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**CYCLE**

XXIX

**THESIS TITLE**

# "OCCUPANTS BEHAVIOR INFLUENCE ON BUILDINGS ENERGY PERFORMANCE. INVESTIGATIONS IN RESIDENTIAL AND OFFICE BUILDINGS"

**Scientific Subject Sector ING-IND/11 FISICA TECNICA AMBIENTALE**


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# PREFACE

This thesis is the result of a research work conducted at the University of Calabria, Italy, Department of Mechanical, Energy and Management Engineering (DIMEG), Arcavacata di Rende, Italy from March 2014 to April 2017. Ph.D. Marilena De Simone supervised the Ph.D. study.

My stay these years in Italy has been made possible, result of a collaboration with the government of Panama, through the financial support of the Instituto para la formación y aprovechamiento de los recursos humanos (IFARHU) and the Universidad Tecnológica de Panamá (UTP).

I would like to express special thanks to Professor Eng. Marilena de Simone for her support and advice on this long path together, for her trust in me and for offering me the opportunity to begin a doctorate and working on this new important research topic of occupant behavior in buildings, that has global implications and I am sure that I will be able to continue this research topic in my country of origin Panama, where it is necessary to develop, propose and implement policies for energy saving.

I am grateful to the University of Calabria and particularly to DIMEG, for providing support, working space and computer tools to develop all of my academic and research activities in these years.

My greatest thanks go to my family in Panama, my mom, dad, nieces and sisters for their unconditional support from the very beginning and until the very end.

Finally, my sincere thanks go to my son Alexis Guillermo, for his courage, strength and patience, and to whom I dedicate this thesis.

Rende, 28 April 2017

## SUMMARY

The general objective of the research was to evaluate the main factors affecting the energy performance of buildings by considering both physical and occupancy variables. The research had two different approaches, one of them was regarding occupant behavior related to energy consumption in residential buildings and the other focused on the office buildings.

The investigations were conducted by means of data collection and statistical analyses in existing residential buildings. Furthermore, different procedures for obtaining occupancy profiles were applied. Finally, a case of design and modeling of Nearly Zero Energy Buildings was developed in order to study the influence of occupancy in high efficient energy buildings. The results showed that different approaches of modeling occupancy can lead to considerable variations in building energy performance.

In office buildings, the detection of occupancy was obtained by an experimental approach. First of all, the state of the art regarding the sensors and devices used for measuring and monitoring indoor parameters was defined. Successively, an experimental setup was created in an office of the University of Calabria in order to collect data on occupancy and energy consumption by means of sensors and manual observations. The criterion of sensor fusion was adopted. Data were processed by using different statistical techniques: clustering analysis, descriptive and stochastic elaborations. The results were models that can be used either to describe or predict occupancy profiles.

*Structure of this work*

The thesis is divided into six chapters. The first chapter is a general introduction titled *Occupant behavior in buildings*, regarding occupant behavior and its relationship to the energy consumption in residential buildings, office buildings, and low energy buildings. At the end of this chapter a brief description of occupant behavior and energy simulation in buildings is presented.

In the second chapter, *Building occupancy* is presented with a description concerning the occupancy sensing techniques used and general classification following different approaches.

*Residential buildings* is the title of the third chapter in which we attempt to describe the objectives and main findings of three investigations regarding residential buildings and occupancy profiles definition by means of the development of cases of study.

The title of the fourth chapter is *Office buildings: the experimental study*. It consists of the description of the experimental study realized at the University of Calabria in an office building. A description of the sensors and the monitored data were presented.

The *Office buildings: data analysis* is the fifth chapter of the thesis, with the different approaches used to analyze experimental data. It begins with the statistical analysis and ends with the results of the modeling based on indoor environment measurements.

The *General conclusions* is the last chapter of the thesis, with a review and discussion of the key contributions of this research work.

## SOMMARIO

L'obiettivo generale della ricerca è stato quello di valutare i principali fattori che influenzano l'efficienza energetica degli edifici, considerando sia le variabili fisiche che quelle di utilizzo. La ricerca ha avuto due approcci diversi: il primo riferito al comportamento degli occupanti correlato al consumo di energia negli edifici residenziali, e l'altro incentrato sugli edifici ad uso ufficio.

In edifici residenziali esistenti, le indagini sono state effettuate per mezzo della raccolta di dati e analisi statistiche. Inoltre, sono state applicate diverse procedure per creare profili di occupazione. Infine, è stato sviluppato un caso esempio di progettazione e modellazione di edifici nZEB, utile a mettere in evidenza l'influenza dell'occupazione in edifici ad alta efficienza energetica. I risultati hanno mostrato che diversi tipi di utilizzo, ovvero di occupazione, possono portare a notevoli variazioni nel rendimento energetico dell'edificio.

Negli edifici per uffici, l'individuazione dell'occupazione è stata ottenuta con un approccio sperimentale. Innanzitutto, è stato definito lo stato dell'arte per quanto riguarda i sensori e i dispositivi utilizzati per misurare e monitorare i parametri interni. Successivamente è stata creata un'installazione sperimentale in un ufficio dell'Università della Calabria per raccogliere dati sull'occupazione e il consumo di energia tramite sensori e osservazioni manuali. È stato adottato il criterio della "sensor fusion". I dati sono stati elaborati utilizzando diverse tecniche statistiche: clustering analysis, elaborazioni descrittive e stocastiche. I risultati offrono modelli che possono essere utilizzati sia per descrivere che per prevedere l'occupazione.

*Struttura del lavoro*

La tesi è suddivisa in sei capitoli. Il primo capitolo è un'introduzione generale intitolata *Comportamento degli occupanti negli edifici*, riguardante appunto il comportamento degli occupanti e la sua relazione con il consumo di energia negli edifici residenziali, negli edifici per uffici e negli edifici a basso consumo energetico. Alla fine di questo capitolo viene presentata una breve descrizione del comportamento degli occupanti e di come questo aspetto viene considerato nella simulazione energetica.

Nel secondo capitolo, *L'occupazione dell'edificio*, è presentata una descrizione relativa alle tecniche di rilevamento e alla classificazione generale secondo approcci diversi.

*Edifici residenziali* è il titolo del terzo capitolo nel quale si descrivono gli obiettivi e le principali conclusioni di tre indagini riguardanti gli edifici residenziali. Le indagini sono state sviluppate mediante casi studio in cui sono stati considerati diversi scenari occupazionali

Il titolo del quarto capitolo è *Edifici per uffici: lo studio sperimentale*. Consiste nella descrizione dello studio sperimentale realizzato presso l'Università della Calabria in un edificio per uffici. Viene presentata una descrizione dei sensori e dei dati monitorati.

*Gli edifici per uffici: l'analisi dei dati* è il quinto capitolo della tesi che illustra i diversi approcci utilizzati per analizzare i dati sperimentali. Comincia con l'analisi statistica e termina con i risultati della modellazione basata sulle misurazioni dell'ambiente interno.

Le *Conclusioni generali* rappresentano l'ultimo capitolo della tesi e contengono la revisione e discussione dei principali risultati ottenuti dal lavoro di ricerca.

# LIST OF PUBLICATIONS

**PAPER I-** Bevilacqua P, Carpino C, Mora D, De Simone M (2015) Energy consumption of buildings and occupant behavior. An investigation in Mediterranean climatic conditions. In: Conference proceedings: Building Simulation Applications BSA 2015. Bozen-Bolzano University Press, Bozen, pp 181–188

**PAPER II-** Mora D, Carpino C, De Simone M (2015) Behavioral and physical factors influencing energy building performances in Mediterranean climate. Energy Procedia 78:603–608. https://doi.org/10.1016/j.egypro.2015.11.033

**PAPER III-** De Simone M, Carpino C, Mora D, Arcuri N (2016) The effect of different users profiles on energy performances of a Nearly Zero Energy Building. In: 16th CIRIAF National Congress. Assisi, Italy.

**PAPER IV-** Carpino C, Mora D, Arcuri N, De Simone M (2017). Behavioral variables and occupancy patterns in the design and modeling of Nearly Zero Energy Buildings. Building Simulation. https://doi.org/10.1007/s12273-017-0371-2

**PAPER V-** Mora D, Carpino C, De Simone M (2017). Energy consumption of residential buildings and occupancy profiles. A case study in Mediterranean climatic conditions. Energy efficiency. https://doi.org/10.1007/s12053-017-9553-0

**PAPER VI-** Mora D, De Simone M, Fajilla Gianmarco, Fábrega José (2017). Occupancy profiles modelling based on indoor measurements and clustering analysis: Application in an office building. 6$^{th}$ Engineering Sciencies and Technology International Conference. Panama, Panama.

**CHAPTER IN A BOOK-** Dong B, Baun Kjærgaard M, De Simone M, O'Brien L, Gunay B, Mora D, Dziedzic J, Goia F, Novakovic V, Zhao J

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# 1. CHAPTER

# OCCUPANT BEHAVIOR IN BUILDINGS

## 1.1. General context

The existing building stock in European countries accounts for over 40% of the final energy consumption in European Union (EU) member states of which 63% represents use in residential buildings (25% of the total). Therefore, an increase of building energy performance can constitute a valuable instrument in the efforts to mitigate the EU energy import dependency (currently at about 48%) and comply with the Kyoto Protocol to reduce carbon dioxide emissions. Italy is one of the four member state countries with a higher final energy consumption in residential and tertiary buildings [1].

In terms of final energy uses, the amount of energy used by residential buildings is dedicated to electrical uses such as lighting, appliances, and air conditioning, while thermal uses are mainly satisfied by fossil sources such as space heating (higher percentage), domestic hot water (DHW) and cooking [2]. Now with the implementation of new technologies oriented to energy saving and green building certifications, a new approach related to how they affect the use of energy due to occupant behavior has emerged [3].

For many years, the occupant behavior in buildings compared to energy consumption has been studied regarding structures with similar characteristics (size, appliances, number of occupants, orientation, windows, curtains); however, a considerable variation in the energy consumption has been reported. This has led to the conclusion that beyond new technology energy saving and renewable energy applications used, it is necessary to approach occupant behavior in building energy consumption; consequently, knowledge about occupancy and occupant behavior is needed. Around the world, this topic is the research object of different research groups with diverse methodologies and specific contexts. The researchers have concluded that is necessary to work together and share advancements, to provide a scientific description and clear understanding of energy related to occupant behavior in buildings, as well as research methodologies and simulation tools to bridge the gap between occupant behavior and the built environment [3].

The International Energy Agency (IEA), Energy in the Buildings and Communities Program (EBC), Annex 53 [4]: Total Energy Use in Buildings, identified six driving factors of energy use in buildings: (1) climate, (2) building envelope, (3) building energy and services systems, (4) indoor design criteria, (5) building operation and maintenance, and (6) *occupant behavior*. The first five areas were developed with significant progress, meanwhile regarding the latter, there are current scientific lacks in the energy model related to occupant behavior in buildings (Figure 1.1).

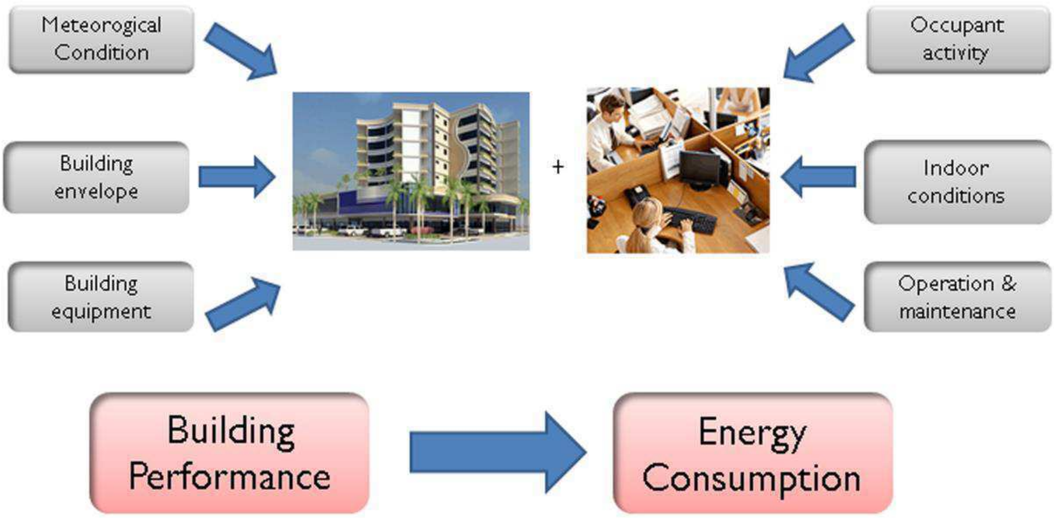


*Figure 1.1 Factors determining the real energy use of buildings*

### 1.2. Occupant behavior definition

The term "behavior" can be defined as the observable actions or reactions of a person in response to external or internal stimuli, or the actions or reactions of a person to adapt to ambient environmental conditions such as temperature or indoor air quality or sunlight [5]. The term 'objects of the behavior' refer to the building elements, such as windows, curtains, and the appliances related to energy use which can be controlled by the occupants. Behavior has been defined as all the activities that people perform in the building, while use refers to the direct interaction between an occupant and an action to achieve a goal.

Behavior can be considered from two points of views, one is how people occupy the building, known as "occupancy", which could be seen as the primary level of occupant behavior modeling. The other is how they interact with devices such as mentioned before (windows, doors, blinds, air conditioning, lights, and equipment). Occupant behavior modeling is much more detailed and complex than occupancy detection. In terms of behavior, occupants in buildings behave in two ways: adaptation to the indoor environment and occupants themselves. Environment-related behaviors may include lighting switch on/off, window opening/closing, or thermostat adjustment, whereas personal behaviors consist of changing the level of clothing, positions or gestures, etc. [6].

### 1.3. Occupant behavior and energy consumption

To evidence the impact that occupant behavior has on energy use, some studies have been carried out in different geographic areas. Figure 1.2 shows some results obtained in the Chinese city of Beijing. The graph shows the measured split-type air conditioner (AC) electricity consumption in 25 apartments, with an identical building envelope in the same climate, where the energy consumption varies in a wide range, between 0 to 14 kWh/m$^2$ with an average of 2.3 kWh/m$^2$ [7]. Thus, the occupant is the driver of energy use, rather than the design of the apartments.

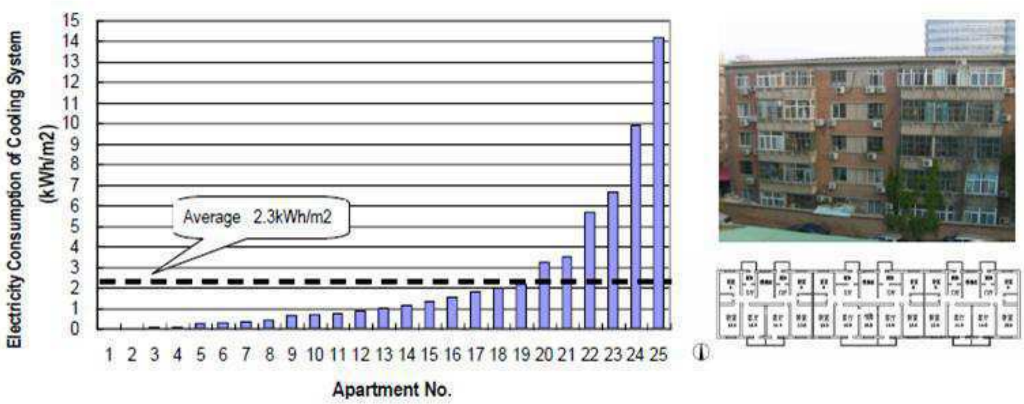


*Figure 1.2 Measured air conditioning electricity consumption per unit floor area in the summer in a residential building in Beijing* [7]

To compare cultural differences between Japan and Norway regarding energy use, aspects such as infrastructure, climate, prices and income, dwelling size, work patterns, and gender roles were considered. The results indicate that the use of energy is related to the cultural patterns and customs of each region, so that one option to reduce energy consumption is to promote technologies that provide the same cultural service with less energy. Thus, energy savings can be integrated into every lifestyle while cultural patterns are maintained. In addition, it is important to raise awareness among users about energy flow in the home through better billing practices and the use of energy audits [8].

Furthermore, a study in Norway allows for explanation of how the consumer is influenced by a combination of activities, preferences, values, technologies and material structures, and the concept of “home” have been developed. Households were classified as: the home as haven, the home as project and the home as arena for activities, where the concept that a person has about their home is related to the energy consumption, rather than seeing the consumer as a static picture [9].

Following the idea of the comparison between different cultures, a study was conducted comparing Denmark and Belgium, including aspects such as energy policies in each region and individual variables were also compared. Related data were collected regarding building characteristics (dwelling type, floor area, and household variables), ownership and use of appliances, washing and drying practices, lighting, PC and TV. The researchers concluded that despite having similar cultures, there are considerable differences in patterns and lifestyles so that differences in the energetic consumption are important [10].

Hetus (Harmonised European Time Use Survey) [11] gives statistical data of people’s use of time in different European countries. The data analysis shows that there are the differences in time spent for different activities are culture dependent. Moreover, there is also a dependency on the climate zone. For example, in the Southern part of Europe people spend more time for eating and leisure compared to the North. In different countries, inhabitants behave differently, and this aspect has to be taken into account when predicting the building energy demand using simulation tools. In [12] the influence of family size, control of the heating system and management of the heated area on the heating loads of a standard dwelling in Belgium is investigated. Simulations of the building with different insulation levels showed that the impact of internal gains (occupant’s lifestyle) on energy consumption is more significant for the case with better thermal insulation. In [13] the effect of building retrofit taking into account different occupancy patterns is analyzed, and the gap between the predicted and actually achieved energy saving is correlated to the indoor temperature takeback.

The occupant behavior studies present differences between residential and office buildings for example (a) different activities performed and who pays the energy bills, (b) the system controls are usually different and, (c) group behavior can be different between commercial setting and domestic conditions [14]. Regarding residential buildings, these contextual differences can be explained with the responsibility of energy bills, need for privacy, social factors, type of activities and others [15]. These differences must be taken into consideration during the data collection and selection of the methodology to follow. For this reason, the thesis was structured by considering these aspects.

### 1.3.1. In residential buildings

In terms of final energy uses, the amount of energy used by residential buildings is dedicated to electrical uses such as lighting, appliances, and air conditioning, and thermal uses mainly satisfied by fossil sources for space heating (higher percentage), domestic hot water (DHW) and cooking [2].

Residential buildings have continuously improved in efficiency. As mentioned earlier, occupant behavior is related to observable actions or reactions of a person to adapt to ambient environmental conditions. These influencing factors can be internal and external and usually are called "Drivers". Figure 1.3 shows a scheme of driving forces of energy-related occupant behavior identified in Annex 53 [4]. These drivers include occupant internal driving forces including biology, psychology and social factors as shown on the left side of Figure 1.3. On the other hand, building equipment, physical environment and time are depicted at the right-had side of Figure 1.3.

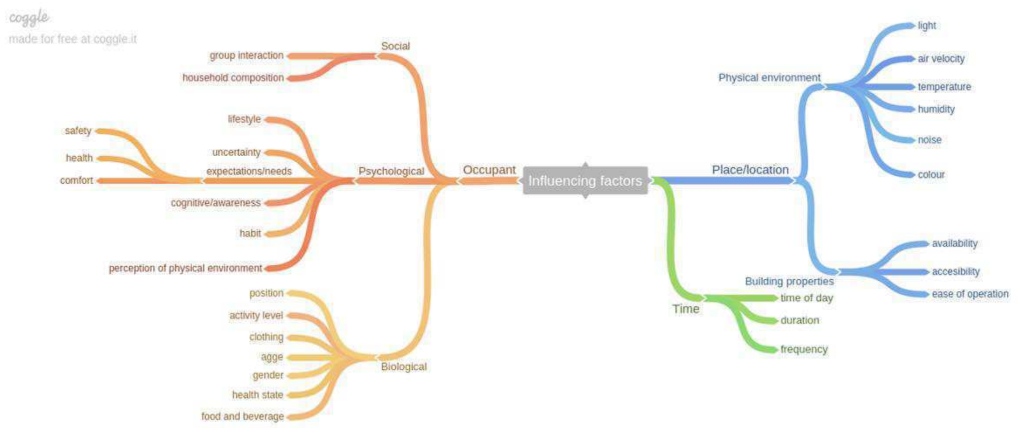


*Figure 1.3 Driving forces of energy-related occupant behavior [4]*

The relationship between residential energy consumption can be categorized into four major groups: external conditions (e.g., weather and location), physical characteristics of the building, appliance and electronic stock, occupancy and occupant according to [16].

Nemry and Uihlein [17], identified the most important options in order to improve the energy efficiency of existing buildings: replacement of windows, additional facade insulation, additional roof insulation and new sealing to reduce ventilation losses, but now occupant behavior represents a critical role as it has been shown that the energy consumption in buildings with identical enclosure and equipment have results very different due to this [3], [18]. This fact has been verified in [19], where the results of projections of energy demand show that technology can overweight behavioral practices and lifestyle changes for some end-uses such as in space heating and lighting. However, the focal point should be given to parameters related to occupant behavior.

Wei et al. [20], have evaluated the actual literature on the occupant space-heating in residential buildings according to simulation studies and monitoring. At least 27 possible factors (Table 1.1) have been assessed as drivers for space-heating behavior, and only five of those 27 factors have been used to model space-heating behavior in building performance simulation (BPS): room type, occupancy, indoor relative humidity, outdoor climate and time of day by typical operational schedules. Ten factors are regularly ignored in the BPS: Social grade, occupant education level, family income, previous dwelling type, health, house ownership, heating price, perceived indoor air quality (IAQ) and noise, energy use awareness and thermal sensation.

*Table 1.1 Factors and their influence on the occupant space-heating behavior [20]*

| Categories of influence | Potential drivers |
|---|---|
| Assumed to be influential on space-heating behavior | Outdoor climate, dwelling type, room type, house insulation, type of temperature control, occupant age, time of day, occupancy |
| Small number of existing studies and no papers reject its influence | Indoor relative humidity, type of heating system, occupant gender, occupant culture/race, social grade, previous dwelling type, perceived IAQ and noise, health |
| Has both been confirmed and rejected in nearly equal numbers of existing studies | Dwelling age, type of heating fuel, occupant education level, household size, family income, house ownership, thermal sensation, time of week, heating price, energy use awareness |

| | |
|---|---|
| Has been rejected in a small number of existing studies and no papers confirm the influence | Dwelling size |

According to the literature survey by Frontczak and Wargocki [21], it is necessary to understand how people behave indoors and how they operate the systems for controlling the indoor environment (thermal, visual, acoustic and air quality) and comfort conditions.

Occupant behavior in residential buildings includes three main categories: the occupancy, the operation of building service and energy systems, and opening windows, curtains, and blinds [5].

In many studies the behavior of people in residential buildings has been investigated, considering the interaction with a single appliance or building component (window, ventilation, lighting, carpets and thermostat) [22]–[24], using measurements or field surveys to obtain data.

Analyses of questionnaires (with multiple choice questions) have been achieved in recent researches. In China, Chen et al. [25], found a negative correlation between occupant age and heating/cooling energy consumption, to explain this relationship it is necessary to look at the thermal comfort perception and distinctive development history of this country. In contrast, investigations developed in countries such as Australia, Denmark, Brazil and China [26], found that age has a positive correlation with residential energy consumption, while Steemers and Yun [27], found that the most significant parameter that determines energy use is the climate and the second most important is the use of heating and cooling systems and their control. Guerra Santín [28], established that occupant characteristics and behavior affect 4.2%, and building characteristics affect 42% of the variation in energy use for heating in the Netherlands.

It is important to understand that people can know of government policies and information about the roles that they can play in energy saving, but sacrificing comfort levels to achieve energy savings is not a believable option, especially for younger people [29].

Kashif et al. [30], stated that dynamic behavior is critical for an accurate energy simulation, to predict energy trends, and reduce waste energy consumption.

Categorical classification of energy consumption by any end use such as heating, cooling, cooking, etc. for residential buildings (in U.S.) is shown in Figure 1.4 [31].

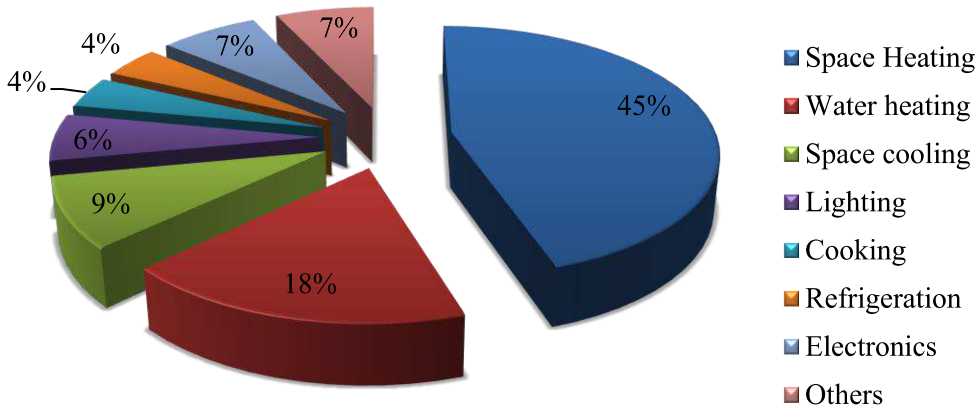


*Figure 1.4 End use energy consumption in residential buildings [31]*

### 1.3.2 In office buildings

National standards and agencies classify commercial buildings according to different criteria. The Commercial Buildings Energy Consumption Survey (CBECS) provides an important Classification: Offices, education, health care, lodging, food service, food sales, mercantile and services, public assembly and warehouse and storage. On the other way, The ASHRAE 1093-RP project focused on the Office buildings category only, divided into three subcategories, based on CBECS: Small (1,001-10,000 $ft^2$), medium (10,001-100,000 $ft^2$) and large (> 100,000 $ft^2$) [32].

Energy consumption in a non-domestic building is a complex problem due to a wide variety of uses and energy services, and consequently, the energy demand of individual buildings needs to be understood.

According to the International Energy Agency, the building sector can reduce energy consumption with an estimated energy savings of 1509 Mtoe (million tonnes of oil equivalent) by 2050. Moreover, through energy-efficient building design, carbon dioxide ($CO_2$) emissions can be reduced, which can possibly mitigate 12.6 Gt (gigatonnes) $CO_2$ emissions from the Baseline scenario level in 2050 [33].

In commercial buildings, the energy consumption can be divided into two categories: the first is the building consumption caused directly by work demands, mostly the energy consumption of equipment, the other one is the energy consumed to provide indoor thermal comfort for occupants, such as building energy consumption of the HVAC and lighting systems. Occupant behavior influences the building energy use both directly and indirectly by the opening/closing of windows, turning on/off or dimming lights, turning on/off office equipment, turning on/off heating, ventilation, and air conditioning (HVAC) systems, and the setting of indoor thermal, acoustic, and visual comfort criteria [34].

In commercial buildings, lighting, heating, ventilation and air-conditioning systems are the main energy consumers, together accounting for about 70% of the total energy consumed in a typical office building [35].

The authors in [36], studied the energy wasted during non-occupied hours in commercial buildings and they found that more energy is used during non-working hours (56%) than during working hours (44%). Despite energy reduction efforts such as the use of more efficient lighting and equipment, insulation, passive architecture, night-time ventilation, phase change materials (PCM), and so forth, all these measures are mostly technological in contrast to behavioral and failure of the human component can fail the whole mission of improving energy efficiency.

With reference to the Building energy data book, commercial buildings include offices, stores, restaurants, warehouses, other buildings used for commercial purposes, and government buildings. In the U.S., space heating consumed 27% of site energy in the commercial sector in 2010, more than any other end use [31]. Figure 1.5 shows the results for commercial buildings.

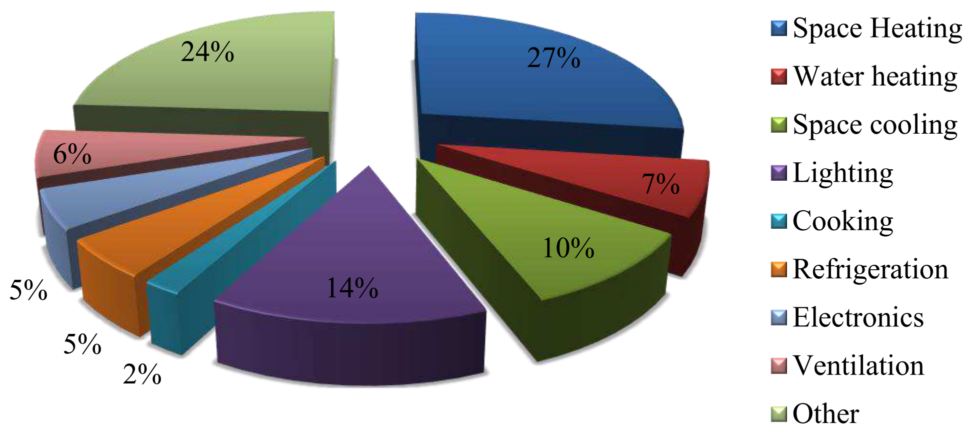


*Figure 1.5 End use energy consumption in commercial buildings [31]*

### 1.3.3 The role of occupant behavior in low energy buildings and nZEB

To reach his comfort condition, the occupant can modify control parameters (thermostat set point, ventilation rate, lighting level and equipment use) invalidating the ideal designed efficient model. For this reason, it is essential to establish the right hypotheses on the air conditioning schedule, utilization of appliances, and comfort level of the building in order to obtain a proper evaluation of the energy consumed in the actual building operation. In nZEB, indoor comfort (thermal and visual) should be achieved mainly thanks to free resources of energy such as solar radiation and natural ventilation. Consequently, the users' behavior has a high impact on the final energy use depending on the correct utilization of passive systems and the operating of active technologies. In low energy buildings, a significant contribution is also represented by the internal gains, and these have a direct relation with the users' behavior and occupancy. The role of the occupant in the building performance and in the resident's perception of low energy homes is not yet known [37], [38].

Brandemuehl and Field [39], studied the effect of occupant behavior in residential nZEB located in different states of the United States to evaluate the effect of house type and climate in the ability to achieve a zero energy goal. The comparison between a conventional single-family residence and a very energy efficient single-family residence confirmed that random fluctuations in the schedules and the level of miscellaneous electrical loads have the highest influence on the second group. Murano et al. [40], demonstrated that the effect of the outdoor climatic data is an important factor in the evaluation of the energy performance of building and is crucial for nZEB.

Some studies on the effect of occupant behavior in nZEB have been specifically developed. Barthelmes et al. [41], investigated a residential nZEB located in Northern Italy by means of energy simulations. The authors took into consideration different occupant behavior lifestyles (low consumer, standard consumer and high consumer) and household composition (family of 4 people, old couple and young couple) to evaluate their effect on energy performance and thermal comfort conditions. The high impact of these two variables was demonstrated. Also, it was concluded that the variation of different types of households increases the discrepancy of the final energy consumption in the several scenarios (~240%). Brahme et al. [42], compared the impact of occupant behavior of a typical and high efficiency residence. They considered three profiles of users (conservation behavior, design point, and wasteful behavior) and concluded that conservation oriented behavior could reduce energy consumption by nearly half in a high efficiency residence. Love (2012) [43], examined the impact of different occupant heating behaviors on a typical semi-detached UK dwelling. The researchers evaluated three different behaviors scenarios (low, middle and high) and three aspects were defined: set point temperature, number of heated rooms, and daily heating periods. They found applicable results about policy regarding the occupant effect in inefficient dwellings and the necessity of selecting the right policies and behavioral change programs.

Becchio et al. [44], evaluated the energy performance of a high-performance building in the Italian context and identified a significant difference between the energy consumptions calculated during the design phase and the monitored phase: +50% for space heating, +19% for DHW and +16% for electricity uses. The authors concluded that these differences were not related to the building features, but, instead, to the occupant behaviors.

A study developed in the UK [45] on a site of 26 ‘low energy’ dwellings evaluated the energy performance of the buildings in terms of water and electricity consumption, and the comfort of users. The authors identified differences in consumption of similar homes by using behavioral surveys and statistical analysis.

The researchers found that energy-efficient behaviors account for 51%, 37%, and 11% of the variance in heat, electricity, and water consumption, respectively.

### 1.4. Occupant behavior and energy simulation of buildings

Occupant interactions with building systems lead to the impact of the occupant on building system performance (e.g. indoor environment, energy consumption, etc.).

Terms of energy balance influenced by occupant behaviors and user profiles are:

| | | |
|---|---|---|
| Thermal losses through glazed | ↔ | Use of shutters |
| Heat lost by natural ventilation | ↔ | Windows opening |
| Solar gains | ↔ | Use of sunshades |
| Internal gains | ↔ | Occupancy, equipment, lighting |

Building simulation tools are based on heat transfer and thermodynamic equations, and they typically model human actions (e.g., operation of lights, blinds, and windows) employing predefined fixed schedules or rules [46]. The influence of occupants' profiles and preferences, for example family size, ventilation, set point temperatures, and management of the heated area, on the indoor conditions are relevant to the final energy usage. For this reason, suitable use profiles should be introduced in energy calculations to deliver a more accurate energy performance of buildings [12], [47], [48].

The heat and mass flow regimes in buildings depend on some aspects regarding physical and behavioral characteristics [49].

There is a wide range of building simulation software (BSS) tools available which analyze energy consumption in buildings (ESP-r, TRNSYS, DOE-2, Energy Plus, IDA ICE, etc). These tools can analyze and predict energy consumption patterns in buildings by specific datasets. Each of them has simplified static and deterministic occupant schedules and profiles used as direct inputs. For BSS, the occupant behavior is described as different schedules of occupancy, heating, cooling, ventilation and window opening, DHW, electrical appliances/lighting, cooking, and sun shading. In [50] a list of building energy simulation programs with their applications, simulation engine and limitations was presented. To include occupant behavior in BSS four main approaches have been used: 1) User defined profiles and rules (include specific deterministic rules), 2) User customized code (the user can write it to implement new or overwrite existing), 3) User customized tools (for open source, users can add new code and changing existing code) and 4) co-simulation (through modules developed by different programming languages can be executed in an integrated manner). ESP-r used approaches 1 and 3, and it has an embedded behavior module, TRNSYS allows approaches 1 and 3, DOE-2 allows approaches 1 and 2, Energy Plus allows all four integration approaches and IDA ICE allows approach 1 through 3 [7] .

Occupant interactions with building systems lead to the impact of the occupant on building system performance (e.g. indoor environment, energy consumption, etc.). These occupant-building interactions are divided into passive and active interactions. Passive effect regards the metabolic heat gain produced by occupants, and the active effect regards the use or operation of building device objects (blinds, windows, lights, air-conditioning, appliances, etc.).

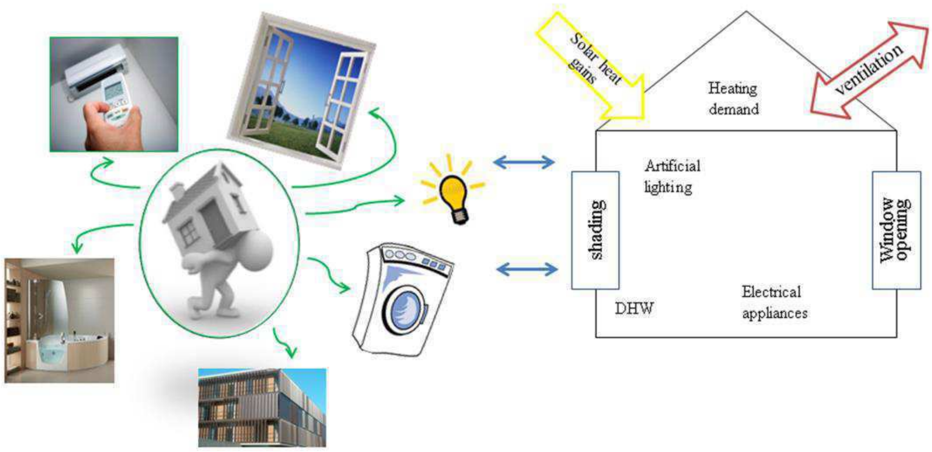


*Figure 1.6 Interaction between occupants and the building system*

Models of human behavior are based on statistical and probabilistic algorithms that predict the probability of an action or event.

The models of user behavior and energy simulations are based on two different approaches, deterministic and probabilistic. In the deterministic approach, human behavior is treated as a fixed schedule or is built on the assumption of purely rational behavior. On the other hand, probabilistic models typically use statistical data to predict the probability that certain activity occurs.

Building energy systems (BES) can be defined as those which are responsible for consumption of energy in buildings (building space, HVAC systems, lighting systems and occupancy and comfort). These can be any physical equipment or machinery or can be a process or a combination of them [50]

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# 2. CHAPTER
# BUILDING OCCUPANCY

## 2.1. Approaches for occupancy monitoring

Occupant movements and presence are fundamental to occupant behavior simulation by providing information about whether a room is occupied, the number of occupants, or the specific individual in the room. The real occupancy patterns in buildings may differ significantly from each other.

Existing research includes numerous data collection approaches including non-invasive occupant observations, observing occupants that have had perturbations applied, surveys, and laboratory studies [1]. Therefore, the occupant monitoring approaches were first divided in three main categories:

(a) *Observational studies*, the occupant behavior and presence and indoor environmental variables are passively monitored. The monitoring can be divided into two groups: occupancy and equipment use monitoring and adaptive behavior monitoring.

(b) *Occupant surveys and interviews*, should be developed by using established methodologies and the complete survey should be published with the results.

(c) *Laboratory studies*, controlled laboratory-based studies in the field of occupant behavior modeling play an important role in assessing occupant comfort conditions and establishing measurements.

Gathering data on human building interaction is a new horizon for achieving energy efficiency in the building sector. Measurements of energy-related behavior are collected using a) physical sensing, and b) non-physical sensing methods [2]. Figure 2.1 shows a scheme of these methods, on the left side objective measurements concern smart metering and building data as well as indoor and outdoor environmental data (details of these tools and techniques are in section 2.2.1) and on the right side the subjective measurements referred to gathered data using surveys or interviews techniques are in section 2.2.2.

In this investigation, the second and third categories were used for data collection. Chapters three and four explain in detail the methodology employed for residential and office buildings.

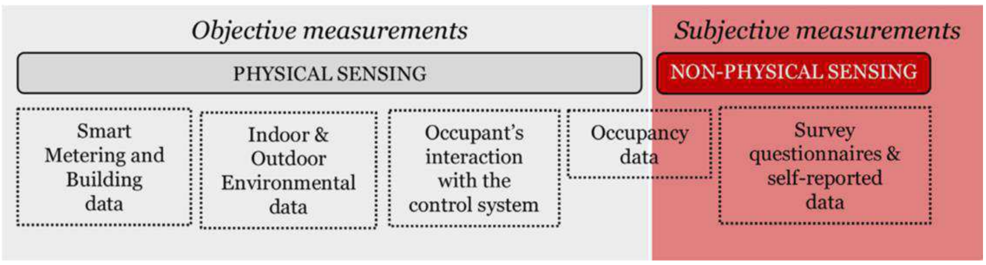


*Figure 2.1 Sensing methodology approach of energy-related occupant behavior in buildings* [2]

Regarding the parameters that must be considered to obtain the information necessary to analyze the behavioral actions in office buildings, the authors in [3] classified it as shown in Table 2.1.

| Outdoor parameters | Indoor parameters | Energy data | Occupants data |
|---|---|---|---|
| Air temperature | Air temperature | Total energy use | Age |
| Air humidity | Air humidity | Submetering | Gender |
| Wind speed | $CO_2$ | Energy production (renewable) | Working profiles |
| Wind direction | Occupancy | | |
| Solar irradiance | Light level | | |
| Illuminance | Window state | | |
| Rain | Shading state | | |
| $CO_2$ | Door state | | |
| | Plug loads | | |
| | Thermostat settings | | |
| | Heating /cooling state | | |
| | VOC (volatile organic compounds) | | |

*Table 2.1 Data gathering to investigate occupant behavior studies in thermal comfort, occupancy, windows, shades and blind, and lighting and electrical equipment [3]*

Sensor fusion approaches build upon the use of multiple sensors or sensing modalities in an attempt to combine their advantages while cancelling out their disadvantages as much as possible [4], [5]. In general, to overcome the disadvantage of an individual detection system, a fusion of multiple sensors is encouraged in occupancy detection. On the other hand, sensor fusion requires more computing and processing power and often the installation and maintenance costs are significant [6].

## 2.2. Occupancy detection

Occupancy detection is defined as the real time detection of occupancy presence status; it has two values: “occupied” and “unoccupied” [7]. The methods used for occupancy detection can be grouped into three categories [8]:

*Direct sensing method*, the direct sensing method of occupancy detection relates to the deployment of sensors or sensor networks for directly sensing or tracking the presence of occupants by the use of motion detectors or mobile unit tracking.

*Modeling method* uses statistical data analysis.

*Combined method,* is a combination of advanced analysis methods, such as statistical methods, with physical measurements, which includes direct or other types of measurements.

Another classification of the occupancy detection system for obtaining spatial-temporal properties and the specific sensor that can be applied was proposed by [9]. It is based on:

- *Method*, regarding the need for a terminal (mobile phone, radio frequency identification tag (RFID) or other);
- *Function***,** individualized or non-individualized, depending on the ability to detect, identify and determine the track of an individual occupant;
- *Infrastructure*, implicit or explicit, depending on whether it was installed for the purpose of measuring the occupation or as a secondary function. Melfi et al. [10], measured building occupancy by using existing network infrastructure.

In Table 2.2 different sensors were classified with reference to the previous criteria.

| | | Sensors | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | $CO_2$ | PIR | Ultrasonic | Image | Sound | EM Signals | Power meters | Computer App. | Sensor fusion |
| **Method** | Terminal | | | | | | x | | | x |
| | Non-terminal | x | x | x | x | x | | x | x | x |
| **Function** | Individualized | | | | | | | | | x |
| | Non-Individualized | x | x | x | x | x | x | x | x | x |
| **Infrastructure** | Implicit | | | | x | | x | | x | x |
| | Explicit | x | x | x | x | x | x | x | | x |

*Table 2.2 Classification of occupancy detection systems* [9]

According to spatial-temporal properties of occupancy measurement, Table 2.3 shows which sensors can measure different properties. In the next section, details of the spatial-temporal properties will be presented.

| | Sensors | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $CO_2$ | PIR | Ultrasonic | Image | Sound | EM Signals | Power meters | Computer App. | Sensor fusion |
| **Location** | x | x | x | x | x | x | x | x | x |
| **Presence** | x | x | x | x | x | x | x | x | x |
| **Count** | x | | | x | | x | | x | x |
| **Activity** | x | | | x | | x | x | x | x |
| **Identity** | | | | x | | x | | x | x |
| **Track** | | | | x | | x | | | x |

*Table 2.3 Sensors classified by granularity* [9]

### 2.2.1. Sensing technologies

Technologies of occupant sensing can be organized into six categories: image-based, threshold and mechanical, motion sensing, electromagnetic signal, environmental, person interactive, and consumption sensing [11].

*Imaged-based Sensing*, image-based occupant detection technologies detect electromagnetic information and convey it in the form of a matrix. The technologies in this category consist of visible light cameras, luminance cameras, IR cameras, light level sensors and stereo cameras. There are high detection accuracies with good quality camera sensors [12]. Image detection systems are non-terminal based and can be used to provide individualized functions [9].

*Threshold and mechanical*, both detect the change in state of a building component with which occupants frequently interact such as a door, window or air conditioning. The examples in this category are reed contacts, door badges, piezoelectric mats, and IR beams. Reed contacts are cheap sensors and low power sensors that are easy to mount on doors or windows.

*Motion sensing,* these sensors detect the presence or absence of an occupant through occupants movements. The most common is the passive infrared (PIR) sensor. All objects including humans with a temperature above absolute zero emit heat energy in form of radiation. The emitted infrared radiation is invisible to the human eye but can be detected by electronic devices such as a PIR sensor [9]. Other types are ultrasonic Doppler, microwave Doppler and ultrasonic ranging.

*Electromagnetic signals*, relevant technologies for occupancy detection include: wireless fidelity (WIFI), Bluetooth, Ultra-wideband (UWB), radio frequency identifications tags (RFID) and the global positioning system (GPS). The system usually consists of a transmitting and a receiving node. The transmitted signal may consist of a short series of pulses or modulated radio signal [9]. It is important to consider that the high frequency signals that are transmitted through the air are affected by humidity, presence of other signals and many other environmental factors.

*Environmental* sensors are a diverse set of sensors. They primarily consist of $CO_2$, temperature, relative humidity, acoustic and volatile organic compounds. Of these, $CO_2$ and acoustic sensors are considered the most effective at detecting occupant presence [13], [14]. For every sensor in this category except acoustic sensors, there is a delay between occupants entering a space and occupant presence detection. With these sensors, it is also possible to achieve mapping of occupant comfort .

*Human in the loop*, the most basic and straightforward methodology used for occupancy information collection is that of the questionnaire and interviews [15]. Human in-the-loop methods are defined by cases where occupancy is measured with a human being involved. Manual observation covers the logging of data performed by a person directly by sensing the information being relayed. The methods in this category are manual observation, internet-based occupant data, and device interactions.

*Consumption sensing*, covers methods that use the correlation between occupancy and occupant actions and the water and energy consumption in buildings. The change in energy consumption when the device changes state from idle to active provides information from which users location and presence could be inferred [9].

Based on the technologies described in the previous section, nine performance metrics can be individuated: cost, deployment area, collection style, power type, sensing range, accuracy, data store, data sensed, and deployment level [11]. Equipment cost is identified as the primary driver in deciding on investing in metering and sensing equipment [16]. The cost consists of some individual costs, such as the cost of the hardware, cost of installing and integrating the hardware and the cost of operating and technology.

In order to set up an experimental setup, it is necessary to evaluate each one of these parameters to identify the combination that allows obtainment of the expected results.

### 2.2.2. Surveys and interviews

As mentioned before, one of the most used methods to collect information is by occupant surveys and interviews. The use of survey questionnaires is widely utilized to identify different variables related to energy consumption [17]–[20]. Some studies were focused on the comfort evaluation [20]–[23], energy consumption [18], [24]–[26], energy policies and energy saving [27]–[30] or occupant behavior aspects [31]–[34].

In a survey research by D'Oca et al. [35], the authors propose a structure of the occupant behavior framework shaped by geographical and climatic contexts, culture and norms for office buildings. The questionnaire explores aspects as: comfort, habits, intentions and control (see Figure 2.2). In fact, different kinds of occupant behaviors can be identified through surveys conducted in various countries, cultures and climates.

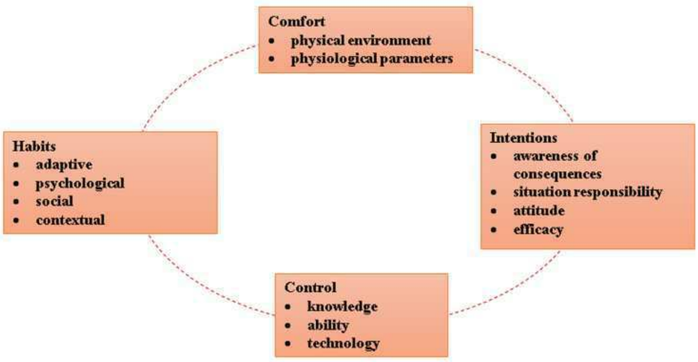


*Figure 2.2 Structure of the occupant behavior motivation survey framework* [35]

One of the key limitations of the survey methodology is the low response rate. In some cases, due to the length and detail of the questionnaire and to the fact that respondents felt uncomfortable with providing personal information about their lifestyle and personal belongings [36]. In some cases to increase the response rate, some incentives can be offered [22], [37].

### 2.2.3. Categories and classification

The impact of occupants' behavior on their daily environment can be divided into various methods of interactions and can be represented as in Figure 2.3.

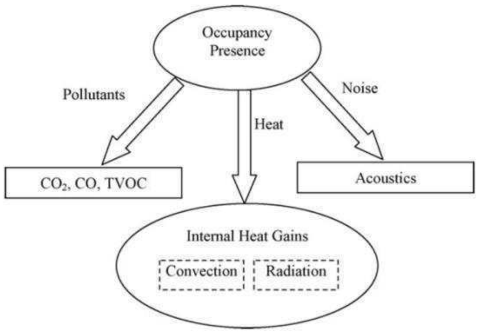


*Figure 2.3 Interaction between occupancy and indoor environment* [38]

Each interaction can be described or defined as a stochastic process. Occupants emit heat, pollutants and odor, and generate sound to the space. These interactions and their effect on the indoor environment can be measured via pertinent environmental sensors [38]. As the human presence emits heat and pollutants, it is related to the indoor environment [39]. Zhang et al. [40], concluded significant correlations between the occupancy and the environmental variables with values of 35.70% for $CO_2$, 32.49% for relative humidity and 11.98% for temperature. On the other hand, information regarding the occupancy level can be found through sensor networks.

Dong et al. [38], investigated the use of ambient sensors for detecting the number of occupants in an office building. The experimental setup was divided into three separate sensor network systems: the wired sensor gas detection sensor network, which measures carbon dioxide ($CO_2$), carbon monoxide (CO), total volatile organic compounds (TVOC), outside temperature, dew point, small particulates (PM2.5); a wireless ambient-sensing network, which measures lighting, temperature, relative humidity (RH), motion detection and acoustics; and an independent $CO_2$ sensor network. The authors concluded that there are significant correlations between measured environmental conditions and occupancy status, in particular with humidity, acoustics, and $CO_2$, while insignificant correlation with temperature data has been reported.

The results in [13] indicate that there are significant correlations between measured environmental conditions and occupancy status, specially acoustics and $CO_2$ measurements. Also, the presence of occupants has a direct effect on the air quality indexes (temperature, $CO_2$, and humidity levels) [14].

The authors in [9] used the chair sensor for occupancy measurement and compared it with $CO_2$ concentration measures; furthermore, values of airflow rate, door state, air volume, thermal comfort conditions (air temperature, mean radiant temperature, relative humidity) were recorded. In this study, the comparisons between chair sensors with $CO_2$ sensors were analyzed, and they concluded that chair sensors provided fine-grained occupancy information for the control of building systems at a low-cost.

Energy monitoring is necessary to understand the sources of consumption inside the building and to take appropriate measures to save energy. To perform energy monitoring, dedicated hardware needs to be situated in the main electric distribution board, in specific branches/circuits or even on wall sockets to measure the consumption of individual electric appliances [41]. The quality of information provided by different types of sensors varies widely and can be thought of like the resolution of the sensor. The notion of occupancy measurement should include information about the space, occupants, and time span [10]. Figure 2.4 shows different levels of occupancy resolution regarding these three parameters.

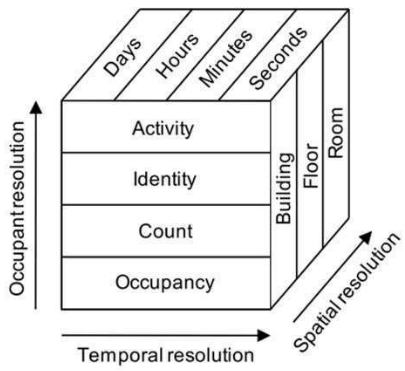


*Figure 2.4 Occupancy resolution* [10]

Kjærgaard and Sangogboye [12] described a categorization for sensor technology with the approach of knowing better sensing systems and their properties and in this way improved the building occupancy sensing systems. In this framework, nine categories were defined (Figure 2.5).

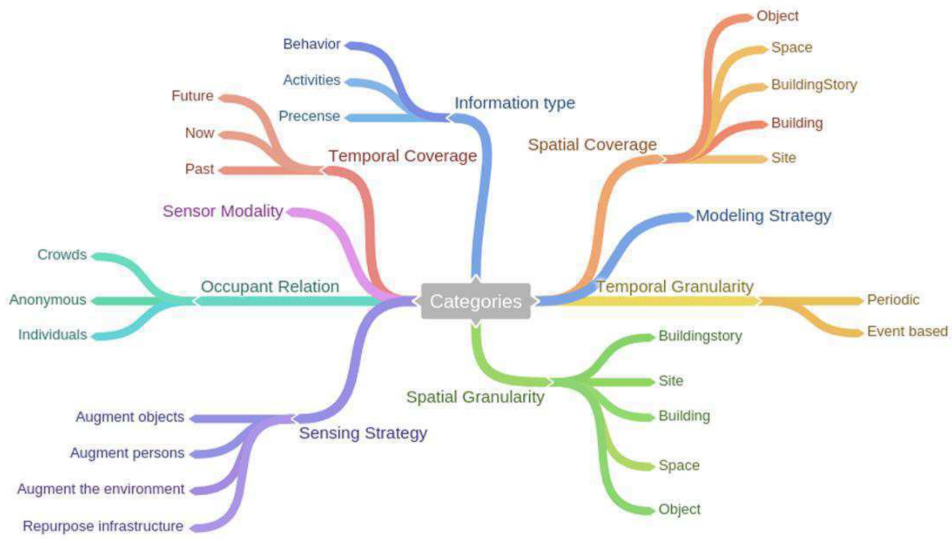


*Figure 2.5 Nine categories for sensor technology proposed by* [12]

It is necessary to know each of these nine categories to develop an experimental setup for the study of occupant behavior and occupancy sensing systems.

Activities drive occupants' movement among rooms and in and out of a building. Occupancy is defined as an occupied status or number of occupants at four levels varied with time: the number of occupants in a building, a space is occupied or not, the number of occupants in a space and in which space and occupant are located [42].

Depending on the type of occupancy measurements systems used, it is necessary to define which information can be obtained concerning occupants' presence and movement. Occupancy information can be classified into three observable categories (Figure 2.6): spatio-temporal properties, behavioral properties, and physiological properties [5].

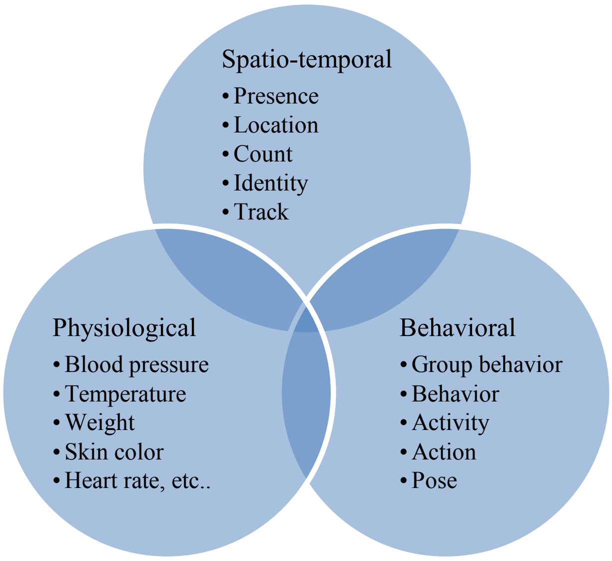


*Figure 2.6 Spatial-temporal, behavioral and physiological properties of occupancy measurement* [5]

Definition of the spatial-temporal properties relating to building energy consumption are:

- *Presence*, the frequency of an occupant leaving his/her office and the corresponding duration of the absence.
- *Location*, where the occupant is in the office.
- *Count*, this property provides information on the 'numbers' of occupants in a particular thermal zone within the building.
- *Activity*, use of appliances and heating/cooling system in the office.
- *Identity*, this property relates to information on 'who' is in a particular thermal zone or space in the building.
- *Track*, this property provides information about the particular occupant's movement history across different thermal zones in the building.

The six properties described above provide an insight into what constitutes comprehensive, fine grained occupancy information [9].

Another aspect to take into consideration for the occupancy sensing system is the granularity related to the characterization of the resolution of occupancy information. Kjærgaard and Sangogboye [12], categorized the granularity according to the criteria of the Industry Foundation Classes (IFC). According to the IFC data model (Figure 2.7), a Site is a physical area, a Building is a physical structure placed on a site, a Building Story is a single story of a building, a Space is a subpart of a story which might correspond to several rooms in the same HVAC zone, a room or a subpart of a room. An object is a physical element placed in a space. The temporal granularity periodic denotes that the sampling and processing of occupancy information is executed at regular periodic intervals and the event-based scheme where new occupancy information is available when an event occurs.

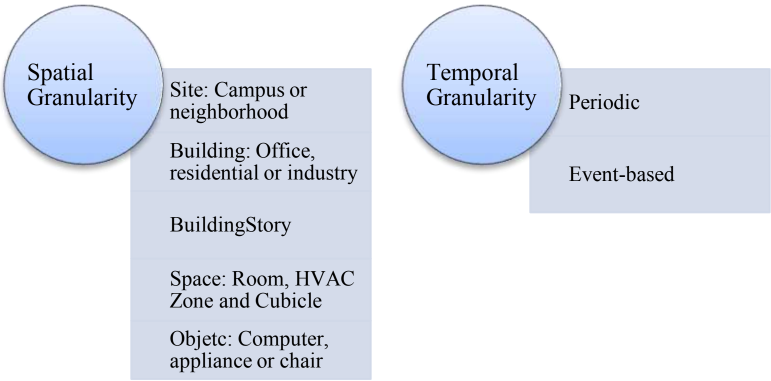


*Figure 2.7 Spatial and temporal granularity* [12]

On the other hand, the temporal and spatial coverage of an occupancy sensing system, for spatial coverage the classification is the same as that of granularity and for temporal coverage it takes into account three times, for the past, present and future.

Another important category is the modeling strategy that characterizes the modeling of occupancy behavior (see Figure 2.8).

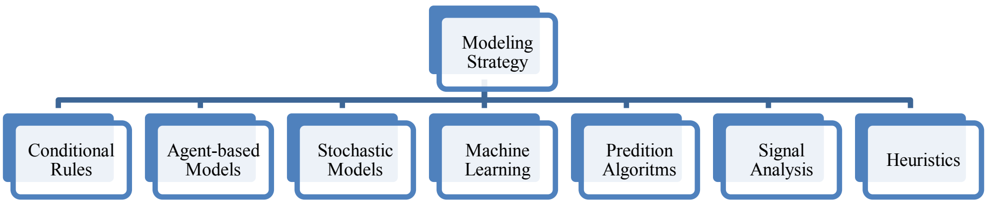


*Figure 2.8 Sensing Modeling* [12]

*Conditional rules*, model the relationship between sensor input as conditional rules; for instance, that a door opening event indicates that the occupancy of a room changes.

*Agent-based Models*, model occupants as agents whose behavior is defined among others by modeling their itinerary, path choices, and walking behavior.

*Stochastic Models*, model the probability and correlation among occupancy behavior events amount others the likelihood of changes in occupant presence.

*Machine learning*, learns models of occupancy information from data including learning the mapping between sensor input and occupancy levels.

*Prediction algorithms*, enable the prediction of future states, e.g., from GPS tracking predict the earliest point in time when an occupant can arrive back home.

*Signal analysis*, covers the use of signal analysis methods including methods for signal decomposition and image processing.

*Heuristics*, cover a broad range of simple algorithm steps that does not fall under any of the other categories. For instance, simple thresholding on values.

Improving the energy performance of buildings is an important goal towards realizing a more sustainable society. A significant challenge for improving the energy performance is the impact of occupancy behavior [43].

The last category regards sensor modality, associated with the modalities for collecting occupancy behavior data is shown in Figure 2.9.

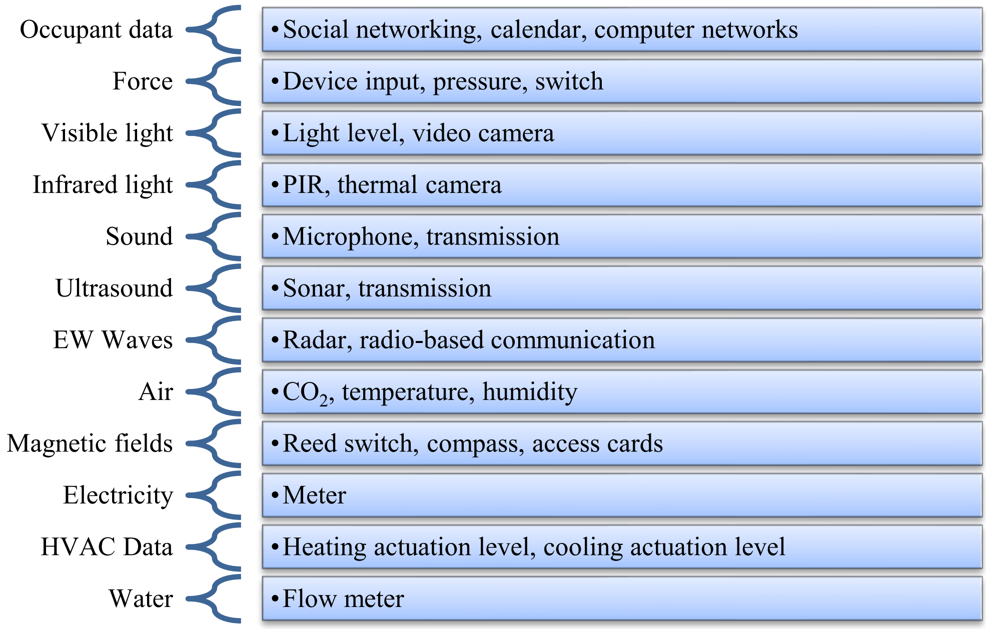


*Figure 2.9 Sensing Modality* [12]

In this work, sensors such as air, magnetic fields and electricity were considered for office buildings in order to do the experimental setup (see details in chapter 4).

Before deciding the configuration of the experimental setup, it is necessary to understand what kind of results we want to know and what type of sensor strategies will be applied, then what types of modeling strategies will be utilized.

## 2.3. Occupancy patterns

Regarding studies to determine occupancy profiles in office buildings or residential buildings, two types can be identified: 1) determination of deterministic occupancy patterns, and 2) development of predictive models of occupancy [34].

For the identification of deterministic occupancy patterns (non-predictive), various sources of information can be used. Occupancy profiles are defined through Time-Use survey (TUS) data. Aerts et al. [44], described a methodology to obtain occupancy profiles based on the 2005 Belgian time-use survey with the aim of using it for user behavior modeling in building energy simulation. The authors of the study developed seven user profiles reflecting realistic user behavior in homes. Similarly, Richardson et al. [45], defined occupancy profiles for UK households by using TUS data describing people habits. The developed models indicate the number of occupants in the house at a given time to have the indication on the sharing of energy use. Wilke et al. [46], used French time-use survey data to calibrate the stochastic model and to predict activity chains. Widén et al. [47], developed for residential buildings, the daily electricity and hot-water demand profiles using a large dataset of time use in Sweden. This model shows more similarity between modeled and measured electricity demand and less for hot water. The Centre for Time Use Research [48] has a list of external links enable to access to some original time use survey data directly.

Guerra-Santin [49], used a survey to identify behavioral patterns through statistical procedures and build user profiles based on the household and building characteristics related to these behavioral patterns.

The studies of development of predictive models of occupancy focus on the development of stochastic occupancy profile. For office buildings, stochastic models capable of simulation occupancy patterns have been presented in various studies [39], [50].

Occupancy profiles in the occupant behavior studies are related to the use of cooling and heating, equipment and lighting, and occupancy. An amply used method in energy simulation is to model the influence of occupants through diversity factors. Diversity profiles for different categories of internal gains and kinds of buildings to estimate the impact of internal heat gains on energy and cooling load calculations [51]. The profiles depend on the type of building and on the type of occupants [52].

Diversity factors are numbers between zero and one, and are used as multipliers of some user-defined maximum load, e.g. occupants, lighting, and equipment. Load variability due to absenteeism or power management features of IT equipment, is ordinarily defined by associating different sets of 24-h diversity factors, or diversity profiles, for weekdays, weekends, holidays, etc. The goal of the ASHRAE Research Project 1093 [51] was to compile a library of schedules and diversity factors based on measured electricity used data for energy simulations and peak cooling load calculations in office buildings [53].

The American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 90.1-2004 includes standardized occupancy diversity factors for different building types which can be used to design occupancy when actual schedules are unknown. These schedules take the form of a daily profile, applied differently to weekends and weekdays, and composed of hourly values, each of which corresponds to a fraction of the occupancy or the energy use [2]. These diversity factors are in tables for different building types and zones by hour of day. Energy modelers account for the variability in occupancy throughout the day and other simulation inputs that vary with time using diversity factors or profiles [54].

Duarte et al. [54], showed occupancy patterns in an 11-story office building by means of the use of 629 pre-existing ceiling-mounted passive infrared occupancy sensors, these sensors are designed to control light fixtures based on a predetermined time delay for this building and only report change of state, it does not count people. An analysis of occupancy sensor data showed variations of occupancy diversity factors for time of day, day of the week and month. It has been demonstrated that measured occupancy data have a lower diversity factor than the ASHRAE 90.1 2004 energy cost method guidelines, the document used by energy modelers for simulations.

The authors in [55] proposed a framework for occupancy schedule learning and prediction, based on a data mining approach, which takes into account six steps: (1) problem framing, (2) acquire and prepare data, (3) methodology selection, (4) learning, (5) prediction and (6) validation. The cluster analysis and decision tree method were used. Moreover, a case study was developed for an office building in Philadelphia (U.S.) based on one-year observed data. The building has a surface of 6410 $m^2$ over three floors and was constructed in 1911. Four sensors are installed at the gates of the building to record the number of occupants entering and exiting. Different patterns of occupant presence were developed with this data. Four clusters of occupant presence were identified: Pattern 1 with the lowest occupancy rate and the shortest working time, Pattern 2 with the highest occupancy rate and the longest working time, Pattern 3 with medium occupancy rate, medium working time, going-to-work later and going-home later and Pattern 4 which is similar to Pattern 3 with a medium occupancy rate and medium working time.

D'Oca and Hong [56] evaluated another data mining framework, using three steps: (1) Decision Tree model, (2) Rule Induction and (3) Cluster Analysis. An office building located in Frankfurt, Germany was used as a case study. Occupancy measurements in 16 private offices with a surface of 20 $m^2$ each built in 2002, with single or dual occupancy, were considered as a dataset. The proposed methods in this study identified rules of occupancy and archetypal user profiles, that can be used as input to current building energy modeling programs, to investigate the impact of occupant presence on design, operation, and energy consumption in office buildings.

Mahdavi et al. [57], realized an experimental setup taking into account measurements of indoor parameters such as temperature, relative humidity and illuminance, and outdoor parameters like air temperature, relative humidity, wind speed and global horizontal irradiance. The state of occupancy and ambient light fixtures were captured using a sensor mounted under the luminaire and state of windows, and shades/curtains were monitored taken digital photographs on the facade

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# 3. CHAPTER

# RESIDENTIAL BUILDINGS

## 3.1. Objectives

The purpose of this part of the investigation is to evaluate which factors affect the energy performance of a housing stock representative of Mediterranean climatic conditions. The residential sector is used to test the relative roles of socioeconomic and behavioral aspects of occupants, as compared with climatic and physical building characteristics. The main parts of the investigation are summarized in Figure 3.1.

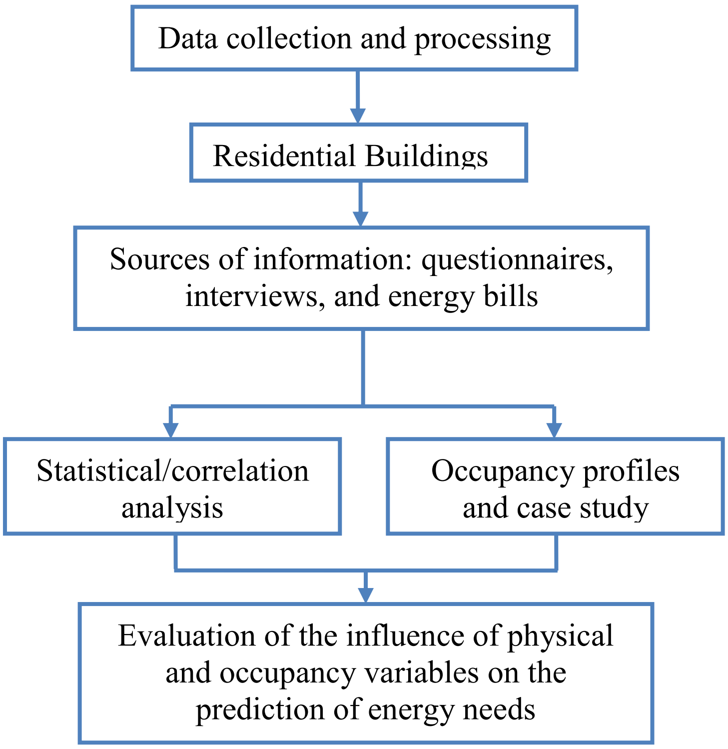



*Figure 3.1 Residential buildings framework*

Information was collected through questionnaires, interviews and energy bills; subsequently, two analyses were conducted with the information from the aforementioned sources. One of them was a statistical analysis and the other involved the definition of occupancy profiles and a case study. The aim of these two analyses was to evaluate the influence of physical and occupancy variables on the prediction of energy needs.

### 3.2. Data Collection

Data collection started in 2012, and the participants were the families of engineering students of the University of Calabria. The investigated area is a region located in Southern Italy typical of Mediterranean climatic conditions. The region has a population of 2 million people and a total of 111 households were interviewed in this study.

Six typologies of parameters are considered to identify and set up a combination of them that allows for the obtainment of high-quality data and get more reliable information how occupant behavior influences energy consumptions. The questionnaire consists of 63 questions divided into six groups of parameters as shown in Figure 3.2.

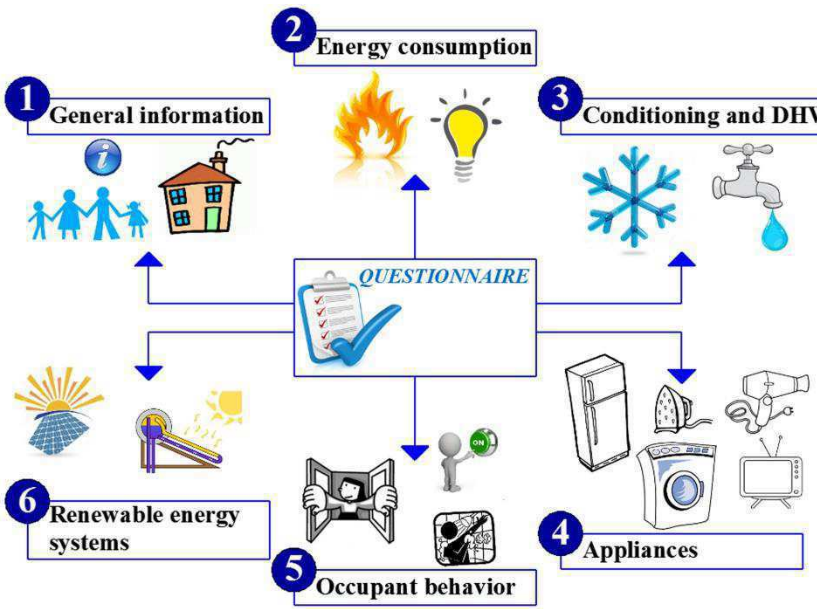



*Figure 3.2 Sections of the questionnaire*

In detail, the survey is structured as follows:

1. General Information:

Containing the key features of the building and family information questions regarding the type of building, size, structure, windows, as well as demographic information relating to the age and gender of the family members and the total household income.

2. Household energy consumption information:

Questions regarding energy consumption addressed the following: real energy consumptions based on data from bills and electricity use of domestic appliances, conditioning, domestic hot water (DHW), and equipment.

3. Conditioning and DHW equipment:

Questions regarding heating system plant typology, air conditioning, DHW and the main control strategies.

4. Domestic appliances and their use:

Questions regarding type, capacity, and energy label of each appliance.

5. Occupant behaviors:

Questions regarding daily routine about the use of heating system, cooling system, DHW. Questions about behavior in relation to window opening, adjusting heating and turning the lights on.

6. Renewable energy system:

Comprising thermal and PV panels. For this sample, none of the participants has an alternative generation system installed.

Additionally, for each dwelling, the energy certification according to the Italian legislation UNI/TS 11300-1 [1] has been realized, and complete data about electricity bills and gas consumption, building features, stratigraphy and transmittance of the walls and features of the system were obtained.

### 3.3. Descriptive analysis of data

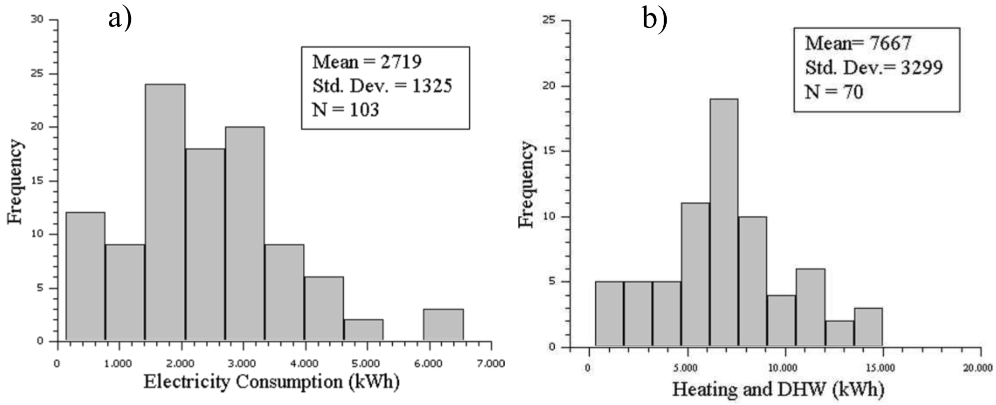
Each section of the questionnaire was analyzed to know and understand the main characteristics of the sample. A statistical analysis of the parameters was carried out using the Software R [2]. The survey responses are presented as categorical and continuous variables. All the parameters were checked for normality and outliers. Normality was verified by the analysis of skewness and kurtosis. Skewness is a measure of symmetry and kurtosis is a measure of whether the data are peaked or flat relative to the normal distribution; a value of zero represents a Gaussian distribution. Variables with a value larger than 1 for these parameters were transformed to improve the normality.

The majority of data were categorical. Table 3.1 reports the descriptive statistics for continuous parameters. Three variables did not meet the criteria for normality and, for statistical elaborations, electricity consumption was transformed into its square root and heating degree days and floor area were converted into logarithm 10 [3], [4].

*Table 3.1 Descriptive statistics of continuous variables*

| | Variables | Mean | Standard Deviation | Number of cases | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| Energy | Electricity consumption (kWh) | 2719 | 1325 | 103 | 0.777 | 0.996 |
| | Energy for heating and DHW (kWh) | 7668 | 3299 | 70 | 0.189 | -0.022 |
| Household | Average age of the family | 35.8 | 8.2 | 95 | 0.202 | 0.462 |
| | Age of the household head | 51.9 | 14.0 | 95 | -0.892 | 0.491 |
| | Number of household members | 3.7 | 1.0 | 98 | -0.332 | -0.390 |
| Building | Floor area ($m^2$) | 141.3 | 75.6 | 98 | 2.062 | 5.780 |
| Weather | Heating degree-days | 1551.2 | 487.4 | 84 | 0.885 | 1.073 |

Figure 3.3 shows a graphical representation of the mentioned parameters and the average age of families.



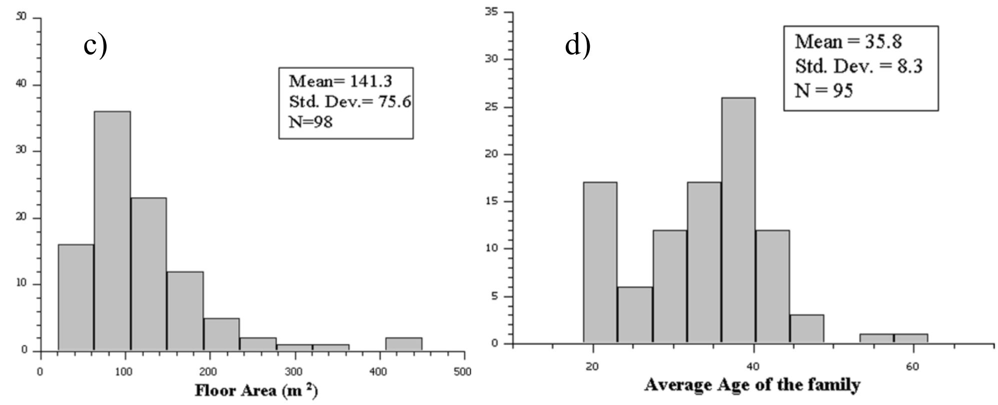



*Figure 3.3 Histogram of (a) electricity consumption, (b) energy for heating and DHW, (c) floor area and (d) average age of the family.*

### 3.3.1. General information

The aim of this section is to examine general information about householders and building constructions. Table 3.2 provides the results about the profile of the respondents. Building parameters describe the physical characteristics of the dwellings, including date of built, floor area, floor number, type of windows and others. The occupant data regard the size of household, the total annual household income, and the age of the householder.

*Table 3.2 Descriptive statistics of categorical variables. Section 1: general information*

| Variables | | Responses | N | Percent (%) |
|---|---|---|---|---|
| Building | Type of house | (a) Single house | 27 | 24 |
| | | (b) Double house | 8 | 7 |
| | | (c) Apartment | 63 | 56 |
| | | (d) Other | 1 | 1 |
| | | (e) Not answered | 13 | 12 |
| | Year of construction | (a) Before 1980 | 32 | 29 |
| | | (b) 1980 - 1990 | 18 | 16 |
| | | (c) After 1990 | 49 | 44 |
| | | (d) Don’t know | 0 | 0 |
| | | (e) Not answered | 13 | 11 |
| | Floor area ($m^2$) | (a) Less than 70 | 9 | 8 |
| | | (b) 70-150 | 62 | 55 |
| | | (c) More than 150 | 27 | 24 |
| | | (d) No answer | 14 | 13 |
| | Floors number | (a) 1 | 64 | 57 |
| | | (b) 2 | 17 | 15 |
| | | (c) 3 | 11 | 10 |
| | | (d) 4 | 6 | 5 |
| | | (e) Not answered | 14 | 13 |
| | Structure | (a) Reinforced concrete | 87 | 78 |
| | | (b) Stone | 7 | 6 |
| | | (c) Wood | 0 | 0 |
| | | (d) Other | 4 | 4 |

| | | | | |
|---|---|---|---|---|
| | | (e) Not answered | 14 | 12 |
| | Type of windows | (a) Double glass | 67 | 60 |
| | | (b) Single glass | 28 | 25 |
| | | (c) Other | 3 | 3 |
| | | (d) Don't know | 0 | 0 |
| | | (e) Not answered | 14 | 12 |
| | Type windows' frame | (a) Aluminum | 46 | 41 |
| | | (b) Wood | 39 | 35 |
| | | (c) Other | 8 | 7 |
| | | (d) Alloy | 1 | 1 |
| | | (e) Thermal break | 4 | 4 |
| | | (f) Don't know | 0 | 0 |
| | | (e) Not answered | 14 | 12 |
| | Type of glass | (a) Double deck vacuum glass | 44 | 39 |
| | | (b) Low-e glass | 3 | 3 |
| | | (c) Clear glass | 34 | 30 |
| | | (d) Other | 3 | 3 |
| | | (e) Don't know | 14 | 12 |
| | | (e) Reflective glass | 0 | 0 |
| | | (f) Not answered | 14 | 13 |
| | Type of external walls | (a) With thermal insulation | 45 | 40 |
| | | (b) Without thermal insulation | 50 | 45 |
| | | (c) Not answered | 17 | 15 |
| | Type of slabs | (a) With thermal insulation | 34 | 30 |
| | | (b) Without thermal insulation | 62 | 55 |
| | | (c) Not answered | 16 | 15 |
| Family information | Age of household members | (a) Less than 19 | 22 | 6 |
| | | (b) 19-30 | 167 | 46 |
| | | (c) 30-50 | 33 | 9 |
| | | (d) 50-65 | 117 | 32 |
| | | (d) More than 65 | 7 | 2 |
| | | (e) Not answered | 15 | 5 |
| | Gender | (a) Female | 181 | 50 |
| | | (b) Male | 156 | 43 |
| | | (c) Not answered | 24 | 7 |
| | Prevalence of gender | (a) Male | 24 | 21 |
| | | (b) Female | 43 | 38 |
| | | (c) Equality | 25 | 22 |
| | | (d) Not answered | 20 | 19 |
| | Total annual income (€) | (a) Less than 30000 € | 43 | 38 |
| | | (b) 30000-70000 € | 33 | 30 |
| | | (c) 70000-100000 € | 2 | 2 |
| | | (d) More than 100000 € | 1 | 1 |
| | | (e) Not answered | 33 | 29 |
| Weather | Heating degree day | (a) A (less than 600) | 0 | 0 |
| | | (b) B (601-900) | 8 | 7 |
| | | (c) C (901-1400) | 28 | 25 |
| | | (d) D (1401-2100) | 39 | 35 |
| | | (e) E (2101-3000) | 10 | 9 |
| | | (f) F (more than 3000) | 0 | 0 |
| | | (g) Not answered | 27 | 24 |

### 3.3.2. Household energy consumption information

In order to know household consumption information for each dwelling, Table 3.3 shows the survey responses as continuous variables. It also presents information about DHW consumption.

*Table 3.3 Descriptive statistics. Section 2: energy consumption*

| | Variables | Mean |
|---|---|---|
| Energy | Electricity consumption (kWh) | 2719 |
| | Energy for heating and DHW (kWh) | 7668 |

### 3.3.3. Conditioning and domestic hot water equipment

The survey questions shown in Table 3.4 were used to obtain more information about the typology of conditioning and DHW equipment,.

*Table 3.4 Descriptive statistics of categorical variables. Section 3: conditioning and DHW equipment*

| Equipment | Variables | Responses | N | Percent (%) |
|---|---|---|---|---|
| Heating system | Typology | (a) District heating | 3 | 3 |
| | | (b) Building centralized system | 0 | 0 |
| | | (c) Autonomous system | 93 | 83 |
| | | (d) Not answered | 16 | 14 |
| | Generation system | (a) Air source heat pump | 2 | 2 |
| | | (b) Electricity | 8 | 7 |
| | | (c) Wall mounted gas boiler | 62 | 55 |
| | | (d) Fireplace | 15 | 13 |
| | | (e) Pellet | 0 | 0 |
| | | (f) Other | 11 | 10 |
| | | (g) Not answered | 14 | 13 |
| | Distribution system | (a) Radiator | 91 | 81 |
| | | (b) Fan Coil | 1 | 1 |
| | | (c) Radiant floor | 3 | 3 |
| | | (d) Radiant ceiling | 0 | 0 |
| | | (e) Other | 3 | 3 |
| | | (f) Not answered | 14 | 12 |
| | Type of local heating equipment | (a) Oil heater | 1 | 1 |
| | | (b) Gas heater | 25 | 22 |
| | | (c) Electric heater | 24 | 21 |
| | | (d) Warm air blower | 4 | 4 |
| | | (e) Electric foot warmer | 5 | 4 |
| | | (f) Electric warm pack | 1 | 1 |
| | | (g) Electric blanket | 1 | 1 |
| | | (h) Other equipment | 10 | 9 |
| | | (i) Not answered | 41 | 37 |
| Air conditioning | Presence of wall mounted or package air conditioner | (a) Yes | 23 | 20 |
| | | (b) No | 20 | 18 |
| | | (c) Not answered | 69 | 62 |

| | | | | |
|---|---|---|---|---|
| DHW | Typology | (a) Centralized system | 37 | 33 |
| | | (b) Decentralized system | 56 | 50 |
| | | (c) Not answered | 19 | 17 |
| | Energy Source | (a) Gas | 68 | 61 |
| | | (b) LPG | 4 | 4 |
| | | (c) Gas +solar | 0 | 0 |
| | | (d) LPG + solar | 0 | 0 |
| | | (e) Electricity | 7 | 6 |
| | | (f) Pellet | 0 | 0 |
| | | (g) Electricity + solar | 0 | 0 |
| | | (h) Other | 16 | 14 |
| | | (i) Not answered | 17 | 15 |

### 3.3.4. Appliances

Information about electricity use of domestic appliances, quantity, capacity, and energy label for twenty-one of the most common appliances in each household was collected (see Table 3.5).

*Table 3.5 Descriptive statistics of categorical variables. Section 4: information of domestic appliances*

| Appliances | Yes | No | Not answered | Mean capacity (w) |
|---|---|---|---|---|
| Small TV ( < 40 cm ) | 65% | 17% | 18% | 111 |
| Big TV | 60% | 22% | 18% | 163 |
| Fridge with freezer | 81% | 1% | 18% | 300 |
| Dishwasher | 41% | 41% | 18% | 1950 |
| Washing Machine | 77% | 5% | 18% | 1974 |
| Coffee Machine | 14% | 68% | 18% | 850 |
| Oven | 63% | 20% | 18% | 1901 |
| Micro Oven | 35% | 47% | 18% | 927 |
| Desktop PC | 54% | 29% | 18% | 175 |
| Laptop | 63% | 20% | 18% | 100 |
| Fan | 29% | 53% | 18% | 436 |
| Dryer | 5% | 77% | 18% | 2000 |
| Mixer | 26% | 56% | 18% | |
| Cooking Robot | 14% | 68% | 18% | |
| Minipimer | 19% | 63% | 18% | |
| Hi Fi | 25% | 57% | 18% | |
| Home Theater | 8% | 74% | 18% | |
| Hair Dryer | 71% | 12% | 18% | 1721 |
| Straightener | 25% | 57% | 18% | |
| Only Freezer | 25% | 57% | 18% | |
| Only Fridge | 5% | 77% | 18% | |

### 3.3.5. Occupant behavior

Individual occupant behavior was studied through the questions reported in Table 3.6. Behavior, habits and preferences related to the use of heating and cooling system, DHW, windows, lighting, curtains, sunshades and renewable system production were collected.

*Table 3.6 Descriptive statistics of categorical variables. Section 5: occupant behavior*

| Equipment | Variables | Responses | N | Percent (%) |
|---|---|---|---|---|
| Heating system | Thermal sensation | (a) Very satisfied | 22 | 20 |
| | | (b) It doesn't matter | 11 | 10 |
| | | (c) Satisfied | 44 | 39 |
| | | (d) Not satisfied. | 19 | 17 |
| | | (e) Not answered | 16 | 14 |
| Cooling system | Thermal sensation | (a) Very satisfied | 18 | 16 |
| | | (b) It doesn't matter | 5 | 5 |
| | | (c) Satisfied | 36 | 32 |
| | | (d) Not satisfied | 2 | 2 |
| | | (e) Not answered | 51 | 45 |
| DHW | Use of hot water | (a) Shower | 92 | 36 |
| | | (b) Wash foods | 29 | 11 |
| | | (c) Wash clothes | 53 | 21 |
| | | (d) Wash dishes | 58 | 23 |
| | | (e) Other | 4 | 2 |
| | | (f) Not answered | 17 | 7 |
| | Kind of shower | (a) Only shower | 67 | 60 |
| | | (b) Shower + bath in a tub | 31 | 28 |
| | | (c) Bath in a tub | 0 | 0 |
| | | (d) Other | 0 | 0 |
| | | (e) Not answered | 14 | 12 |
| | Frequency of shower during summer | (a) Almost every day | 80 | 71 |
| | | (b) 3-5 times/ | 9 | 8 |
| | | week | 0 | 0 |
| | | (c) 1-2 times | 9 | 8 |
| | | /week | 14 | 13 |
| | | (d) Other | | |
| | | (e) Not answered | | |
| | Frequency of shower during winter | (a) almost every day | 32 | 29 |
| | | (b) 3-5 times/ | 43 | 38 |
| | | week | 15 | 13 |
| | | (c) 1-2 times | 7 | 7 |
| | | /week | 15 | 13 |
| | | (d) Other | | |
| | | (e) Not answered | | |
| | Shower time | (a) More than 2 hours | 0 | 0 |
| | | (b) 1 hour | 6 | 5 |
| | | (c) Half an hour | 11 | 10 |
| | | (d) 10-20 minutes | 64 | 57 |
| | | (e) Less than 10 minutes | 14 | 13 |
| | | (f) Other | 3 | 2 |
| | | (g) Not answered | 14 | 13 |
| Windows | Opening living room | (a) Always open | 18 | 16 |
| | | (b) Always closed | 7 | 6 |
| | | (c) Open at fixed time | 31 | 28 |
| | | (d) Other | 35 | 31 |
| | | (e) Not answered | 21 | 19 |

| | | | | |
|---|---|---|---|---|
| | Opening bedroom | (a) Always open | 11 | 10 |
| | | (b) Always closed | 2 | 2 |
| | | (c) Open at fixed time | 41 | 37 |
| | | (d) Other | 36 | 32 |
| | | (e) Not answered | 22 | 19 |
| Lighting | Type of lighting | (a) All are energy saving | 29 | 26 |
| | | (b) Some are energy saving | 61 | 54 |
| | | (c) No energy saving lamps | 8 | 7 |
| | | (d) Not answered | 14 | 13 |
| | Switch lamp-Living Room | (a) Always switch on as long as entering room | 9 | 8 |
| | | (b) When too dark | 82 | 73 |
| | | (c) Other | 4 | 4 |
| | | (d) Not answered | 17 | 15 |
| | Switch lamp-Bedroom | (a) Always switch on as long as entering room | 8 | 7 |
| | | (b) When too dark | 82 | 73 |
| | | (c) Other | 5 | 5 |
| | | (d) Not answered | 17 | 15 |
| Curtain | | (a) Yes | 71 | 64 |
| | | (b) No | 26 | 23 |
| | | (c) Not answered | 15 | 13 |
| Sunshade | | (a) Yes | 24 | 21 |
| | | (b) No | 41 | 37 |
| | | (c) Not answered | 47 | 42 |

### 3.4. Survey limitations and representativeness

To collect meaningful information from a population sample investigated by questionnaire, the respondents must be somewhat representative of the general population. The data set was compared with data provided by the National Institute of Statistics [5], to ascertain if it was representative of the population. The average age of interviewees was 36 years, which is consistent with the median age of the population of 43 years. In particular, 43% of the respondents were males and 50% females (7% not answered), in agreement with the regional gender distribution (49% males and 51% females). The average annual household electricity consumption was 2719 kWh and consistent with the average regional value of 2509 kWh.

The most common type of dwelling in the sample was the apartment (56.3%) followed by the single house (24%). The majority of the constructions were built after 1990 (44%). The average area of dwellings was 141 m$^2$, a large percentage of buildings had a reinforced concrete structure (78%), exhibit uninsulated external walls (45 %) and had double-glazed windows (59.8%). With regard to the heating system, 83% of the houses were equipped with an autonomous generator, 55% of the respondents had a wall mounted gas boiler and natural gas was the most commonly used fuel both for heating and domestic hot water production; 13 % of houses were heated by fireplaces, and minor percentages were heated by air source heat pump (2%) and electric heater (7%).

Climatic conditions were considered by means of climatic zones defined according to heating degree days (HDD) as established by the national regulation [6]. Most buildings were located in C and D climatic zones (25% and 35% respectively). Information about the quantity per household of 21 appliances was asked. The most used appliances were fridge with freezer and washing machine (81% and 77%, respectively). Data reveal that 80% of the houses used energy saving lightbulbs.

Regarding occupants, on average families consisted of 3.7 members. Most of the interviewed subjects (46%) were in the age class of 19 - 30 years. The regional data show a contrast from the sample because the majority age is between 30-50 with 29% of the total population. This result is explained because the surveys were conducted by students enrolled on a bachelor's degree programme at the University of Calabria, and their family structure is restricted by the existence in every household of a member aged 19-30 and thus other relatives between 50-65 years. 39% of occupants were satisfied with the internal comfort, and the majority of them have a shower with an average duration of 10-20 minutes with a higher shower frequency during summer. Occupants switch lamps on when it is too dark, and generally they open windows at a fixed time.

Electricity consumption refers to the equipment and lighting, and 21% of the cases included air conditioning. Figure 3.4 illustrates the distribution of fuels for heating and DHW production resulting from the surveys compared with national data [7]. Comparable percentages of natural gas and liquefied petroleum gas (LPG) are found, differences emerge for diesel and biomass: in the sample diesel consumption is lower than the national value while biomass seems clearly higher in agreement with the local tradition that adopts firewood for domestic use. The percentage of other fuels is negligible. Renewable energy systems are not in the selected sample.

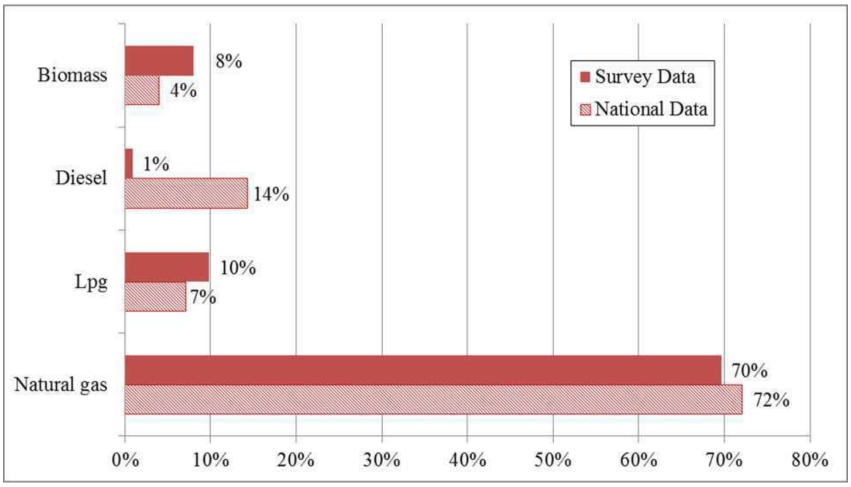



*Figure 3.4 Fuel types for heating and DHW resulting from the surveys compared with National data for the civil sector* [7]

### 3.5. Data processing

Different analyses were developed by using the survey results. One of them was through statistical analysis and the other to define case studies and occupancy profiles. The influence of occupant behavior on energy performances was investigated by simulations using DesignBuilder, which is an interface of the simulation engine EnergyPlus [8]. Both studies were used with the aim to evaluate the influence of physical and occupancy variables on the prediction of energy needs.

#### 3.5.1. Correlation analysis

The purpose of this part of the thesis is to evaluate the main factors affecting the energy performance of a housing stock in Mediterranean climatic conditions through correlation analysis [9]. The investigation is carried out to test the importance of physical and occupancy variables by means of a statistical approach. The questions of the questionnaire relating to physical characteristics, occupants, and energy were considered.

To describe the relations between household energy consumptions and the physical and behavioral variables the General Linear Model was used. Regression analyses are used for continuous variables, a one-way analysis of variance (ANOVA) is applied for categorical variables, and independent-samples t-tests were performed for dichotomous variables. Statistics of electricity consumption are shown in Table 3.7. The F-statistic provides a measure of the probability that energy consumption and the variable have the same variance, where its value is near 1 the null hypothesis is correct. The p-value is a measure of the probability of obtaining a result at least as extreme as the one that is actually observed, so the lower the value (usually below 0.05 or 0.01), the more significant the result. The coefficient of determination ($R^2$) represents the proportion of variability in one variable that is accounted by another variable; it indicates how well data fit a statistical model. The Pearson correlation coefficient (r) is a measure of linear dependence between two variables with a value between -1 and +1 inclusive. The t-statistic aims to analyze the differences between the means of two groups, if the t-statistic is less than the significance level (or error), the null hypothesis is rejected.

*Table 3.7 Correlation between physical and occupant's variables and electricity energy consumption (kWh)*

| Variables | Statistic | *p*-value | $R^2$ | Pearson(r) |
|---|---|---|---|---|
| Type of house | $F_{(3,83)}=1.18$ | >.05 | 0.040 | |
| Year of construction | $F_{(2,84)}=0.647$ | >.05 | 0.015 | |
| Log10 floor area ($m^2$) | $F_{(1,86)}=13.19$ | <.05 | 0.133 | 0.365 |
| Structure | $F_{(2,84)}=0.299$ | >.05 | 0.007 | |
| Type of windows | $F_{(2,84)}=2.386$ | >.05 | 0.053 | |
| Prevalence of gender | $F_{(2,78)}=1.012$ | >.05 | 0.025 | |
| Income (€) | $F_{(3,66)}=2.916$ | <.05 | 0.117 | |
| Average Age | $F_{(1,82)}=9.864$ | <.05 | 0.107 | 0.328 |
| Age of the household head | $F_{(1,82)}=8.251$ | <.05 | 0.091 | 0.302 |
| Number of household members | $F_{(1,85)}=5.944$ | <.05 | 0.065 | 0.256 |
| Heating degree-days | $F_{(3,74)}=3.194$ | <.05 | 0.115 | |
| Energy saving lamps | $F_{(2,83)}=0.787$ | >.05 | .018 | |
| Type of external wall | t(78.60)=0.427 | >.05 | | |

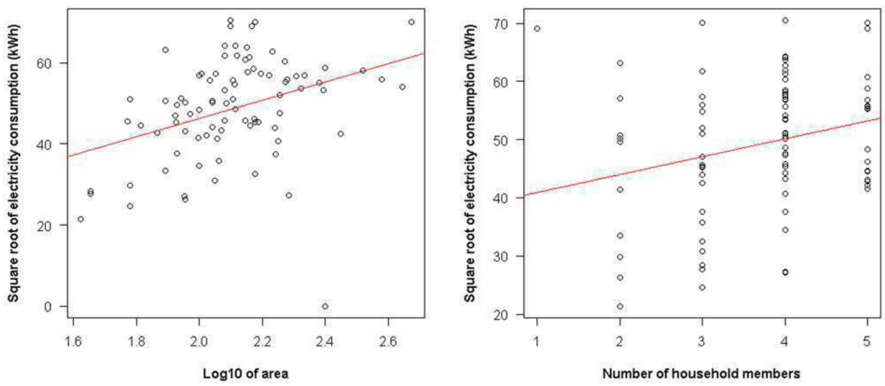



*Figure 3.5 Scatter plot of electricity energy consumption (square rooted) and (a) Log10 of area, (b) family size.*

With regard to the variables that have significant relations with electricity consumption (p<0.05 based on F-tests of all variables), four of them can be mentioned concerning the occupants: average age, age of the household head, number of family members and annual income. Two parameters are related to physical characteristics, the floor area, and the heating degree-days. The relation with the climatic variable can be explained because the use of electricity is also associated with air conditioning. Besides, $Log_{10}$ floor area is the most significant variable influencing electricity energy consumption ($r=0.37$ and $p<0.05$). The square root of electricity consumption has a direct connection with the Log10 floor area, average age, age of household head and number of family members, with a positive Pearson correlation coefficient positive. Figure 3.5 shows the dependence of the floor area and family size.

The correlation analysis between physical and occupant variables and the heating and DHW energy consumption demonstrated that individual predictors are not significant. This study in the investigated region presents complexity due to the double use of the fuel. The results suggest that the formulation of the questions in the survey has to be improved to better describe both lifestyle and types of heating system.

A multiple linear regression analysis was employed to determine the effect of physical characteristics and occupant variables on electricity energy consumption, taking into consideration the six variables described above (all with $p<0.05$), see Table 3.8, and introducing only physical characteristics as reported in Table 3.9.

The first model determines that the selected physical factors and occupant variables explain 48.7% of variation in the square root of electricity energy consumption and the second model shows that physical characteristics can explain 32.7% of variation. Even if both the models are significant overall ($p<0.001$), most of the individual predictors do not seem to be significant. The insufficient number of samples in some categories could also cause the non-significance of the independent variables. To evaluate multicollinearity, the variance inflation factor (VIF) was calculated, leading to a value lower than 10 for both the models (1.94 and 1.49 respectively). Significant predictors are floor area and number of members per household. The families with an income in the €70000-100000 range do not consume more energy than families with an income between €30000-70000, indicating that the relation between income and energy consumption is not linear.

*Table 3.8 Regression model for the electricity energy consumption (sqrt of kWh)*

| Coefficient | $b_i$ | Standard error | *p*-value | t-value |
|---|---|---|---|---|
| $R^2$= 0.4865, p<0.001 | | | | |
| Constant | -9.205 | 14.501 | 0.529 | -0.635 |
| Log 10 of floor area | -23.846 | 7.351 | 0.002 | 3.244 |
| Heating degree days- C vs B | -4.505 | 5.114 | 0.383 | -0.881 |
| Heating degree days-D vs B | -7.213 | 4.985 | 0.155 | -1.447 |
| Heating degree days-E vs B | -9.461 | 6.585 | 0.158 | -1.437 |
| Average age | 0.504 | 0.418 | 0.134 | 1.207 |
| Age of the household head | -0.285 | 0.264 | 0.287 | -1.079 |
| Number of household members | 3.661 | 1.896 | 0.060 | 1.931 |
| Income- 30000€-70000€ vs Income < 30000€ | -3.643 | 2.647 | 0.176 | -1.376 |
| Income- 70000€-100000€ vs Income < 30000€ | 5.363 | 7.474 | 0.477 | 0.718 |
| Income- more than 100000€ vs Income < 30000€ | -28.150 | 9.192 | 0.004 | -3.062 |

*Table 3.9 Regression model for the electricity energy consumption (sqrt of kWh) and physical variables*

| Coefficient | $b_i$ | Standard error | *p*-value | t-value |
|---|---|---|---|---|
| $R^2$= 0.3268, p<0.001 | | | | |
| Constant | -4.804 | 12.525 | 0.703 | -0.384 |
| Log 10 of floor area | 28.287 | 5.906 | 0.000 | 4.790 |
| Heating degree days-C vs B | -2.301 | 4.991 | 0.646 | -0.461 |
| Heating degree days-D vs B | -7.64 | 4.777 | 0.115 | -1.599 |
| Heating degree days-E vs B | -1.335 | 5.806 | 0.819 | -0.230 |

The results reveal that floor area and climate are the most significant physical parameters for electricity consumption; age, number of household members and income can be mentioned concerning the occupants. Physical factors and occupant parameters explain 48.7% of variation in electricity energy consumption, only physical factors can explain 32.7% of the variation. Otherwise, the analysis on heating and DHW energy consumption show critical aspects because it is related to a specific use by the consumers. As a consequence, more detailed investigation methodologies should be applied in future investigations.

### 3.5.2. Occupancy profiles and cases of study

#### *3.5.2.1. Case of study I: Preliminary investigation in existing buildings*

To analyze the importance of the use of real occupancy profiles in determining energy needs by simulation, two case studies of residential buildings in Mediterranean climatic conditions have been chosen according to the results of the questionnaire data analysis [10].

Data processing was used to individuate reference construction types, family composition, and occupancy profiles. Also, representative occupant behaviors in managing windows and lighting are evidenced.

The study was carried out by comparison of the results obtained adopting the Standard procedure [1] and those based on real occupancy profiles achieved by interview. The considered houses are situated in the climate zone C, the heating period is from 15 November to 31 March. The climate file used for dynamic simulations was created from the data reported in the Standard UNI 10349 for the city of Cosenza [11].

For both the cases, dynamic calculations of heating energy need are carried out considering inputs data provided by the Standard UNI/TS 11300-1 [1], with reference to the most common situation in which occupant behavior is not available, and introducing successively as inputs real modalities about occupancy, ventilation, appliances, lighting, windows components. In particular, a single family house and an apartment were analyzed.


*Figure 3.6 The cases study views: (a) of the single family house and (b) of the apartment in condominium in the local context*

a) b)

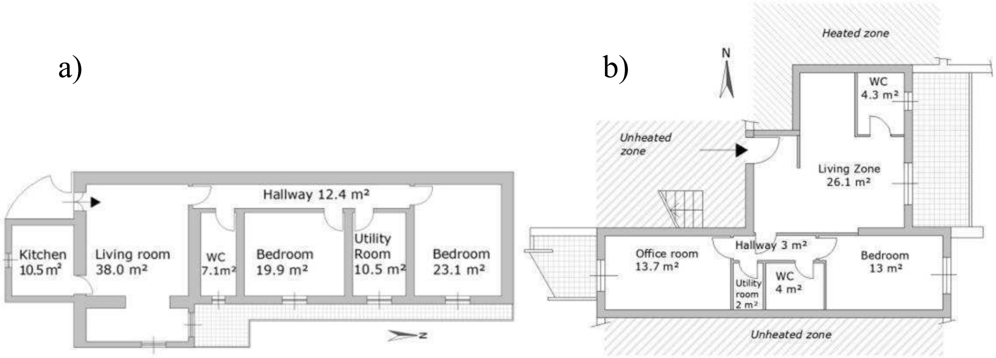



*Figure 3.7 (a) Map of the single-family house and (b) of the apartment in condominium*

The single-family household was built in 1978 (Figure 3.6a), the external walls are in masonry without thermal insulation, and the thermal transmittance is equal to 1 $W/m^2K$. The building consists of two floors with a net area of 134 $m^2$. Transparent surfaces have single glazing, the frames are made of wood. The family is constituted by three people and inhabited zones are located on the first floor. The house has seven rooms, five of which are heated (living room, two bedrooms, bathroom and utility room); in the kitchen and hallway, there is no control of the internal conditions (see Figure 3.7a). The generator system is a wood-burning boiler fireplace; the internal air temperature is controlled by a thermostat.

The second case study is an apartment of 80 $m^2$, built in 2008 in reinforced concrete (Figure 3.6b). The insulated walls have a thermal transmittance of 0.6 $W/m^2K$. The windows consist of double glazing and frame with thermal break. The apartment is located on the second floor, and there is one inhabitant, the heated zones are shown in Figure 3.7b. The generation system, used both for heating and DHW production, is an autonomous wall mounted gas boiler, natural gas is the fuel, and the efficiency of the system is 88%. A zone thermostat regulates the operating of the heating system, and the emission terminals are aluminum radiators.

a. Occupancy profile according to UNI/TS 11300-1

The operation of the heating system is in continuous regime with a fixed set point temperature of 20°C. The internal heat loads are evaluated by using the relation:

$$\Phi_{\mathrm{int}} = 7.987\mathrm{A_f} - 0.0353\mathrm{A_f^2} \qquad (1)$$

where $A_f$ is the usable floor area of the house [$m^2$].

The internal heat loads are obtained by the sum of sensible contribution, calculated in relation of the floor area or equal to 450 W/m$^2$ for dwellings with a floor area greater than 120 m$^2$, and latent contribution evaluated using the relation:

$$Q_{wv,int} = \frac{h_{wv} \times (G_{wv,Oc} + G_{wv,A}) \times t}{3600} \quad (2)$$

where $h_{wv}$ is the specific enthalpy of water vapor, conventionally set equal to 2544 J/gr; $(G_{wv,Oc} + G_{wv,A})$ is the flow rate of water vapor due to the presence of people and equipment, mediated on time, set equal to 250 gr/h for dwellings. The total value of internal loads amounts to 4.7 W/m$^2$ for the single house and 8.1 W/m$^2$ for the apartment.

Following the indications of the Standard, in DesignBuilder internal loads were entered through a single value, grouping all contributions of occupancy, miscellaneous equipment, catering process, and lighting.

Regarding natural ventilation, the Standard assumes a constant air change that includes both the effect of infiltrations, due to air permeability of the envelope, and external flow rate provided for environmental comfort.

The air flow rate $q_{ve,k,mn}$ is calculated according to the procedure of the "Ventilation flow in reference conditions":

$$q_{ve,k,mn} = q_{ve,O,k} \times f_{ve,t,k} \quad (3)$$

where $q_{ve,O,k}$ is the minimum amount of outdoor air [m$^3$/s]; $f_{ve,t,k}$ is a correction factor representing the fraction of time in which takes place the k-th air flow and considers the use profile and infiltrations that occur even when the ventilation is not operating, its value is set at 0.60, $q_{ve,O,k}$ is evaluated using the relation:

$$q_{ve,0,k} = n \times {}^{V}/_{3600} \quad (4)$$

where $n$ is the air change for hour and $V$ is the net volume of the thermal zone, including kitchens, bathrooms, hallways, and utility rooms. The flow rate obtained is equal to 0.3 ach.

In DesignBuilder the ventilation mode which permits the setting of air changes per hour for each zone was adopted. Table 3.10 summarizes the terms of the energy balance influenced by occupant behaviors and the heating energy need obtained by simulation.

In particular, thermal losses through glazed surfaces, the heat lost by natural ventilation, solar and internal gains are considered in order to quantify in a detailed way the effects of user profiles.

*Table 3.10 Standard procedure application. Seasonal energy contributions and heating need*

| | **Glazing [kWh/m$^2$]** | **Natural Ventilation [kWh/m$^2$]** | **Solar gains [kWh/m$^2$]** | **Internal loads [kWh/m$^2$]** | **Heating [kWh/m$^2$]** |
|---|---|---|---|---|---|
| **Single house** | -13.4 | -9.2 | 10.3 | 14.2 | 48.4 |
| **Apartment** | -8.0 | -9.7 | 7.0 | 26.6 | 16.5 |

For the single house the thermal losses through the windows represent the prevalent negative contribution, solar gains and internal loads are comparable. The heating energy need is 48.4 kWh/m$^2$.

For the apartment, the evaluated energy performance is 16.5 kWh/m$^2$ and it results as being significantly influenced by the internal loads that are about triple if compared with the other energy inputs.

b. Real use profile

In the single house the heating system is switched on from 8:00 to 23:00 during all the days and the set point temperature is 20°C.

Internal gains of occupants, equipment and lighting were defined by schedules in order to specify in each zone use time-profiles.

The presence of occupants was detailed considering the sensible and latent thermal loads related to the specific activity [12]. Also for lighting, operating schedules were created and its thermal input was calculated taking into account that 75% of the electric power is converted into thermal power.

Air changes were treated by adopting the mode which allows for determination of the airflow between the internal and external environment, according to the building orientation and wind exposure, envelope air permeability and window openings.

Generally, windows are opened every morning from 8:00 to 9:00 and one hour after midday. External shutters operate during the night in order to reduce heat losses. A similar approach was used in order to create user profiles for the apartment.

c. Results and discussion

In Table 3.11, the results obtained by energy simulation of both the case studies are summarized.

*Table 3.11 Real occupancy profile application. Seasonal energy contributions and heating need*

| | Glazing [kWh/m²] | Natural Ventilation [kWh/m²] | Solar gain [kWh/m²] | Internal loads [kWh/m²] | | |
|---|---|---|---|---|---|---|
| | | | | Lighting | Equipment | Occupancy |
| **Single house** | -11.4 | -46.3 | 10.3 | 0.8 | 5.9 | 6.8 |
| **Apartment** | -6.2 | -8.0 | 5.7 | 1.5 | 6.2 | 3.1 |
| | | | **Heating [kWh/m²]** | | | |
| **Single house** | | | 77.8 | | | |
| **Apartment** | | | 20.9 | | | |

The use of real occupancy profiles for the single house determines a substantial increase of the energy need, equal to 61%, compared to the value obtained by application of the Standard calculation. Fundamentally this result is a consequence of the considerable increment of the thermal losses by natural ventilation. In fact, the adoption of real scenarios in window opening increases the air changes from 0.3 ach to 1.28 ach.

The results of energy simulation highlight the importance of occupancy contribution on the final thermal performance of dwellings.

For the single-family house, window opening has the most important role and determines an increase of 61% in energy demand when real profiles are applied.

The application of the standard procedure for the apartment causes the overestimation of internal loads and the energy need increases by 27% in actual usage conditions.

The main findings of this preliminary analysis were used as starting point for more detailed investigations, as reported in the following section.

#### *3.5.2.2. Case of study II: Procedures for obtaining occupancy profiles and energy consumption evaluation*

In this second step of the study, different procedures for obtaining occupancy profiles were applied considering a residential building stock located in Mediterranean climatic conditions (Southern Italy) [13]. In this case study was include information about representative use profile with information collected at the local level with the data available for the specific context.

The analysis is focused on the prediction of heating and domestic hot water (DHW) energy consumption by simulation, introducing occupancy profiles created through three approaches: using surveys and interviews, application of the National Standards, and elaboration of statistical data available from diverse sources. Furthermore, the energy demand was studied at variation of the set point temperature and ventilation to evaluate the effect of occupants' preferences.

The energy simulations are carried out using the following occupancy profiles:

i. STANDARD-USE PROFILE obtained by using the inputs provided by the National Standard UNI/TS 11300 part 1 and 2 [1], [14]. The Standard provides a simplified procedure which allows for the calculation of internal gains due to occupants, lighting, and equipment in relation to the net surface area of the dwelling ($m^2$), without considering the family composition and occupants' habits.
ii. REAL-USE PROFILE defined by direct interview of the resident. The simulation results were compared with the actual consumption acquired by bills.
iii. REPRESENTATIVE-USE PROFILE built by combining information collected at the local level with the data of Hetus (Harmonised European Time Use Survey) for Italy [15].

The different occupancy, cooling and heating, equipment and lighting profiles are scheduled by means of DesignBuilder [8], and heating and DHW energy consumptions were calculated.

The most frequent physical parameters and characteristics of residents were identified from the questionnaire and are shown in Table 3.12.

*Table 3.12 Summary of the data obtained by analyzing the sample buildings*

| | | |
|---|---|---|
| | **BUILDING** | |
| **Type of house** | Apartment | 56 % |
| **Year of construction** | After 1990 | 44 % |
| **Floor area (m$^2$)** | 70 – 150 | 55 % |
| **Structure** | Reinforced concrete | 78 % |
| **Type of windows** | Double glass | 60 % |
| **Type of external walls** | With thermal insulation | 40 % |
| | **HEATING** | |
| **Typology** | Autonomous system | 83 % |
| **Generation System** | Wall mounted gas boiler | 55 % |
| **Fuel** | Natural gas | 69 % |
| | **DHW** | |
| **Typology** | Decentralized | 50 % |
| **Fuel** | Natural gas | 61 % |
| | **HOUSEHOLD** | |
| **Age of household members** | 19 - 30 | 46 % |
| | 50 - 65 | 32 % |
| **Number of household members** | 4 | 37 % |
| | **BEHAVIOR** | |
| **Thermal sensation** | Satisfied | 39 % |
| **Bath or shower** | Shower | 60 % |
| **Frequency of shower during summer** | Almost every day | 71 % |
| **Frequency of shower during winter** | 3 – 5 times/week | 38 % |
| **Average shower type (minutes)** | 10 – 20 | 57 % |

These results allowed to identify in the sample a representative building that has been considered by the authors for the successive study regarding the creation of occupancy profiles and energy simulation. The representative dwelling is the apartment described in section 3.5.2.1.

***Energy consumption from bills***

Bills concerning gas and water consumption of the last three years were provided by the owner.

In order to determine the gas consumption for DHW production, an average monthly value was estimated by considering the bills of the period when the heating system does not operate. Thus, the DHW annual primary energy was determined and is equal to 1813 kWh; subsequently, using the difference from the total energy consumption (4473 kWh), the heating energy consumption was calculated resulting in an average value of 2660 kWh.

The hot water consumption rate in l/m$^2$day is required in DesignBuilder. By means of the water consumption from bills equal to 2.94 l/m$^2$day and the primary energy for DHW production, the rate of consumed hot water is calculated in proportion equal to 1.23 l/m$^2$day.

***Occupancy profiles and calculation methods***

The dynamic simulations were performed by using the occupancy profiles illustrated in Table 3.13. Each of these occupancy typologies will be described in the next sections.

*Table 3.13 Description of occupancy profiles*

| Occupancy profile | Information source | Family composition | Operation of heating system |
|---|---|---|---|
| **Standard Use** | Inputs by National Standard UNI/TS 11300 [1], [14] | Not specified | Continuous operation<br>$T_{set\ point} = 20°C$ |
| **Real Use** | Questionnaire, interview, and bills | 1 person | Operation schedule:<br>18:30-23:00 weekdays<br>15:00-24:00 Saturday<br>9:00-24:00 Sunday<br>$T_{set\ point} = 23°C$ |
| **Representative Use** | Questionnaires and Hetus | 4 people, parents, and two sons | Operation schedule:<br>6:30-8:00/16:00-22:00 weekdays<br>7:30-10:30/15:00-23:00 Saturday<br>8:00-23:00 Sunday<br>$T_{set\ point} = 23°C$ |

a. *Standard use: Occupancy profile according to UNI/TS 11300-1*

This profile was built with reference to UNI/TS 11300-1 [1] and the procedure is described in section a.

The operation of the heating system is in a continuous regime with a fixed set point temperature of 20°C. The internal heat loads are evaluated by using the relation:

$$\Phi_{int} = 7.987A_f - 0.0353A_f^2 \quad (5)$$

where $A_f$ is the usable floor area of the house [m$^2$].

The calculated value amounts to 5.56 W/m$^2$.

Primary energy for domestic hot water is calculated as a function of the water flow rate needed for different uses and the difference between outlet and inlet water temperature [14]. For residential buildings, the volume of water required for domestic uses does not take into account the number of users, it is estimated considering the area of the dwelling by means of the equation:

$$V_w = a \times S_u + b \qquad [\text{l/day}] \qquad (6)$$

where $a$ and $b$ are parameters tabulated as a function of the housing surface $S_u$ [$m^2$]. The value to be entered in DesignBuilder is related to the net area of the apartment and it is equal to 1.6 [$l/m^2$day]. The supply temperature of cold water is set to 15°C while the delivery temperature is set to 60°C.

*b. Real use profile*

The apartment is occupied by one person, a woman working from Monday to Friday and at home at weekends. Through the questionnaire and interview it was possible to characterize her specific habits; the more detailed information collected was used to create a more detailed simulation model.

Internal gains are defined in DesignBuilder by separating the contribution of occupancy, equipment, and lighting. Dedicated schedules specify the use-profile for each zone. The presence of occupants is detailed considering the sensible and latent heat load related to the specific activity [12]. Figure 3.8 depicts hourly occupancy density in a day.

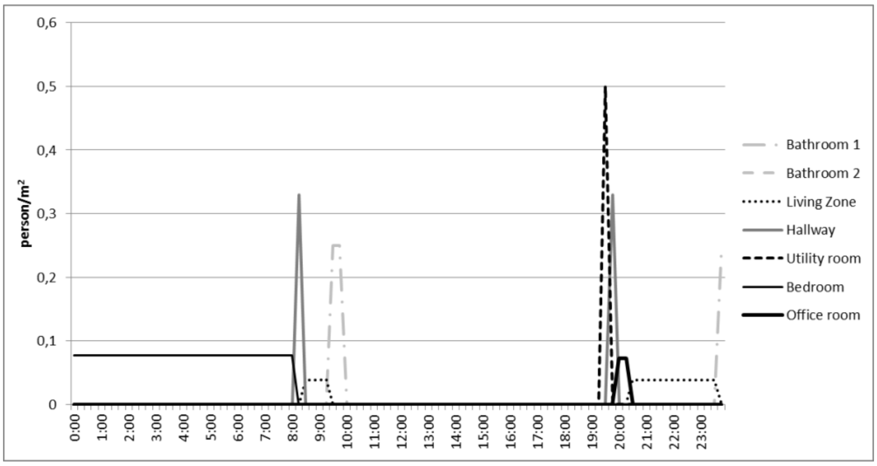



*Figure 3.8 Daily occupancy profile for the real use*

Knowing the electrical power and the hourly usage of each appliance, the corresponding thermal power per unit area was obtained. An hourly average value of internal thermal contribution due to equipment was calculated for each room.

Also, lighting operating schedules were created and the thermal input was calculated taking into account that 75% of the electric power is converted into thermal power.

Air changes were treated by adopting a calculation mode in the simulation software, which allows determining the airflow between internal and external environment, according to the building orientation and wind exposure, envelope air permeability, and windows opening. The occupant stated that living room and bedroom windows were opened every morning from 8 am to 9 am. This ventilation schedule was applied for the whole year, both for weekdays and weekends.

c. *Representative occupancy profile*

The representative occupancy profile was built by using data collected by questionnaires and statistical elaborations. By combining the data collected at the local level with the more extensive Hetus data for Italy, a family-model was created. The family consisted of four people: two parents aged between 50 and 65, one of whom works full-time and the other part-time, two sons aged between 19 and 30, a student and a full-time worker.

The inputs of occupancy for both the real and representative use are compared in Figure 3.9.

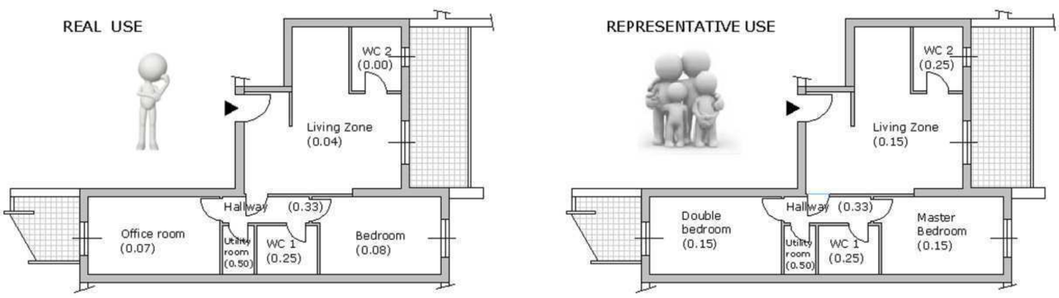



*Figure 3.9 Use of the dwelling in the real and in the representative occupancy profile. Details of the maximum value of occupancy density for each room [person/m²]*

With respect to the real-use profile, in the representative profile the occupancy mode varies in terms of number of occupants and occupancy hours. The family spends more hours at home, and the representative occupancy profile was defined detailing the activities in the different rooms of the apartment. Table 3.14 describes some Hetus data used for the investigation. Figure 3.10 depicts the daily occupancy density and Figure 3.11 reports, as an example, the specific occupancy schedule for the living room in DesignBuilder, where occupancy density is entered as a fraction of the maximum occupancy.

*Table 3.14 Data on time use for Italy from Hetus survey* [15]

| **Room** | **Activity** | **Time per activity (hh:mm)** | **Time in the room (hh:mm)** |
|---|---|---|---|
| Living room | TV and video | 01:40 | 07:33 |
| | Reading, except books | 00:13 | |
| | Leisure, social, and associative life | 04:35 | |
| | Household upkeep except cleaning dwelling | 00:06 | |
| | Cleaning dwelling | 00:47 | |
| | Study | 00:12 | |
| Kitchen | Eating | 01:54 | 03:00 |
| | Food management except dish washing | 00:46 | |
| | Dish washing | 00:20 | |
| Bedroom | Sleep | 08:18 | 09:15 |
| | Homework | 00:08 | |
| | Resting | 00:32 | |
| | Computer games | 00:01 | |
| | Hobbies and games except computing and computer games | 00:08 | |
| | Reading books | 00:05 | |
| | Radio and music | 00:03 | |
| Bathroom | Other and/or unspecified personal care | 01:01 | 01:01 |
| Unoccupied dwelling | Activities taking place outside | 03:11 | 03:11 |
| **Total** | | | **24:00** |

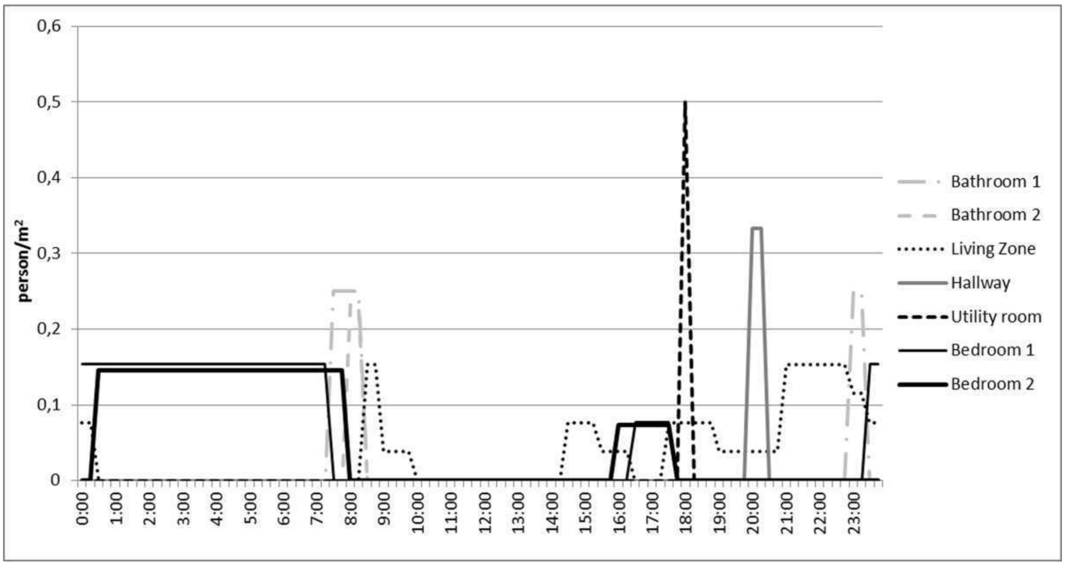



*Figure 3.10 Daily occupancy profile for the representative use*

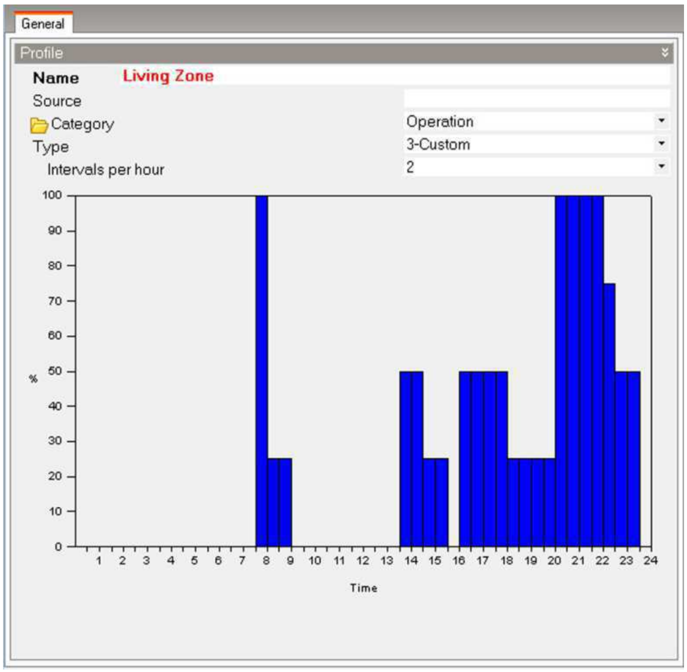



*Figure 3.11 Daily occupancy pattern for the living zone (maximum occupancy rate equal to 0.15 person/m²)*

With regard to the DHW demand, considering an average consumption of 60 l/day per person [16], the DHW rate results equal to 3.53 l/m$^2$day.

Regarding natural ventilation, such as in the real case, the air changes were determined by considering the windows opening and the percentage of open windows.

It was assumed that occupants open the windows every morning for one hour (from 8:00 to 9:00) in the living zone and in the bedrooms, and for a half hour (from 8:00 to 8:30) in the two bathrooms. In the afternoon windows are opened from 14:30 to 15:00 in the living zone and in the bedrooms. The percentage of open windows was set equal to 70%.

*d. Results and discussion*

The three occupancy profiles were simulated considering the selected building. The aim was to highlight how different occupancy scenarios lead to substantial differences in energy consumption. The energy really consumed, obtained from bills, allowed verification of the reliability of the model. It was proved that simulation results for the real use of the apartment and energy derived from bills differ by less than 5%. The validated model was used to simulate the representative occupancy profile.

Figure 3.12 shows the values of primary energy for heating obtained for the three analyzed use profiles.

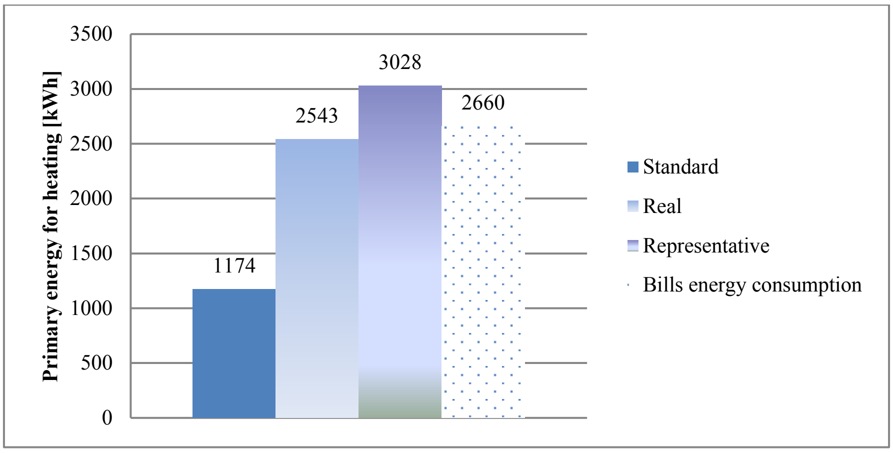



*Figure 3.12 Primary energy for heating obtained for the three occupancy scenarios and consumption from bills*

Compared with the real use, the standard occupancy profile produces a significant underestimation, while considering the family representative profile the consumption for heating increases by 19%.

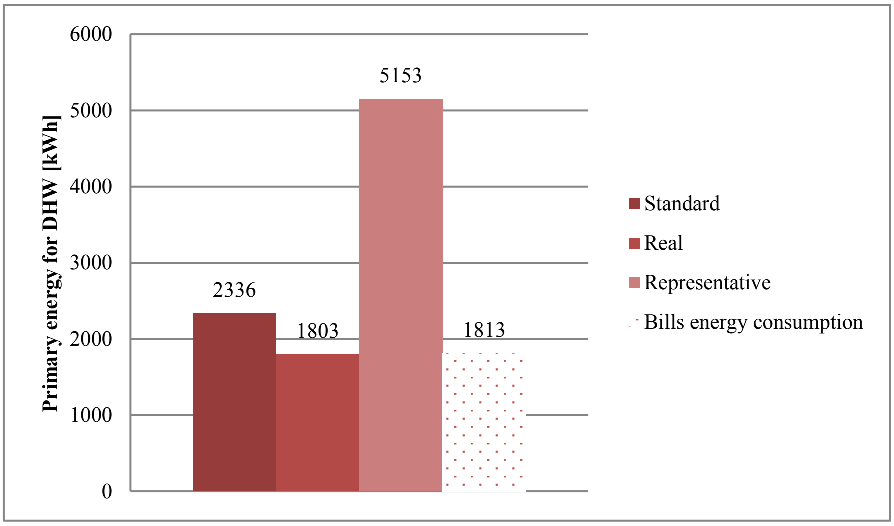



*Figure 3.13 Primary energy for DHW obtained for the three occupancy scenarios and consumption from bills*

Considering the DHW consumption obtained by the standard and determined as a function of the area of the apartment, the primary energy turns out to be higher than the ones calculated for the real use by an amount of 23%. For the representative profile the energy requirement considerably increases.

Figure 3.14 represents the total primary energy consumption for the analyzed occupancy profiles. The figure highlights that the modeling proposed by the regulations can produce misleading results and is not suitable to correctly represent all the occupancy scenarios.

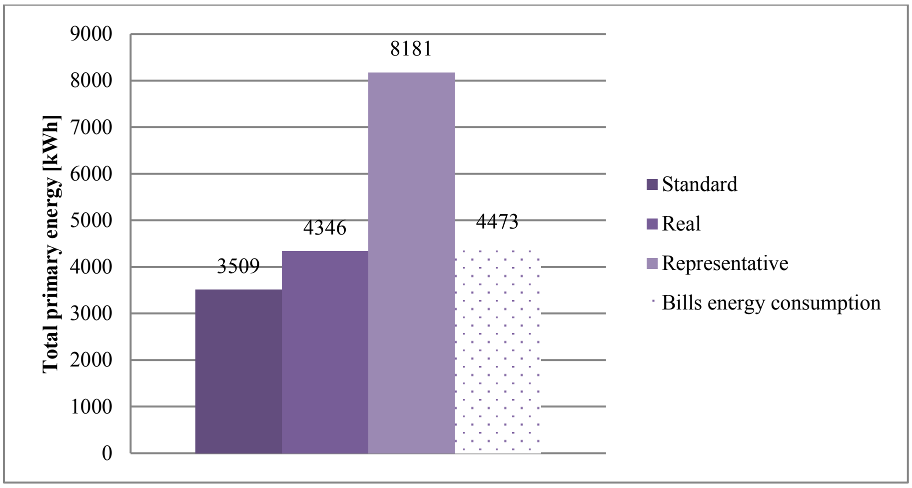



*Figure 3.14 Total primary energy obtained for the three occupancy scenarios and consumption from bills*

The differences resulting in energy consumption are due to the ways of using the dwelling that determine variations in heat losses and gains. With reference to ventilation strategies some detailed results were analyzed. Figure 3.15 and Figure 3.16 report the ventilation rate and heat losses due to ventilation, respectively.

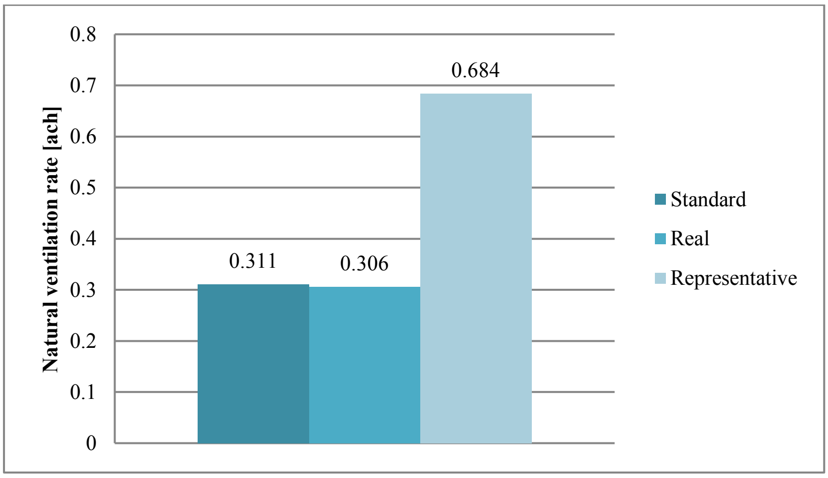



*Figure 3.15 Natural ventilation rate obtained for the three occupancy scenarios*

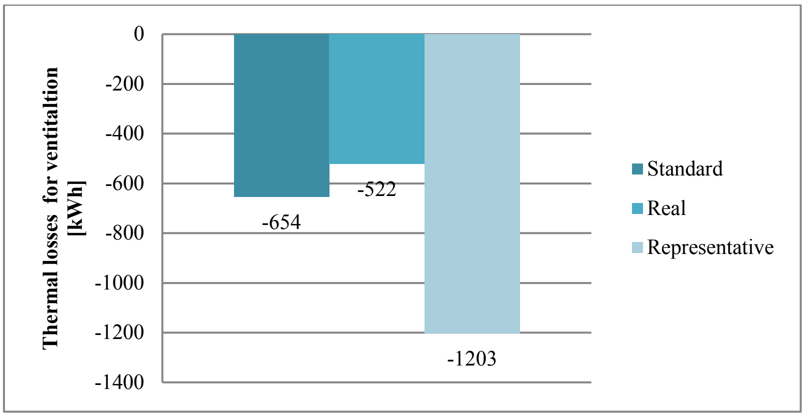



*Figure 3.16 Thermal energy losses due to ventilation obtained for the three occupancy scenarios*

The thermal gains differ with a variation in the number of occupants.

Figure 3.17 details the internal gains for occupancy in both real and representative profiles. For the standard profile the contribution of occupancy is not specified separately.

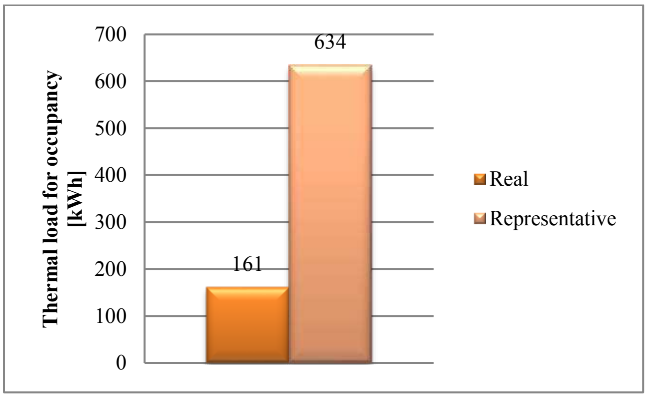



*Figure 3.17 Thermal energy contribution due to the occupants for the real and representative profiles*

It can be noted that as the number of family members increases, sensible and latent thermal loads due to the occupants proportionally enlarge.

Figure 3.18 presents the percentage increase in heating primary energy if the set point temperature is modified.

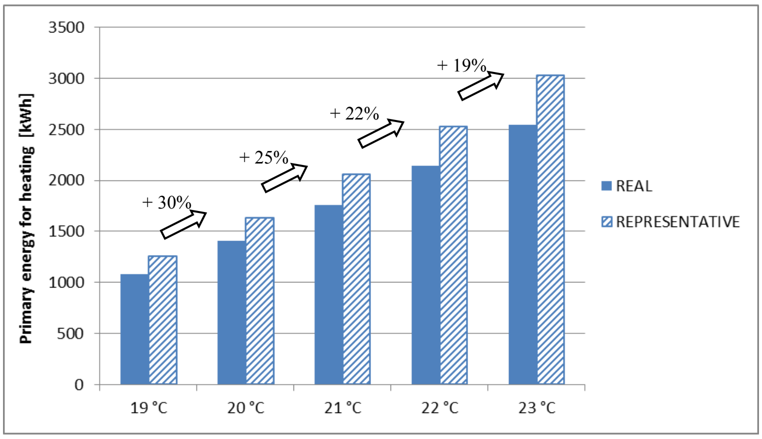



*Figure 3.18 Heating primary energy for different values of the set point temperature*

Figure 3.19 shows the primary energy required for DHW for the two different occupancy profiles increasing the production temperature of 5°C progressively. This increment determines constant absolute increases of the DHW primary energy and different relative percentages of increase. The results are equivalent for the two analyzed profiles.

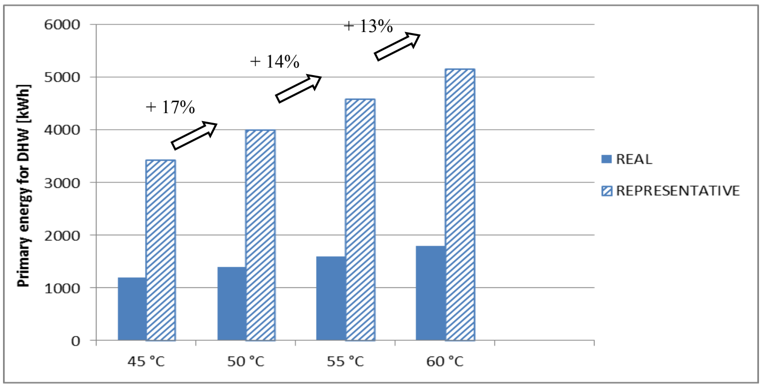



*Figure 3.19 Primary energy for DHW on variation of temperature production*

The occupant can decide to adjust the temperature to a higher or lower value according to their intended use.

Heating the water to 60°C instead of 45°C will lead to a consumption of 50% more energy.

The effect of ventilation on energy consumption was analyzed through the variation of two parameters: the percentage of the open glazed surface and the time that the windows are open. By varying the percentage of open windows between 50% and 100%, not significant variations on primary energy for heating were registered.

More interesting results were obtained with regard to the duration of ventilation, as reported in Figure 3.20.

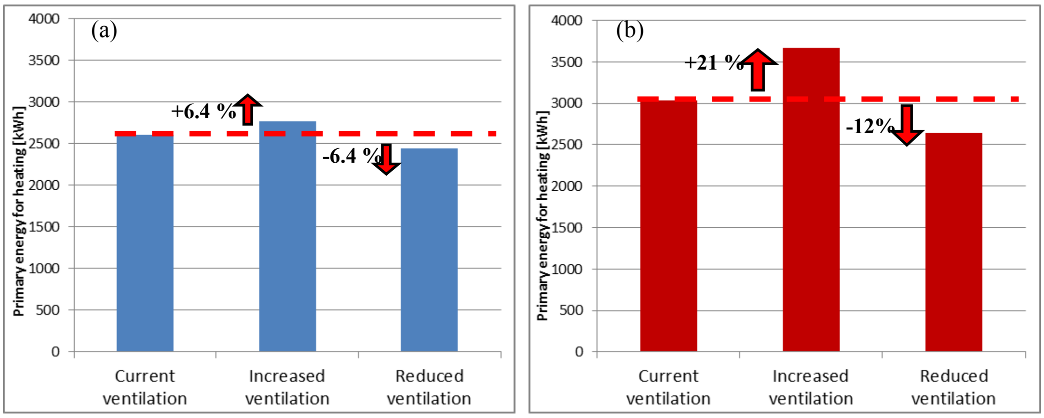



*Figure 3.20 Heating energy consumption as a function of the time of window opening in a) real profile and b) representative profile*

In particular, the effect of an increase and of a reduction of half an hour of ventilation in the morning was analyzed because in the investigated area it is customary to open the windows at this time of the day. In the case of real profile, when only two rooms are ventilated, this change leads to a variation in the energy consumption for heating by 6%. Considering the representative profile, where more spaces are occupied and simultaneously ventilated, an increase of half an hour of opening windows in all rooms could increase heating primary energy by 21%.

As final considerations, we can mention that Standard occupancy profile produces a significant underestimation of heating energy consumption if compared to the real scenario. For the representative family, the consumption for heating increases by 19%.

Considering the DHW, the primary energy obtained for standard occupancy is higher than the one calculated for the real use by 23%. For the representative profile this energy requirement considerably increases.

Occupant preferences are investigated in terms of internal set point temperature, DHW temperature production, and windows opening.

Changing from a temperature of 20°C, that is the value indicated by the standard, to 23°C in the real use, the gas consumption for heating increases by 81%. Heating the water to 60°C instead of 45°C requires 50% more primary energy.

The change in the percentage of open windows does not result in significant variations in primary energy. By contrast, the extension of the duration of ventilation can increase primary energy for heating by 21% if the representative profile is considered.

#### *3.5.2.3. Case of study III: Effect of different users profiles on energy performance of Nearly Zero Energy buildings*

In this third step of the investigation, the aim is to evaluate the influence of user patterns on the energy consumption of a residential nZEB in Mediterranean climatic conditions [17]. Furthermore, the investigation takes into account the socio-demographic context by means of the collection and accurate analysis of National and local statistical data. The study considers the variability of the family composition and the occupancy scenarios. Also, the needs and preferences of occupants in using energy systems and equipment are included in the energy performance assessment.

The investigation was conducted by considering important aspects contemporaneously: nZEB definition and technical issues, application of Standards and Regulations that do not consider the "occupancy" variable in their formulation, adaptability of renewable energy systems in relation with the occupancy profiles, identification of a simple method for creating housing occupancy patterns by using free available data.

An energy efficient building was designed according to the Italian Standard [18]. The building is a two storey detached house with a total net area of 110 $m^2$. The ground floor consists of the living zone while bedrooms are on the first floor. The construction was intended to consume low energy: the ratio between dispersing surface and air conditioning volume is set to minimize losses, all the housing components are well insulated, the air conditioning system has high efficiency and uses energy from renewable sources available on site. However, the actual consumption for the management of the house depends on the type of family occupying the dwelling and on the interaction of the occupants with it. Two different occupancy scenarios, defined according to statistical data [5], were proposed in order to understand how the occupancy typology and the various modes of use of the house and its facilities can affect energy consumption. For each occupancy scenario and mode of use, the annual energy balance in terms of primary energy (kWh/m$^2$year) was considered with the aim of verifying the achievement of the nZEB objective.

Regarding climatic conditions [19], file for the City of Cosenza, Calabria Region (South Italy) was adopted. The site, classified as "Csa" according to the Köppen climate classification [20] is characterized by a typically Mediterranean climate, with hot and dry summers and mild, wet winters, resulting in a dominant cooling demand. The mean annual value of the outdoor dry bulb temperature is equal to 16.3 °C; the direct normal solar radiation is 1564.8 kWh/year and the diffuse solar radiation on the horizontal plane is 613.8 kWh/year. The heating system functions from 15$^{th}$ November to 31$^{st}$ March, according to Italian Regulations for climatic zone C (HDD=1317), in which Cosenza is located [6]. The remaining months are considered for the cooling season.

*a. Occupancy scenarios and house management*

The building is now defined by its physical characteristics and it is classified as nZEB according to the Italian Standard. However, different types of households could occupy the house. Moreover, the family members, following their typical habits and needs, may decide to use the amenities of the dwelling differently. Therefore, the actual consumption of the building may differ from that estimated, thus negating the "zero" balance. In order to analyze the variability of consumption under different types of occupancy, the use of the house by different family typologies has been supposed. Two occupancy scenarios have been created from statistical data, describing the socio-demographic situation of the concerned area. Data regarding the "family structure" provided by the National Institute of Statistics [5] report that in the region of Calabria, four component households account for the majority in families with children, representing 46% of the total in the last two years. Table 3.15 presents two scenarios considered.

*Table 3.15 Occupancy profiles*

| Occupancy profile | Use of the dwelling |
|---|---|
| **Four member family (F4)** | All room of the house are generally occupied |
| **Two member family (F2)** | Only a few rooms in the house are occupied |

Occupancy density (person/m$^2$) is calculated for each room and varies according to the number of components. To define how much time people spend at home, data on time use provided by ISTAT [5] have been examined. The respondents reported the daily time dedicated to different activities for each interval of 10 minutes. In particular, investigations on the activities were carried out and allowed for identification of the total number of hours that a person spends on average at home, in relation to the size of the family. With reference to a "weekly average day", a person spends on average 16 hours per day at home for a family of four, while 17 hours per day are spent at home in the case of a two-member household. Data showing the frequency of people participation in the frequented places have been considered to identify the periods of time during the day when people are at home (see Figure 3.21).

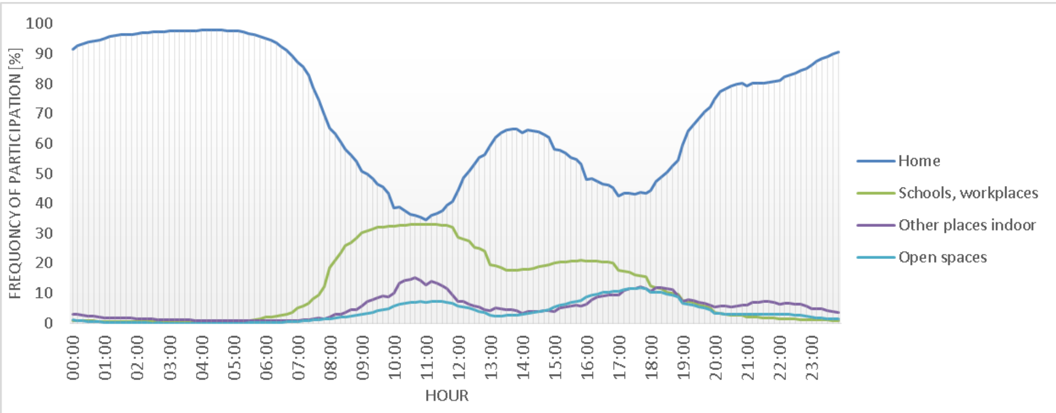



*Figure 3.21 Frequency of participation of people to the places frequented in a weekly average day* [5]

The time ranges reveal that the greatest percentage of people at home is overnight and in the early morning, in two hours at lunch, and in the evening after 7 p.m.

Combining the information about the number of hours of presence at home and the most populated time bands, occupancy profiles for the average weekly day have been constructed for both F4 and F2 scenarios, as shown in Figure 3.22

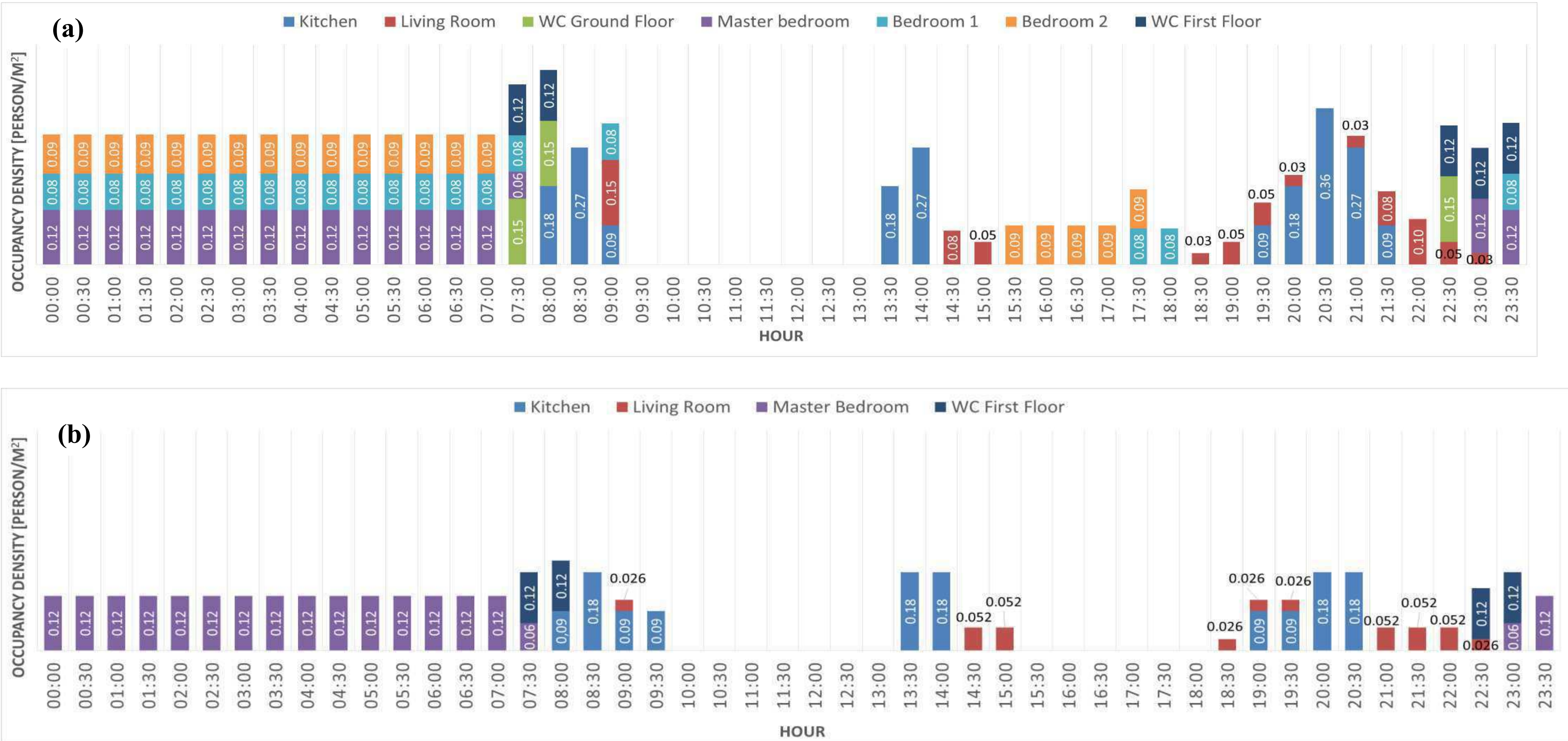



*Figure 3.22 Occupancy profiles for the F4 (a) and F2 (b) occupancy scenarios for an average weekly day*

*Lighting*

Statistical data [21] show that for the considered geographic area, artificial lighting is used on average less than four hours per day (about 75%). 22% of people use artificial lights from 4 to 12 hours per day and only a very small fraction (3%) turns on the lights for more than 12 hours per day. Consistently, in the designed building the use of artificial lighting has been set at less than four hours in each room. Furthermore, two types of lighting have been analyzed in the study: traditional light bulbs, for example halogen bulbs, with a lighting power density (LPD) equal to 10.2 W/m$^2$, and energy saving light bulbs, such as compact fluorescent lights (LPD=7.5 W/m$^2$).

*Equipment*

The provision of dwelling appliances is typical of a contemporary house [21]. The frequency and hours of use were defined by considering available statistical data. In particular, the ISTAT survey reveals the use of the washing machine and the dishwasher on variation of the family size.

Generally, a family of four components, on average, does about six washing machine loads and dishwasher washings per week, while a two member family uses the washing machine three times per week, and the dishwasher four times per week.

Since the building is expected to be zero energy, the installation of low energy appliances is suggested. However, in order to evaluate the influence of the energy efficiency of the equipment on the annual consumption of the house, the use of different energy labeled household appliances have been analyzed, considering different levels of energy efficiency for appliances for which energy labelling is mandatory [22], [23].

*Heating and cooling system*

Settings on the operation of the heating and cooling systems have been made according to statistical information for the considered climatic conditions [21].

The heating system, on average, is switched on for about seven hours per day, while the cooling system operates four hours per day.

*DHW production*

The demand of domestic hot water has been fixed at 60 l/day per person [16], with 55 °C hot-water temperature production. The solar system is prioritized for the production of DHW. However, an integration system is provided to satisfy the DHW demand when the solar source is not sufficient, consisting of an electrical resistance with a maximum heater capacity of 1.5 kW installed in the 300 liter storage tank.

a. *Behavioral variables*

The use of the house by families with diverse sizes implicates differences in the number of rooms generally used and in the occupancy density of each room. Also, the utilization of heating and cooling systems, DHW, lighting, and household appliances has been defined.

However, variables related to the users' choices regarding heating and cooling set point temperature, and ventilation control strategies are not provided by the statistical survey. With reference to these variables, occupants can behave differently in the house management. In particular, a category of users could have a more aware behavior aimed at saving energy. On the other hand, users could also have a wasteful behavior, without caring about the amount of energy spent and often persisting in squandering habits. In many studies considering different occupancy profiles in energy consumption investigations, differences in baseline temperature assumptions were considered to assess their impact. Set-point temperatures have been chosen by individual approaches, such as starting from values of local Standards [24], in other cases the set point values were estimated by means of contextual data [25], [26].

In order to analyze the impact of occupant preference on final energy consumption, and therefore, on actual nZEB building performance, different behaviors have been analyzed for both F4 and F2 family models. The set point temperatures were established by assuming the reference values indicated in the Standards and Regulations [1] in order to define the medium profile. Saver and Waster behaviors were obtained by considering lower and higher set point temperature values, respectively.

- Saver – "S": set point temperature is 19 °C for heating and 27 °C for cooling. Ventilation takes place when the plant is switched off: half an hour before turning on the system in the morning in the bedroom area and half an hour before turning on the system in the afternoon in the living area.

- Medium – "M": heating set point temperature is 20 °C, while cooling set point temperature is 26 °C. Ventilation is the same for all areas, from 7:00 to 8:00 in the morning and in all the rooms, and it overlaps in part with the period when the plant is switched on.
- Waster – "W": the user who does not care about energy saving sets the heating temperature at 23 °C and the cooling temperature at 24 °C. He opens the windows when the system is operating.

Both family compositions have been simulated with the three occupants' behaviors typologies and considering, alternatively, the installation of traditional or low energy consumption appliances and lights.

*b. Results and discussion*

Figure 3.23 shows the annual energy balance carried out for all the analyzed scenarios.


*Figure 3.23 Net annual energy balance of the building for the F4 and F2 occupancy profiles, in presence or absence of low energy consumption lighting and household appliances, and for three different occupants' behaviors (Waster, Medium, Saver)*

The results demonstrated that in the case of using no energy saving appliances and traditional lightings the annual energy balance is always negative. A positive balance is achieved only in the case of a two-member family who uses the house partially, and by equipping the rooms with energy efficient appliances and lights. Moreover, it is noteworthy that even in this configuration, if the users belong to the category of "Wasters", the annual energy balance is negative.

Consequently, the house that is classified as a nearly zero energy building according to the calculation procedure proposed in the National Regulations cannot satisfy this qualification as it consumes more energy than it produces throughout a year.

Further processing of the results has been conducted in order to more thoroughly investigate the reasons for this inconsistency.

First of all, the incidence of the different energy uses on the total annual consumption has been determined.

In particular, the percentages of the annual total energy consumption for the different family scenarios, occupant behaviors, and both the equipment and lighting typologies are represented in Figure 3.24.

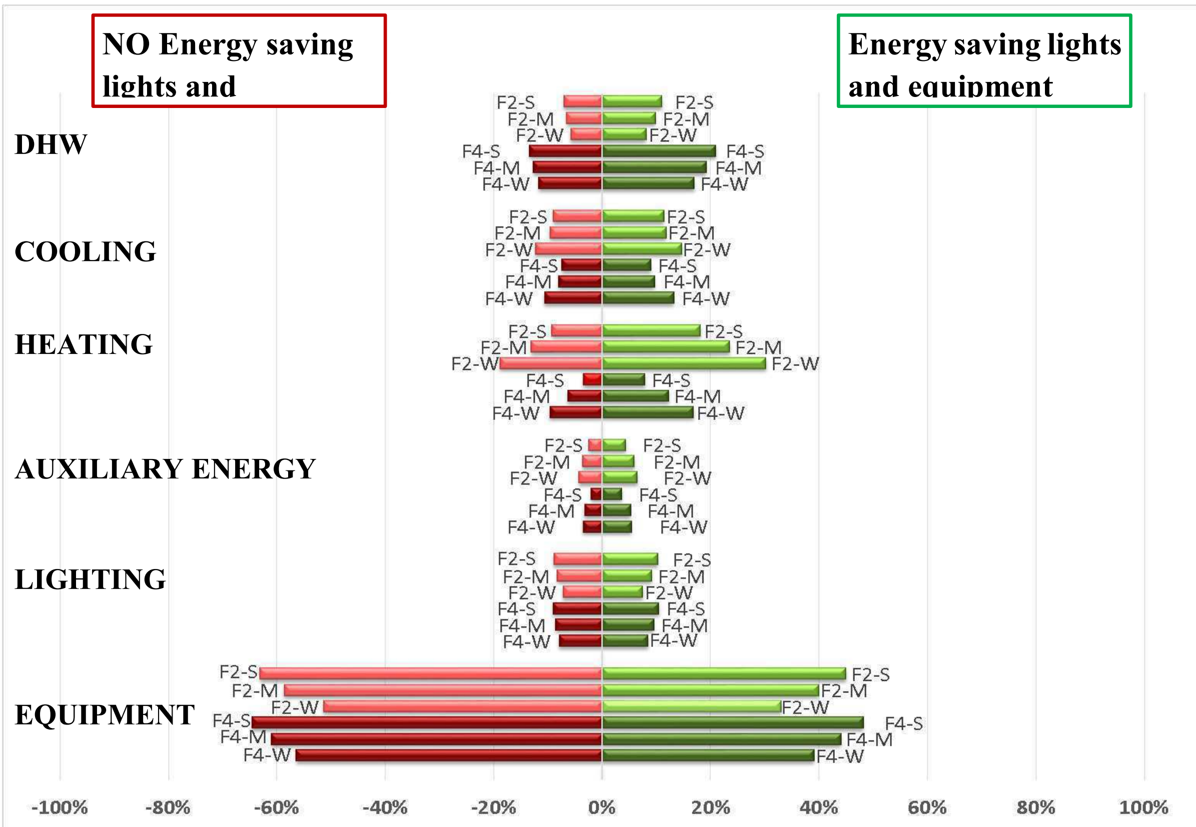



*Figure 3.24 Influence of separated energy uses on final energy consumption upon variation of family size, occupants' behavior, and equipment typology*

The incidence of various electric uses on the total consumption of the house seems to be the same for both the cases "NO-energy saving lights and equipment" and "Energy saving lights and equipment." In particular, it is worth highlighting that in all the analyzed cases, the household appliances are responsible for the major fraction of electrical consumption of the dwelling. Moreover, it is interesting to note that moving from the Waster profile to the Saver one, the percentage of consumption attributable to household appliances, artificial lighting, and domestic hot water production tends to have an increasing impact on the total consumption, while the energy for heating, cooling and plant auxiliary decreases with the improvement of occupant behavior. In the case of the use of traditional household appliances, the equipment consumption reaches 65% while using energy efficient equipment their consumption weights up to a maximum of 50% and more influence is associated with heating, cooling and DHW. The fraction of consumption due to artificial lighting varies from 7% to 10%.

The energy produced on site is not enough to cover all the energy uses of the house. Thus, the building classified as nZEB according to the Italian Regulations is not zero energy. The reason is that Italian Legislation does not consider electrical purposes (lighting and appliances) in the calculation of the energy performance of buildings, and consumptions associated with these uses tend to have an increasing importance upon the decrease of consumption for air conditioning. This means that the more the building is carefully designed to contain the energy demand for winter heating and summer cooling, the more electricity consumption for lighting and appliances has a higher weight in the final energy balance.

The building designed according to the reference calculation model certainly offers good performances in terms of air conditioning energy requirements and hot water production. In fact, considering only the consumption for heating, cooling, DHW, and auxiliary systems, the annual energy balance is positive for all the occupancy profiles and utilization modalities, as reported in Figure 3.25.

*Figure 3.25 Net annual energy balance considering only consumption for heating, cooling, DHW and auxiliary energy*

The analysis leads to conclude that the assertion of a "nearly" zero energy building is justified, as the fact of being zero energy is not linked exclusively to construction and plant solutions, but is also dependent on occupant related factors. In fact, minimizing the energy consumption for heating and cooling by adopting a high-efficiency envelope and plants, the consumption of lighting and appliances depending on user behavior becomes prevalent.

Therefore, to facilitate the achievement of a balance as close as possible to zero, the adoption of energy saving appliances and lights should be forced, because it permits obtainment of a reduction of the energy consumption independently of the use. In fact, the results show that also the wasteful family, who does not care about the use of air conditioning and ventilation, could almost double the surplus energy to be allocated to electrical needs. Indeed, the percentage of consumption that can be covered by renewable sources passes from 18% to 33% using low-power electrical appliances and lights.

However, to obtain buildings that are concretely nearly zero energy, technical parameters associated with the energy consumption for electricity uses inside the dwelling (equipment and lights), should also be included among the requirements to be complied with for classification as an nZEB. In fact, the total energy consumed by the building also includes these uses, which are closely linked to the behavior of occupants, and which tend to have an increasing impact on the final energy balance, at a decrease of consumption for conditioning, as happens in nZEBs.

Moreover, in the evaluation of energy performance of buildings, not only a reference building should be considered, but also a reference occupancy and a reference users behavior. Otherwise, the designed building is likely to move away from the theoretical formulation of nZEB; the real consumption could be very different from predicted consumption, and the final balance may mismatch the estimated zero goal.

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# 4. CHAPTER
# OFFICE BUILDINGS: EXPERIMENTAL STUDY

## 4.1. Experimental Setup

The experimental setup was built with the intention to observe occupancy patterns and control actions relating to window, door, and office equipment use, including monitoring indoor and outdoor conditions under which such actions take place.

To obtain information regarding user presence and absence intervals, occupancy sensors were installed. Measurements of occupancy with indoor and outdoor environmental variables were conducted in one office located at the University of Calabria, Italy. The study used data collected for weekdays, weekends, and holidays from February 2016 to January 2017.

The scale of occupancy measurements was the presence (the frequency of an occupant leaving his/her office and the corresponding duration of the absence). The collected data were primarily analyzed to compare different techniques for occupancy monitoring. The data were then analyzed to explore relationships between the occupancy and the magnitude of indoor and outdoor environmental changes and energy consumption through different statistical analyses. The collected data were stored and processed in a database.

According to the categorization survey [1], the experimental setup can be classified as reported in Table 4.1.

*Table 4.1 Classification of the experimental setup*

| **Category** | |
|---|---|
| **Information type** | Presence-Boolean |
| **Occupant relation** | Anonymous |
| **Spatial granularity** | Space (Room) |
| **Temporal granularity** | Periodic |
| **Spatial coverage** | Space (Room) |
| **Temporal coverage** | Present |
| **Sensor modality** | Air, Magnetic Fields-Reed Switch, power |
| **Sensing strategy** | Augment the environment |
| **Infrastructure Requirements** | Wireless sensor nodes and base stations |
| **Installation complexity** | Install infrastructure and configuration equipment |

The presence and habits of occupants influence the use of equipment and indoor conditions. To study this correlation, the experimental setup consists of instruments to measure environmental quantities, electricity consumption and sensors for occupancy detection positioned following the criterion of sensors fusion.

#### 4.1.1. Description of the office and occupants

Data was collected in one office at the University of Calabria, Italy. Figure 4.1 illustrates an external view of the university buildings known as "Cubes," and Figure 4.2 shows the location of the office considered for the analysis.

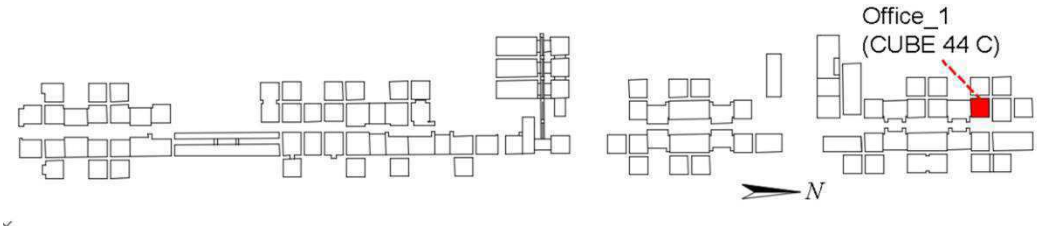


*Figure 4.1 General plan of the University of Calabria and display of the cube containing the office*

*Figure 4.2 External view of cube 44 C*

The office is located on the third floor of Cube 44 C. It has an area equal to 19 m$^2$ and a height of 2.50 m. The room presents a single wall facing outside Westwards and a two-wing window of 68x76 cm. The office is regularly occupied by one person. In Figure 4.3 a more detailed description of the office is reported.

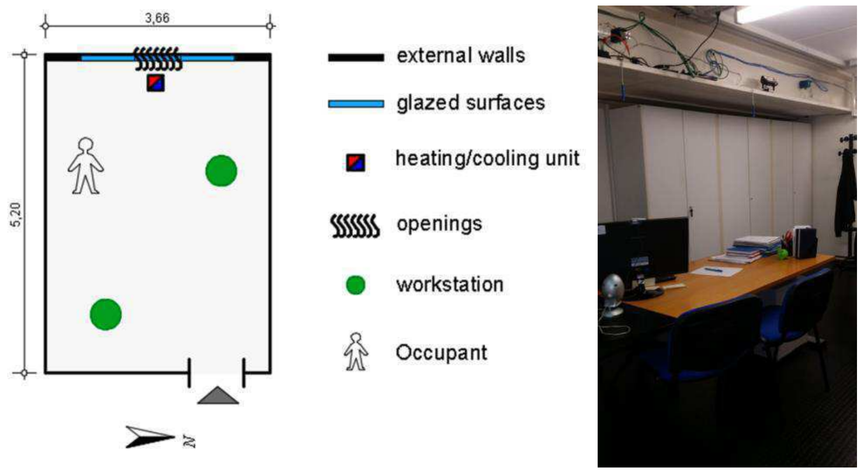


*Figure 4.3 Layout and internal views of the office*

The office is equipped with desktop computers and printers.

Table 4.2 and Table 4.3 summarize, respectively, the physical features of the office and how it is utilized by the occupants. This information was collected by interviewing the occupant.

*Table 4.2 Physical characteristic of the investigated office*

| | PHYSYCAL CHARACTERISTICS | OFFICE |
|---|---|---|
| STRUCTURE | Area [m$^2$] | 19.0 |
| | Height floor [m] | 2.50 |
| | External wall [N°] | 1 |
| | Orientation of glazed surfaces | West |
| HVAC | Heating system typology | Autonomous |
| | Heating period | November - March |
| | Heating generation system | Multisplit Heat Pump |
| | Heating terminal unit | Fan coil |
| | Cooling system typology | Autonomous |
| | Cooling period | June - September |
| | Cooling generation system | Multisplit Heat Pump |
| | Cooling terminal unit | Fan coil |
| LIGHTING AND EQUIPMENT | Lighting (typology, N°) | Neon (n°2) |
| | Number of computers | 2 |
| | Number of printers | 1 |
| | Additional equipment | - |
| | Type of solar shading | Internal blinds with dark coloured horizontal slats |

*Table 4.3 Occupant information and habits*

| | OCCUPANT BEHAVIOR | OFFICE |
|---|---|---|
| PRESENCE | Working day per week | Monday - Friday |
| | Work starting time | 9:00 |
| | Work ending time | 19:00 |
| | Lunch break time | 13:00 – 14:00 |
| | Meeting days per week | Everyday |
| | Meeting time | Afternoon |
| PREFERENCES | Heating set point temperature | 22 °C |
| | Hours of heating | 9:00 – 19:00 |
| | Cooling set point temperature | 26 °C |
| | Hours of cooling | 13:00 – 19:00 |
| | Hours of light ON | 15:00 – 19:00 |
| | Hours of computer use | PC1: 9:00-19:00<br>PC2: 50% |
| | Printer use | ≈ 4 times per day |
| | Equipment use | - |
| | Windows opening | SUMMER: 9:00 – 9:30<br>WINTER: 9:00 – 9:30 |
| | Percentage of windows opening | 50 % |
| | Use of solar shading | Afternoon (50% shading) |
| | Satisfaction comfort | Not satisfied due to overheating in summer |

### 4.1.2. Monitored parameters

Occupancy sensors were installed/used to obtain information regarding user presence and absence intervals. Data are automatically queried every one-minute and stored in central embedded MySQL database. The number of observations in the dataset was 1440 per day for each parameter, and the experiment has nine parameters monitored inside.

The experimental apparatus is designed to monitor presence and movement of the occupants in the office as well as thermophysical properties of the internal environment and the electricity consumption connected to the use of computers.

The main components of the system are:

1. Data Acquisition (DAQ) and Control System;
2. Sensors for environmental parameters and for human presence
3. Smartphones for presence and localization.

In the following paragraphs, a description of the first and second component is presented, an illustration of the third technique is reported in the next section.

### a. DAQ and control system

A DAQ and control system is constituted by a combination of hardware and software that is able to measure and control physical quantities.

The architecture of the DAQ and control system is based on:

- a pc that loads a set of instructions of a specific program, which can acquire, manipulate and save data.
- a data acquisition plug-in board (that fits in a pc expansion slot), a chassis external to the pc, an external USB or Ethernet device, a measurement instrument which connects to the pc through an RS232 port (serial port) or a GPIB (general purpose interface bus) port.

In this case, the necessity to work with remote input/output led us to choose devices that transmit data over standard hardware technology, “Ethernet” (hardware protocol) and standard HTTP (Software protocol). Furthermore, the system has to be able to gather, monitor and archive analog and digital I/O values over the internet/intranet. In Figure 4.4 a schematization of the operating strategy is presented with reference to the collection of quantities such as current, voltage, temperature, humidity and air quality measurements.

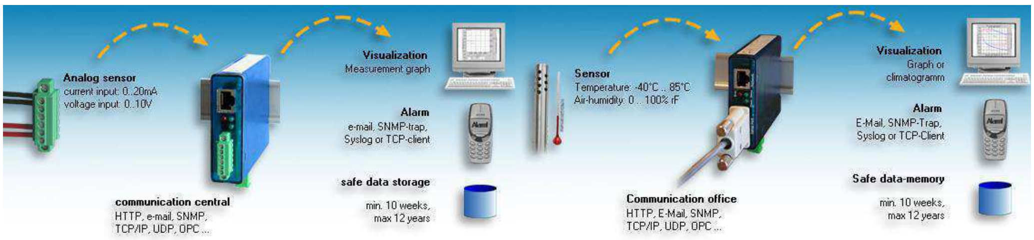


*Figure 4.4 Analog I/O acquisition*

A motherbox is used to collect data from digital and analog Web-IOs in a central embedded database. For this component, low energy consumption products were chosen.

### b. Sensors for environmental parameters and human presence

The presence and habits of occupants influence the use of equipment and indoor conditions. To study this correlation, the experimental setup consists of instruments to measure environmental quantities, electricity consumptions and sensors for occupancy detection positioned following the criterion of sensors fusion.

The following internal variables were regularly logged each minute.

*Comfort and Indoor environment factors:*

- Air temperature [°C]
- Relative humidity [ %]
- Air pressure [hPa]

*Presence Occupancy (present/absent)*

Indirect Sensors:

- Indoor Carbon dioxide ($CO_2$) concentration [ppm]
- Air quality conditions, VOC concentration [ppm]

Direct Sensors:

- Beacons
- Video camera for people presence

*Electricity consumption*

- Power meters (AC Devices), AC Transformers (AC current monitoring)

*Behavior*

- Window/Door position (open/closed)
- Air conditioning (on/off)

The external weather conditions were monitored using a weather station, mounted on the top of a building close to the office.

*Outdoor environmental factors measured every one minute.*

- Air temperature [°C]
- Relative humidity [%]
- Wind speed [$ms^{-1}$] and wind direction
- Solar radiation (beam and horizontal global irradiance [$W\ m^{-2}$])

Table 4.4 gives the characteristics of sensors used for the experimental setup and in the following section, other details will be specified.

*Table 4.4 Specification of sensors*

| Sensor | Variable | Measuring error | Measuring range and resolution |
|---|---|---|---|
| Wieseman & Theis 57613 Web-Thermo-Hygrobarograph | Air temperature [°C] | typ. @ 25 °C ± 0.3 °C max. @ -40..85°C ± 1.5°C | -40°C..85°C 1/10°C |
| | Relative humidity [%] | typ. @ -20..60°C (normal range) ± 1.8% rH (10-90% rH) max. @ -20..60°C (normal range) ± 4% rH (0-100%rH) | 0..100% rF 1/10% rH |
| | Air pressure [hPa] | typ. @ 25°C ±0.8hPa (750..1100 hPa) max. @ 25°C ±2.5hPa (750..1100 hPa) | 10-1100 hPa 0.1 hPa |
| Wieseman & Theis 57018 $CO_2$ sensor | Carbon dioxide [ppm] | Measuring range: 0..2000ppm $CO_2$ ±30ppm,±5% | Analog |
| Wieseman & Theis 57618 Web-Graph Air Quality | Volatile organic compounds [ppm] | Measuring range: 450..2000ppm VOC as $CO_2$ equivalent | |
| | Air temperature [°C] | typ. @ 25 °C ± 0.3 °C max. @ 0..50°C ± 1.2°C | 1/10°C, |
| | Relative humidity [%] | typ. @ 25°C ± 3% rH max. @ 0..50°C ± 7% rH (0-100% rH) | 1/10% rH |
| Wieseman & Theis 57645 AC Device | Electricity power | Range 0..50A AC, 30-6000Hz (all waveforms) | - |
| ABUS FU7350W Abus rectangular, NC,0.2 A Reed Switch | Window/door position (open/closed) Air conditioner (on/off) | Contact sensor | - |

### c. Smartphones for presence and localization

The first phase of the experiment consisted in changing one or more factors to observe the effect that modification has on the accuracy of the occupants' indoor location. The study considers as factors the number of beacons and their position within the examined area, then we examined how well beacons and smartphone sensor positioning data matches a set of known location points.

For the experiments, several beacons and a set of smartphones with a dedicated application that supports Bluetooth Low Energy technology to intercept beacons signals are used. Each smartphone identifies an occupant whose movements are constantly monitored and juxtaposed to the energy consumption values using time as a common factor.

The smartphone and energy consumption sensors data overlay requires synchronization of all devices. A significant number of studies from the scientific community has focused on time synchronization [2]–[5].

The approach that has most commonly been adopted is the Network Time Protocol (NTP) that uses round-trip message delay averaging to set times. To benchmark the performance of NTP running on the phone the OS Timestamping bounds, that in this case is Unix Timestamp, can be employed. In this way, through NTP and time provided by a server, it is possible to adjust the clock rate and synchronize data from different sources.

During the localization algorithms calibration phase, the occupants walk on pre-sets known as indoor paths with stops decided in advance. In addition to this, the algorithms calibration requires several configurations of the beacons number and their position within each room (Figure 4.5).

In particular, two different scenarios have been defined. The first scenario is characterized by the presence of only one device, while the second scenario reckons on two or more beacons within the room, in order to evaluate the best trade-off based on number of devices and accuracy of the surveys.

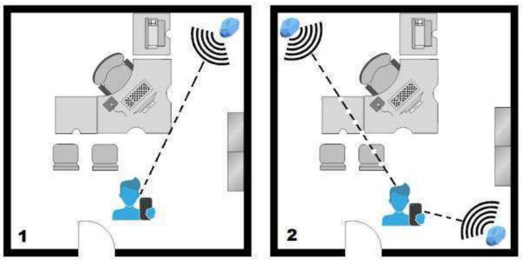


*Figure 4.5 Configurations of beacon location*

Regarding the use of smartphones as a tool to detect the presence of a person or several people in a room, at an early stage an Android Application has been developed, specifically for Operating System 4.3 or higher, as this is the minimum version supporting the BLE protocol adopted by the beacons.

The smartphone application works in the background and is in a constant listening state, allowing the detection of beacons at each instant. In this way, the application is able to send the exact position of the occupant, calculated using specific algorithms based on the information received from beacons at a specific time, to the central embedded database.

The centralized platform receives occupancy data from smartphones and environmental parameters from sensors. By synchronizing data through the use of NTP servers, all data are combined in order to identify the possible correlation between the presence of individuals and energy consumption in the studied environment.

It is important to highlight that beacons were installed in the office. Due to time constraints, the data analysis remains for future work, but the data are being recorded.

## 4.2. Measurements

Figure 4.6 depicts the office layout as well as the general configuration of the sensors.

The traditional integrated sensors are divided into three parts: (a) the sensing element (e.g. resistors, capacitor, transistor, piezo-electric materials, photodiode, etc.), (b) signal conditioning and preprocessing (e.g., amplifications, linearization, compensation, and filtering), and (c) sensor interface (e.g. the wires, plugs and sockets to communicate with other electronic components) [6].

In the successive section, all of these three parts will be described.

### 4.2.1. Descriptions of the sensors

In order to managing and inventory data we used the W&T Network Device Utility Version 4.30 [7], which automatically generated an inventory list with device data and status. WuTility is the free central management tool for all W&T network components. It does not only provide support in initial startup and configuration of the devices, but its archiving and inventory functions are also an administration level aid during operation [7].

The data can be downloaded at intervals of 1, 5, 15 or 60 minutes, and the value it takes is the value measured by the sensor in the corresponding minute.

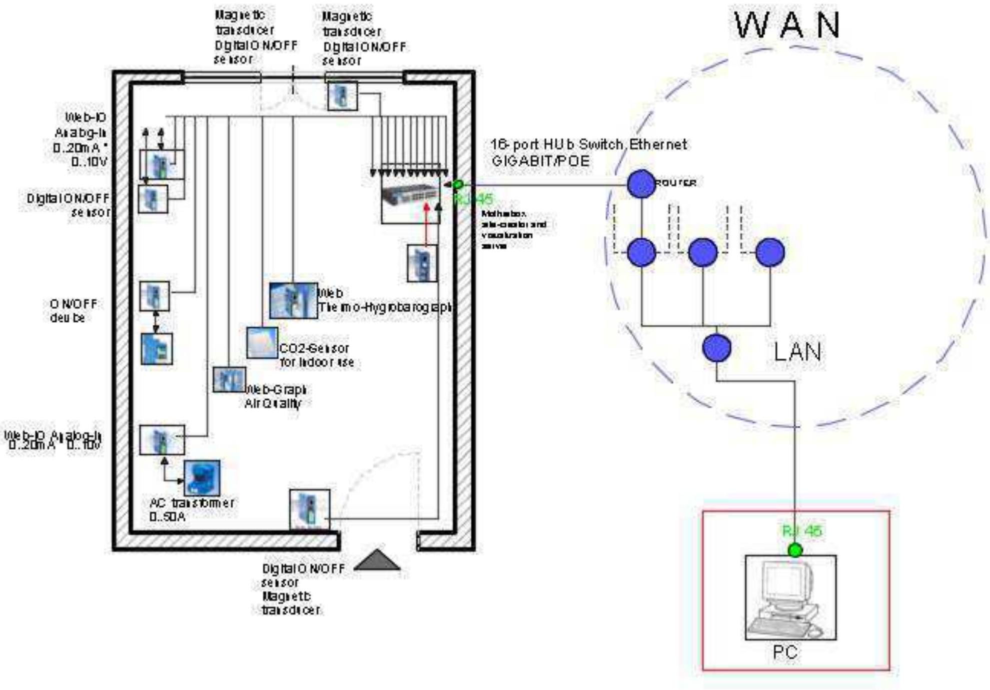


*Figure 4.6 Test bed layout*

All sensors have been connected to the Web-IO Analog-In 0.20mA/0.10V #57641 (Figure 4.7) to gather, monitor and archive analog measurement values over the internet/intranet.

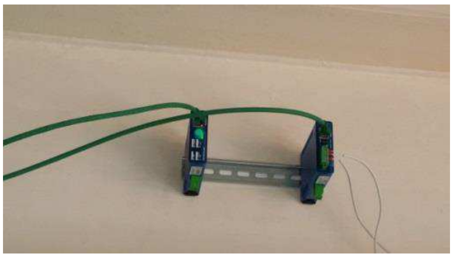

*Figure 4.7 Web-IO Analog-In 0.0020mA/0..10V*

Each sensor has its own panel and DIN rail power supply Switching ELC ALE2401,30W, input 190 →253V ac, 24V DC output, 1.25 A (see Figure 4.8), in order to ensure continuity of measurements.

*Figure 4.8 DC Power supply switching ELC ALE2401 for each sensor*

<u>*Comfort and Indoor environment factors:*</u>

Figure 4.9 shows the sensor layout for comfort and indoor environment factors.

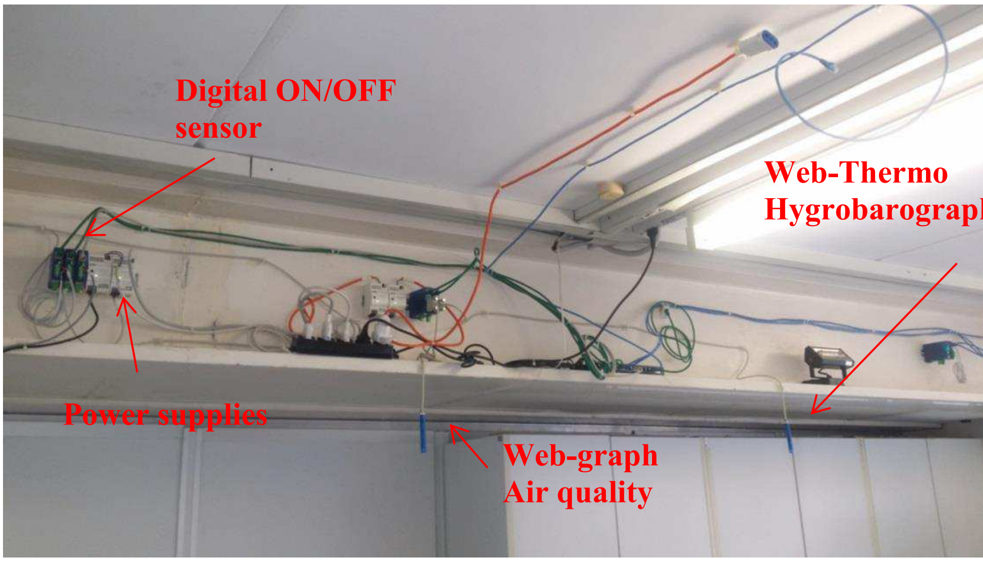


*Figure 4.9 Sensor layout for comfort and indoor environment factors*

The indoor environment measurements were carried out with Web-Thermo-Hygrobarograph #57613 as shown in *Figure 4.10*.

| | |
|---|---|
| Measuring range: | -40°C…85°C,0..100% rF, 10-1100 hPa |
| Resolution: | 1/10 °C, 1/10% rF, 0.1 hPa |
| Measuring error: | |
| Temperature: | typ. @ 25 °C ± 0.3 °C<br>max. @ -40..85°C ± 1.5°C |
| Relative humidity: | typ. @ -20..60°C (normal range) ± 1.8% rH (10-90% rH)<br>max. @ -20..60°C (normal range) ± 4% rH (0-100%rH)<br>temporary @ -40..85°C (max range) +3% rHnach 60h Operation outside normal range<br>Long-term stability typ. <0.5% rH/year |

Atmospheric pressure: typ. @ 25°C ±0.8hPa (750..1100 hPa)

max. @ 25°C ±2.5hPa (750..1100 hPa)
max. @ -40..85°C ±3.5hPa (300..1100 hPa)
Long-term stability typ. -1hPa/year
Measuring frequency: 4s
Storage frequency: 1,5,15, 60 min

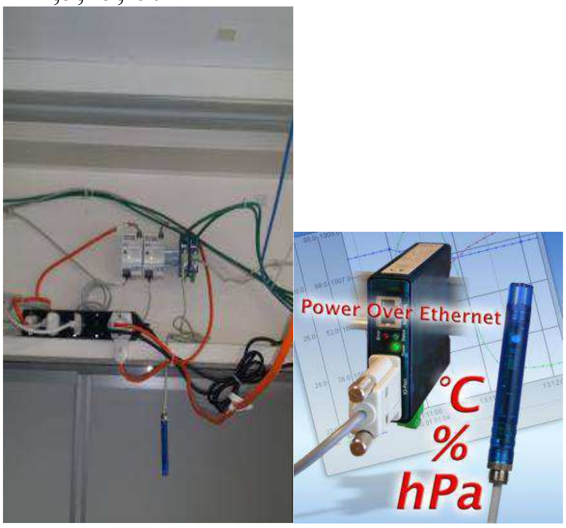


Figure 4.10 Picture of the instrument used to detect the indoor environment measurements #57613

*Presence Occupancy (present/absent)*

*Indirect Sensors*

The measured parameters were indoor carbon dioxide ($CO_2$) concentration [ppm] and VOC concentration [ppm]. Figure 4.11 shows the $CO_2$ sensor.

*Figure 4.11 Picture of the $CO_2$ sensor #57018*

The measurement of $CO_2$ is through a non-dispersive infrared sensor (NDIR) that takes 6 values per minute. The room $CO_2$ sensor #57018 is connected to the Web-IO Analog-In 0..20mA/0..10V #57641.

| | |
|---|---|
| Measuring range $CO_2$: | 0..2000ppm $CO_2$ |
| Output $CO_2$: | 0-10V |
| Measuring error: | ±30ppm,±5% |
| Measuring frequency: | 6 values/minute |

Operating ambient temperature: 0..50ºC

One sensor is installed near the desk at + nose level (when seated, 1.1 m) above the ground [8]. For this sensor, the $CO_2$ output was in Volts, and conversion was necessary to obtain the measurements in ppm.

Indoor air parameters were measured by using Web-Graph Air Quality #57618 shown in Figure 4.12.

| | |
|---|---|
| Measuring range: | 0°C..85°C, 5..95% RH, 450-2000ppm VOC as $CO_2$ equivalent |
| Resolution: | 1/10 °C, 1/10% rH |
| Measuring error: | |
| Temperature: | typ. @ 25°C ± 0.3 °C |
| | max. @ 0..50°C ± 1.2°C |
| Relative humidity: | typ. @ 25°C ± 3%rH |
| | max. @ 0.050°C ± 7%rH (0-100%rH) |
| | Long-term stability typ. <0.5% rH/year |
| Air quality sensor: | Measuring range 450..2000ppm VOC as $CO_2$ equivalent |
| Measuring frequency: | 4s |
| Storage frequency: | 1, 5, 15, 60 min |
| VOC sensor, detects substances: | Aldehydes, Aliphatic hydrocarbons, Alcohols, Amines, Aromatic hydrocarbons, Ketones, organic acids, CO, $CH_4$, LPG. |

*Figure 4.12 Pictures of the instrument used to estimate air quality #57618*

<u>Direct Sensor / Beacons</u>

Two types of beacon are used for the selected scenarios fully compliant with Apple IBeacon (TM) standard, and compatible with iPhone and Android devices: a low-medium range beacon (Figure 4.13a), and a medium-high range beacon(Figure 4.13b). Table 4.5 summarizes the features of the devices.

(a)

(b)

*Figure 4.13 Low-medium range (a) and medium-high range (b) Beacons*

The graphical user interface for an Android app and the locations on the top corners of the office are shown in Figure 4.14.

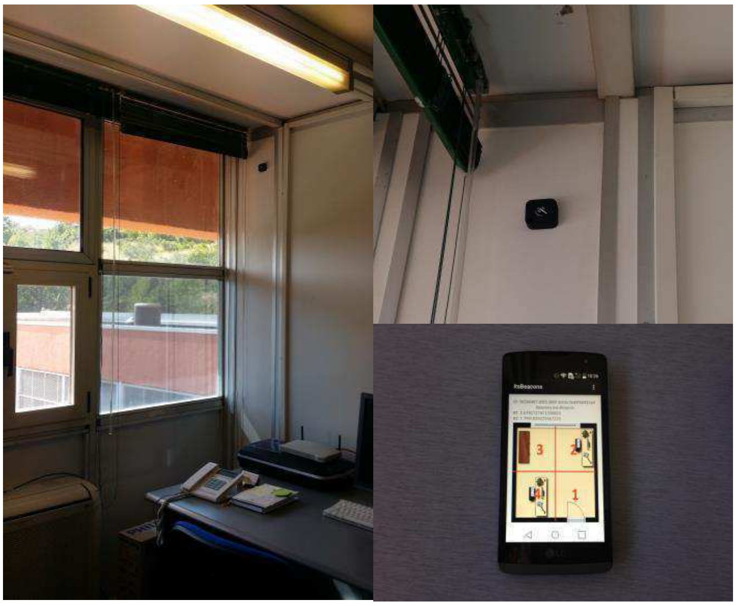

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*Figure 4.14 Locations of the beacons in the office and graphical user interface for an Android app*

*Table 4.5 Beacon features*

| | ***TECHNICAL FEATURES*** | **LOW-MEDIUM RANGE** | **MEDIUM-HIGH RANGE** |
|---|---|---|---|
| **POWER** | Operation voltage | 2.0 – 3.6 V | 2.0 – 3.6 V |
| | Battery model | CR2450 | CR2032 |
| | Battery life | Default 3 years (max 5+ years) | Default 18 months (max 2+ years) |
| | Operation frequency | 2400 – 2483.5 MHz | 2400 – 2483.5 MHz |
| | Frequency error | +/- 20 KHz | +/- 20 KHz |
| | Modulation | Q – QPSK | Q – QPSK |
| | Standby current | 12 µA | 12 µA |
| **SENSITIVITY/ SIZE** | Output power | 4 to -40 dBm (programmable) | 4 to -40 dBm (programmable) |
| | Receiving sensitivity | -93 dBm | -93 dBm |

| | | |
|---|---|---|
| Transmission distance | Up to 70 meters | Up to 25 meters |
| Antenna | 50 ohm (onboard) | 50 ohm (onboard) |
| Size | 4 x 4 x 1.3 cm | 2.7 x 2.7 x 0.7 cm |

*Electricity consumption*

For measuring electric power an AC transformer 0..50 A #57645 connected to the Web-IO Analog-In 0..20mA/0..10V #57641 as shown in Figure 4.15, was used.

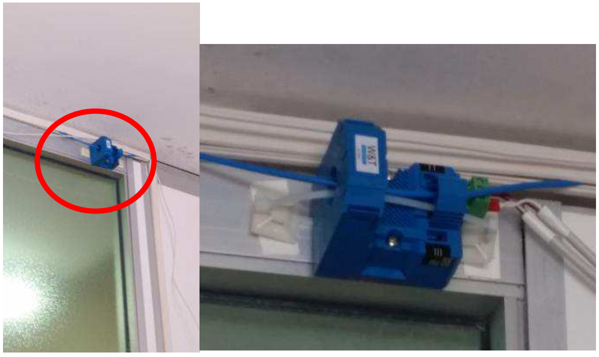


*Figure 4.15 Instrument used to measure the electric power, AC transformer 0..50A #57645*

*Technical specifications*

Range 0..50A AC, 30-6000Hz (all waveforms)
Isolation voltage 5000V

Analog output 0..5V DC or 0..10V DC
The output of this sensor was in ampere and we considered the phase angle equal to zero, so that only active power ($P = V * I * \cos \alpha$) for the conversion was assumed and the measurements were reported in watts.

*Behavior*

Figure 4.16 shows three threshold and mechanical sensors. Window position (open/closed), door position (open/closed), and switching of equipment (air conditioner - on/off) were measured using Web-IO 2x digital input, 2x digital output #57637 with and reed switch Abus rectangular with cable as shown in

Figure 4.17.

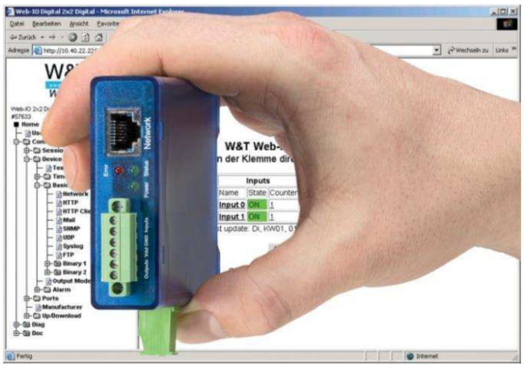
Figure 4.16 Reed switch to measure the window, door position and on/off air conditioner

*Technical specifications*

Storage temperature: -25ºC – 70ºC

Operating temperature: 0°-60°C

(a)



(b)

*Figure 4.17 Instrument used to measure the window position (open/closed) Digital ON/OFF sensor (a) #57637 and (b) Reed switch Abus, rectangular with cable*

As mentioned above, for the data acquisition (DAQ) and control system a suitable combination of hardware and software was used.

A motherbox 3 #50504 is applied to collect data from digital and analog Web-IOs in the central embedded database as shown in Figure 4.18.


*Figure 4.18 Motherbox 3 #50504*

Meteorological data were obtained from the weather station nearby to the building. The meteorological data were merged with the indoor environment observations and the occupancy observations to form one database.

The occupants in the office recorded their presence, and this information was used to test the specific sensors by comparison their outputs with the real information of occupancy. Table 4.6 shows the format used by the occupant to record the presence each minute in the office.

*Table 4.6 Format to record the presence in the office*

| Monday | | | Tuesday | | | Wednesday | | |
|---|---|---|---|---|---|---|---|---|
| Time | In | Out | Time | In | Out | Time | In | Out |
| 09:05 | 1 | | | | | | | |
| 09:20 | 2 | | | | | | | |
| 09:32 | | 2 | | | | | | |
| 10:18 | | 1 | | | | | | |
| 11:31 | 1 | | | | | | | |
| 11:51 | 1 | | | | | | | |
| 12:20 | | 1 | | | | | | |
| 14:05 | | 1 | | | | | | |
| 14:48 | 1 | | | | | | | |
| 17:57 | | 1 | | | | | | |

### 4.2.2. Installation, calibration and preliminary test

The sensor's location was carefully selected to ensure that the sensors are triggered when occupants are in the office. The indoor environment sensors were placed on internal walls at the height of roughly 1.8 above the floor [9], avoiding direct sunlight. One $CO_2$ sensor is installed near the desk at nose level (when seated, 1.1 m) above the ground [8]. All occupancy sensors were factory calibrated, and control systems were commissioned before data collection. For management and inventorying the WuTility Version 4.30 tool was used [7].

Sensor installation began in order to set up all sensors together. The first sensor installed was the air quality, then indoor environment sensor and indoor carbon dioxide. With these three first sensors installed, the results were checked and clock synchronization was set up..

Successively, tests for window/door position sensors were carried out in order to decide the place and reference to install the W&T Network Device Utility Version 4.30 [7], in this case for an open window we used 1 and 0 for a closed window. The same designation was used for both the door and the air conditioning sensor.

The person's presence in the office is not absolutely given for the single value of the parameters, instead, it is given by the variation of the parameters. For example, for $CO_2$, it is given by the variation of the $CO_2$ concentration in the air. If a person leaves or enters the office, the value could decrease or increase. If the derivative is positive, it could mean that a person arrives, instead if it is negative then the person left the office. For the binary data such as the window, door and air conditioning status, the first variation of each value to a new status ON means that a person is in the office.

Some preliminary tests were conducted with the $CO_2$ sensor to assess differences in measurements with respect to the location of the sensor, of the person and his/her presence. The first sensor was installed near the desk at nose level (when sitting, 1.1 m) above the ground and another sensor was positioned at three different heights compared to the first sensor. This second sensor, both when the office was unoccupied or occupied, records higher values than the first one. Furthermore, differences were reported regarding the long unoccupied period (weekends and holidays), probably due to changes in indoor relative humidity. In fact, the sensor detects in the IR band emitted by the $CO_2$ that is very similar to the IR emission of Oxygen in the water molecule. Then the moisture can have an effect on the measurements, especially when the room is unoccupied. At the end of the tests, the first position of the installed sensor was chosen because such a location ensured more stable $CO_2$ values during the unoccupied periods.

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# 5. CHAPTER
# OFFICE BUILDINGS: DATA ANALYSIS

## 5.1. Objectives

In this part of the investigation, different analyses were done with the sensor data to answer some related research questions identifying typical occupancy profiles in the office building.

First, data were analyzed to explore relationships between the occupancy and the magnitude of indoor environmental changes with the aim of identifying which sensor is more suitable to measure occupancy in an office. Another analysis was dedicated to estimate the office occupant profiles by the use of direct observations. Two different approaches were defined, a) a heuristic approach via clustering analysis, logical flow charts, and conditional stages and b) a stochastic approach using probabilities. The statistical software R [1] was used for the statistical analysis and modeling. The main parts of the investigation are presented in Figure 5.1.

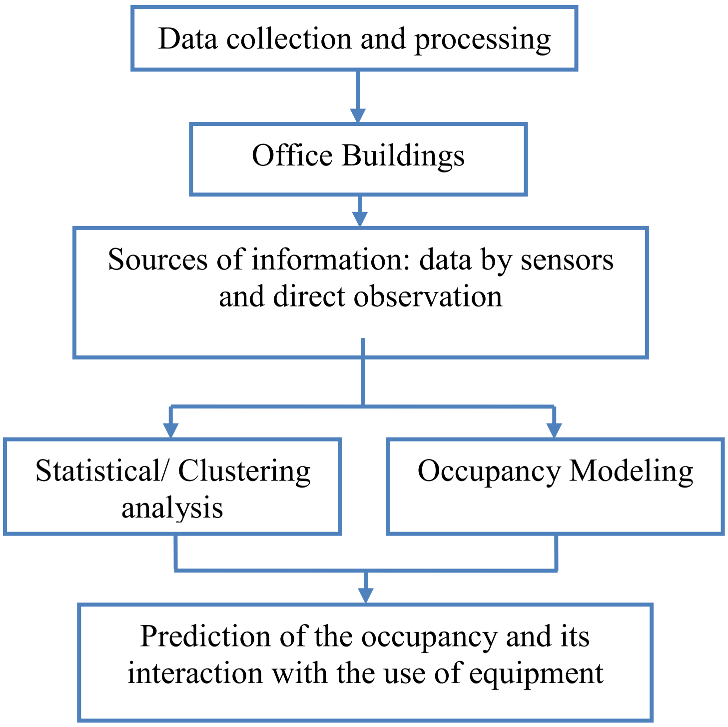


*Figure 5.1 Office building framework*

## 5.2. Clustering analysis application

Clustering is the unsupervised classification of patterns (observations, data items, or feature vectors) into groups (clusters). A hierarchical algorithm yields a dendrogram representing the nested grouping of patterns and similarity levels at which groupings change. Most hierarchical clustering algorithms are variants of the single-link and complete-link. It differs in the way they characterize the similarity between a pair of clusters. A distance measure is a metric (or quasi-metric) on the feature space used to quantify the similarity of patterns. In the single link method, the distance between two clusters is the minimum of the distances between all pairs of patterns drawn from the two clusters, while in the complete-link algorithm, the distance between two clusters is the maximum of all pairwise distances between patterns in the two clusters [2].

In a hierarchical cluster tree, any two objects in the original data set are eventually linked together at some level. The height of the link represents the distance between the two clusters that contain those two objects. This height is known as the cophenetic distance between the two objects. One way to measure how well the cluster tree generated by the linkage function reflects your data is to compare the cophenetic distances with the original distance data generated by the pdist function. If the clustering is valid, the linking of objects in the cluster tree should have a strong correlation with the distances between objects in the distance vector. The cophenetix function compares these two sets of values and computes their correlation, returning a value called the cophenetic correlation coefficient. The closer the value of the cophenetic correlation coefficient is to 1, the more accurately the clustering solution reflects your data. The cophenetic correlation coefficient is used to compare the results of clustering obtained by using the same data set and by utilizing different distance calculation methods or clustering algorithms [3].

$$c_{coph} = \frac{\sum_{i<j}(d(i,j)-d)(t(i,j)-t)}{\sqrt{[\sum_{i<j}(d(i,j)-d)^2][\sum_{i<j}(t(i,j)-t)^2]}} \qquad (1)$$

In single linkage clustering, the cophenetic distances are as long as or shorter than the observed distances: the distance between groups is the shortest possible distance between its members. In complete linkage clustering, the cophenetic distances are as long as or longer than observed distances: the distance between two groups is the longest possible distance between groups. In average linkage clustering, the cophenetic distance is the average of observed distances [4].

### 5.2.1. Case of study

To obtain information regarding user presence and absence intervals, occupancy sensors were applied. Furthermore, thermophysical properties of the internal environments and the electricity consumptions connected to the use of computer and printer were stored.

Occupancy was recorded by manual observation and indoor parameters such as air temperature, relative humidity, carbon dioxide ($CO_2$), volatile organic compounds (VOC) were monitored. Some occupant behaviors with regard to door/window (open/closed) and use of air conditioning were considered. With these data, the clustering analysis was utilized to identify similarities in the days or months and possible occupancy profiles. Similar clustering analysis was carried out with each parameter monitored and compared with the real occupancy profiles to identify which sensor is better to measure the occupancy in an office. The data were analyzed to explore relationships between the occupancy and the magnitude of indoor environmental changes with the aim to identify patterns in the days, weeks, or months. Different occupancy patterns were identified starting from the data collected through person interactive surveys.

With the results of the correlation between variables, three parameters were identified and used in the clustering analysis to identify similarity in the days and possible occupancy profiles and determine the minimum quantity of sensors necessary to define the occupancy profiles.

We applied single-linkage, complete linkage, and average linkage clustering of the dataset for occupancy, $CO_2$, electric power consumption and door status. The cophenetic correlation coefficient was used to verify the quality of the results with each variable, and the complete linkage was selected to define the groups.

#### *5.2.1.1. Occupancy manual observations*

Data collected for weekdays, holidays and weekends from May 13 through September 30, 2016 (excluding August) were used. The range of data considered was limited to working days (from Monday to Friday) between the hours 8:00 to

21:00. In addition to the sensor measurements, people recorded their presence each minute.

Table 5.1 summarizes the days of each month envisaged for the data analysis. Furthermore, the analyzed days were divided into time slots. Table 5.2 shows the four-time intervals in which the occupancy can be considered. The days were identified with the first letter of the month, then the day of the week and the number of days (e.g. JF24 is Friday, June 24).

*Table 5.1 Days of each month considered for the data analysis*

| | Occupied days | Unoccupied days | Total |
|---|---|---|---|
| May | 11 | 20 | 31 |
| June | 12 | 18 | 30 |
| July | 13 | 18 | 31 |
| September | 16 | 14 | 30 |
| Total | 52 | 70 | 122 |

*Table 5.2 Time slot for the data analysis*

| | Interval | Hours | Minutes |
|---|---|---|---|
| **I** | Morning | 08:00 - 13:00 | 300 |
| **II** | Lunch time | 13:00 - 15:00 | 120 |
| **III** | Afternoon | 15:00 - 21:00 | 360 |
| **IV** | All day | 08:00 -21:00 | 780 |

Each sequence in turn is constructed by 780 characters, one for each 1-minute time step, with a value that corresponds to binary data (1 is Occupied and 0 is unoccupied).

Descriptive statistics for monthly occupancy hours are provided in Table 5.3. The highest occupancy rate is in July, and the lowest value is in June. Mean occupancy hours per time slots are shown in Figure 5.2. For the morning hours, the mean occupancy does not vary significantly in the months of the measurement period, indicating that the person is present in the mornings on a regular basis. On the other hand, the occupancy patterns for lunch period are similar to May and September. In the afternoon period, similarities are recognized in May and July.

*Table 5.3 Descriptive statistics for occupancy hours by month. All day period*

| | | Daily hours | | | | |
|---|---|---|---|---|---|---|
| **Month** | **Total hours** | **Mean** | **Median** | **Max** | **Min** | **Standard deviation** |
| May | 50.2 | 5.6 | 6.2 | 7.0 | 2.1 | 1.6 |
| June | 34.7 | 5.0 | 5.4 | 7.2 | 1.8 | 1.7 |
| July | 81.3 | 6.3 | 5.9 | 10.8 | 4.0 | 1.8 |
| September | 82.1 | 5.1 | 5.9 | 7.3 | 1.4 | 1.8 |

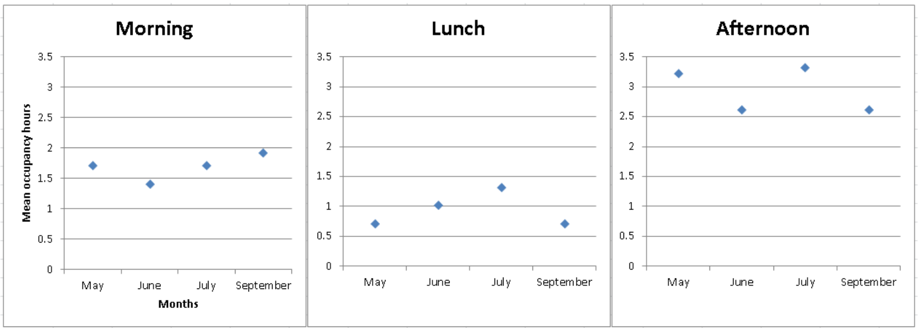


*Figure 5.2 Mean occupancy hours per time slots*

Daily occupancy hours from Monday to Friday are compared in Figure 5.3. It shows that the characteristics of each weekday are different. In particular, the results indicate that the maximum occupancy rate is on Friday and the lowest one is on Wednesday.

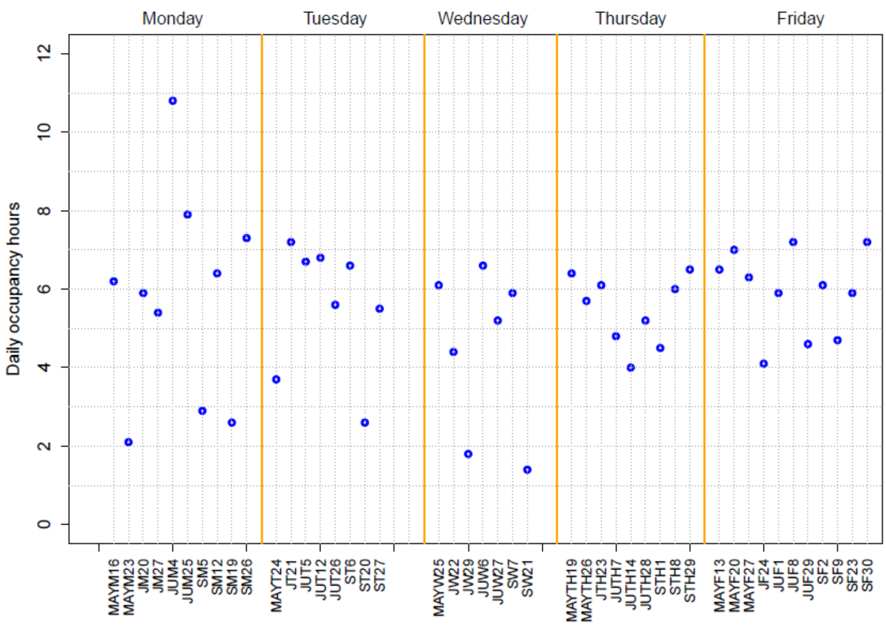


*Figure 5.3 Daily occupancy hours from Monday to Friday*

These data were used for clustering analysis to identify typical occupancy profiles and then to compare the measured parameters to select the one that is near to make an occupancy prediction.

#### *5.2.1.2. Measured data and correlation with the occupancy*

Figure 5.4 shows hourly data of $CO_2$, VOC, temperature, relative humidity, window state, electric power consumption and door opening for a typical summer day. The occupancy is illustrated in each curve by dashed line.

As is shown in the graphs, just after the first person arrives in the office, all the sensors indicate a change in their measurements. In the first typical day, the $CO_2$ sensor seems to have a morning maximum reading around 11:00 with the office occupancy of three people and window closed. When the room is not occupied around 13:00 to 13:40, all sensors register a decrease in their readings. When the office is left vacant after 17:00, the first sensor in drop is the $CO_2$, although it returns to the $CO_2$ values of the unoccupied office after about two or more hours; while the temperature and humidity sensors take more time to stabilize to the empty office values. The $CO_2$ and electric consumption curves and occupancy show similar patterns.

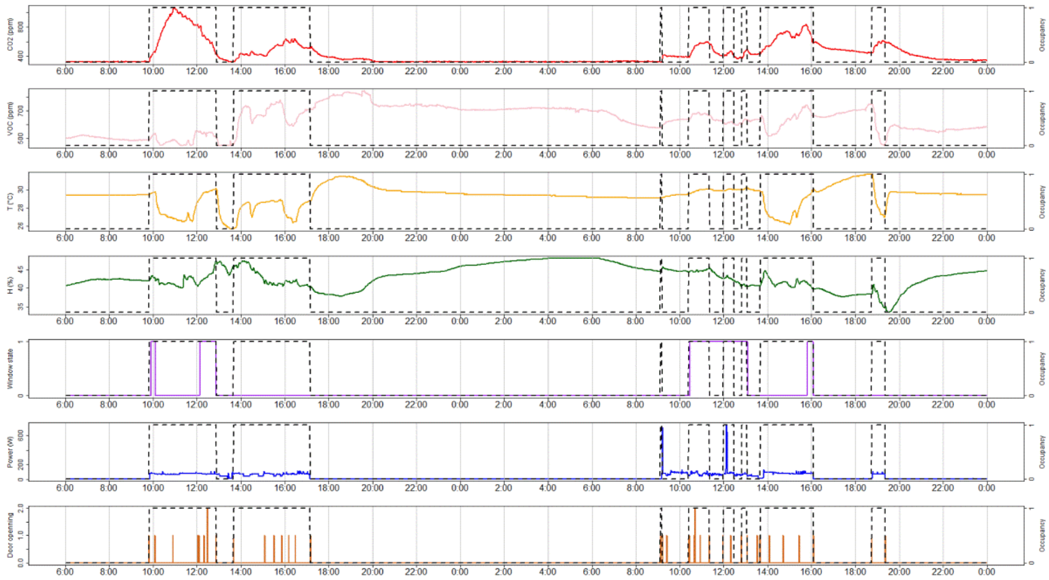

*Figure 5.4 Measurements profiles for two typical summer day*

Furthermore, the outdoor $CO_2$ concentration was measured for six weeks in the summer period and has a mean value of 356 ppm.

A correlation analysis was realized to know the relationship between the occupancy and the measured parameters. Figure 5.5 shows the correlation plot with the corresponding correlation coefficients displayed positive correlations in blue and negative correlations in red color. The p-values are less than 2.2e-16 for all correlations. The p-value is a measure of the probability of obtaining a result at least as extreme as the one that is actually observed, so the lower the value (usually below 0.05 or 0.01) the more significant the result. Correlations are significant for the

$CO_2$, electric power consumption, and door status, in contrast with the other parameters in which the correlations are not significant.

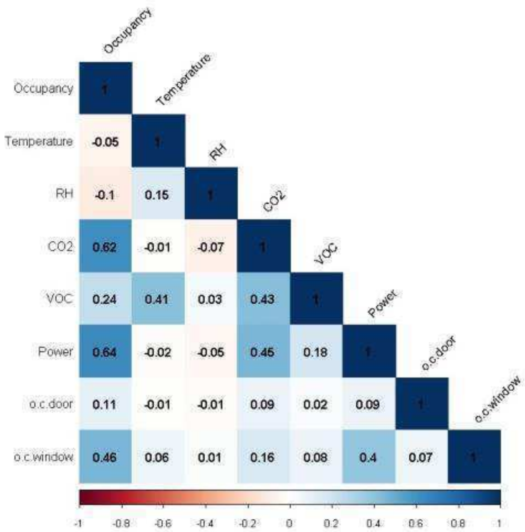


*Figure 5.5 Correlation plot. Pearson's correlation coefficients, by color and values*

#### ***5.2.1.3. Results and discussion***

*a. Occupancy*

Hierarchical clustering found different occupancy profiles for each time slot. The cophenetic correlation coefficients and the distance measured used for each method are listed in Table 5.4. The method that presents the highest value of the cophenetic correlation is the complete, and the results of this approach will be presented for each parameter and compared with clustering of real occupancy data.

*Table 5.4 The cophenetic correlation coefficients for all methods and time slots considered*

| Distance measure | Clustering method | Morning | Lunch | Afternoon | All day |
|---|---|---|---|---|---|
| Euclidean | Single | 0.75 | 0.77 | 0.78 | 0.50 |
| | Complete | 0.80 | 0.71 | 0.81 | 0.70 |
| Squared Euclidean | Average | 0.78 | 0.79 | 0.80 | 0.66 |

In addition to the cophenetic correlation, a visual inspection of each dendrogram was done, and the results confirm that the complete method provides specific clusters of each time slot.

In the dendrogram for all day slot, three clusters were identified and defined as three occupancy levels: Low with a mean daily occupancy of 3.8 hours, Medium with mean occupancy of 5.9 hours and High with 6.4 of mean daily occupancy hours (see Table 5.5). Also, the minimum and maximum occupancy hours were shown. For the first cluster, 36% of cases are Monday, in the second cluster 27% are

Tuesday, and in the last cluster, 50% of cases are Friday. Figure 5.6 presents three dendrograms for each method used. Figure 5.6b shows three clusters found with different colors for each type of occupancy level respectively.

*Table 5.5 Values in hours for each cluster obtained by means of the complete method*

| | Low<br>Cluster 1 (11 days) | Medium<br>Cluster 2 (22 days) | High<br>Cluster 3 (12 days) |
|---|---|---|---|
| Mean | 3.8 | 5.9 | 6.4 |
| Min | 1.4 | 2.9 | 4.4 |
| Max | 6.4 | 7.9 | 10.8 |

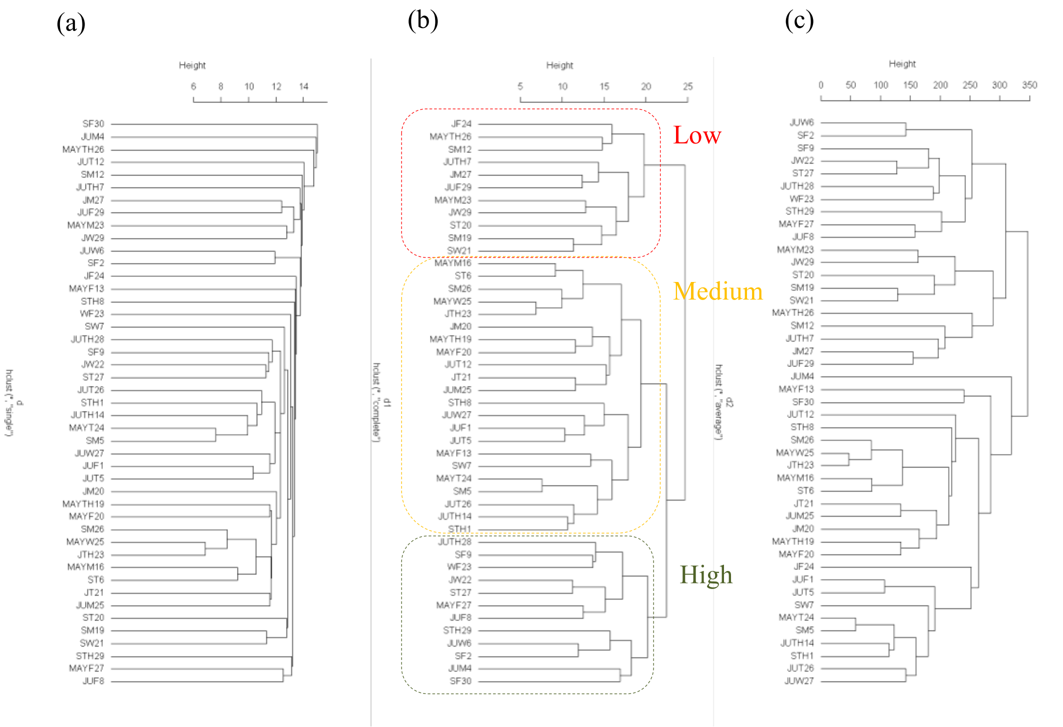


*Figure 5.6 Dendrograms from hierarchical cluster analysis with single a), complete b), and average c) linkage.*

**Morning Hours:** As shown in Table 5.6, two clusters were identified. The first with a mean morning occupancy of 0.9 hours (defined as Low occupancy) and the second with a mean morning occupancy of 2.5 hours (high occupancy). No similarities were found regarding hours of arrival or leaving the office, or total occupancy hours.

*Table 5.6 Descriptive statistics values in hours for each cluster for complete method*

| | Low<br>Cluster1 (23 days) | High<br>Cluster 2 (22 days) |
|---|---|---|
| Mean | 0.9 | 2.5 |
| Min | 0.0 | 1.2 |
| Max | 2.6 | 3.8 |

**Lunch Hours:** The two considered clusters are reported in Table 5.7, the first one with a mean lunch occupancy of 1.6 hours. The second one has a mean lunch occupancy of 0.50 hours.

*Table 5.7 Descriptive statistics values in hours for each cluster for complete method*

| | High<br>Cluster 1 (14 days) | Low<br>Cluster 2 (31 days) |
|---|---|---|
| Mean | 1.6 | 0.5 |
| Min | 1.1 | 0.0 |
| Max | 2.0 | 1.4 |

**Afternoon Hours:** Two clusters were identified for the afternoon hours, one with 24 days and another with 21 days. The first cluster has mean occupancy of 3.9 hours and the second cluster of 1.9 hours. See Figure 5.8.

*Table 5.8 Descriptive statistics values in hours for each cluster for complete method*

| | High<br>Cluster 1 (24 days) | Low<br>Cluster 2 (21 days) |
|---|---|---|
| Mean | 3.9 | 1.9 |
| Min | 2.9 | 0.0 |
| Max | 5.1 | 3.5 |

b. *Electricity power consumption*

In the same way as with occupancy data, with daily measurements of electric power consumption, clustering analysis was done. Visual inspection of the dendrograms showed similarities, reported in Table 5.9 For the all day period, similarities were found between the medium occupancy profile and cluster 1 (42%) and 3 (67%) of electric power and high occupancy profile with the second cluster (88%). For lunch time, non-similarities were found between different clustering. A possible explanation is that when the user leaves the office for lunch, equipment is not turned off. Also for morning and afternoon period were in accordance in approximately more than a half of cases.

Figure 5.7a illustrates occupancy dendrogram, and Figure 5.7b electric power dendrogram for all day slot with the three clusters identified in different colors.

*Table 5.9 Comparison between occupancy and electric power clusters for different time slots*

| Time slot | Clusters | |
|---|---|---|
| | Occupancy | Electric power |
| All day | 1- Low | 1-29% |
| | | **2-42%** |
| | | 3-29% |
| | 2- Medium | 1-25% |
| | | 2-8%, |
| | | **3-67%** |
| | 3- High | 1-12% |
| | | **2-88%** |
| | | 3-0% |
| Morning | 1- Low | 1-44% |
| | | **2-56%** |
| | 2- High | **1-63%** |
| | | 2-37% |
| Lunch | Non similarities were found | |
| Afternoon | 1- High | **1-95%** |
| | | 2-5% |
| | 2- Low | 1-23% |
| | | **2-77%** |

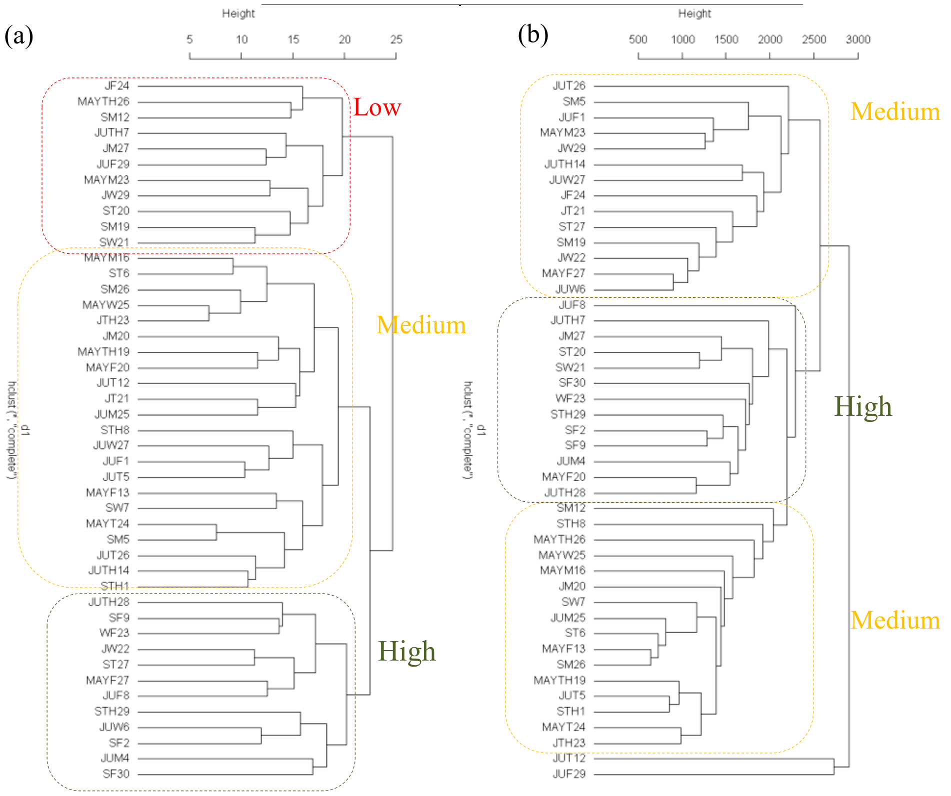


*Figure 5.7 (a) Occupancy and (b) Electric power dendrogram from hierarchical cluster analysis with complete linkage. Schedule All day*

### c. $CO_2$ data

The Occupancy and $CO_2$ clusters are compared in Table 5.10 and Figure 5.8. In the diverse time slots, correspondences were found, for all day the occupancy was registered with a medium and high occupancy, while in the other intervals the presence could be identified through this sensor.

*Table 5.10 Comparison between occupancy and $CO_2$ clusters for different time slots*

| Time slots | Clusters: Occupancy | Clusters: $CO_2$ |
|---|---|---|
| All day | 1- Low | 1- 31% |
| | | **2- 62%** |
| | | 3- 7% |
| | 2- Medium | 1- 27% |
| | | 2- 18% |
| | | **3- 55%** |
| | 3- High | 1- 0% |
| | | 2- 50% |
| | | 3- 50% |
| Morning | 1- Low | **1- 61%** |
| | | 2- 39% |
| | 2- High | 1- 0% |
| | | **2- 100%** |
| Lunch | 1- High | **1- 82%** |
| | | 2- 18% |
| | 2- Low | 1- 15% |
| | | **2- 85%** |
| Afternoon | 1- High | 1- 30% |
| | | **2- 70%** |
| | 2- Low | **1- 60%** |
| | | 2- 40% |

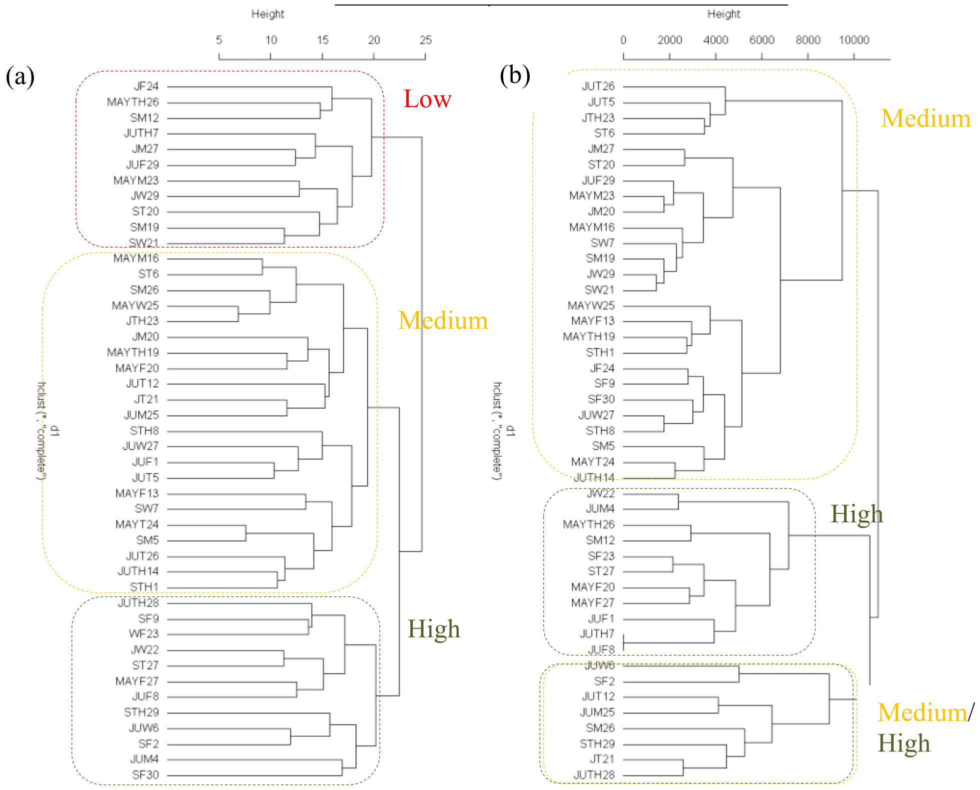


*Figure 5.8 (a) Occupancy and (b) $CO_2$ dendrogram from hierarchical cluster analysis with complete linkage. Schedule All day hours: From 08:00 to 21:00 occupied days*

d. Door status

With the open/closed door records, data transformation was done in order to do the cluster analysis. Each change in the door status was counted as a presence of a person until the last one when people left until the next working day. Figure 5.9 summarizes the similarities between groups.

*Table 5.11 Comparison between occupancy and door status clusters for different time slots*

| Time slots | Clusters | |
|---|---|---|
| | Occupancy | Door status |
| All day | 1- Low | 1- 12% |
| | | **2- 59%** |
| | | 3- 29% |
| | 2- Medium | 1- 37% |
| | | 2- 37% |
| | | 3- 26% |
| | 3- High | 1- 22% |
| | | **2- 56%** |
| | | 3- 22% |
| Morning | 1- Low | **1- 63%** |
| | | 2- 37% |
| | 2- High | 1- 50% |
| | | 2- 50% |
| Lunch | 1- High | 1- 41% |
| | | **2- 59%** |
| | 2- Low | 1- 21% |
| | | **2- 79%** |
| Afternoon | 1- High | **1- 67%** |
| | | 2- 33% |
| | 2- Low | **1- 52%** |
| | | 2- 48% |

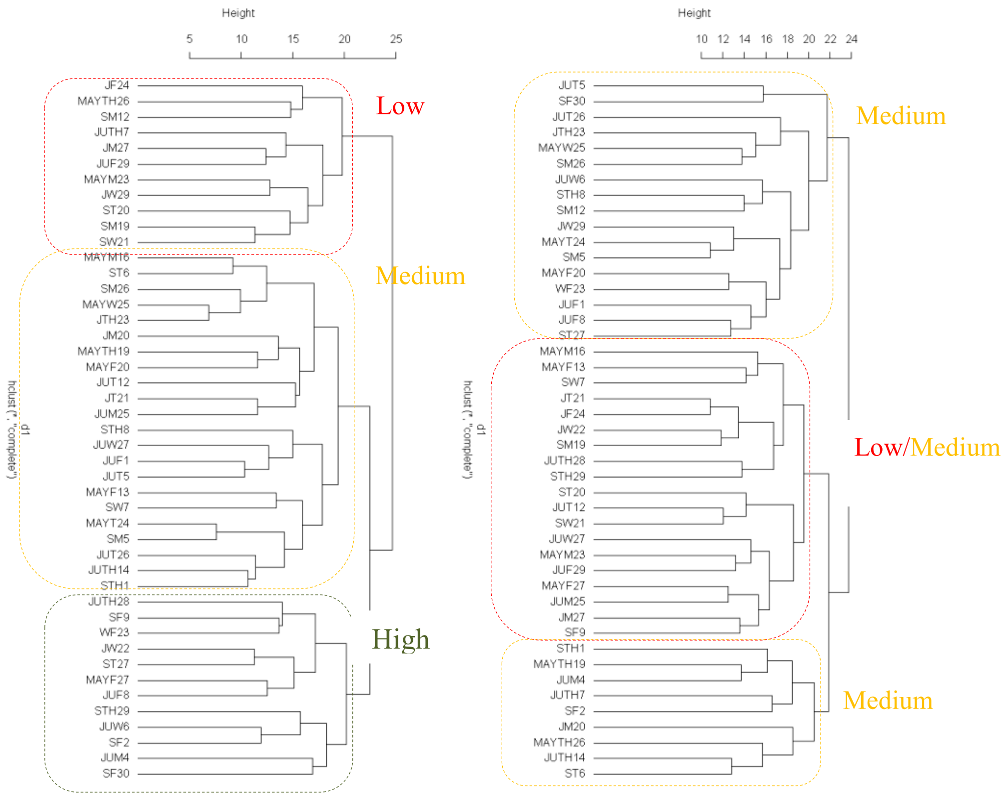


*Figure 5.9 (a) Occupancy and (b) Door status dendrogram from hierarchical cluster analysis with complete linkage. Schedule All day hours: From 08:00 to 21:00 occupied days*

The comparison between occupancy real data clustering and VOC and open/closed window groups did not demonstrated similarities. The electricity consumption, carbon dioxide data, and door status transformed data showed some similarities, and this confirms that with the single installation of one of these sensors an occupancy profile can be estimated, with the limitations of lack of fine-grained granularity related to each typology of sensor.

## 5.3. Occupancy profile modelling based on indoor environment measurements

Given our experimental test design and results, one can be subjected to set out a mathematical formulation that could model the occupancy profile using indoor environment data. From the point of view of the process outcome, the occupancy state could be modelled using two approaches:

i. A heuristic approach via logical flow charts and conditional stages
ii. A stochastic approach using probabilities

Now, the only resulting outcome of the process (the model variable) is $O_{\mathcal{S}}$, which represents the occupancy state of the office. Let us also consider that the model variable could evolve deterministically or randomly in time, from a point of view. The latter is to analyze the model variable as stochastic, and the former to analyze it as deterministic. Either way, the evolution of the model variable through time will be described using the index $\mathcal{S} \in T$. It will only takes discrete values so that $\{O_{\mathcal{S}}, \mathcal{S} = 0, 1\}$, where $\mathcal{S} = 0$ indicates no occupancy or absence and $\mathcal{S} = 1$ represents presence. Indoor environment measurements are considered to be continuous through time: $T = [0, \infty)$. When discussing all the indoor environment measurements, we will refer to them as $\mathrm{M} = \{CO_2, Power, WS, AA, T, H, VOC\}$. Table 5.12 shows the indoor environment variables with their unit of measure.

*Table 5.12 Indoor environment variables measured: All variables are measured each minute (time step or sampling rate of 1 minute)*

| Indoor environment variable | Units |
|---|---|
| Carbon dioxide ($CO_2$) | ppm |
| Utilities power (Power) | W |
| Window state (WS) | Boolean |
| Air conditioner: on/off (AA) | Boolean |
| Indoor temperature (T) | °C |
| Indoor humidity (H) | % |
| Volatile organic compound (VOC) | ppm |
| Occupancy state ($\boldsymbol{O_{\mathcal{S}}}$) | Boolean |

Here after, we will first announce the hypothesis made. Second, we will seek to isolate the variables that have the strongest correlation with the occupancy profile ($O_{\mathcal{S}}$), which would allow us to reduce the parameters measured for the model's input. Third, we will formulate the model with a heuristic approach as previously stated. Fourth, the model will be formulated again using a stochastic approach. Finally, the outcome $O_{\mathcal{S}}$ from both approaches will be presented and simultaneously compared.

The first 45 days or first measurement campaign (13$^{th}$ May 2016-30$^{th}$ September) of the selected sample were used to develop the model and finally, for the validation of the method, a further 40 days or second measurement campaign (3$^{rd}$ October 2016- 20$^{th}$ January 2017) were used.

### 5.3.1. Hypotheses

Hypotheses will be used only when mentioned:

*1:* Whenever the window is open, and the air conditioning is on, the office will be considered as being occupied (not accounting for the possibility that the occupant has arrived but is not currently in the office) or as occupied (the occupant is currently in the office).

### 5.3.2. Determination of the input variables for the model

The variables which will be used as inputs to the model will be the most representative from a statistical and physical point of view. From experimentation, one can induct which variables react or change more rapidly and considerably when the office is occupied, and based on statistical methods one can evaluate their correlation strength in relation with the occupancy profile ($O_S$).

The following image (see Figure 5.10) presents a brief view of the indoor parameters measured plotted along with the real occupancy of the room. The air conditioning usage is not presented.

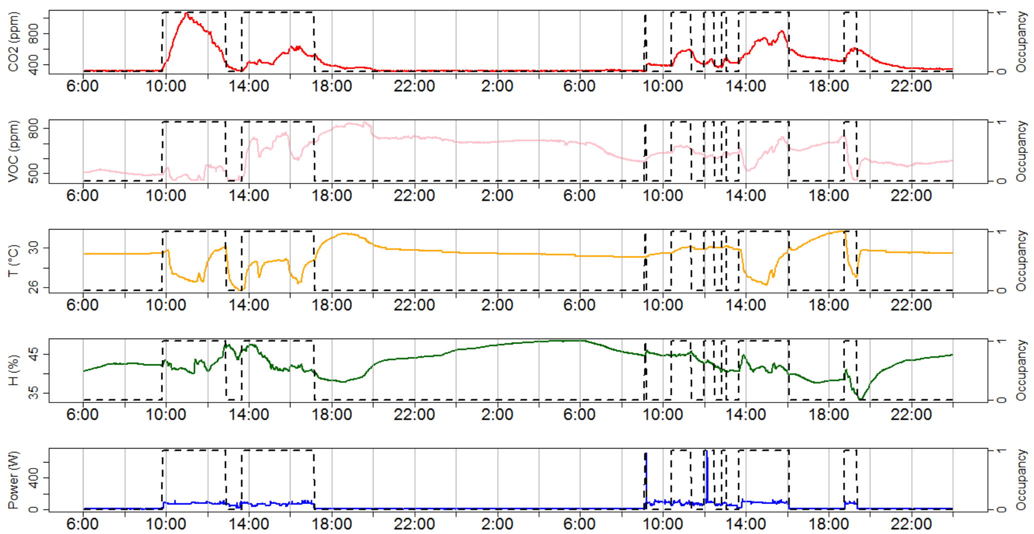


*Figure 5.10* . Indoor environment parameters and power consumption for a typical summer day. *The dashed black line represents the occupancy profile.*

One thing we can infer from examining at these 5 plots is that, there is a clearer correlation between the $CO_2$ levels (first plot), the energy consumption (last plot) and the occupancy profile (dashed black line) than there is for the other three parameters.

Now, we will perform a correlation plot; the resulting charts are presented in Figure 5.11 for the first measurement campaign.

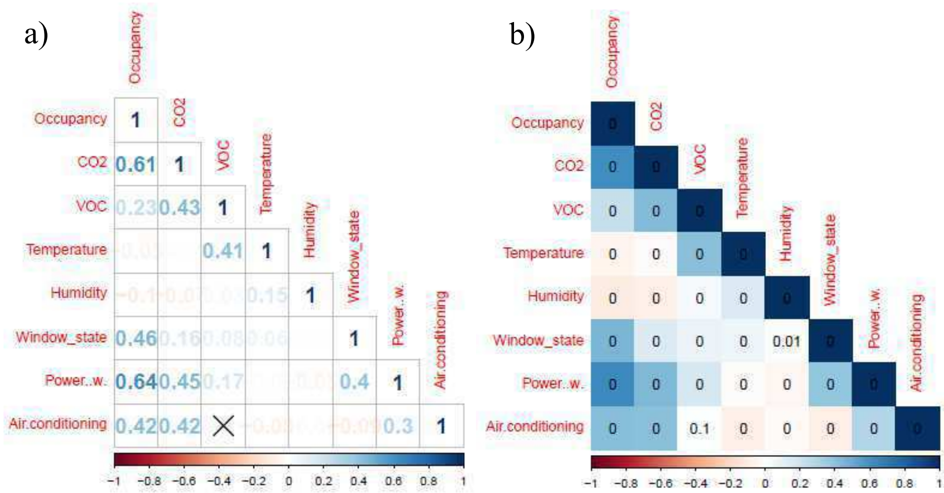


*Figure 5.11 Correlation plot for the first measurement campaign. a) Pearson correlation coefficients, by color and values and b) Pearson correlation coefficients represented by color and p-values*

On the Figure 5.11a, the Pearson correlation coefficients are presented in a correlation plot. The correlation strength of the variables with each other variable and with themselves are represented by color and by values. The stronger the correlation, the higher the value showed is, and the darker the color. On the Figure 5.11b, the Pearson correlation (by color) and the p-value are shown. The null-hypothesis test (testing the correlation between the variables) for each variable gives the p-values. It can be observed that all p-values are lower than 0.05 except for the test between the air conditioning and VOC variables (which gave 0.1). This indicates that the correlation between them, is statistically non-significant. Values showing zero, are actually, lower than 2.2 x$10^{-16}$.

One can see immediately which variables are strongly correlated with the model variable $O_S$ (see first column on Figure 5.11a). In Figure 5.11 it is called “Occupancy”. Listing these variables by the decreasing correlations coefficients, would be as: power (0,64), $CO_2$ (0,61), window state (0,46), air conditioning (0,42) and VOC (0,23). If explanation is needed, about why they are correlated with $O_S$ in this order; the variable power represents the energy consumption of some electronic devices in the office and they are more likely to be used when the office is occupied, the variable $CO_2$ represents the levels of this gas inside the office produced by the bodies and these levels are more likely to become higher when the office is occupied, the window state variable represents only whether the window is open or not and it is more likely to be open when the office is occupied, likewise for the air conditioning state variable, and the variable VOC represents the levels of volatile organic compounds and they are also more likely to be higher when the office is occupied. This leads us to question why the $CO_2$ levels are less strong correlated with the occupancy state. This can be explained by several facts: this gas is produced at a height of approximately 1.0 m (when the occupants are seated) and 1.70 m (when standing up); the sensor is placed at 1.1 m height above the ground (near the occupant's nose); this gas is produced at a specific temperature, which if higher than the indoor air could result in an ascending flow depending on their densities relation; the air-change-rate in the office would help the indoor air recirculate, moving the gas away from the sensor.

Consequently, it led us to decide the input variables of the model which are the power, the $CO_2$ levels, the window state and the air conditioning state. The variable VOC will not be used as an input variable to the model due to its weak correlation coefficient value, compared with the other four variables. Now, we can proceed to describe the first approach to model the office occupancy profile.

### 5.3.3. A heuristic approach via logical flow charts and conditional stages

Our first attempt to model the occupancy state has a simple approach. The basic idea is to take the four measured variables and set a conditional setpoint or level for each one, in order to determine (if the variable value reaches or exceeds this setpoint) whether the office is occupied or not. This will be done using a logical flow chart containing two conditional stages as presented in Figure 5.12.

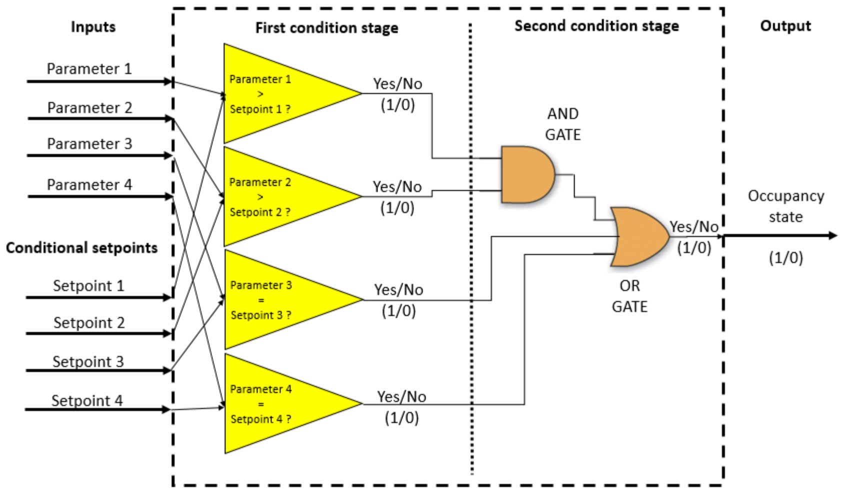

*Figure 5.12 Schema of the logical flow chart, the heuristic model*

Each stage of the logical chart in Figure 5.12, can be described as:

i. *Inputs.* Here are the parameters measured and the conditional setpoints.

ii. *First condition stage*. In this stage, the parameters are compared with their conditional setpoint value. The condition "greater than" was used for the parameters that evolves as T (the power and the $CO_2$ levels), stating that if the parameter value lays above its conditional setpoint value, one will interpret this as: the office is occupied. The condition "equal to" was used for the variables that evolves discretely in time (the window and air conditioning state), stating that if the parameter value is equal to its conditional setpoint value, will be interpreted as: the office is occupied.

iii. *Second condition stage*. This stage is basically to couple the resulting outputs from the first condition stage. Here, we have 4 logical entries to interpret. It is easy for the conditions "equal to", because if its value results to be 1, one could be certain that the office is occupied (hypothesis n°1). Thus, an OR gate is used to state that, the occupancy state will be 1, if either one or both conditions give 1. The addition of an AND gate, is a little bit more difficult to explain. Based on previous attempts, the lower error of the model was achieved when adding this AND gate, to evaluate the continuous variables before the OR gate.

iv. *Output.* The result of the model, a logical value for the occupancy state, is given.

*Conditional setpoint values*

The designation of the conditional setpoint value for each variable, was based on experimentation results. For the $CO_2$ variable, the conditional setpoint was chose by calculating the mean of all $CO_2$ measurements only when the occupancy state is equal to zero. Then, when the currently measurement is higher than the setpoint, the occupancy state will be considered as 1. Figure 5.13 shows results for the first and second measurement campaign. The resulting setpoint value for the $CO_2$ variable was 368 ppm. Doing the same for the power variable, its resulting setpoint value was 14.1 W.

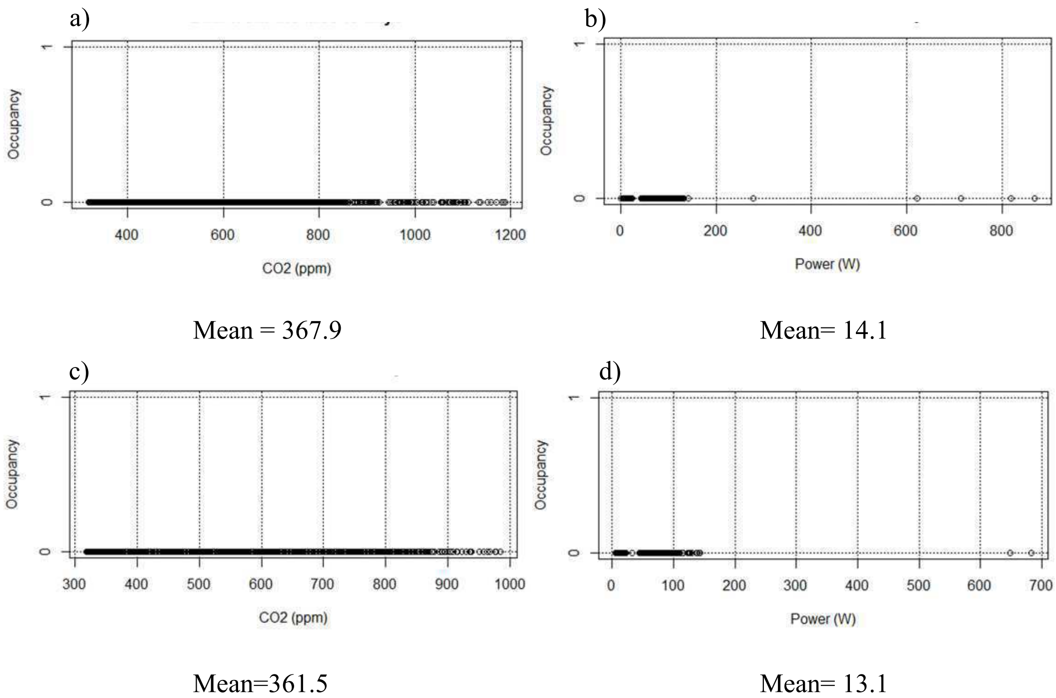


*Figure 5.13 Mean for $CO_2$ and power a) , b) for the first measurement campaign and c), d) for the second measurement campaign*

The values measured for each of the four variables chosen to be the inputs of the model, compared to the occupancy state of the office, are presented in Figure 5.14. As presented before (the evolution of each variable in $\mathcal{M}$ through $T$, see Figure 5.10), looking at Figure 5.14, one can observe that the occupancy state could take both values, 1 or 0, when the variables measured give the same value, i.e. a value of 519 ppm for the $CO_2$ measurements was encountered, when the occupancy state was 1, but also, when it was 0. The same for the power measurements, and for the data collected for the window state and air conditioner state. Here, the issue of the position of the $CO_2$ sensor returns again.

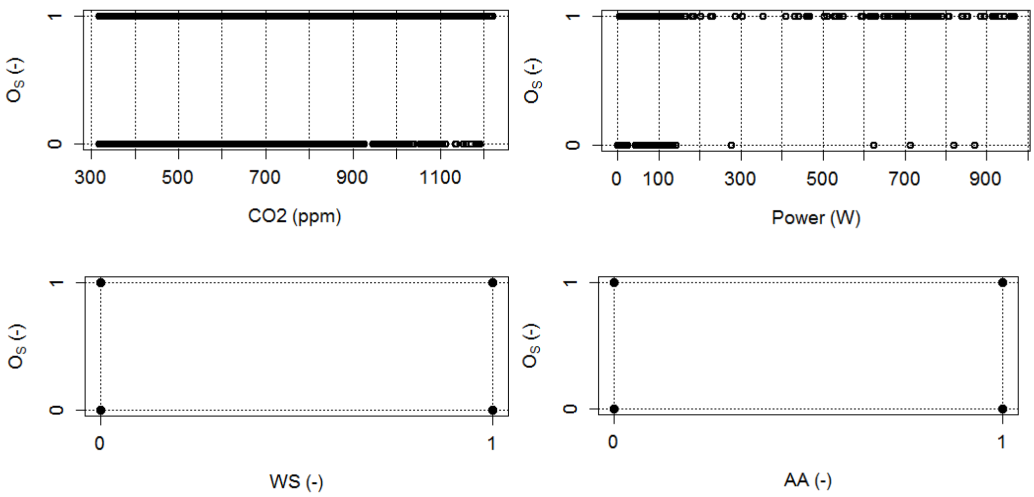

*Figure 5.14 Occupancy state evolution with respect to the 4 variables chosen as inputs of the model. From left to right and up to down: $CO_2$ levels, power, window state (WS) and air conditioner state (AA)*

We, therefore, revised our first approach and realized that a better way to model the occupancy state might be one that includes probabilities. The next section presents our second approach.

### 5.3.4. A stochastic approach via conditional probability equations

This time, on the attempt to model the occupancy state as a random process, it is necessary to use probabilities**.** The notion of a random process is based on, as previously stated, the fact that the same measured value in $\mathcal{M}$ can be encountered twice: when the occupancy state equals 1 and 0; no variable in $\mathcal{M}$ alone can perfectly predict the occupancy state value (see Figure 5.14). Thus, as for our first approach, we propose to use the four chosen variables and predict the occupancy state by including "classes" where there will be conditional setpoints along with a set of probabilities (probabilities based on the frequentist approach), where the values in $\mathcal{M}$ indicate whether the occupancy state equals 1 or 0, and we will refer to this as the "parametric-classification-probability array". We will also introduce another set of probabilities to represent the strength of each variable in $\mathcal{M}$ with the occupancy state, and we will refer to this as the "ponderation-probability matrix". Finally, once each input is evaluated, in the probability array, we will combine this with the ponderation values using conditional probability equations to calculate the probability of presence and absence (the model's outputs); the resulting probabilities will be used to recreate the occupancy profile. All this, will be performed at each time step that $\mathcal{M}$ is measured; each minute, in our case. A schema of the process described here before, is presented in Figure 5.15.

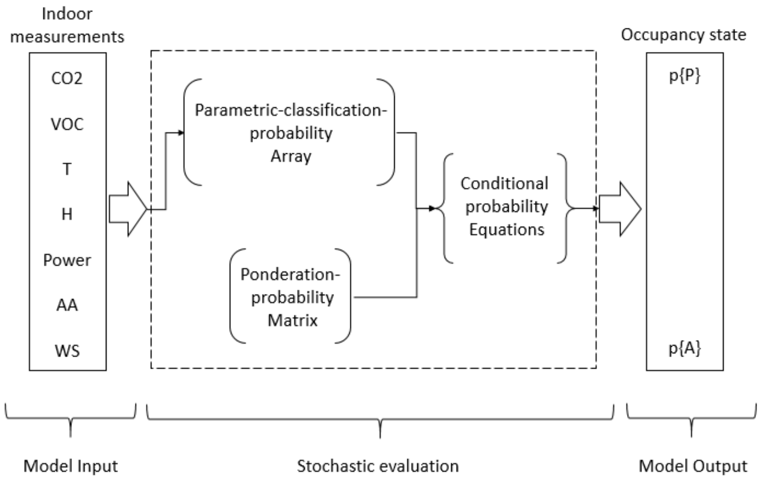


*Figure 5.15 Schema of the stochastic model*

From left to right: first, there is the model input including the variables in $\mathcal{M}$ chosen (all the variables are presented in Figure 5.15 to generalized). Second, there is the "stochastic evaluation" where the value measured from each variable will be evaluated, reviling first, the chances that each variable can tell whether the occupancy state equals 1 or 0, and second, the chances that the latter equals 1 or 0, when all variable first evaluations are combined. The following details this "stochastic evaluation".

#### *5.3.4.1. Parametric-classification-probability array*

Here we propose to have two class levels (range of values), for convenience. Choosing two levels keeps the model time calculation short and simple. This, it will be two classes for each of the four variables chosen. Each class will include a subarray with probability values indicating the chance that the office could be occupied or not (base on the frequentist approach). Then, one is asked to read this as: "if the measured value lays within a specific class, the chance that the office is occupied is…". Figure 5.16 presents this before for the first and second measurement campaigns.

| VARIABLE | $O_S$ | CO2 (p) | Power (p) | WS (p) | AA (p) |
|---|---|---|---|---|---|
| CLASS | | [0, 368) | [0, 14.1) | 0 | 0 |
| | 0 | 0.97 | 0.97 | 0.83 | 0.83 |
| | 1 | 0.03 | 0.03 | 0.17 | 0.17 |
| CLASS | | [368, +∞) | [14.1, +∞) | 1 | 1 |
| | 0 | 0.48 | 0.32 | 0.17 | 0.20 |
| | 1 | 0.52 | 0.68 | 0.83 | 0.80 |

*Figure 5.16 Parametric-classification-probability matrix, from the first measurement campaign*

Taking the same conditional setpoint values used on the heuristic model, for the $CO_2$ variable, the classes are chosen to be, first, [0, 368 ppm) and second, [368 ppm, +∞). The same for the power variable, which was [0, 14.1 W) and [14.1 W, +∞). On the contrary, for the window state and air conditioning state, the classes are, when the value is 0 and when it is 1.

Each probability value "p" is calculated using the frequentist approach, which estimates the likelihood that a specific value will appear in any single trial by performing previously several trials and counting the times it is encountered in comparison with the total of trials.

#### *5.3.4.2. Ponderation probability matrix*

The ponderation matrix is based on the correlation between each variable measured and the occupancy state. This matrix is presented in Figure 5.17, the column named "correlation strength" contains the Pearson correlation coefficient values taken from the correlation plot (in Figure 5.11). Then, the ponderation of each variable is calculated by taking the relative correlation strength of each variable, so they sum up 1 as we want to use them as probability values. This before, was done by adding up all the correlation coefficient values of the variables (0.61 for $CO_2$; 0.64 for power; 0.46 for WS; 0.42 for AA), which gives 2.13. The ponderation values are then: 0.61/2.13; 0.64/2.13; 0.46/2.13 and 0.42/2.13, respectively.

| VARIABLE | Correlation strength | Ponderation |
|---|---|---|
| CO2 | 0.61 | 0.28 |
| Power | 0.64 | 0.30 |
| WS | 0.46 | 0.22 |
| AA | 0.42 | 0.20 |

*Figure 5.17 Ponderation-probability matrix, from the first and*

These ponderation values along with the Parametric-classification-probability-matrix values, will be used to estimate the probability of presence and absence in the office, by calculating the total probability using conditional probability equations.

### *5.3.4.3. Conditional probability equations*

The total probabilities were defined from the point of view of stochastic modeling, as conditional probabilities [5]. For any events A and B, the conditional probability of A given B is written as p{A|B} and defined by,

$$p\{A|B\} = \frac{p\{A \cap B\}}{p\{B\}} \qquad \text{for } p\{B\} > 0 \qquad (2)$$

or in a stochastic way,

$$p\{A \cap B\} = p\{A|B\}\, p\{B\} \qquad (3)$$

then, if there are various events B (denoted $B_j$), the probability of the event A would be calculated by using the law of total probability, as follows:

$$p\{A\} = \sum_{j=1}^{\infty} p\{A|B_j\} p\{B_j\} \qquad (4)$$

extrapolating this before to our case; the event A would be, for instants, the occupancy state being equal to 0 or 1, and the event B would be, the happening of $\mathcal{M}$ (when indoor measurements take place):

$$p\{\mathcal{O}_{\mathcal{S}} = 1\} = \sum_{j=1}^{\infty} p\{\mathcal{O}_{\mathcal{S}} = 1|\mathcal{M}_j\} p\{\mathcal{M}_j\} \qquad (5)$$

Here, is obvious that $p\{\mathcal{M}_j\} = 1$, since indoor measurements are always performed. Thus, equation 5 does not represent our stochastic process. A more suitable way to represent it, is as follows:

$$p\{\mathcal{O}_{\mathcal{S}} = 1\} = \sum_{j=1}^{\infty} p\left\{\mathcal{O}_{\mathcal{S}} = 1 \,\middle|\, \begin{matrix} \mathcal{M}_j = [0, m_j) \\ \mathcal{M}_j = [m_j, +\infty) \end{matrix}\right\} p\{\mathcal{M}_j\}\, w\{\mathcal{M}_j\} \qquad (6)$$

and,

$$p\{\mathcal{O}_{\mathcal{S}} = 0\} = 1 - p\{\mathcal{O}_{\mathcal{S}} = 1\} \qquad (7)$$

where $w$ stands for weighting or ponderation, and $m$ represents the limit value of the range. To calculate the total probability using equation 6, we will define the probability "$w\{\mathcal{M}_j\}$" where $\mathcal{M}_j$ contain only $CO_2$, power, WS or AA, as the ponderation values showed in Figure 5.17. The probability $p\left\{\mathcal{O}_\mathcal{S} = 1 \,\middle|\, \begin{matrix}[0, \mathcal{M}_j) \\ [\mathcal{M}_j, +\infty)\end{matrix}\right\}$ will be defined as the probability that the occupancy state equals 1, given the value of $\mathcal{M}_j$ using the values from the Parametric-classification-probability matrix, showed in Figure 5.16. Then, equation 5 should be defined as:

$$\begin{aligned} p\{\mathcal{O}_\mathcal{S} = 1\} = {} & p\left\{\mathcal{O}_\mathcal{S} = 1 \,\middle|\, \begin{matrix} CO2 = [0, 368\,ppm) \\ CO2 = [368\,ppm, +\infty) \end{matrix}\right\} w\{CO2\} \\ & + p\left\{\mathcal{O}_\mathcal{S} = 1 \,\middle|\, \begin{matrix} Power = [0, 14.1\,W) \\ Power = [14.1\,W, +\infty) \end{matrix}\right\} w\{Power\} \\ & + p\left\{\mathcal{O}_\mathcal{S} = 1 \,\middle|\, \begin{matrix} WS = 0 \\ WS = 1 \end{matrix}\right\} w\{WS\} \\ & + p\left\{\mathcal{O}_\mathcal{S} = 1 \,\middle|\, \begin{matrix} AA = 0 \\ AA = 1 \end{matrix}\right\} w\{AA\} \end{aligned} \quad (8)$$

##### *5.3.4.4. Occupancy state reconstruction based on resulting probabilities*

The occupancy state, from the total probability results, given by equation 5, is proposed to be reconstructed by considering the office as occupied when the total probability value is higher than 0.5; when this happens, the reader is asked to interpret this as: there is a higher chance the office is occupied. On the contrary, if the total probability value lays below 0.5, this means that there is a higher chance that the office is not occupied.

### 5.3.5. Error estimation

The error (e), in estimating the occupancy state, of each model could be calculated using the following expressions. First, evaluate the occupancy profile model by comparing the model output with the measured or "real" occupancy as follows:

$$Model\ evaluation{:}\ occupancy\ model == real\ occupancy? \quad (9)$$

This expression will give a logical value TRUE or 1 if the condition equal to "=" is verified and a logical value FALSE or 0, if not. In other words, expression (9) is asking: Is the occupancy model response equal to (or has the same value as) the real occupancy? Or, does the occupancy model output match the real occupancy? Then, the model's error will be determined by the relative number of matches between these two, as follows:

$$e = \left(1 - \frac{occupancy\ model\ matches}{real\ occupancy}\right) x100 \qquad (10)$$

This can express this before in a more statistic way:

$$e = \left(1 - \frac{number\ of\ matches\ of\ the\ occupancy\ model}{total\ number\ of\ observations}\right) x\ 100 \qquad (11)$$

In our case, the “total number of observations” would be 45 days multiplied by the sample rate (1440 minutes in a day), giving 64800 observations. Note here that the real occupancy data is assumed to have not associated uncertainty or error in the collection process.

### 5.3.6. Results and discussion

For the stochastic model, the criterion used, for reconstruction the occupancy profile, as mentioned before in section 5.3.4.4, was as follows:

$$\text{If } p\{O_S = 1\} > 0{,}5 \rightarrow O_S = 1 \qquad (12)$$

The error as previously said was calculated on the matches between the real occupancy and the occupancy models. The error of each model will be estimated using the method. The prediction of both models will be compared with the occupancy state whose data were collected during the experimental campaign.

In Figure 5.18 and Figure 5.19, the real occupancy profile for two typical days, is presented by a tick dashed line to compare with the others two lines: the heuristic model output (in red) and the stochastic model output (in blue). It can be confirmed, at a glance, that the heuristic approach is, somewhat, better than the stochastic approach used.

a) b)

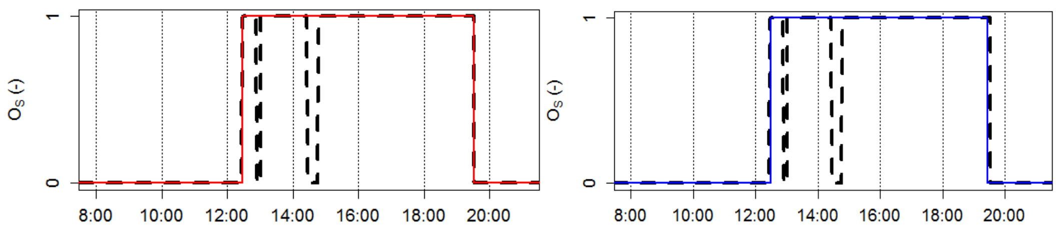


*Figure 5.18 Real occupancy profile (dashed line) compared with both, a) heuristic (red line) and b) stochastic (blue line) model results, for day 19th of measurement campaign*

a) b)

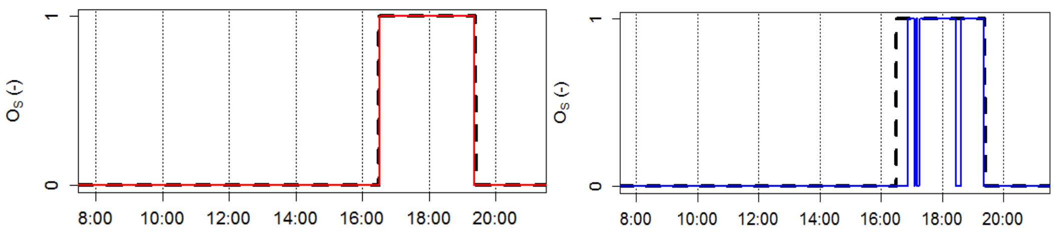


*Figure 5.19 Real occupancy profile (dashed line) compared with both, a) heuristic (red line) and b) stochastic (blue line) model results, for day 32$^{th}$ of the measurement campaign.*

Applying each model to the entire first measurement campaign (45 days) and comparing them with the real occupancy; the error, for the heuristic model, gave 8.47%. However, for the stochastic model, gave 12.87%.

Moreover, if we focus on a single day prediction, the errors are quite different than these presented before.

Using all the 1440 observations (from 0:00 to 23:59):

- For the 19$^{th}$ day: 1.94% of error for the heuristic model and 2.43% of error for the stochastic model.
- For the 32$^{th}$ day: 0.21% of error for the heuristic model and 2.85% of error for the stochastic model.

### 5.3.7. Validation of the method

The same methodology described in the section 5.3.4 was applied. First of all, a correlation plot with the second measurement campaign was performed. The resulting charts are presented in Figure 5.22.

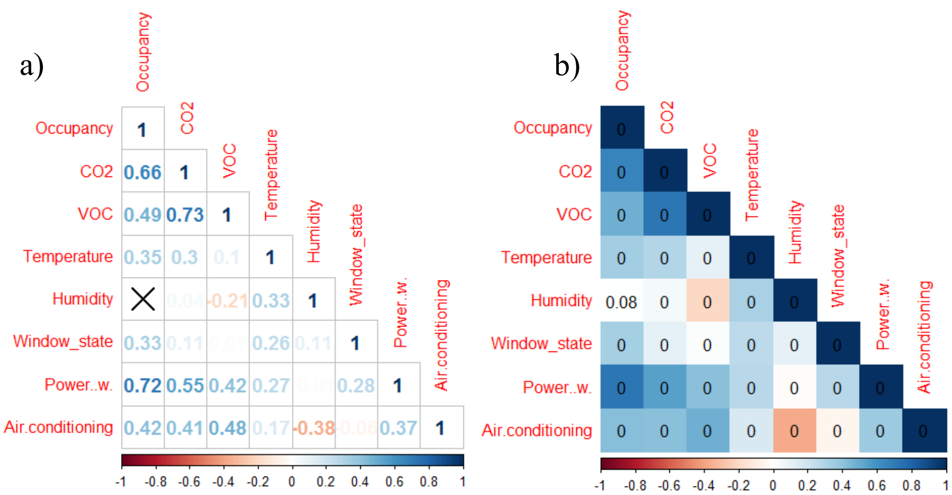


*Figure 5.20 Correlation plot for the second measurement campaign. a) Pearson correlation coefficients, by color and values and b) Pearson correlation coefficients represented by color and p-values*

For this second measurement campaign, the variables strongly correlated with the model variable $O_s$ are quite different. See first column on Figure 5.20a, the decreasing correlations coefficients, would be as: Power (0.72), $CO_2$ (0.66), VOC (0.49) , AA (0.42), T (0.35) and WS (0.33).

Due to these results, the ponderation-probability matrix changes (see Figure 5.21). The WS parameter does not have a strong correlation with $O_s$ and it did not take into consideration as input variable to the model due to its weak correlation coefficient value. This result could be explained because the second measurement campaign was in the winter season and the window opening decreases related to the spring-summer season (first measurement campaign).

Second measurement campaign

| VARIABLE | Correlation strength | Ponderation |
|---|---|---|
| CO2 | 0.66 | 0.30 |
| Power | 0.72 | 0.31 |
| AA | 0.42 | 0.18 |
| VOC | 0.49 | 0.21 |

*Figure 5.21 Ponderation-probability matrix, from the second measurement campaign*

The conditional setpoint designed for the first measurement campaign staying the same (368 ppm for $CO_2$ and 14.1 W for power). However, some changes regarding the values for class levels in the parametric-classification-probability matrix were done, according to the collected data. Looking at Figure 5.22, one can observe that for the $CO_2$ values greater than 1000 the office is always occupied. Also, the $CO_2$ values are higher than in the first measurement campaign (see Figure 5.14).

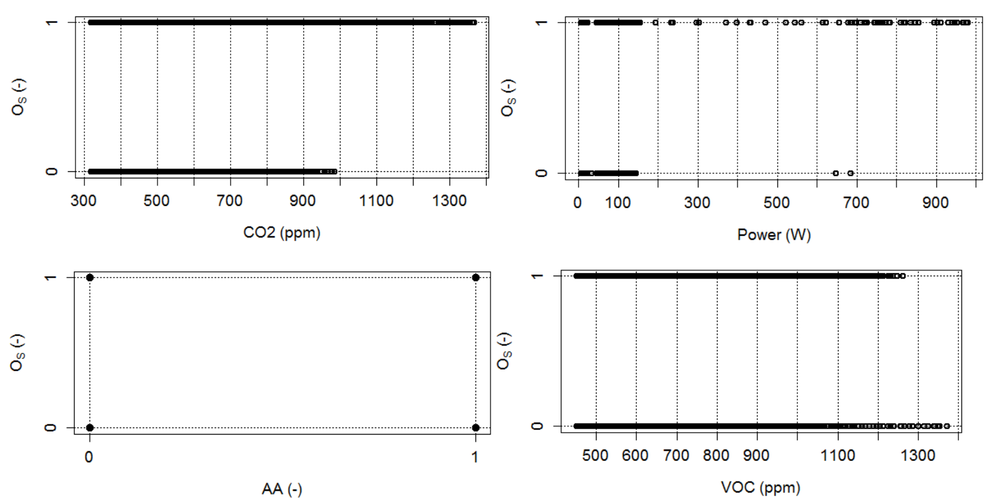

*Figure 5.22 Occupancy state evolution with respect to the four variable for the second measurement campaign. From left to right and up to down: $CO_2$ levels, power, AA and VOC*

The parametric-classification-probability matrix, from the second measurement campaign was defined (see Figure 5.23).

| VARIABLE | CLASS | $O_s$ | p |
|---|---|---|---|
| CO2 | [0, 368) | 0 | 0.97 |
| | | 1 | 0.03 |
| CO2 | [368, 1000) | 0 | 0.48 |
| | | 1 | 0.52 |
| CO2 | [1000, +∞) | 0 | 0 |
| | | 1 | 1 |
| Power | [0, 14.1) | 0 | 0.99 |
| | | 1 | 0.01 |
| Power | [14.1, 200) | 0 | 0.28 |
| | | 1 | 0.72 |
| Power | [200, +∞) | 0 | 0.03 |
| | | 1 | 0.97 |
| AA | 0 | 0 | 0.84 |
| | | 1 | 0.16 |
| AA | 1 | 0 | 0.27 |
| | | 1 | 0.73 |
| VOC | [0, 537) | 0 | 0.93 |
| | | 1 | 0.07 |
| VOC | [537, +∞) | 0 | 0.63 |
| | | 1 | 0.37 |

*Figure 5.23 Parametric-classification-probability matrix, from the second measurement campaign.*

After to calculate the values of probability for each parameters the results showed that they are equal to those of the first measurement campaign as you can see in Figure 5.23.

Second measurement campaign

| VARIABLE | Correlation strength | Ponderation |
|---|---|---|
| CO2 | 0.66 | 0.30 |
| Power | 0.72 | 0.31 |
| AA | 0.42 | 0.18 |
| VOC | 0.49 | 0.21 |

*Figure 5.24 Ponderation-probability matrix, from the second measurement campaign*

The validation of the method had les us the conclusion that: the classification-probability matrix values should be left as in Figure 5.16 and the ponderation-probability matrix changes or depends on the season of the year.

Later to validate the method with the data of the second measurement campaign the results are:

Error of the heuristic model for the whole second measurement campaign (or overall error): 7.73%

Error of the stochastic model for the whole second measurement campaign (or overall error): 13.63%

Figure 5.25 shows the real occupancy profile (dashed line) compared with a) heuristic model and, b) stochastic model.

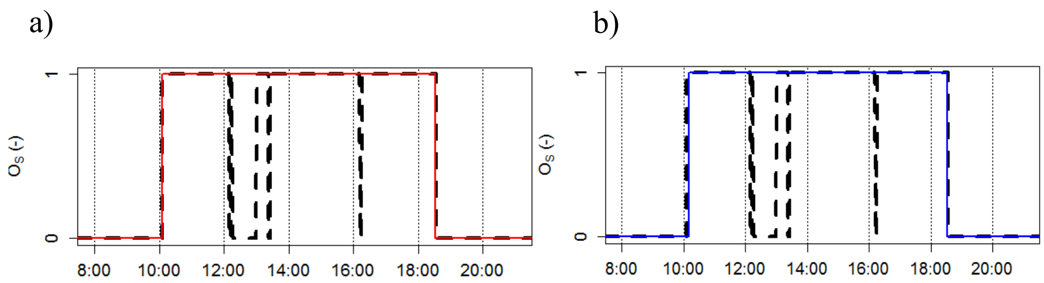


*Figure 5.25 Real occupancy profile (dashed line) compared with both, a) heuristic (red line) and b) stochastic (blue line) model results, for day 32th of measurement campaign*

Using all the 1440 observations (from 0:00 to 23:59):

Error of the stochastic model for the 32th day of the second measurement campaign: 4.23%

Error of the heuristic model for the 32th day of the second measurement campaign: 3.89%

The results suggest that the behavior of the measured variables with respect to the occupancy varies between summer and winter.

Without considering that the real occupancy profile used for calibrating and comparing the models has an error associated with the collection technique employed.

The methodology utilized for the development of both models based on parameter measurements that characterize the internal environment of the office consistently predicts the occupancy profile in the global field (for an experimental campaign) and local (for a specific day), with respect to the errors found.

#### *5.3.7.1. Testing the heuristic model on data collected in further experiments*

Until this point, the data used to test the model were collected at a sampling rate of a minute. There is not always the possibility of measuring at this small sampling rate. Then, let us compare the model for data collected at different sampling rates: 15 and 30 minutes, and on days that are not part of the 45 day sample used to build the model.

*Table 5.13 Model's error with different sampling rate*

| Sampling rate (minutes) | Model's error (%) |
|---|---|
| 1 | 8.12 |
| 15 | 6.19 |
| 30 | 8.16 |

The following 3 figures (from Figure 5.26 to Figure 5.28) are presented to compare the occupancy model error at different sampling rates, for the measurements on June 27th:

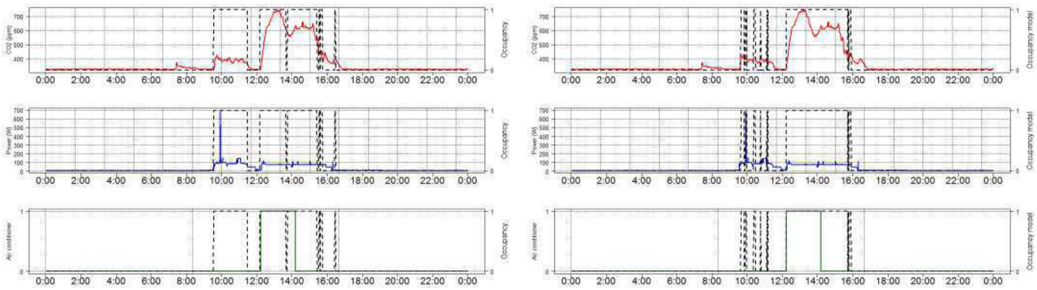

*Figure 5.26 Test of the occupancy model for the data collected on June 27th at a sampling rate of a minute. At the left: $CO_2$ levels and power with the real occupancy profile. At the right: with the occupancy model profile*

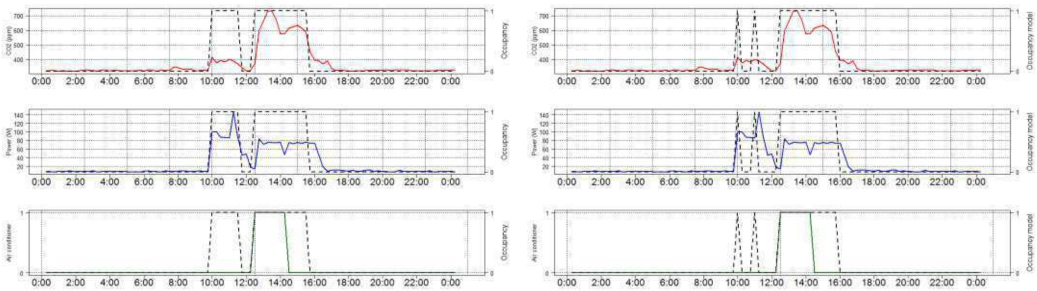

*Figure 5.27 Test of the occupancy model for the data collected on June 27th at a sampling rate of 15 minutes. At the left: $CO_2$ levels and power with the real occupancy profile. At the right: with the occupancy model profile.*

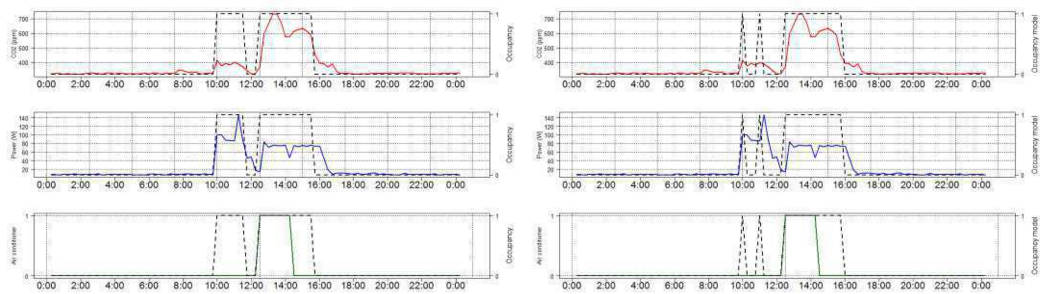

*Figure 5.28 Test of the occupancy model for the data collected on June 27th at a sampling rate of 30 minutes. At the left: CO2 levels and power with the real occupancy profile. At the right: with the occupancy model profile.*

### 5.3.8. Sources of error

At this moment, only five parameters of the data collected were used to build the occupancy model: $CO_2$ levels, power consumption from computers and printers, air conditioning usage, window status and the real occupancy.

The first source of error that should modify our model the most is in the real occupancy data collected, as this parameter is used to calculate the model's error. The error in the collection of the real occupancy might be caused by the fact that the experimenters could have forgotten to note or mark manually, each time they enter the office or, for some reason, left the office, which is normal to happen. Also, errors can occur in noticing the time.

## 5.4. Energy consumption influenced by occupant's behavior in the office

The office was instrumented to characterize the occupant's behavior and the energy consumption. The behavior has been described by window opening, by office occupancy profile and by the air conditioning usage. In respect to the office: the lights, the desktop computers and printers, the air conditioning and the occupancy profiles were used to estimate the energy consumption. This is done each month as the experimental data are collected daily and can be represented in a plot, having the relation we want to establish (energy consumption as function of the occupant's behavior).

### 5.4.1. Energy consumption estimation:

Assumptions:

- Only the days of occupancy have been considered.

- Lights are turned on only in the afternoon: from 15:00 to 19:00 when the office is occupied. This occurrence was obtained by interview.

1. Lights:

In order to estimate the energy consumption, we followed the next steps:

a. We took the occupancy profile, specifically the occupancy profile on the period from 15:00 to 19:00.
b. We calculated the total hours of occupancy within this period. These are the hours that the lights were on.
c. The lights power consumption is 75 W.

2. Desktop computers and printers:

As the power consumed by the computers and printers was measured in a sampling rate of a minute, we have calculated the integral of the power to estimate their total energy consumption per day. To calculate the integral, we used the trapezoidal method.

3. Air conditioning:

The air conditioning power consumption was estimated as 3500 W. This is the capacity of the air conditioning equipment in the office.

To estimate the energy consumption, we followed the same steps as those for the lights, except of point a. Here, the air conditioning usage is recorded by sensors, thus the total usage time can be known.

### 5.4.2. Occupant's behavior characterization

Assumptions:

Window open, stands for any position of the window. The exact opening percentage is not considered here, as it was not recorded by the sensor.

The occupancy profile collected manually is considered to have no uncertainty associated with the collection process.

*Time window opened:*

The state of the window was recorded whenever it changed, thus to calculate the time the window was kept open, we only sum up the period it was open.

*Air conditioner usage:*

Same as the window state, data were recorded by a sensor placed in the air conditioning slats with a sampling rate of a minute.

### 5.4.3. Results and discussion

For a very brief data analysis, the energy consumption was compared with the hours the window was kept open and separately with the hours of occupancy, in a plot. The hours of air conditioning usage were confronted with the days within the month, so this could give us information on its usage tendency. First we plotted the results for a month of recorded data. Finally, a regression line was included to show the energy consumption tendency.

For example in September (16 working days), as can be observed in Figure 5.29, the energy consumption tends to increase when the hours of occupancy increase, as expected. On the contrary, it tends to decrease when increasing the time the window is open. The latter, have total sense if we consider that the outdoor temperature becomes lower as we approach autumn, refreshing the office indoor environment.

a) b)

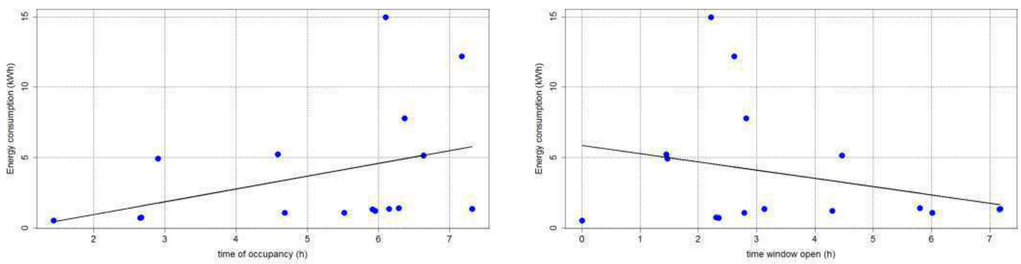


*Figure 5.29 Energy consumption tendency in respect to the hours of occupancy a) and to the hours in which the window was kept open b)*

As observed before, we can expect that the air conditioning usage will decrease over time, since opening the window was sufficient to consistently refresh the office indoor environment. Furthermore, Figure 5.30 shows the hours of air conditioning usage over the days of September. We can observe and conclude that the air conditioning usage decreases over time as expected (also as the regression line suggests).

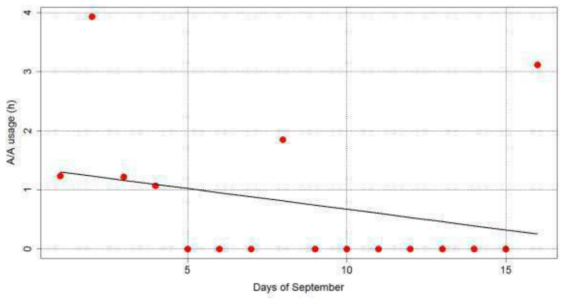


*Figure 5.30 Air conditioning usage in hours as the day past in September*

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# 6. CHAPTER

# GENERAL CONCLUSIONS

In this final chapter, we review and discuss the key contributions of this research work.

## 6.1 Concluding remarks

The thesis was divided into two main parts regarding different typologies of building use, residential and office. For residential buildings, the main objective was to evaluate the effect of behavioral factors on the energy performance of a housing stock representative of Mediterranean climatic conditions. In particular, three alternative procedures for modeling occupancy in buildings were proposed and applied by energy simulation. The investigation highlighted the importance of how the modeling of the occupancy may produce different results in the prediction of the energy performance. Also, a case study was developed, including a residential nZEB model, to evaluate the influence of users' patterns on the energy consumption of this building type. The following can be deduced:

- Regression models are used to determine the significance of selected parameters and their interrelations. Physical factor and occupant parameters explain 48.7% of the variation in electricity energy consumption; the only physical factors can explain 32.7% of the variation. These results are relevant in the specific context.
- The analysis highlighted how the availability of data and information concerning occupancy is essential for the modeling of the profiles to be used in design or assessment phase. In fact, the prediction of energy consumption differs significantly according to a way through occupancy is modeled.
- The modeling procedure depends on the level of detail of the available information. The study demonstrated that the calculated energy consumption by using the Standards prescriptions could be not representative of the real energy performances.
- In the nZEB case study, the results show that even the wasteful family, who does not care about the use of air conditioning and ventilation, could almost double the surplus energy to be allocated to electrical needs. In fact, the

percentage of consumption that can be covered by renewable sources Passes from 18% to 33% using low-power electrical appliances and lights.

The analysis conducts the authors to conclude that the assertion of a “nearly” zero energy building is justified, as the fact of being zero energy is not linked exclusively to the construction and plant solutions, but is also dependent on occupant related factors. Indeed, minimizing the energy consumption for heating and cooling by adopting high-efficiency envelope and plants, the consumption of lighting and appliances depending on user behavior becomes prevalent. On the other hand, for office buildings, the first part of the analysis was dedicated to investigate the data collected by sensors to explore relationships between the occupancy and the magnitude of indoor environmental changes with the aim to identify what sensor or sensors fusion is more suitable to describe the occupancy. In the second part, a heuristic approach via logical flow charts and conditional stages, and a stochastic approach using probabilities were applied to estimate the office occupancy profiles by the use of direct observations and sensors network. The following can be concluded:

- The comparison between occupancy real data clustering and VOC and open/closed window groups did not demonstrate similarities. Otherwise, electricity consumption, carbon dioxide, and door status showed some similarities, confirming that occupancy profiles could be estimated with a single sensor installation. On the other hand, the quality of the results is affected by the limitations of lack of fine-grained granularity related to the characterization of the spatial resolution of occupancy information which can be obtained.
- The methodology utilized for the development of both models (descriptive and predictive) based on parameter measurements that characterize the internal environment of the office consistently predicts the occupancy profile in the global field (for an experimental campaign) and local (for a specific day), with respect to the errors found.

### 6.2 Future developments

In this section, we will list several limitations with our current research and suggest ideas for future works. Similarly, as before, the considerations are separated by residential and office buildings use.

Take into account other sensors installed in the office, as proximity beacons and micro camera through raspberryPI, different scales of occupancy measurement can be considered in the future, not only the presence, but also location, count, and activity (use of appliances and heating/cooling system in the office).

It can be made a comparison of traditional sensors such as $CO_2$ and air quality with smartphones for presence and localization and video camera.

Regarding sensors fusion for occupancy detection, we suggest an investigation on how to combine data from multiple sensors allow to obtain more information about occupancy and how new technology as beacons can be taken into account to generate accurate occupancy information with the advantage of low-cost.

The mobile application allows the indoor localization of any individual involved in the experiment. In other words, in a more realistic scenario, the occupancy detection process should consider the presence of other occupants (i.e. visitors) in each room, not only those who use the application. Future development of the present study will certainly cover this aspect, with the consideration of different technologies allowing the passive presence detection by integrating a tagging mechanism.

Regarding residential building, this thesis analyzed just some of the possible solutions to address the problem of occupancy modeling in buildings. The study considered two existing buildings, with the aim of not involving the variability of the physical aspects and the technical-constructive characteristics of the dwelling, rather focusing attention on the occupancy typologies and on how to describe occupancy in the model. Being an existing building, the climatic conditions are those of the site, a typically Mediterranean location. Future studies could consider newly designed structures, to assess the influence of occupancy in buildings with specific design features, such as buildings designed according to high standards of energy efficiency. Besides, different climatic conditions could be simulated, to explore the interaction between the energy performances of the building, climatic factors, and occupancy profiles. Moreover, additional occupancy scenarios could be explored with the aim of investigating further household composition, and mode of use of the house.