. Meantime, the formation of the clusters by means of the non-hierarchical process is interactive: the element once designated as the centroid (multivariate mean) of a cluster may change throughout the process, according to the new multivariate mean of each step (Hair *et al.*, 2009; Schaefer; Ghisi, 2016). Consequently, in the non-hierarchical method, an object that belonged to one cluster at the beginning of the process may belong to another cluster at the end of the process, if it comes to resemble it better.

Figure 2 - **Dendrogram obtained from the hierarchical cluster analysis**

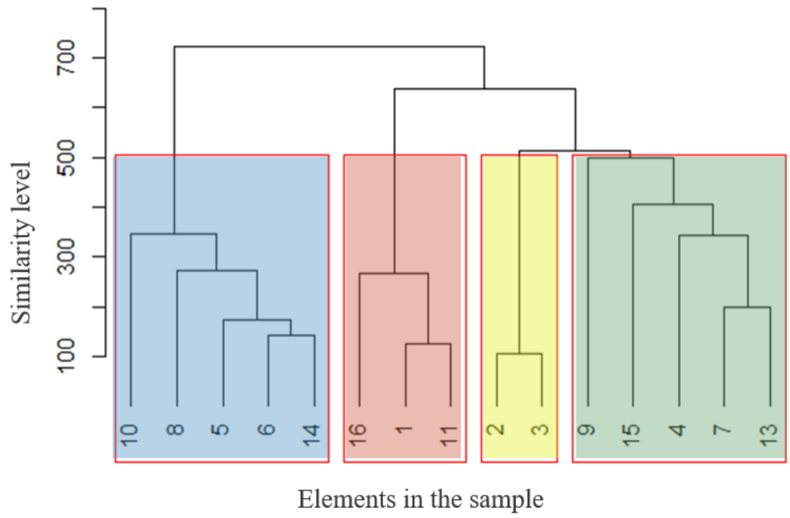


Table 3 - **Formation of clusters and definition of the reference profiles**

Cluster	Cluster formation through a hierarchical technique	Cluster formation through a non-hierarchical technique	Difference of each case in relation to the cluster centroid	Element defined as the reference profile
1	1 11 16	1 11 13 16	54.0 65.0 64.0 73.0	1
2	2 3	2 3	31.5 31.5	2
3	5 6 8 10 14	4 5 6 8 10 14	102.8 86.2 65.2 80.5 96.7 72.5	6
4	4 7 9 13 15	7 9 15	85.7 95.3 94.3	7

Elements allocated in the same cluster have similar behaviour, while elements allocated in different clusters represent different occupant behaviour. Thus, the formation of different clusters from the data sample shows the need to obtain more than one reference profile to represent them, in order to consider the variability of the occupancy. When researching the occupancy behaviour and schedule modelling through data mining, Zhao *et al.* (2014) also identified the existence of different occupant profiles. The simulation results showed that the building performance has a large variation when applying the different occupancy schedules. Similarly, some authors (Bonte; Thellier; Lartigue, 2014; Andersen; Fabi; Corgnati, 2016; Balvedi *et al.*, 2018) verified the need to adopt more than one occupant reference profile in residential buildings, after identifying considerable differences in the performance of the environments due to the influence of the forms of interaction of each profile with the elements of the building.

The occupant reference profiles of each cluster were determined by comparing each of the elements with the multivariate (centroid) mean of their cluster. Table 3 shows the distances of each element to the centroid of the group and the elements defined as reference profiles.

Reference profiles

In this section, the reference profiles are described according to the number of occupants, the occupancy pattern and the operation pattern of doors and windows of each room.

Figure 3 shows the differences between the four reference profiles in terms of occupancy hours for both weekdays and weekends. The same colour bars represent the schedules of the same reference profile. The bars height indicates the number of hours that the room is occupied within a three-hour interval of a certain period of the day. It is possible to observe some differences in the pattern of occupancy of rooms for the reference profiles. Reference profile 1 is the one with more hours of occupancy of bedroom #1, being the only reference profile in which this room is occupied during the afternoon. However, there is no occupancy in bedroom #2 either during the week or at weekends, which happens in the other reference profiles. In addition, it is observed that there is no occupancy in the living room during the day, unlike the other cases, i.e. it is occupied only at night. The reference profiles 2 and 3 presented the most similar behaviour throughout the day, differing only in the occupancy of the living room during the lunch period (which occurs in case 3) and occupancy of bedroom #1 during the morning on weekends (also in case 3). In reference profile 2, there is occupation in the afternoon in bedroom #2, which does not occur in any of the other three reference profiles. Reference profile 4 is the case with the shortest occupancy time, of which the living room is only occupied for a few hours in the morning and the bedrooms almost exclusively at night (with a few hours early in the morning).

The number of occupants per room for the reference profiles are shown in Table 4. It can be observed that there are no occupants in bedroom #2 in reference profile 1.

Based on the occupancy schedule of each room and the number of occupants every hour, it is possible to obtain the occupancy rate of each room. The occupancy rate is a ratio between the number of people occupying the room in a time interval and the maximum number of people who use that room. This is a variable of interest because it is possible to describe routines of use and apply them in computer simulations. It is possible to obtain, for example, the internal heat gains due to the occupancy of that room. Table 4 shows the occupancy rates for each reference profile. It also shows the maximum number of occupants in each room and their occupancy schedules. The information is displayed for both weekdays and weekends.

According to Zhao *et al.* (2014), the occupancy schedule can influence the performance of the room actively (by operating its elements, such as doors and windows) or passively (as “mobile heat and CO_2 sources”). Additionally, finding distinct profiles is important to guarantee the variability of occupancy of users in simulations, which may lead to inconsistences otherwise (Andersen *et al.*, 2013; Andersen; Fabi; Corgnati, 2016). Besides, several studies have verified the importance of adopting occupancy schedules based on actual data, such as (Page *et al.*, 2008; Mo *et al.*, 2019; Aerts *et al.*, 2014; Zhao *et al.*, 2014). In this sense, the schedules presented in Table 4 can assist in the development of thermal and energy performance studies, by applying them in computer simulations. Results may show the best strategy (in terms of building performance) for a specific type of occupant or for a general purpose.

Figures 4 and 5 show the number of hours in which windows and doors remain open in each reference profile over weekdays and weekends. The height of the bars indicates the number of hours that the window remains open, within the indicated time interval. It is expected that these different opening patterns may lead to a great impact in buildings performance, even if the same building is applied as a case study (Sorgato; Melo; Lamberts, 2016; Wang; Greenberg, 2015). Similar to occupancy schedules, openings operation schedules can be very useful for computer simulation of building performance (Pan *et al.*, 2019; Moghadam *et al.*, 2015). The opening schedule of a door or window has a great impact on the thermal performance of a room not only due to the time (i.e. amount of hours) it remained open, but also due to the period of the day it remained open. For example, a window that is opened at noon, on a sunny day, can lead to an increase in the internal temperature of the room, while a window that is opened at night can promote passive cooling of the room. Several studies corroborate with the claim that applying more than one opening schedule, based on actual data, is indispensable for obtaining reliable results on the performance of buildings (D'Oca; Hong, 2014; Andersen; Fabi; Corgnati, 2016; Balvedi *et al.*, 2018).

Based on Figures 3 to 5, it can be observed that the difference between reference profiles in terms of operation of doors and windows is not as great as observed in the occupancy pattern. Nevertheless, it was still possible to verify some differences. Reference profile 1 shows a standardised operating schedule. In all rooms, all windows and doors remain open from 10:00 to 18:00. In reference profile 2, this pattern is found only for windows, which remain open for a slightly longer period: from 9:00 to 20:00. As for the doors, the living room door (which is opened to the outdoor) remains open from early morning until the end of the day, being closed only during lunch period. The bedroom #1 door remains open all day long, while that of bedroom #2, only at night. The windows of reference profile 3 are opened in the middle of the morning and are closed a little earlier than the other cases, i.e. at 17:00, as well as the living room door. The bedroom doors (interior doors) remain open for the entire period. Finally, reference profile 4 shows a more irregular operation of doors and windows throughout the day. The window of bedroom #1 remained open for a longer period, from 07:00 to 21:00, while that of bedroom #2 only from 12:00 to 18:00. The door of bedroom #2 remained always closed.

Figure 3 - **Hours of occupancy for each room over weekdays and weekends**

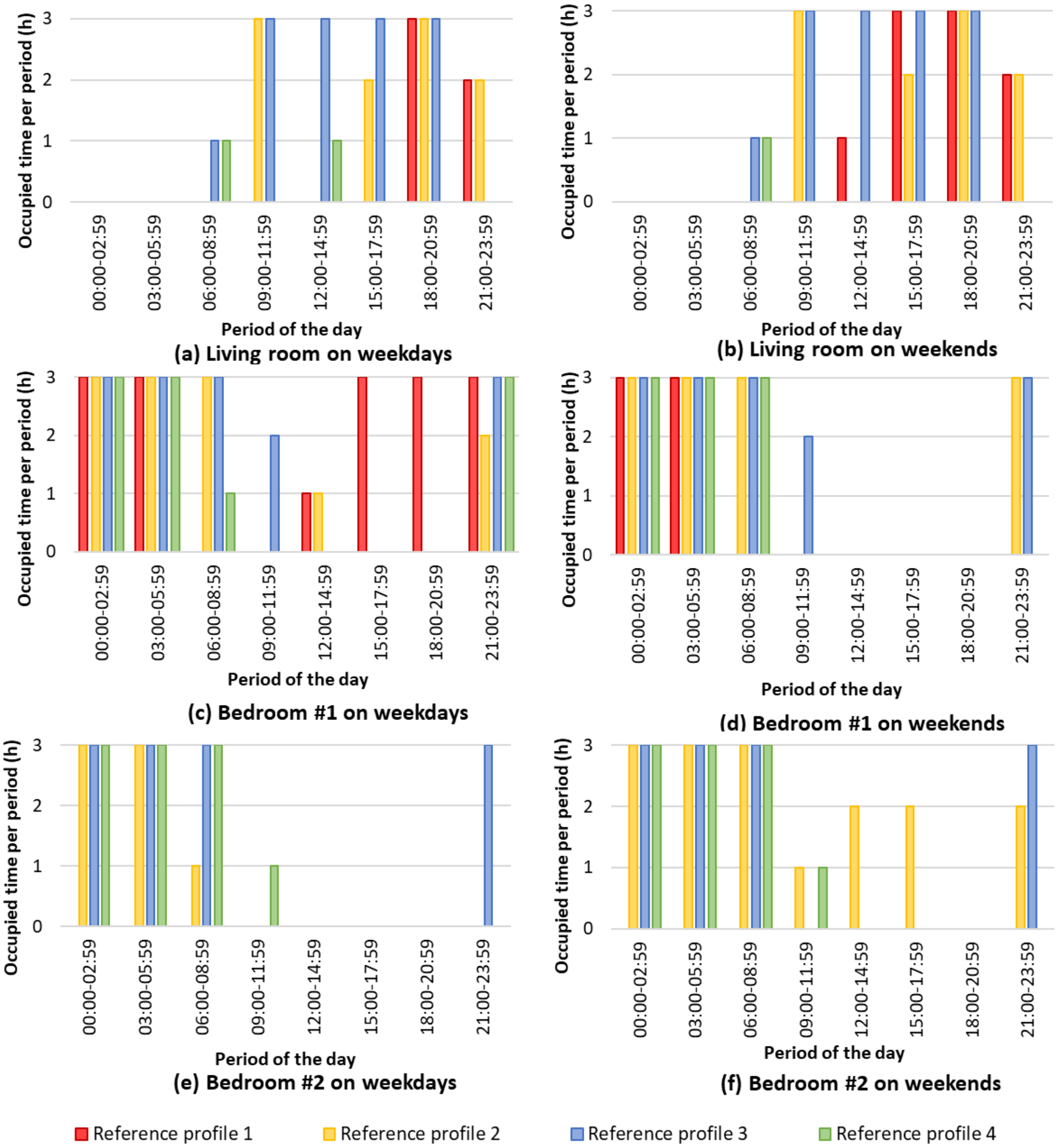


Table 4 – **Occupancy schedules and occupancy rates for each reference profile**

Room	Occupancy data	Reference profile 1	Reference profile 2	Reference profile 3	Reference profile 4
Living room	Maximum number of occupants	3	5	4	3
	Weekday	00h–18h (0.00) 18h–23h (0.66) 23h–24h (0.00)	00h–09h (0.00) 09h–12h (0.60) 12h–16h (0.00) 16h–17h (0.40) 17h–18h (0.80) 18h–23h (1.00) 23h–24h (0.00)	00h–08h (0.00) 08h–12h (0.75) 12h–21h (1.00) 21h–24h (0.00)	00h–08h (0.00) 08h–09h (0.66) 09h–12h (0.00) 12h–13h (0.60) 13h–24h (0.00)
	Weekend	00h–14h (0.00) 14h–23h (0.66) 23h–24h (0.00)	00h–09h (0.00) 09h–12h (0.60) 12h–16h (0.00) 16h–17h (0.40) 17h–18h (0.80) 18h–23h (1.00) 23h–24h (0.00)	00h–08h (0.00) 08h–12h (0.75) 12h–21h (1.00) 21h–24h (0.00)	00h–08h (0.00) 08h–09h (0.66) 09h–24h (0.00)
Bedroom #1	Maximum number of occupants	3	3	2	2
	Weekday	00h–06h (0.66) 00h–14h (0.00) 14h-24h (0.33)	00h–09h (1.00) 09h–12h (0.00) 12h–13h (1.00) 13h–22h (1.00) 22h–24h (1.00)	00h–08h (1.00) 08h–11h (0.50) 11h–21h (0.00) 21h-24h (1.00)	00h–07h (1.00) 07h–21h (0.00) 21h–24h (1.00)
	Weekend	00h–06h (0.66) 06h–24h (0.00)	00h–09h (1.00) 09h–21h (1.00) 21h–24h (1.00)	00h–08h (1.00) 08h–11h (0.50) 11h–21h (0.00) 21h-24h (1.00)	00h–09h (1.00) 09h–24h (0.00)
Bedroom #2	Maximum number of occupants	0	2	2	1
	Weekday	00h–24h (0.00)	00h–06h (1.00) 06h–07h (0.50) 07h–24h (0.00)	00h–09h (1.00) 09h–21h (0.00) 21h–24h (1.00)	00h–10h (1.00) 10h–24h (0.00)
	Weekend	00h–24h (0.00)	00h–06h (1.00) 06h–10h (0.50) 10h–13h (0.00) 13h-17h (0.50) 17h-22h (0.50) 22h–23h (0.50) 23h–24h (1.00)	00h–09h (1.00) 09h–21h (0.00) 21h–24h (1.00)	00h-10h (1.00) 10h–24h (0.00)

Note: occupancy rate is shown within round brackets.

Figure 4 - **Number of hours windows remain open in each room over weekdays and weekends**

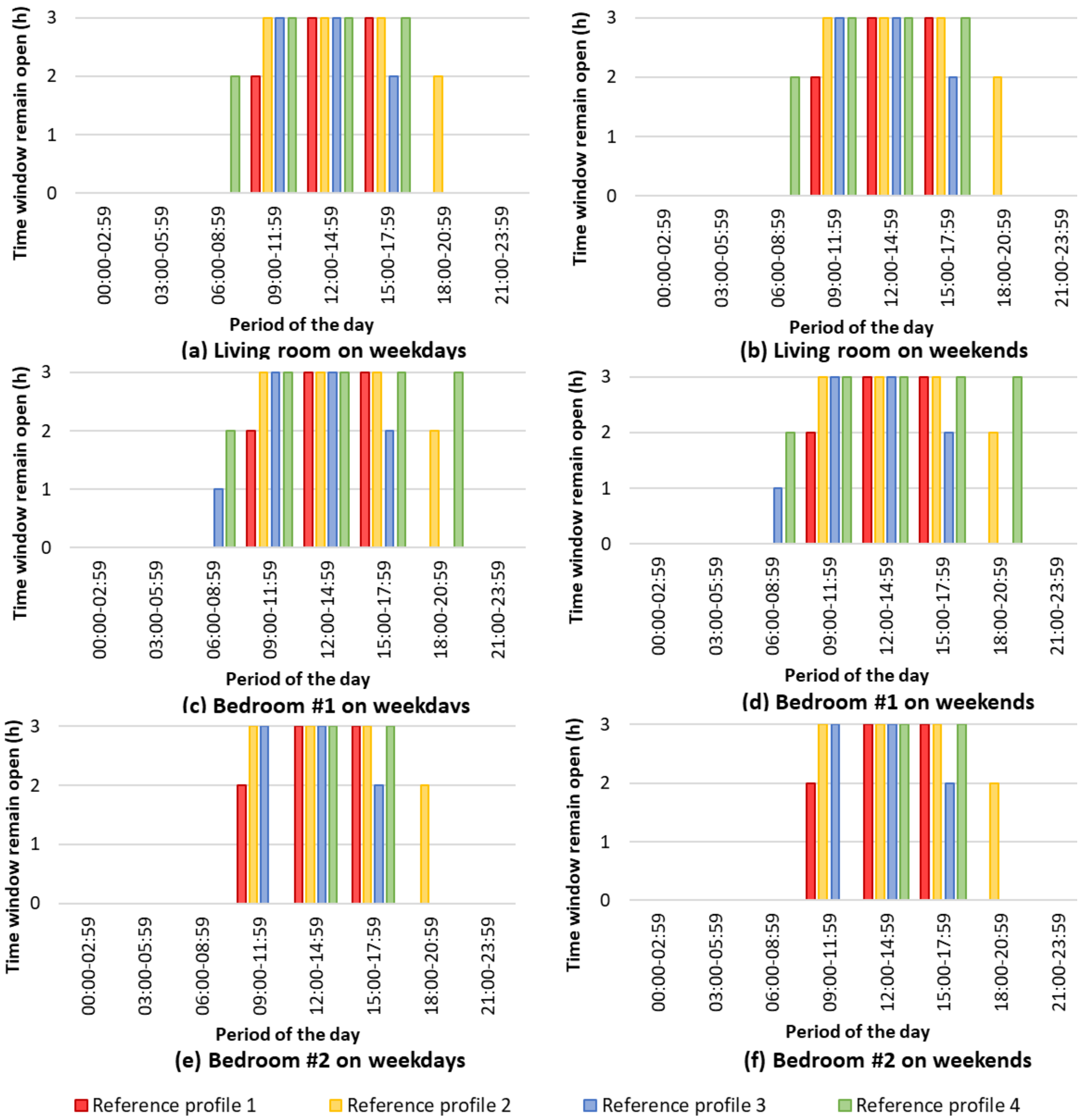


Figure 5 - **Number of hours doors remain open in each room over weekdays and weekends**

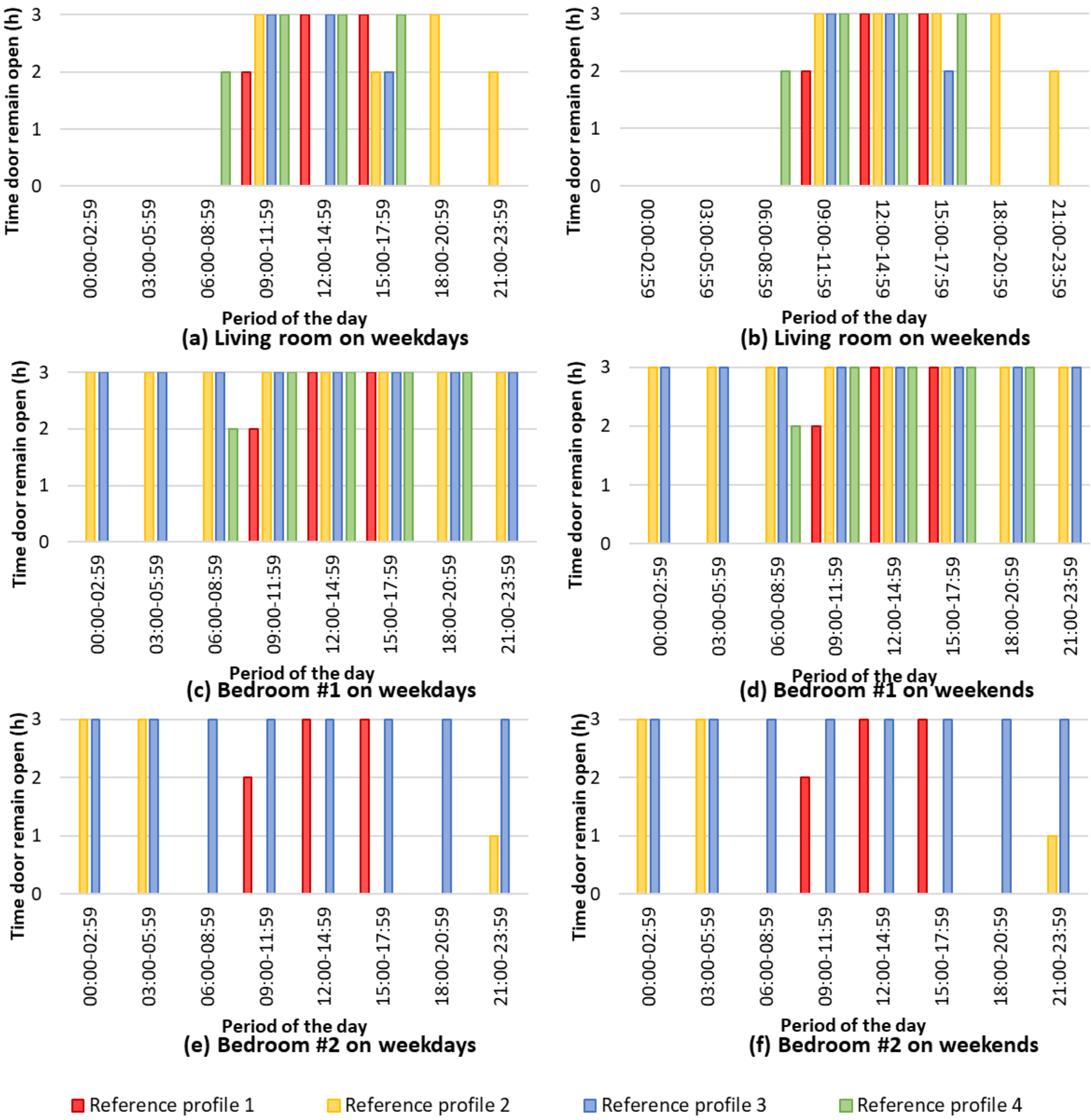


Table 5 shows the operation of doors and windows on an hourly basis. By analysing the results of schedules of occupancy and operation of doors and windows for each reference profile, one can observe a significant change of pattern in the behaviour of occupants. This strengthens the importance of having more than one single reference profile to represent occupants of a set of buildings, even if these buildings are identical, as pointed out in the study developed by Andersen *et al.* (2013). Additionally, the profiles obtained in this study also differ when compared to those found for occupants of other types of buildings, such as multifamily residential buildings. Balvedi *et al.* (2018) identified three occupant profiles for multifamily buildings, located in the same climate region adopted in this study. The most relevant differences correspond to the closing time of the windows of the living room (after 22:00 in all profiles, while in this study it was around 18:00) and the opening time period of the bedrooms' windows (usually closed all day long, while in this study, it remained open throughout the day, in general), in addition to the external door remaining closed for the entire period. This fact is related both to the social behaviour of residents of this type of building and to security issues. Residents of single-family low-income housing have a strong neighbourhood relationship. Therefore, they tend to keep their home open to promote interaction with neighbours, which is normally not the case in multifamily buildings. On the other hand, due to the altitude of the different floors in multifamily residential buildings, to keep windows open at night does not pose a threat to the safety of residents (such as robberies, etc.), unlike single storey houses (which is the case for most buildings in this study), where the tendency is to close them late in the afternoon or early evening.

Another point of interest is that, contrary to what is usually observed in buildings of other standards and types, it was not possible to establish a direct relation between the occupancy hours and the operation of doors and windows. On the contrary, one observed that there is a tendency to keep windows and doors open throughout the day even when the rooms are unoccupied. This is a very important finding because in computer simulations the windows are usually considered open only when the room is occupied, and the external doors are considered closed for the whole period. Jia, Srinivasan and Raheem (2017) observed that occupancy information is mainly used in studies as a system control: when a room is not occupied, building systems stop operating. This type of consideration may imply serious errors when analysing the thermal performance of a building since natural ventilation impacts the thermal comfort of users in the building.

Thermal performance for each reference profile

From computer simulations, it was possible to obtain indicators to compare the performance of the house for each reference profile and thus to verify the impact that different occupancy schedule and operation of doors and windows have on the building.

Table 5 – **Operation of doors and windows for each reference profile**

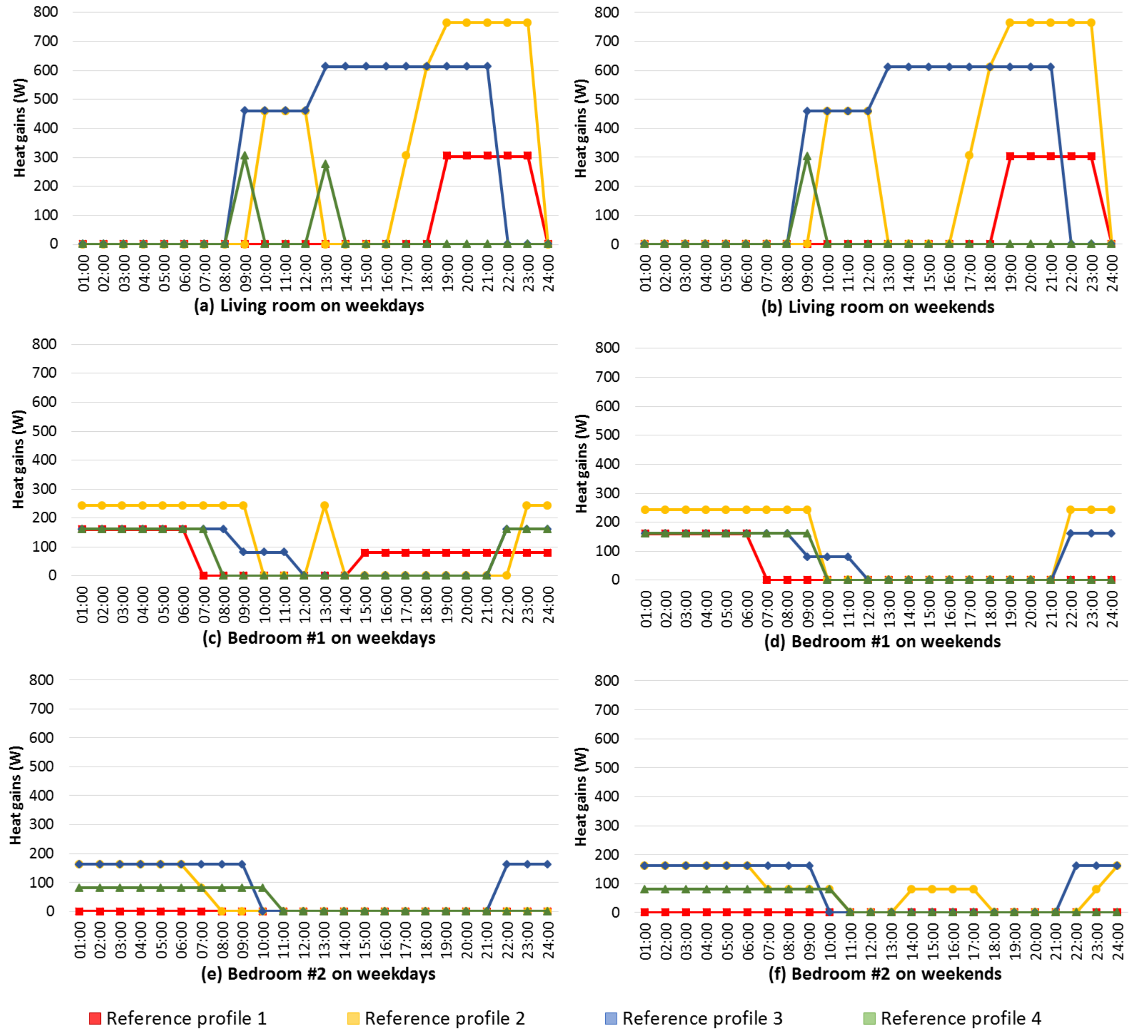
Room	**Opening**	**Reference profile**			
		1	**2**	**3**	**4**
Living room	Door	**For all days** 00h – 10h (0) 10h – 18h (1) 18h – 24h (0)	**Weekdays** 00h – 09h (0) 09h – 12h (1) 12h – 16h (0) 16h – 23h (1) 23h – 24h (0) **Weekends** 00h – 09h (0) 09h – 23h (1) 23h – 24h (0)	**For all days** 00h – 09h (0) 09h – 17h (1) 17h – 24h (0)	**For all days** 00h – 07h (0) 07h – 18h (1) 18h – 24h (0)
	Window	**For all days** 00h – 10h (0) 10h – 18h (1) 18h – 24h (0)	**For all days** 00h – 09h (0) 09h – 20h (1) 20h – 24h (0)	**For all days** 00h – 09h (0) 09h – 17h (1) 17h – 24h (0)	**For all days** 00h – 07h (0) 07h – 18h (1) 18h – 24h (0)
Bedroom #1	Door	**For all days** 00h – 10h (0) 10h – 18h (1) 18h – 24h (0)	**For all days** 00h – 24h (1)	**For all days** 00h – 24h (1)	**For all days** 00h – 07h (0) 07h – 21h (1) 21h – 24h (0)
	Window	**For all days** 00h – 10h (0) 10h – 18h (1) 18h – 24h (0)	**For all days** 00h – 09h (0) 09h – 20h (1) 20h – 24h (0)	**For all days** 00h – 08h (0) 08h – 17h (1) 17h – 24h (0)	**For all days** 00h – 07h (0) 07h – 21h (1) 21h – 24h (0)
Bedroom #2	Door	**For all days** 00h – 10h (0) 10h – 18h (1) 18h – 24h (0)	**For all days** 00h – 06h (1) 06h – 23h (0) 23h – 24h (1)	**For all days** 00h – 24h (1)	**For all days** 00h – 24h (0)
	Window	**For all days** 00h – 10h (0) 10h – 18h (1) 18h – 24h (0)	**For all days** 00h – 09h (0) 09h – 20h (1) 20h – 24h (0)	**For all days** 00h – 09h (0) 09h – 17h (1) 17h – 24h (0)	**For all days** 00h – 12h (0) 12h – 18h (1) 18h – 24h (0)

Note: the number within round brackets indicates if the door/window is closed (0) or open (1).

Figure 6 shows the heat gains due to occupancy in each room. This variable represents the total amount of heat that is produced by the occupant and transmitted to the room, according to the metabolic level of the activity being performed. The heat gains for each reference profile are presented on an hourly basis for both weekdays and weekends. One can identify that occupancy patterns clearly affect the performance of rooms. Reference profile 2, which has a greater number of inhabitants and also more hours of occupancy, resulted in the greatest heat gains in all rooms, reaching almost 800W in the living room at the end of the day. Reference profile 3 was the one with the second most significant contribution of internal heat gain. Reference profile 4, with a lower occupancy, presented a small contribution in the heat gains, but greater only in relation to reference profile 1 in bedroom #2, because such bedroom is always occupied.

Besides occupancy, another way in which the occupant can influence the performance of the building is by means of the operation of doors and windows. Air change between the internal and external environment through the external doors and windows, can greatly impact the internal temperatures and the thermal comfort of the occupant. The operation of internal doors, in a lesser degree, can also influence the internal temperature in the rooms as it allows different levels of pressure to take place inside the building; and this favours cross ventilation and heat transfer between rooms.

Figure 6 - **Internal heat gains due to occupancy in each room over weekdays and weekends for each reference profile**



Figures 7 and 8 show the results of the operation of doors and windows for each reference profile. Figure 7 shows the air changes in each room for each reference profile on an hourly basis. Data are presented for two typical weekdays, one in the hot season (21 February) and the other in the cold season (19 July).

One can observe very different patterns of air changes for each day. This happens because the natural ventilation pattern in the climate file is not constant throughout the year. Nevertheless, the simulation for each reference profile was configured for the same climatic conditions. This means that, on 21 February, for example, all models were submitted to the same boundary conditions. Because of that, the differences shown in Figure 7 on 21 February only reflect the effects of the different schedules of operation of doors and windows of each reference profile. The same happens on 19 July. Even for the same rooms and climatic conditions, the air changes were different for each reference profile (except for bedroom #2, on 21 February). In addition to the differences between profiles, it is also possible to observe that air changes occur as the doors and windows are opened and closed by the occupants (as shown in Figures 4 and 5 and Table 5). Reference profile 2, for example, in which the doors are kept open until the end of the day, also maintains air changes for a longer period than the other models.

It is also possible to observe the influence of the opening of the internal doors. In bedroom #1, where the doors remain open most of the day, air changes are much more intense for the same climatic conditions than in bedroom #2, where doors remain closed. Reference profile 3, in which the door to bedroom #2 is open for the entire period, resulted in more significant air changes for this room. The influence of the combination of these behaviours can be studied more deeply in future studies.

Figure 7 - **Air changes per hour due to operation of doors and windows in each room over two typical weekdays, one in the hot season (21 February) and the other in the cold season (19 July) for each reference profile**

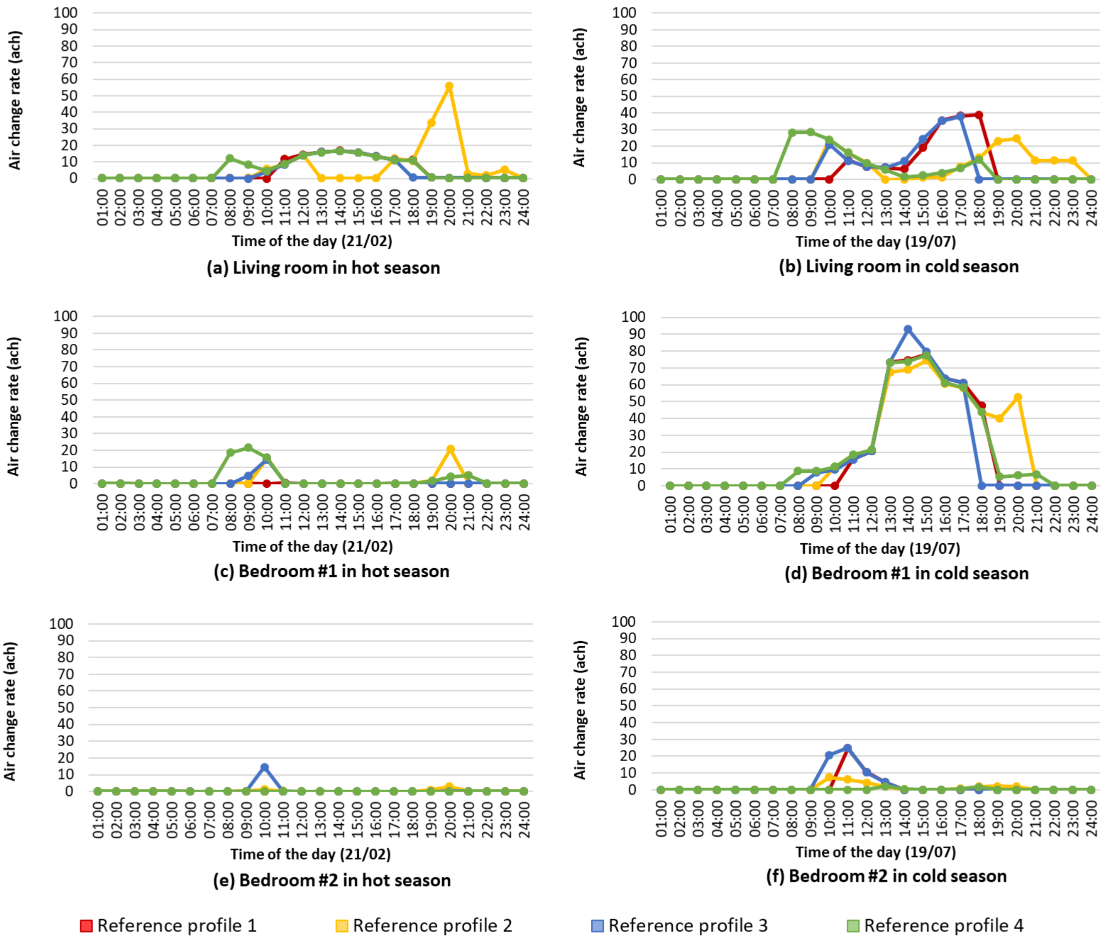
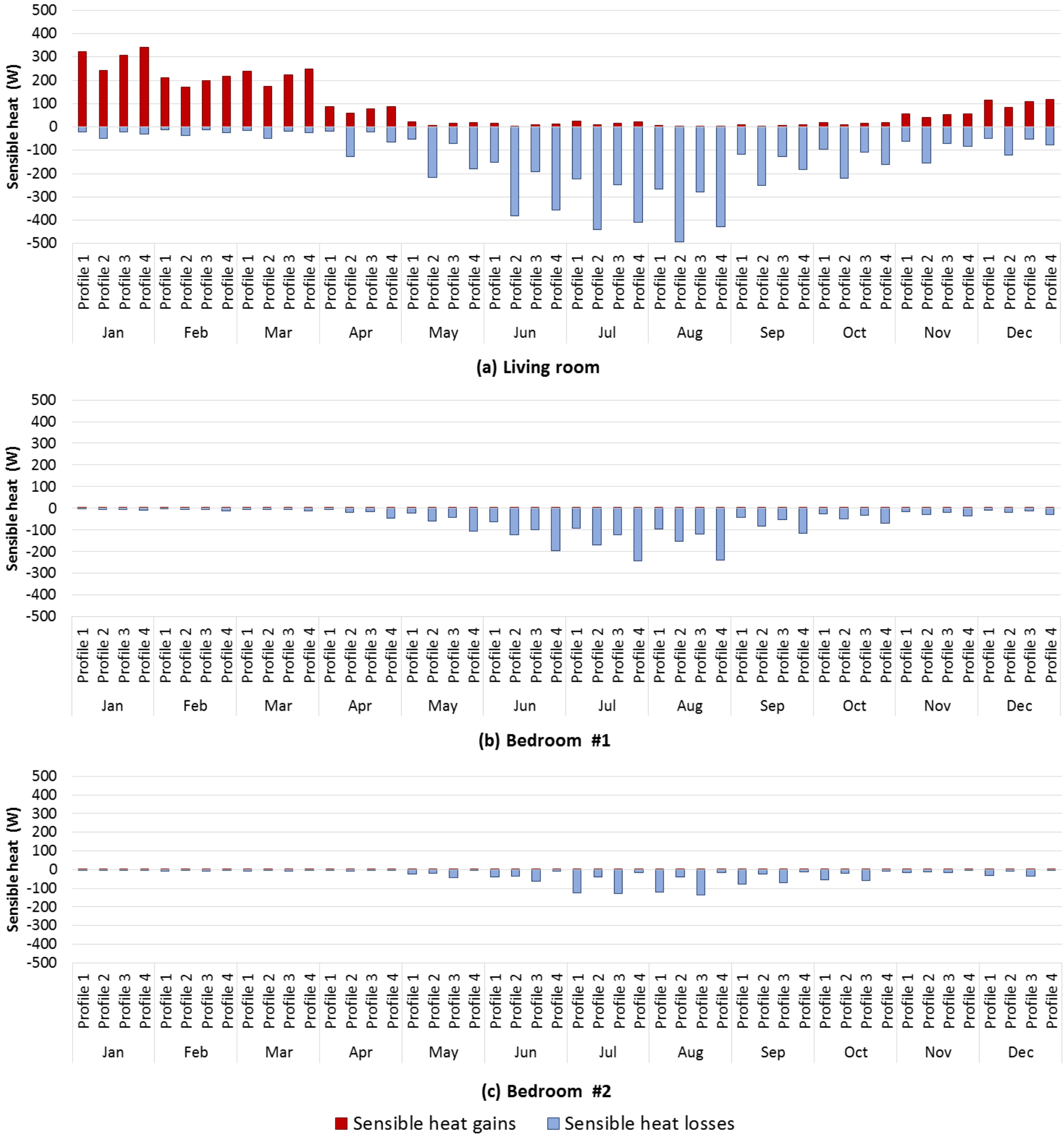


Figure 8 shows a summary of monthly sensible heat gains and losses for each room throughout the year, for each reference profile. It is possible to verify again the effects that different patterns of operation of doors and windows have on the thermal performance of buildings. In general, the profiles had more heat losses than gains during the year. This behaviour is in line with what was expected, given the contribution of natural ventilation to the passive cooling of rooms (Wang; Greenberg, 2015). The bedrooms presented lower heat gains; the greatest gains were observed in the living room in January. Reference profile 4 showed greater sensitivity to the effects of air infiltration, as it had the highest gains in the hot season and high losses in the cold season. Reference profile 2 was the one that suffered the greatest heat loss in both winter and summer. Reference profiles 1 and 3 had similar results for both sensible heat gains and losses, but losses were slightly higher for reference profile 3; these two profiles had similar operation of doors and windows.

Figures 9 and 10 show the degree-hours based on operative temperatures obtained through the computer simulations. Figure 9 shows the monthly cooling degree-hours (on the left) and heating degree-hours (on the right) for each room and each reference profile. Figure 10 shows the annual cooling and heating degree-hours for each room and each reference profile.

Figure 8 - **Sensible heat losses and gains due to air infiltration throughout the year for each reference profile**



(a) Living room

(b) Bedroom #1

(c) Bedroom #2

Figure 9 - **Monthly cooling and heating degree-hour throughout the year for each reference profile**

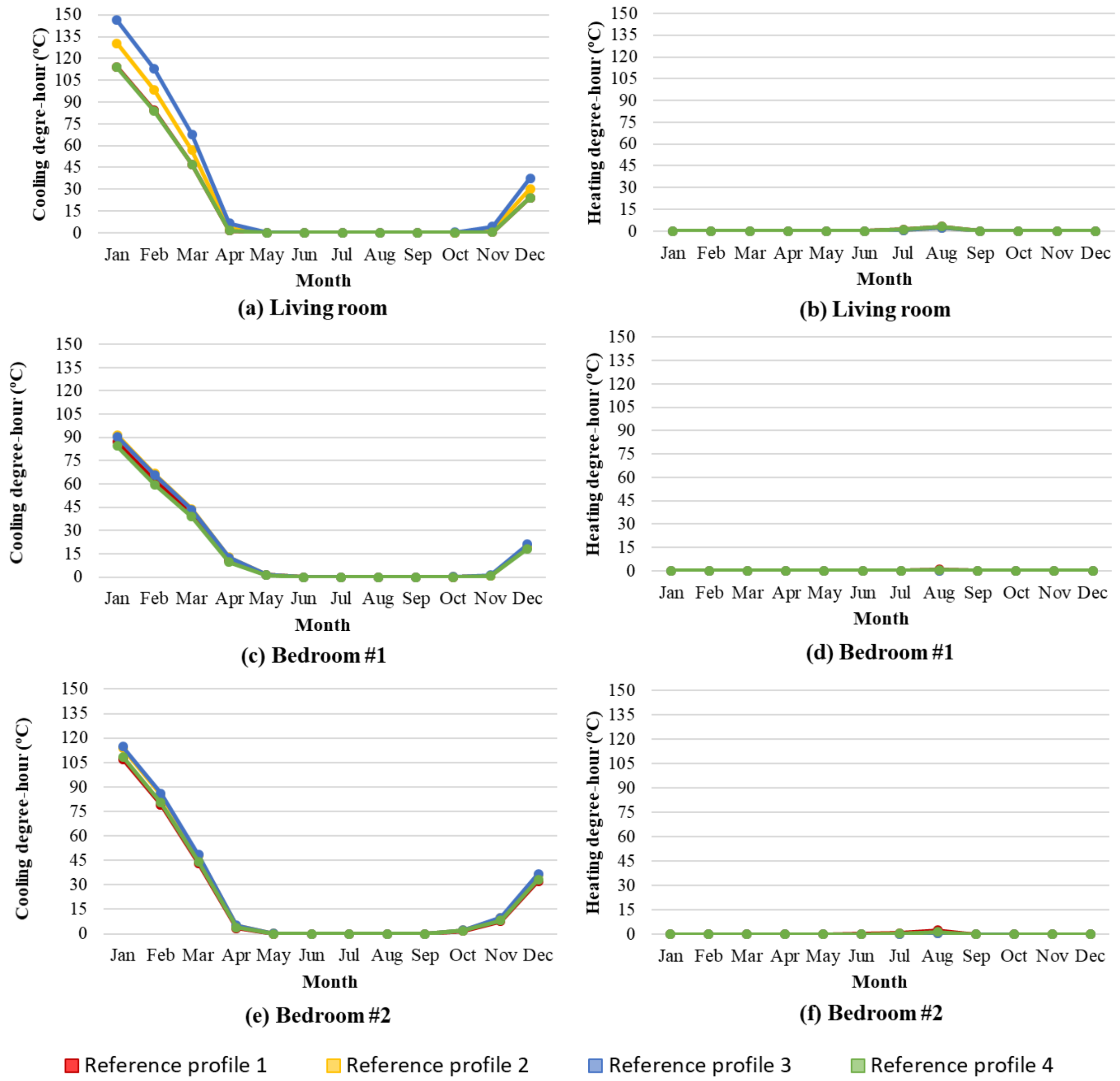
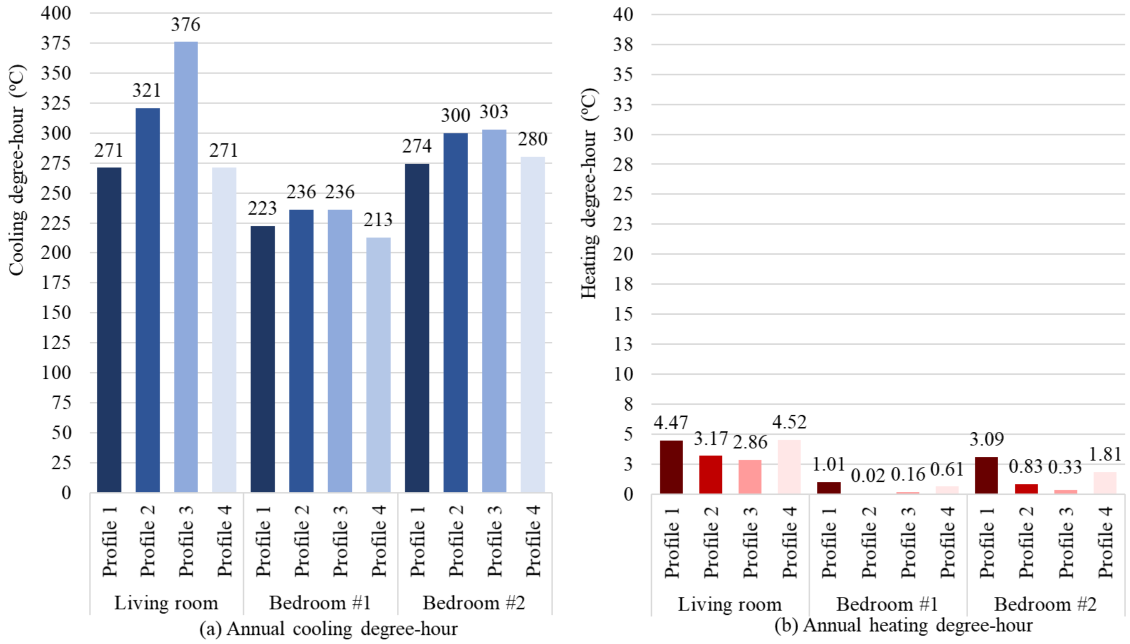


Figure 10 – **Annual cooling and heating degree-hours for each room and each reference profile**



One observed that the cooling degree-hours were much higher than the heating degree-hours for all rooms and reference profiles, as it was expected for Florianópolis climate. The living room presented the highest degree-hour for both cooling and heating. Regarding the reference profiles, reference profile 3 presented the worst performance for cooling. Reference profiles 1 and 4 had similar behaviours, obtaining the lowest cooling degree-hours. Concerning heating, reference profile 4 had the worst performance for the living room, while for bedrooms #1 and #2, the worst performance was found for reference profile 1.

Finally, the thermal loads obtained from the computer simulations, both for heating and cooling, are shown in Figures 11, 12 and 13. Thermal loads represent the amount of energy required to maintain the internal environment temperature within a certain threshold and can be used to complement the degrees-hours assessment. Figure 11 shows the thermal loads for each room and each profile throughout a weekday for a typical summer day (21 February) and a typical winter day (19 July). Figure 12 shows the monthly heating and cooling thermal load and Figure 13 shows the annual heating and cooling thermal load for each room and each profile.

For the cooling thermal loads, it was observed that the variation is similar to the effects of thermal inertia on the envelope, i.e. growing throughout the day and decreasing in the evening. As for the heating thermal load, there is an increase at the beginning of the morning, which coincides with the opening of doors and windows. The thermal load for cooling was higher than the thermal load for heating (as it was found for the degree-hours), and it was even more significant for the living room. Reference profile 3 had the worst performance for cooling, while model 1, for heating. Reference profile 2 showed similar behaviour to profile 4 regarding the heating thermal load. In addition to the thermal loads for cooling and heating, reference profile 4 had the worst global performance. Its annual thermal load was 4971W, 1725W and 868W for living room, bedroom #1 and bedroom #2, respectively.

Figure 11 - **Thermal load for each reference profile throughout the day**

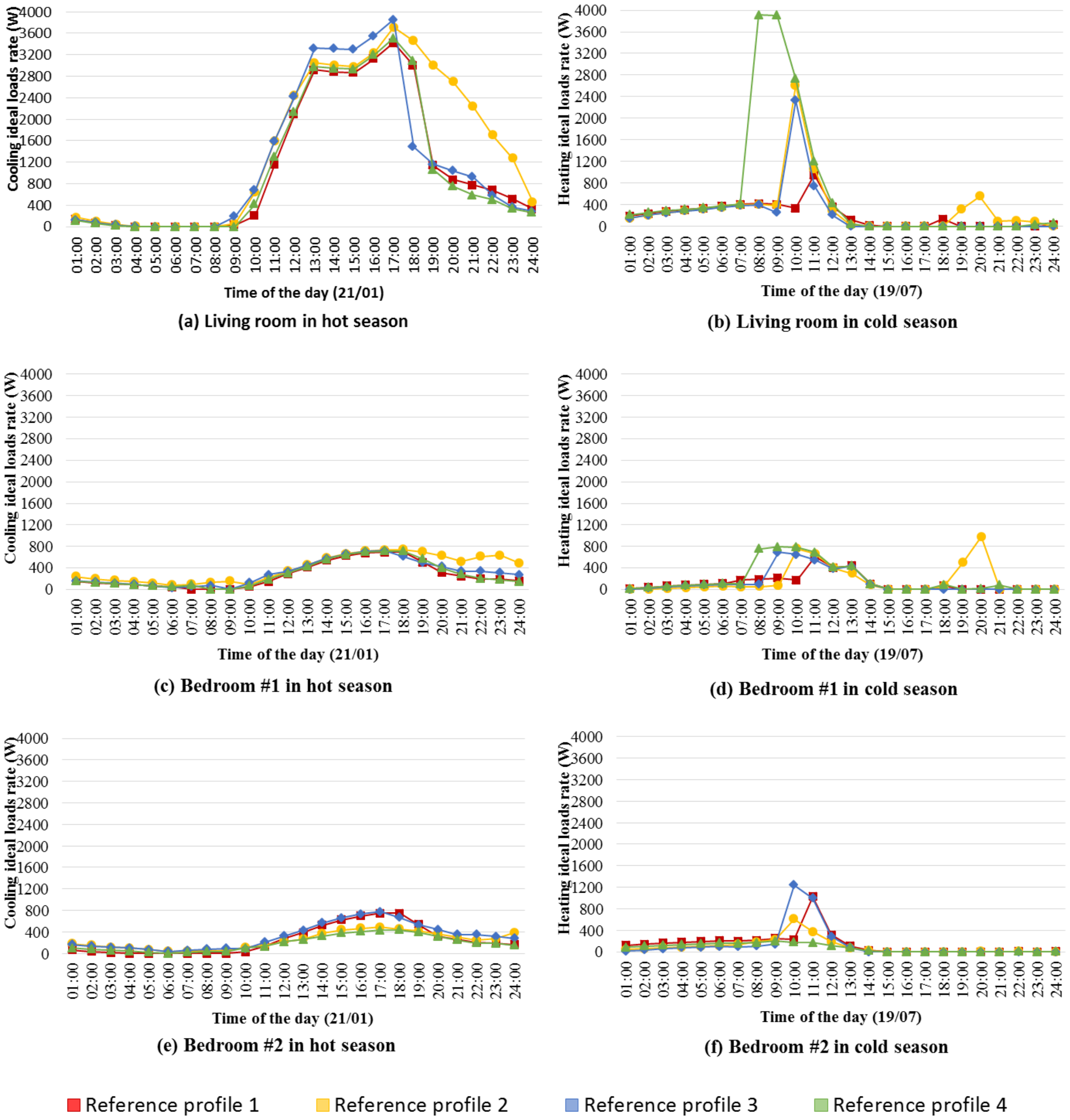


Figure 12 - **Monthly load for heating and cooling for each reference profile**

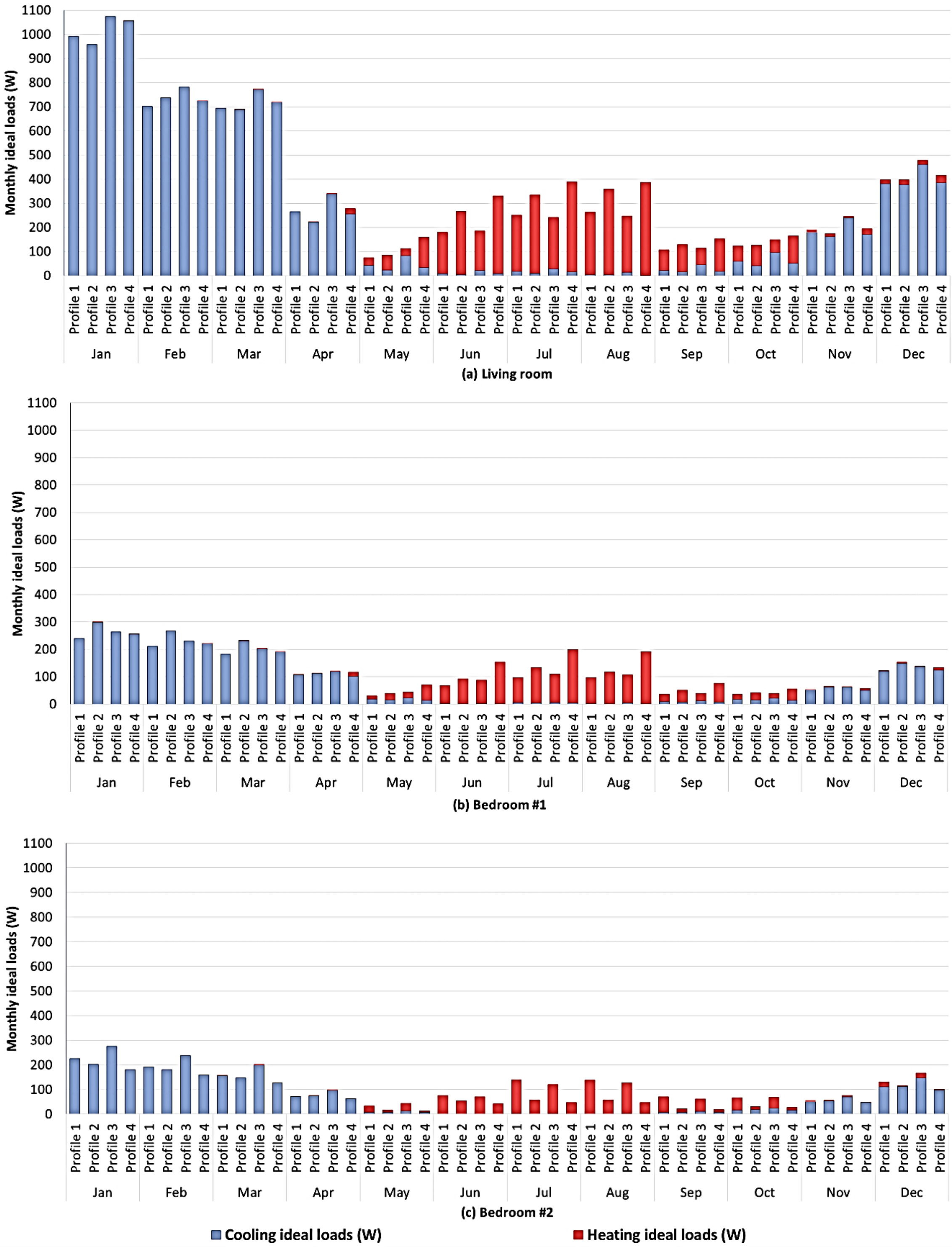
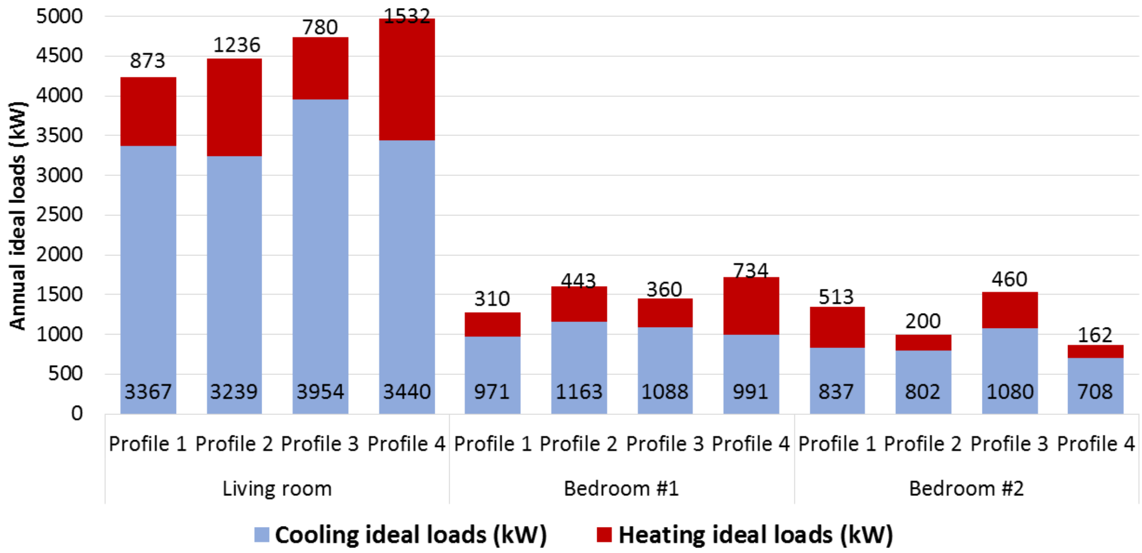


Figure 13 – **Annual load for heating and cooling for each reference profile**



Conclusions

The objective of this paper was to verify the influence of using occupant reference profiles based on actual data on the thermal performance of houses. Four occupant reference profiles were found, which referred to patterns of occupancy and operation of doors and windows. The four reference profiles were submitted to computer simulations, from which indicators were obtained to verify the impact that different patterns of occupancy and operation of doors and windows had on the thermal performance of the house.

It was not possible to establish a direct relationship between the occupancy pattern and the operation of doors and windows as these usually remain open regardless of whether the room is occupied or not. This is a finding of great relevance since the opening of windows is usually determined as a function of the occupancy of the rooms. Ignoring this behaviour can be a source of errors in computer simulations.

In general, the degree-hours and the thermal load were much more significant for cooling than for heating. All four reference profiles showed quite different results for such two indicators, some of them being more vulnerable to external conditions (winter or summer).

One of the main contributions of this paper to the research area is the provision of schedules of occupancy and operation of openings according to residents of single-family low-income housing behaviour, from southern Brazil, for building performance simulation purpose. The analysis of the creation and use of reference profiles based on actual data proved to be of great value for application in building performance studies. Due to the great variability among profiles and the corresponding impact on the thermal performance of the building, restricting the simulations to the use of only one profile leads to inaccurate results. Therefore, it is important to use more than one reference profile when it is desired to represent a whole set of buildings, even if they have the same boundary conditions, such as climate conditions and building features. It is concluded that the cluster analysis helps in a simple and direct way in obtaining such profiles, which leads to more reliable results in the proposition of strategies for energy efficiency and thermal comfort in buildings.

Although the reference profiles were based on actual data, they have limitations, as it was considered the same behaviour pattern for all 365 days of the year, not taking other also relevant parameters into account, as seasons, for instance. The impact of adopting such "hard" pattern can be minimised by combining standardised comfort limits in simulations, such as those proposed by the ASHRAE standard. In addition, access to data obtained from sensors and monitoring in this type of building is limited, requiring the application of an objective and less intrusive method as possible. Such limitations can be improved in future studies.

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