UNIVERSIDADE DE SÃO PAULO
INSTITUTO DE ARQUITETURA E URBANISMO

Camila C. A. Grassi

Algorithm to simulate occupant behavior in mixed-mode office buildings

São Carlos

2018

Camila C. A. Grassi

Algorithm to simulate occupant behavior in mixed-mode office buildings

Memorial de Qualificação apresentada ao Programa de Pós-Graduação em Arquitetura e Urbanismo do Instituto de Arquitetura e Urbanismo, Universidade de São Paulo, como parte dos requisitos para a obtenção do título de Doutor em Arquitetura e Urbanismo.

Área de concentração: Arquitetura, Urbanismo e Tecnologia

Supervisor: Profa. Dra. Karin M. S. Chvatal

São Carlos

2018

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

ABNT	Associação Brasileira de Normas Técnicas
MMV	Mixed Mode Ventilation
AIC	Akaike Information Criterion
HVAC	Heating Ventilation and Air Conditioning
GP	Gaussian Process
NV	Natural Ventilation
RH	Relative Humidity

CONTENTS

1 ACTIVITIES

1.1 Activities within the graduate program

The following table presents all the classes taken, credits and grades, totaling 32 credits, which are required by the graduate program. There was an internship period that accounted for part of the credits. This item also presents a brief description of each class taken and the work developed in each of them.

Class	Grade	Credits
IAU5822: Research Methods in Arch. and Urbanism's Technology	A	8
IAU5808: Thermal performance of residencies	A	8
IAU5958: Energy efficiency in buildings	A	8
IAU5918: Teaching procedures and methods in arch. and urbanism	A	4
Program's Activity: Supervised Internship in the Teaching Program	N/A	4
TOTAL	-	32

Table 1: Classes taken and credits received

IAU5822 - Research Methods in Architecture and Urbanism's Technology

This class presented different research methods that encompassed both focus areas in the program; Theory and History, and Technology. The students had the opportunity to present their initial research plans and received advices, critics and help from peers and professors to develop a more robust and complete plan. There were exercises to complete in and out of the classroom, to practice what was given during the classes. This course contributed to better delineate the research plan, aided by the exercises that resulted in a project with an overall higher quality.

IAU5808 – Thermal performance of residencies

Several passive strategies for conditioning were presented, and each professor presented a technique that is more related to their respective research area. Thermal performance according to the Brazilian Standard NBR 15575-3 was presented and studied, and exercises were given to apply the method presented in the standard. The adaptive model from ASHRAE-55 was also presented and an exercise was proposed to learn and practice its application. The student was able to aid her classmates in this exercise, given that the adaptive model was part of her master's and she had previous knowledge on how to apply it. As part of the work developed for this class, the student presented summaries on articles pertaining topics related to the class' theme and wrote an extended essay on evaluation methods for thermal comfort based on the available literature, proposing a brief method to create an adaptive model.

IAU5958 – Energy efficiency in buildings

Passive and active strategies for energy savings were presented. There was a strong emphasis on developing a good design and the importance of the engineer, architect or designer to know the physical phenomena to which a building must respond, so that it is possible to achieve energy efficiency with low costs. Exercises to implement and apply methods given by the Brazilian Standard were performed. The students gave presentations on themes related to their research projects so that they would each get to know each other's projects. At the end of the course, there was a final presentation in groups formed by blocks of themes within the same field of research. The class was important for the student to be in touch with different techniques and passive strategies to implement in building design, since it is one of the areas of interest in the research being developed.

IAU5918 – Teaching procedures and methods in architecture and urbanism

This short-term class had as its objective to prepare the student to be an intern in teaching. A teaching panorama of the Brazilian reality was presented and there were discussions about education in universities, national and international. Questions about where the curricula seems to be lacking in some aspects were raised, and there were talks about schools where this seems to be a bigger issue. Possible solutions were discussed as a group. An intermediate exercise was performed, so the students could practice what was discussed and presented up to that point. The exercise required that a curricula from another institution be analyzed and altered according to the discussions in class in an attempt to improve it. The alterations and how each student thought it was best to improve each chosen document was presented in class. Suggestions were made during the presentation and the students altered and/or included what classmates and professors observed. This class gave the student the opportunity to build a curricula with a topic that was specific to her research area, therefore allowing the application of her previous knowledge in the field, to contribute to the bibliography proposed and enrich the program.

1.2 Extracurricular Activities

1.2.1 Proficiency Exam

Language: Spanish

Institution: CICBEU, São Carlos

Status: Approved

1.2.2 Teaching Internship Program

The student participated in the Teaching Internship Program as a Teaching Assistant (TA) in the undergraduate class IAU0649 – Environmental Comfort in Buildings during the first semester of 2017. The student organized the schedule for the classes throughout the semester combining the necessary amount of classes to the available days in the semester. During the internship period she participated in all classes and helped the students with the exercises given in class. Every week there was a new exercise for the students to prepare for the following week. The Teaching Assistant was responsible for sending such exercises on the class' email and made herself available during the week and during classes, should any student need her help. She also corrected all the exercises, handed them back to the students and cleared any doubts that they might have. The TA prepared a booklet with all the exercises given to the students during the semester, including their answers when possible. She also taught part of a class, under supervision, explaining the FAST Diagram, which is a method to aid in ranking the variables to be included in a design, so the designer is better guided when making his/her decisions. It is a way to define what the most important aspects are in the design given one's design focus. The TA also helped the students develop this diagram and use them in their final project for this class. At the end, the student organized all the projects, grades and attendance; contributing with opinions on the final projects.

1.2.3 Workshops

- Web of Science at USP: Chemistry Institute of São Carlos
- Meet the Editors: Physics Institute of São Carlos
- Training School - Design Process for Building Rettrofit: University of Campinas e HafenCity University
- Information, Visualization and Comprehension: design as a resource for graduate school

1.2.4 Courses

- Mini Arduino Course: TOPUS Aerospace Research Group
- Introductory Course to Thermal Load Calculation: IAU – Prof. Dr. Anderson Ubices (UFSCar)

1.2.5 Conferences

1st Conference on Environmental Quality and Energy Efficiency in Buildings, São Paulo, SP, Brazil.

Conference Article: Windsor Conference 2018

Developing user profiles for mixed-mode office buildings operation based on occupant behaviour evaluation

Abstract: User profiles can generate discrepancies between the measured and simulated data, when building performance simulation tools provide the latter. Nevertheless, specialized literature observed the inadequacy of using current thermal comfort models to describe occupant comfort in mixed-mode buildings and no specific guidelines are provided in current standards. This paper addresses occupant behaviour within mixed-mode office buildings controlled by occupants, located in a Brazilian humid subtropical climate, with the objective to develop user profiles of operation to be used as input data in computer simulation analyses. Three office rooms operating in a concurrent mixed-mode configuration were investigated in a field research. Indoor climatic measurements monitored the environmental variables (dry bulb temperature, radiant temperature, air velocity and relative humidity) and user control variables (manual operation of the air-conditioning and natural ventilation systems) in situ. Field surveys were simultaneously conducted with the offices' occupants. As a result, occupant behaviour regarding the building's controls is analysed and compared to the static and adaptive thermal comfort models from ASHRAE Standard 55-2013. In conclusion, a user profile to be used as input data for computer simulations is developed, aiming to support more accurate investigations about the thermal and energy performances of mixed-mode office buildings.

Keywords: mixed-mode buildings; occupant behaviour; thermal comfort; field research.

2 PRELIMINARY THESIS STRUCTURE

2.1 Abstract

The way buildings are operated greatly influence energy consumption, and occupants play a significant role in it. However, occupant behavior is a variable that generates high levels of uncertainty in computer simulation, making it difficult for architects, designers and engineers to accurately predict energy consumption in buildings. Studies have identified that there is a gap between real and simulated data concerning energy use, which can, in great part, be attributed to occupant behavior and how this is inputed into energy simulation software. In an effort to fill this gap, researchers have been conducting in situ measurements to collect data on occupant behavior regarding the actions taken to better adjust and perform in their environment, such as window opening, adjusting blinds, lighting and thermostat temperature. The collected data is then used to create stochastic models to provide more accurate input data for simulations. This research intends to create an algorithm to simulate occupant behavior, in relation to window opening/closing an AC activation/deactivation, in mixed-mode office buildings in a high altitude tropical climate (São Carlos, SP, Brazil). The method consists of four main stages; (a) Buildings data collection and pre-test: where buildings to be monitored were selected and a trial monitoring performed; (b) In situ measurements and data analysis: monitoring of ten mixed-mode offices over a twelve month period; (c) Statistical methods' application and creation of algorithm; and (d) Validation and test. The main objective of this study is to provide more accurate input data on occupant behavior to be used in simulation programs, so more accurate output data can be achieved.

2.2 Resumo

A maneira como os edifícios são operados tem grande influência em seu consumo energético, no qual os usuários têm um papael importante. Contudo, o comportamento do usuário é uma variável que gera altos níveis de incerteza na simulação computacional, dificultando para arquitetos, projetistas e engenheiros prever com precisão o consumo de energia de um edifício. Diversos estudos identificaram uma lacuna entre os dados reais e os simulados, no tangente ao uso de energia elétrica, que pode, em grande parte, ser atribuída ao comportamento do usuário e como este é inserido nos programas de simulação computacional. Para preenceher esta lacuna, pesquisadores têm conduzido medições *in loco* para coletar dados sobre o comportamento do usuário em relação às ações que tomam para melhor se ajustarem e desempenharem em seu ambiente, como abertura de janelas, ajuste de cortinas, iluminação e temperatura, por exemplo. Os dados coletados são então utilizados para criar modelos estocásticos para proporcionar dados de

entrada mais precisos para simulações. Esta pesquisa tem a intenção de criar um algoritmo para simular o comportamento do usuário, em relação a abertura/fechamento de janelas e acionamento/desacionamento do ar condicionado, em escritórios de modo-misto em um clima tropical de altitude (São Carlos, SP, Brasil). O método consiste em quatro etapas principais; (a) Coleta de dados dos edifícios e pré-teste; (b) Medições *in loco* e análise de dados; (c) Aplicação de métodos estatísticos e criação do algoritmo e; (d) Validação e teste do algoritmo. O principal objetivo desta pesquisa é proporcionar dados de entrada mais precisos sobre o comportamento do usário para serem utilizados em programas de simulação, para que dados de saída mais precisos possam ser obtidos.

2.3 Introduction

Over the past 15 years there has been an increase in the evaluation and use of energy in buildings. The need for more sustainable solutions has become a global concern and energy analysis has been one of the focuses of such discussions. A raise in energy consumption has occurred due to the constant technological development and shown itself in alterations in the use pattern in a global context. Such consumption has presented an impact on the urban and global contexts, resulting in a raise in green house gas emissions (GHG), global warming and a decrease in natural resources. As foreseen, one of the consequences are climate changes, which have become a threat. Several international agreements, such as the Kyoto Protocol have taken place in an effort to remedy the situation. However, climate changes have already occurred, resulting in higher temperatures, leading to an intensified use of air conditioning in buildings. The building sector consumes 20% of the total energy in the world, as stated by the U.S. Energy Information Administration (Energy Information Administration, 2016). In Brazil, office buildings contribute to 15% of the energy consumed (BEN, 2016), and of these 15%, the total energy consumption with artificial conditioning and lighting is of approximately 69% (Eletrobrás, 2009). Nevertheless, this same sector presents great potential to reduce climate changes, since it presents great opportunities of energy savings (IPCC, 2014).

The way air conditioning is used in buildings can cause high impacts on their energy consumption, given that the same building can present very divergent energy uses depending on how it is operated by users (Li et al, 2007 apud (YAN et al., 2015). However, there are strategies that can be implemented to decrease energy consumption, one of which is mixed-mode ventilation (MMV). MMV is a combination of natural ventilation and a mechanical ventilation system, which can be activated when solely using natural ventilation is not enough to maintain the environment comfortable. In this system, natural ventilation is used when the external conditions are favorable, thus activating the mechanical system when the opposite situation occurs (DEUBLE; DEAR, 2012), the system combines natural ventilation and the use of air conditioning units to reduce energy consumption. This is a relatively new solution, and there are no standards or guidelines that indicate how it should be operated or even how to use its control strategies. Besides, there is no guide on how to simulate or even design buildings of this kind (SALCIDO; RAHEEM; ISSA, 2016), making it difficult to simulate this scenario in computational programs, which can often lead to non reliable results.

Although passive strategies, such as natural ventilation (NV) reduce the needs for energy use, they increase the levels of uncertainty by reinforcing the central role of occupants, as they become the essential elements in control of the building and its environment (HALDI et al., 2016). With the growing public concern regarding climate change, more attention has been drawn towards energy consumption in buildings (JANDA, 2011), and predicting energy demand has gained significant relevance in designing and constructing buildings, from the early design stages to post occupancy (DELZENDEH et al., 2017). Such is the need for the decrease of energy consumption that regulatory conditions have been established for all European countries, in an effort to decrease the energy required for heating, cooling, ventilation and lighting (DELZENDEH et al., 2017). Energy consumption is related to several different factors, such as the thermo-physical properties of a building, construction techniques implemented, climate and location, quality and maintenance of the installed systems and occupants' behavior and activities (DELZENDEH et al., 2017).

Computer simulation is an important and useful tool to predict energy consumption in buildings based on design information. However, several studies (FABI et al., 2013; CALÌ et al., 2016b; STAZI; NASPI; D'ORAZIO, 2017a; YAN et al., 2015; SCHAKIB-EKBATAN et al., 2015) have shown that there is a discrepancy between the real and predicted data regarding energy consumption in buildings. Studies have demonstrated that the real energy consumed in buildings can be up to three times greater than the predicted values (FABI et al., 2013; CALÌ et al., 2016b). This evidences a performance gap, which can be attributed to, amongst other factors, a disregard of occupant behavior in the simulation process. Martinaitis et al. (2015) conducted five different studies to show that buildings do not perform as predicted even when using very accurate simulations and concluded that user behavior and preferences are significant contributors to the identified gap. Schakib-Ekbatan et al. (2015) identified occupant behavior as possibly the most overlooked parameter, and that it might not be properly considered as an integral part of the energy design, thus resulting in discrepancies in the data.

Occupants adapt within their environment in order to achieve comfort in ways that are convenient to them, and not necessarily energy conserving (RIJAL et al., 2007; NICOL; HUMPHREYS, 2002). They may act in unexpected ways to respond to a crisis of discomfort, and such actions are on the opposite end of the static assumptions designers tend to make when portraying such parameter in simulation. Therefore, user behavior can be considered one of the variables that generate great amounts of uncertainties in simulation results. Users can affect the indoor environment as well as energy consumption, depending on how they behave in the environment and on how they interact with the building and the controls available to them, as windows, ventilation systems and shading devices (ANDERSEN; FABI; CORGNATI, 2016), for example, becoming a very significant variable.

Several studies have addressed the issue of occupant behavior within different types of buildings and with emphasis on different influential parameters (PISELLO et al., 2016; CALÌ et al., 2016a; SCHAKIB-EKBATAN et al., 2015; STAZI; NASPI; D'ORAZIO, 2017b; RIJAL; HUMPHREYS; NICOL, 2014). Most of the studies focus on residential and office buildings, since these show greater impact on global energy use. Great part of the work in this area study one particular type of user interaction; the use of electricity and plug loads being the most researched subject, followed by window opening behavior and the use of fans and/or air conditioning (DELZENDEH et al., 2017).

However, even with efforts being made to diminish the gap between predicted and actual data and to better understand occupant's actions, Andersen et al. (2013) states that there are still few models relating occupant behavior and window opening, presenting a difficulty to computer simulation users, who have little or no information on how to model such behavior to acquire precise results.

This research proposes the study of occupant behavior in mixed-mode office buildings related to the opening/closing of windows and the activation/deactivation of the air conditioning. These buildings display operable windows and individual air conditioning (AC) units in the offices, all of which the users are free to operate at any given time. There are no automation systems, nor any temperature indication of any kind. This work intends to create an algorithm to be implemented in computer simulation programs, to provide more accurate input data for simulations of mixed-mode office buildings related to energy use and thermal comfort, once there is a discrepancy between the real and simulated data referring to occupant behavior (ANDERSEN et al., 2013).

2.4 Objectives

The main objective of this work is to create an algorithm to be implemented in simulation programs to provide more precise input data on occupant behavior, specifically related to window opening/closing and air conditioning activation/deactivation as a function of the environmental variables being considered. The algorithm is to be used within a mixed-mode scenario, where there are operable windows and AC units that the user can freely operate at any time, and no automation systems. The specific objectives to be achieved as the research progresses are:

- To identify the main driving factors that lead to window opening and AC activation in the different seasons of the year in mixed-mode office buildings.
- To contribute to other researches in the field by developing, applying and testing the methodology used in this work.

2.5 Literature Review

This item presents the main themes studied in this research, such as occupant behavior, mixed-mode ventilation, computer simulation and statistical methods applied to data sets to create stochastic models portraying user behavior. This section also counts with an item that describes several works developed applying similar methodologies.

2.5.1 Occupant Behavior

In a general sense, occupant behavior can be defined as the interactions with a building's systems in an effort to control the indoor environment for health and comfort, be it thermal, visual and/or acoustic (DELZENDEH et al., 2017). Improving air quality, by ventilating and eliminating odor and pollution, visual or lighting quality, by controlling glare, reflections and the amount of illuminance, acoustical conditions, by avoiding noise, and aesthetics, as well as improving thermal comfort in the indoor environment are prerequisites established by buildings' users so they are able to adjust and adapt systems and components according to their preferences (BLUYSSEN, 2012).

The term 'alliesthesia' is the combination of the words 'changed' (allios) and 'sensation' (aisthesis) (CABANAC, 1971), that can be used to describe that an external stimulus can be understood as pleasant or unpleasant, depending on the signals sent from the body. It is human nature to search for pleasant conditions and avoid unpleasant ones. As stated by Nicol e Humphreys (2002), if there is a change that causes discomfort, people will act in ways to regain their comfort. However, because of people's different backgrounds and preferences, also their physical, physiological and psychological differences, and several other influential external drivers such as economic and regulatory, for example, they don't perceive and respond in the same manner (BLUYSSEN, 2012).

Occupants play a very significant role in a building's energy performance, as they are present, move around and interact with the building and its systems to better fit their purposes and comfort needs, resulting on an impact in energy consumption (HONG et al., 2017). Occupant behavior is among the six most influencing factors of a building's performance, along with climate, building envelope, equipment operation and maintenance, and indoor environment conditions (YOSHINO, 2013). As there is a growing concern for sustainability and low energy buildings using passive strategies, such as natural ventilation, the role of occupants in a building is reinforced, as they become the most important elements controlling their environment (HALDI et al., 2016).

Occupants present the individual aspect that is related to personal experiences, preferences and expectations, which can affect the total energy consumption in a building. Their active use of energy, as in the way they interact with control systems and their available building elements to reach their desired levels of thermal comfort have a significant impact on the total amount of energy consumed (DELZENDEH et al., 2017). Such interactions happen in different ways; window opening and closing, lighting, shading devices, HVAC (Heating, Ventilation and Air-Conditioning) systems, hot water and appliances (Figure 1).

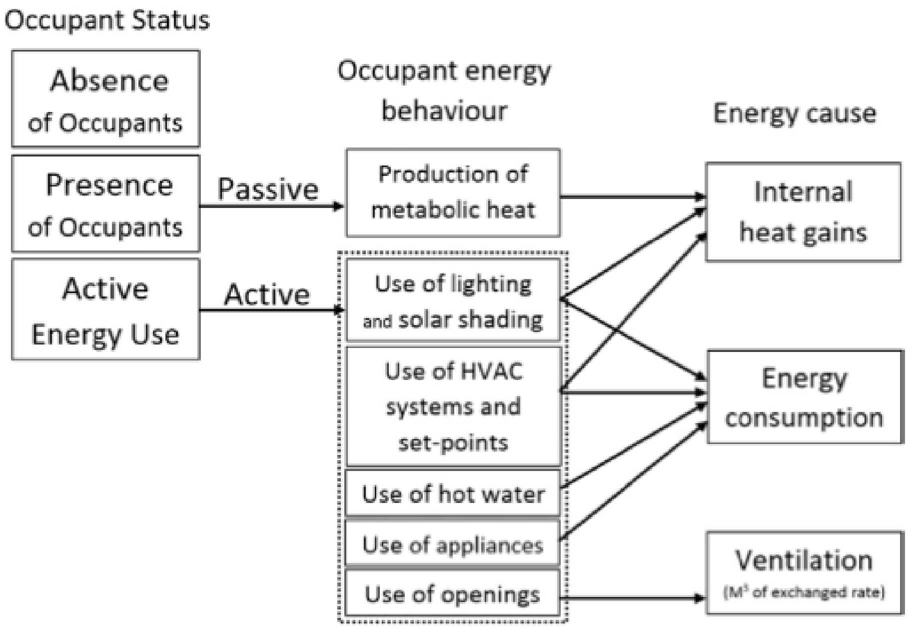

Figure 1: Occupants' types of activities affecting building energy consumption (DELZENDEH et al., 2017)

Hong et al. (2015) identified actions and inactions that users may take to regain comfort. Actions can be adjusting the level of clothing, opening a window or adjusting the thermostat. As for inactions, it could be, for example, moving to a different location and tolerating some degree of discomfort. Different actions and inactions can be taken by different users in response to the same kind of situations, thus impacting in very different ways how energy is consumed in the same environment. Therefore, it is critical to understand the relationship between the building and its occupants' activities, lifestyle and behavior.

In an effort to better portray occupants and their impact on the built environment, researchers have categorized occupants into different groups according to their energy use. D'Oca et al. (2014) created the groups active, medium and passive regarding occupants and their energy use. The active users are the ones that change the heating/cooling set point, whereas the passive user does nothing and continues to tolerate some degree of discomfort. Other categorizations, such as the one made by Hong et al. (2015), described with more accuracy people's actions, classifying them as; "energy frugal", "energy indifferent" and "energy profligate". Using another method, which classified behavioral factors in residential buildings, Chen et al. (2015) categorized users into three levels referring to their complexity, that is; simple, intermediate and complex. Each level was developed for a different application; the simple level was for statistical analysis, the intermediate, with more parameters, for case studies, and the complex was meant for detailed simulations. This division, using occupants' behavior to create profiles, could aid in leading to more accurate assumptions when performing energy analysis. Nonetheless, there is still a need to perform large scale studies to gather comprehensive data to create such profiles.

Occupant behavior is a contributing variable to the uncertainty of building performance, and it can significantly affect building energy consumption. According to Hoes et al. (2009), it is the leading source of uncertainty in predicting energy use in buildings.

The International Energy Agency (IEA), lists occupant behavior, among other factors such as climate and building envelope, as one of the driving forces of energy use in buildings (IEA, 2012). Schweiker (2010) defines occupant behavior as "a human being's unconscious and conscious actions to control the physical parameters of the surrounding built environment based on the comparison of the perceived environment to the sum of past experiences." Some of these actions can be interactions with windows, lights, blinds, thermostats, air conditioning and plug-in appliances.

Based on the definition above, it is possible to state that occupant behavior is uncertain because it can be influenced by a number of factors, be them external to the occupant, such as air temperature and wind speed, or internal or individual, such as personal background and preferences, as well as building properties, which can be perceived as ownership or the availability of heating devices, for example (FABI et al., 2012).

Traditionally, occupant behavior has been connected to indoor and outdoor thermal conditions, leading to interactions with building control systems, which are only one aspect of occupant behavior. Human behavior, when in the field of social sciences, can be set in relation to causes that are called "internal or individual factors", which in addition to external factors, influence the occupant behavior with a variety of perceptions and actions in complex ways (SCHWEIKER, 2010).

2.5.1.1 Parameters Influencing Occupant Behavior

Energy consumption is largely affected by occupant behavior, as they respond differently to regain their levels of thermal comfort, which can vary according to their personal (psychological, physiological) and social parameters (DELZENDEH et al., 2017). In addition, parameters such as climate, economy, regulations and policies, architecture and interior design of the spaces can also influence energy use (Figure 2).

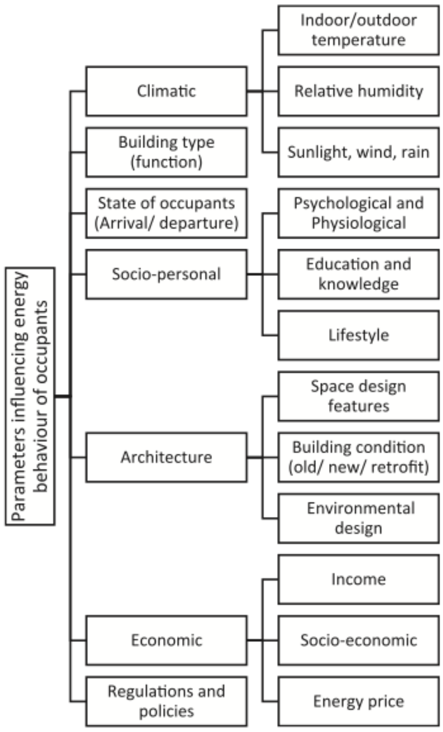

Figure 2: Factors influencing occupants' behavior regarding energy use (DELZENDEH et al., 2017)

Climatic parameters, including outdoor temperature, relative humidity, solar radiation, wind and rain are very significant influences on occupant behavior and their interaction with a building's systems to achieve thermal comfort (DELZENDEH et al., 2017). Several researchers have studied the influence of climatic parameters on occupant behavior (SCHAKIB-EKBATAN et al., 2015; RIJAL; HUMPHREYS; NICOL, 2015; LI et al., 2015), and because such parameters are time/date dependent, stochastic models are the most common method in these studies, estimating the probability of given outcomes.

In order to attain more accurate results from simulation programs, it is important to consider and understand the reasons that lead users to take actions and interact with the building and its systems. Factors that influence occupant behavior, either external or individual, have been categorized and denominated as "Drivers", which are described as the reasons that lead the occupant to react in a building and suggests that such occupant acts, thus driving the occupant to take an action (FABI et al., 2012).

Several researchers have divided driving factors into categories,Peng et al. (2012), when conducting a residential study, classified behaviors in three main categories:

- Environmentally related: actions triggered by environmental factors
- Time related: actions repeated within certain time frames

- Random: actions taken depending on uncertain/non quantifiable factors.

The main three categories defined by the authors can be applied to other types of building, such as an office building, where environmental factors will be an important influence, as will time related actions, which can be related to routine. Random related actions can also be observed in both types of building. Depending on the action under consideration, some drivers can have a greater impact on triggering an action than others.

Another influential parameter is the building type and the types of activities performed by the users within the built space. The building type usually determines the activities performed in it, which in turn, sets a clothing type, metabolic rates and the occupants' specific needs and expectations related to such activities, as well as the way they interact with the building. Studies have mostly focused on residential and office buildings given their impact on the total energy consumption of the sector.

Social and personal parameters are also critical when investigating occupants' comfort and energy attitude. Social and personal factors have been identified as also being influential on energy behavior in residencies, such as users' awareness of energy issues, gender, age, employment, family size and social-cultural belonging (MARTINAITIS et al., 2015). Janda (2011) also highlights the effect of education and growth in awareness in people's attitude towards energy use. Other relevant and influencing factors, such as energy regulations, policies and economical parameters, as energy price and employment, have been discussed in the literature. As part of such discussion, several studies have investigated the influence of the above-mentioned parameters on occupants' energy consumption behavior (MARTINAITIS et al., 2015; CALÌ et al., 2016b; RIJAL et al., 2011). It is possible to observe that when occupants are directly responsible for paying the bills, they save more. A study by Park e Kim (2012) identified, by means of questionnaires, that occupants tolerated a certain amount of discomfort on account of energy prices, thus affecting the way energy is consumed. Ownership of the unit, be it residential or at an office, also affects the way energy is consumed by occupants.

The state of occupants, that is, their arrival, presence and departure has been studied and revealed that users tend to adjust given building systems upon arrival more than at departure. This parameter has been considered and modeled in several studies (YUN; STEEMERS, 2008; PAGE et al., 2008) to investigate the connection between occupants' movements and their behavior. Architecture and interior design can also influence users in the way that the space may change their perception. However, the impact of interior design has not been broadly studied.

Fabi et al. (2012) classified drivers into five groups, namely: physical environmental factors, psychological factors, physiological factors, social factors and contextual factors. The latter was included when the authors made a review on window opening, showing how one action can indicate to different drivers. Their descriptions are as follows:

a) Physical environmental: Environmental aspects that lead occupants to act and that have an impact in energy consumption: temperature, humidity, air velocity, noise, illumination and odor.

b) Contextual: factors that do not influence in a direct way, but are determined by the context, such as building insulation, façade orientation and heating system type, for example.

c) Psychological: occupants seek to satisfy their needs regarding thermal comfort, acoustic comfort, health, among other factors. They also have expectations for their environment, such as temperature and indoor environmental quality.

d) Physiological: some factors, such as age, gender, health condition, clothing and activity level are physiological driving forces that can determine the physiological condition of occupants.

e) Social: social driving forces are related to the interaction between the occupants.

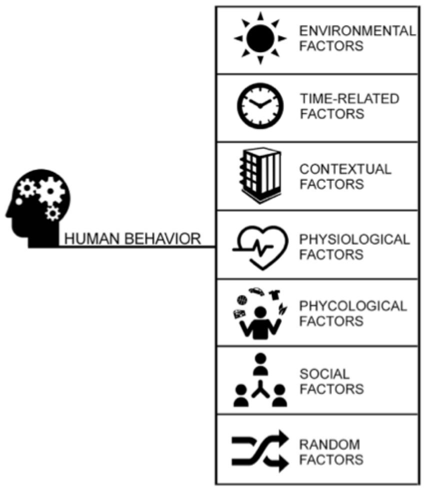

Figure 3: Categories of the factors that influence occupant behavior in building (STAZI; NASPI; D'ORAZIO, 2017a)

All operations taken to improve or maintain adequate thermal comfort levels have an impact and a consequence on the indoor environment. Figure 3 presents a combination of the above-mentioned drivers' categories that can influence occupant behavior. By taking actions, the occupant becomes the central operator who controls the energy consumption and indoor environmental quality in a building (FABI et al., 2012).

2.5.2 Mixed-mode Ventilation

Natural ventilation is a passive strategy that can provide good levels of thermal comfort in buildings. It can offer good air quality while improving thermal comfort by increasing air speed during daytime, ventilation rates during the night and by removing heat from the environment, all without consuming a significant amount of energy. In hot climates, the most common method to maintain adequate levels of thermal comfort is air conditioning, which consumes large amounts of energy, resulting in increased costs and green house emissions (KRAUSSE; COOK; LOMAS, 2007; VANGTOOK; CHIRARATTANANON, 2007). In light of the amount of energy consumed with cooling and mechanical ventilation in commercial buildings, it is critical that such strategies are considered when designing.

Due to an increased concern to improve energy efficiency and the need to pursue a greater use of passive strategies for thermal comfort, new alternatives for design strategies discourage the use of mechanical cooling systems where and when natural ventilation can be used (SALCIDO; RAHEEM; ISSA, 2016). However, studies have shown that when in extreme weather conditions, using only natural ventilation can lead to higher levels of discomfort (BAKER; STANDEVEN, 1996). As a response, a type of hybrid ventilation system, denominated “mixed-mode” has been studied and evaluated during the past years (SALCIDO; RAHEEM; ISSA, 2016). According to Holmes e Hacker (2007), the Mixed-Mode Ventilation (MMV) system is a hybrid ventilation approach to condition the indoor environment using a combination of natural ventilation from windows, that can be either manually or automatically controlled, and mechanical air conditioning that can provide air distribution and cooling when (or where) needed.

There are other kinds of ventilation modes that can be combined with natural ventilation, such as low power fans and passive inlet vents. Whichever choice the designer makes, the main objective is to maximize thermal comfort in the building, while avoiding unnecessary use of energy during the year with mechanical air conditioning (CBE, 2013).

According to the Center of the Built Environment (CBE) at the University of California, there are three types of mixed-mode ventilation buildings, classified as shown in Figure 4. The *concurrent mixed-mode operation* uses natural ventilation and air conditioning in the same space and at the same time; the air conditioning serves as a complement to natural ventilation, and users are free to operate windows based on their preferences. In the *change-over design*, both situations occur in the same space, though at different times; the change-over can happen on a seasonal or daily basis. This design uses one system or the other, and in several cases it involves an automated system that shuts down the air conditioning when windows are open and vice-versa. As for the *zoned system*, it refers to different zones within the same building, each making use of a different cooling system.

The mixed-mode ventilation system is especially significant in hot climates, for example, where it is not possible to solely rely on natural ventilation, and thermal comfort levels are harder to achieve using only passive strategies. Comfort levels are expected to be met to ensure good indoor environmental quality for users. Using only natural ventilation in such climates has been proven insufficient to meet requirements and user satisfaction.

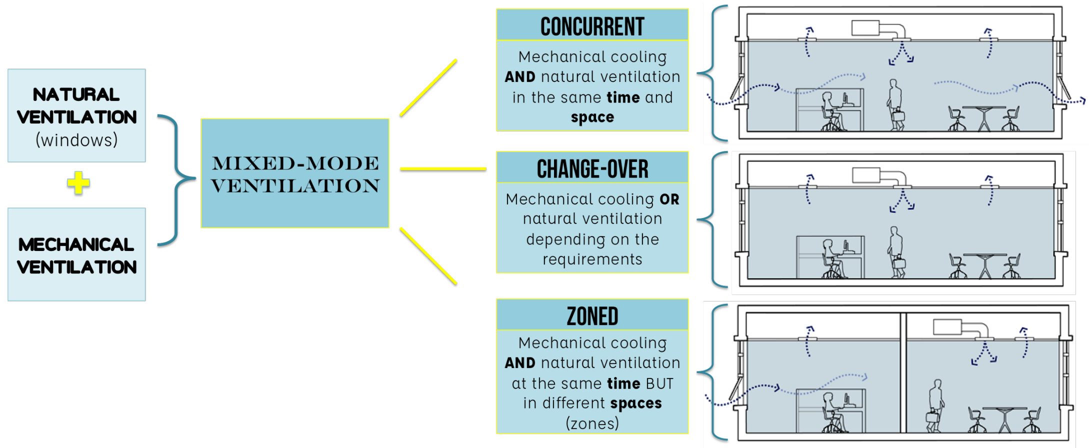

Figure 4: Types of MMV buildings (Adapted from Salcido; Raheem; Issa, 2016 and CBE, 2013)

Therefore, a possible strategy is the combination of natural ventilation and mechanical cooling systems, in a mixed-mode ventilation system (BUONOMANO; SHERMAN, 2009). It is a viable solution to provide cooling, air ventilation, indoor air quality (IAQ) and thermal comfort for the users of a given building (SALCIDO; RAHEEM; ISSA, 2016).

As stated by Salcido, Raheem e Issa (2016), mixed-mode ventilation strategies have been used and shown effective results in energy saving, while still maintaining indoor air quality for occupants. The authors also state that mixed-mode buildings can save up to 40% of HVAC energy when optimizing window operation schedules thus considering such strategy a sustainable way to condition buildings. However, since it is a new subject, there are no complete guides on how to simulate and/or design mixed-mode office buildings.

2.5.3 Computer Simulation

Computer simulation increasingly became more affordable and possible, both to researches and designers, due to the fast progress seen in the computer industry and in computational techniques.

Such tools and techniques are believed to accelerate the design process and optimize building performance at what can be considered a low cost (AUGENBROE, 2002). During the 1990's, there was a considerable growth in the use of computer simulation tools, due to a greater availability both of hardware and software. Personal computers became more affordable in industry and research, leading to a progress in computer simulation in the field of techniques and tools. Today, as stated by Wang and John (2016), building simulation is involved in several stages, such as design, engineering, operation and management of buildings, becoming an integral part of building design and industry.

There are several advantages to the use of simulation tools, with the growing need for energy savings and reduction of environmental impacts, simulation based design is an important tool to achieve such targets.

According to Wang and John (2016), the main goal for developing building simulation techniques and tools is to assist in the creation of a built environment that meets all the existing needs and criteria and presents the least cost with construction and operation, as well as a low amount of resource consumption. One of the greatest advantages to the simulation tools is that they are able to provide quantitative data and thus aid in the decision making process. One of the main reasons why such tools are being promoted and enforced is the increasing number of building performance codes and standards. Therefore, the adoption of simulation tools has been enforced to evaluate a building's performance compliance. As exemplified by Wang and John (2016), ASHRAE 90.1 requires that the whole year building energy simulation results are presented in order to rate the building's energy performance. The Green Building Rating System adopts the same policy. Various governments also demand, and with that accelerate, the use of simulation tools for building design to achieve low energy buildings and to meet their energy and greenhouse gas (GHG) reduction targets (WANG; JOHN, 2016).

Building energy simulation programs are based on a building's basic physical parameters, such as heat transfer, occupant density and operation schedules.They are very precise in simulating deterministic factors influencing buildings' energy balance. However, when representing non-deterministic variables, their accuracy to faithfully represent reality diminishes. Occupant behavior is by nature stochastic, and many times remains neglected when represented in simulation programs because it is accounted for as a fixed presence, such as schedules or deterministic interaction strategies (HALDI et al., 2016). Yan et al. (2015) stated that the adoption of standard schedules to portray occupant behavior is an incorrect way to represent the dynamic human-building interaction. Dar et al. (2015) also state that using 'average behavior can be a major cause of the gap between the actual and predicted energy use of the building'.

This is mainly the reason why energy simulation of buildings offering adaptive opportunities to their occupants present such discrepancies between the simulated and real data. Buildings with the same physical features can show great differences in energy consumption, which can be related to occupancy patterns, users' lifestyle, comfort preferences and interactions with the buildings systems. However, most programs have little consideration of the impact of occupant behavior on energy use (LI et al., 2015).

This situation is true for residential and office buildings. Several studies conducting field survey monitoring indicate a large difference between identical buildings, attributed to differences in occupant behavior. As stated by Haldi et al. (2016), it is necessary to reliably represent occupants within a building, so low-energy free running buildings can be correctly designed and thus avoid contradictions between occupants' freedom and sustainability.

2.5.4 Statistical Methods

A mathematical model of a natural phenomenon is a quantitative description of that phenomenon (TAYLOR; KARLIN, 1994). There are several examples in different subject areas, such as biology and physics, of mathematical models portraying natural phenomenons. In the context of architecture, for instance, a model can provide qualitative information about the relationships between several factors that might influence a given event. Ultimately, a model is judged by its usefulness, and such criterion allows the existence of more than just one model for the same event; that is, there isn't one best model for a given phenomenon (TAYLOR; KARLIN, 1994). Within the realm of models, there are deterministic and the stochastic models. The word deterministic means "certain", and these models are able to predict a single outcome from a given set of circumstances, whereas stochastic models, the word "stochastic" meaning "random", "predict a set of possible outcomes weighted by their likelihoods, or probabilities" (TAYLOR; KARLIN, 1994).

According to Taylor e Karlin (1994), there are three components to scientific modeling: (a) a natural phenomenon being studied; (b) a logical system to deduce the implications about the phenomenon; and (c) a connection that links the elements of the natural systems being studied to the logical system applied to model it. Several methods, bu using the logical system, can be applied to generate stochastic models to be used in simulation programs. According to Schweiker e Wagner (2016), simulating user behavior in a given context of building modeling from an energetic point of view is mostly done by aggregated stochastic models based on logistic regression, Markov chain or similar methods (FABI et al., 2013; HALDI; ROBINSON, 2009; RIJAL et al., 2007; SCHWEIKER; SHUKUYA, 2009). Several authors have used the above-mentioned methods in their studies, (ANDERSEN et al., 2013; CALÌ et al., 2016a) and some have combined such methods to achieve their desired results (JONES et al., 2017; SHI; ZHAO, 2016). The following sections are a brief description of commonly used methods to create such models.

2.5.4.1 Markov Chain

A stochastic process is a random process, which is a collection of random values in a common probability space (BOROVKOV, 2014). It is an abstract notion that describes quantities that happen at random and can be altered with the passing of time (ITÔ, 2006). It is possible to notice in random processes that the outcome of a given trial usually depends on the previous trial. When that outcome is known, there is practically no dependence on the preceding trial, which is known as the Markov property. A random sequence that takes values in a measurable space is a Markov Chain (BOROVKOV, 2014). More specifically, a Markov chain is a collection of random variables that, given the present, past and future states are independent (GAMERMAN; LOPES, 2006). Therefore, a Markovian process is a stochastic process that only considers the previous state to predict the next one, being independent of the process (HALDI; ROBINSON, 2009).

According to Fritsch et al. (1990), a Markovian process does not have a memory, and the prediction of the next state will depend only on the present state and no other. The authors made a first attempt to develop a mathematical model to predict the state of windows by using a discrete-time Markov process model to predict transitions between sets of data of opening angles for four office rooms. Studies that use Markov chain technique, intend to generate synthetic data that can portray the overall statistics of the measured data (RICHARDSON; THOMSON; INFIELD, 2008).

2.5.4.2 Logistic Regression

'Regression is the process of learning relationships between inputs and continuous outputs from example data, which enables predictions for novel inputs' (STULP; SIGAUD, 2015). Regression methods are an integral part of any data analysis that intends to describe the relation between a response variable and one or more explanatory variables (HOSMER; LEMESHOW, 1989).

Logistic regression is a statistical method commonly applied to predict the probability of a binary response variable when explanatory variables are at given values (JAMES et al., 2007). Such method has been used in several studies (HALDI; ROBINSON, 2009; JONES et al., 2017), analyzing user behavior in relation to the opening/closing of windows to describe the probability of a window being open or closed, thus configuring the window's state (HALDI; ROBINSON, 2009; RIJAL; STEVENSON, 2010; SHI; ZHAO, 2016), or alterations to the window's state (ANDERSEN et al., 2013; CALÌ et al., 2016a) with a set of explanatory variables. The relation between the 'correct' probability for the binary response and the several explanatory variables can be described by multivariate logistic regression. The univariate logistic regression expresses the probability function of a certain event occurring, and can be used in the multivariate logistic regression, which describes the probability of an event occurring depending on an explanatory variable (CALÌ et al., 2016). To select the most significant variables and to build a better model, the Akaike Information Criterion (AIC) is commonly applied, where the forward and backwards procedure is used.

2.5.4.3 Akaike Information Criterion (AIC)

According to Burnham e Anderson (2004), AIC is calculated considering the adjustment in the model in comparison to the data set with the amount of variables used in the model. The lowest AIC value must be calculated for the value that best describes the measured data using the least amount of variables. The authors describe that when comparing two models, only the absolute difference between the AIC values must be assessed, and not the absolute values.

Schweiker e Shukuya (2009) state that the formula for this method represents a commitment between the model's precision and complexity. Therefore, the use of AIC is to select the models and not to test a hypothesis. Moreover, AIC is based on the assumption that there is no real model, but a better model that describes the data collected (BURNHAM; ANDERSON, 2004).

2.5.4.4 Gaussian Process

A Gaussian process model is a non-parametric technique that is mainly used in regression problems (YOON; MOON, 2018) and can be defined as a collection of random variables (GRAY; SCHMIDT, 2018). Common to all Gaussian process models is that they assume a 'directional dependency between an input or covariate $\mathbf{x}$ and the corresponding observable output or response y' (KUSS, 2006). It provides good prediction accuracy for regression problems as a data-driven model. According to Davis (2006), 'the class of Gaussian processes is one of the most widely used families of stochastic processes for modeling dependent data observed over time, or space, or time and space.' Its popularity is due to two essential properties; a) A Gaussian process is entirely determined by its mean and covariance functions, making model fitting easier, since only the first and second order moments of the process need to be specified; and b) Solving the prediction problem is uncomplicated, 'the best predictor of a Gaussian process at an unobserved time point or location is a linear function of the observed values and, in many cases, these functions can be computed rather quickly using recursive formulas' (DAVIS, 2006).

Gaussian process regression is a statistical machine learning model that has gained popularity among building modeling researchers only recently, given its ability to 'capture non-linearity with more simplicity than Bayesian models or artificial neural networks' (RASMUSSEN; WILLIAMS, 2006). The Gaussian process was proposed as a replacement for supervised neural networks (MACKAY, 1997), due to its reasonably simple implementation, as well as the small number of parameters to model (YOON; MOON, 2018). In the context of machine learning, Gaussian process refers to its use for Bayesian inference. As stated by (GRAY; SCHMIDT, 2018), Gaussian processes can be used to classify problems where the output is discrete, or even for regression problems, where the output is continuous. The work developed by the authors used Gaussian processes to carry out regression problems, specifically to predict a building's zone temperature and energy consumption over time. As stated by Carpenter, Woodbury e O'Neill (2018), when compared to typical regression analysis, as for example, change-point, which has a predetermined relationship between the dependent variable and the independent variables, a GP model is non linear and relates the dependent variables, that is, y, to the independent variables (x) through a covariance matrix and a mean function. For this regression, the main assumption is that the output data can be seen as a multivariate Gaussian function.

2.5.5 Studies creating stochastic models for occupant behavior based on measured data

Occupant behavior impacts the way energy is consumed in buildings, and has become a growing topic of research, due to the need to investigate the factors that lead and influence actions taken by users. Because it is necessary to reduce energy consumption, there have been numerous studies on occupant behavior, trying to minimize the gap observed between measured and simulated data. Designers, architects, engineers and researchers need to improve the way energy consumption is calculated in buildings, and considering occupant behavior is one way to achieve that. However, this poses a challenge, due to the complexity and dynamic nature of behavior, that can be influenced by internal and/or external, individual and contextual factors. Also, because the data is monitored on site, the models created can be "locally" applied, that is, the scope of applicability of such models can be limited by the location where the measurements took place. This characteristic reinforces the need to create models for different locations and climates, this expanding their applicability.

Several researchers have developed models from measured data as a means to provide more accurate input data on occupant behavior to achieve results showing less discrepancy from the real data when simulating. The main sectors studied have been residential and office buildings, therefore these are presented in the following items.

2.5.5.1 Residential Buildings

Andersen et al. (2013) proposed a model to quantify the influence that environmental factors have on occupants' window opening behavior in residential buildings in Denmark. The study measured 15 apartments from January to August 2008, recording the following indoor environmental factors every 10 minutes: dry bulb temperature, relative humidity, illuminance and CO_2 concentration. The windows were monitored using sensors registering open/closed. The authors used multivariate logistic regression and Akaike Information Criterion (AIC) to create four models, which can be implemented into simulation tools, increasing the validity of the simulation outputs.

Rijal, Humphreys e Nicol (2014) recorded measurements of indoor air temperature and relative humidity in 121 residencies in the Kanto region of Japan for over 3 years. The model was created using logistic regression, and the predicted data matched well the measured one, meaning this model could be used in simulation tools.

Calì et al. (2016a) developed a study with the purpose of analyzing occupant behavior regarding window opening in residencies, in order to investigate the drivers that lead occupants to take action and interact with windows and how such actions can be modeled. The measurements took place in three refurbished buildings in Southern Germany for the period of one year. The variables recorded were air temperature, relative humidity, CO_2 concentration and volatile organic compounds, and the windows were monitored with sensors (open/closed). The statistical method applied in this study was logistic regression, and the authors concluded that the occupants' window opening behavior was driven by activities that remove pollutants from the indoor air. The most common drivers registered for window opening were time of the day and CO_2 concentration, and for closing were daily average outdoor temperature and also time of the day.

In a more recent study, Jones et al. (2017) also developed stochastic models of window opening and closing behavior for UK residencies, using a range of indoor and outdoor factors for different seasons and time of day. The measurements took place in 10 residencies for a period of one year, recording at every 10 minutes data for air temperature and relative humidity. The authors used multivariate logistic regression and AIC to create the models, which, as concluded, can be used in simulation tools.

2.5.5.2 Office Buildings

The work by Fritsch et al. (1990) was the first attempt to create a stochastic model to predict occupant behavior in regards to natural ventilation in office buildings. They performed measurements in 4 offices in the LESO test facility in Switzerland during a heating season (October to May). They recorded the following indoor variables: room temperature, wind speed, radiation and ambient temperature. They found that the outdoor temperature acted as a driver for window opening and closing. Their model was developed using Markov chains to predict window operation, however it is only valid for the winter period.

Later, Nicol (2001) proposed the first coherent probability distribution to predict the state of windows as logit functions for indoor and outdoor temperatures. As stated by the author, this method assumes that the probability of an event happening increases as its stimulus increases, or the intensity of it . The measuring campaigns took place in Pakistan, the United Kingdom and five European countries, from 1993 to 1996. It is observed that in most of the cases, the correlation with indoor temperature is similar to the one with outdoor temperature, and in this study, Nicol recommends the use of outdoor temperature, based on the fact that it is an input in any simulation tool, whereas indoor temperature is an output. However, the author later reported that a more consistent predictor for the use of windows was the indoor and not the outdoor temperature (Nicol; Humphreys, 2004 apud (HALDI; ROBINSON, 2009)).

Rijal et al. (2007) had as their objective the creation of a model to predict the behavior of occupants for a given situation, in relation to window opening, and to incorporate such behavior in the modeling of a building in a computer simulation software to asses the building's performance for energy use and thermal comfort. The study took place in 15 office buildings in the United Kingdom from March 1996 to September 1997. The model considered both indoor and outdoor temperatures, and a multiple logit distribution was derived to predict the probability of a window being opened. Among more specific conclusions, the authors state that when the algorithm is embedded in a simulation software, it provides results otherwise not available when using more conventional methods.

Haldi; Robinson (2009), based on nearly seven years of continuous measurements, investigated the influence of occupancy patterns, indoor temperature and outdoor variables on window opening and closing behavior. The measurements were recorded in office buildings in Switzerland. The authors tried different modeling approaches, such as logistic probability distribution, Markov chains and continuous-time random processes. Combinations of the approaches were tested, and a hybrid model was selected to be implemented in building simulation tools.

Zhang e Barrett (2012) developed a study focusing on investigating the drivers that influence occupants to open windows, as shown by the proportion of windows opened. The measurements took place in an office building in Sheffield, UK, from, January 2005 to April 2006 and recorded variables such as, air temperature, relative humidity and wind speed, among others. Using probit analysis, the authors concluded that window opening behavior has a strong correlation with outdoor air temperature, season, time of day and occupancy pattern.

Study	Location	Units	Variables	Measured Period	Interval	Method
Andersen et al. (2013)	Denmark	15 apts.	Dry bulb temp, RH, Illuminance, CO_2	Jan to Aug 2008	10 min.	Multivariate logistic regression and AIC
Rijal, Humphreys e Nicol (2014)	Kanto region, Japan	121 residencies	indoor air temp and RH	3 years (2010-2013)	10 min.	Logistic Regression
Calì et al. (2016a)	Germany	60 apts.	air temp, RH, CO_2, volatile organic compounds	1 year (2012)	1 min.	Logistic regression
Jones et al. (2017)	UK	10 residencies	air temp, RH,	1 year	10 min.	multivariate logistic regression and AIC
Fritsch et al. (1990)	Switzerland	4 offices (LESO)	room temp, wind speed, radiation, ambient temp.	Heating season (Oct. to May)	30 min.	Markov Chain
Nicol (2001)	Pakistan, UK, Europe	25 buildings (existing database)	air and globe temp., humidity, air speed	1993 to 1996	Not specified	Logit function
Rijal et al. (2007)	UK	15 office buildings	Temperature (and others, not specified)	Mar 1996 to Sep 1997		Multiple logit distribution
Haldi e Robinson (2009)	Lausanne, Switzerland	Office buildings	Occupancy, indoor and outdoor temp.	7 years	Continuously	Markov Chains and continuous-time random processes
Zhang e Barrett (2012)	Sheffield, UK	Office building	Air temp, RH, wind speed (outdoor)	Jan 2005 to Apr 2006	Hourly	Probit analysis

Table 2: Summary of studies creating stochastic models

2.5.6 Conclusion

Numerous other studies have been developed in the field, mainly focusing on residential and office buildings, although there are studies on commercial and educational buildings as well. Delzendeh et al. (2017) performed a review of research articles focusing on the impact of occupants on building energy analysis, and concluded, among other findings, that: the parameters that influence occupant behavior need a more multi-disciplinary approach to better combine the effects of the different areas that affect occupant behavior, and; that although there are detailed methodologies being applied, there is still a need to better translate and integrate the findings from the studies into the existing simulation tools, presenting a challenge to researchers in this area.

2.6 Method

The study of occupant behavior is challenging, due to the fact that each occupant may react in a different manner to the same situation. This is a factor that causes discrepancy between measured and simulated data on energy consumption, emphasizing the need for more field studies, in an effort to collect data on occupant behavior and provide more precise input data for simulations. Several studies have been conducted focusing on occupant behavior and their impact on the indoor environment, with special attention being given to the actions taken by users to control their environment to regain or achieve thermal comfort. This research proposes a method to create an algorithm to be implemented in computer simulation programs that better represent occupant behavior, in relation to window opening and AC activation, in mixed-mode office buildings. The method for the research being conducted was developed following the guidelines provided by Shipworth e Huebner (2018). It is composed of two initial stages entitled *Development of Theoretical Model* and *Definition of Units of analysis, population and scope*, to establish the research's model to be built and its applicability. The main body of the method is divided into four main steps: (a) buildings' data collection and pre-test; (b) in situ measurements and data analysis; (c) statistical methods' application and creation of algorithm; (d) algorithm's validation and tests.

2.6.1 Development of Theoretical Model

The main objective of the research is to create an algorithm to predict occupant behavior in relation to window opening/closing and AC activation/deactivation in mixed-mode office buildings. One of the objectives to be achieved during the process, is establishing relationships between the variables being monitored, that is, the exterior environment, the building (interior environment), occupant behavior and energy consumption. When studying occupants in buildings, relevant concepts include temperature, comfort, glare, productivity and adaptive response (SHIPWORTH; HUEBNER, 2018). Such concepts can be used to build a theoretical model of how occupants react and respond to their physical environment.

It can be useful to make a distinction between concepts and constructs, the one proposed by Markus (2008) defines concepts as the comprehension of all real and possible occasions in a set of experiences in reality, and constructs as the occurrences of such in a given population. Both can be considered the same thing when inserted in the same population however, the distinction becomes relevant in international comparative work, where concepts can transfer between populations, and constructs cannot (SHIPWORTH; HUEBNER, 2018). In the area of occupant behavior, the distinction becomes especially relevant due to the fact that this is a highly international area, and researchers can measure the same concepts, but knowing how they are constructed and conducted demands taking into consideration the differences in climate and culture. With the constructs being well distinguished from the concepts, the process of determining how to measure such constructs begins, which is further detailed in Pre-test (Item 2.6.3).

To aid in further specifying the relationships between the concepts being studied, it is important to establish questions, such as; (a) what triggers occupants to open/close windows and/or activate/deactivate AC?; (b) Do occupants open/close and/or activate AC more frequently as indoor (or outdoor) temperature rises?; and (c) How differently do occupants respond to environmental changes during each season and in between seasons (transition periods)? From such questions, hypothesis can be drawn, as for example, as outdoor temperature rises, so does the indoor temperature and the probability of occupants closing windows and activating the AC is higher. To assist the researcher in establishing such connections, Shipworth and Huebner (2018) suggest identifying the concepts to be measured and how they link to each other. This is further assisted by the use of a graphical representation, creating a map that leads to the theoretical model. Figure 5 represents the theoretical model for the research in question, establishing links from the concepts intended to be measured to the actions taken by the users according to the conditions created by such measurands, and finally leading to energy use and/or thermal comfort in a mixed-mode office building scenario.

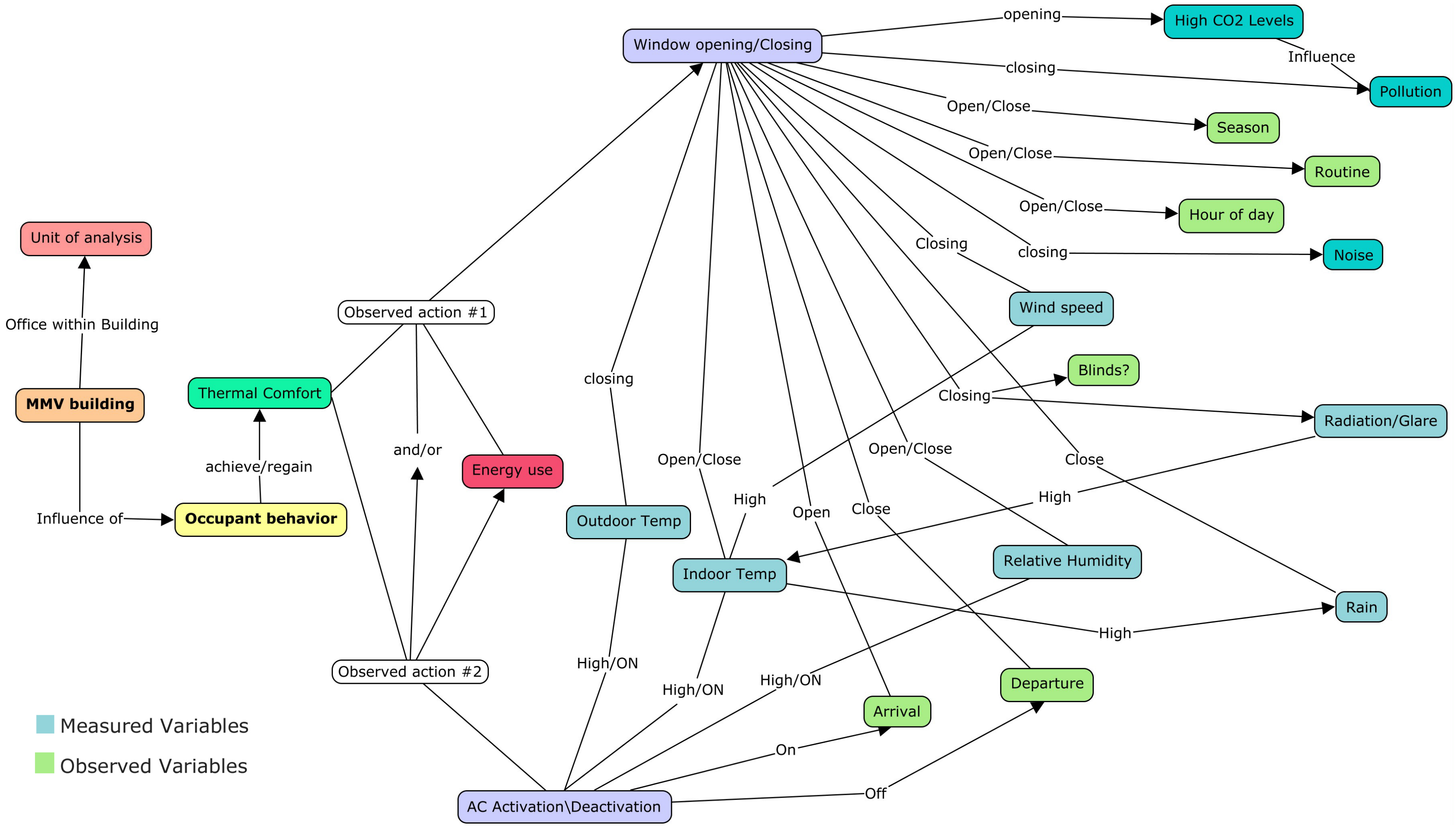

Figure 5: Graphical representation of the relationships between concepts.

2.6.2 Units of analysis, population and scope

Once the theoretical model is established, it is then necessary to define the scope of its applicability, which requires a statement of the population of interest to which the findings will apply (SHIPWORTH; HUEBNER, 2018). The population of interest can be expressed as the unit of analysis that the model intends to represent, and what the data is being collected about. In the context of this study, the unit of analysis is the mixed-mode office, which can be studied within a multistory building or a house, as long as it meets the defined criteria (3). Because the mixed-mode office is the unit of analysis in this study, the population of interest and scope's definition are also related to it. In regards to the population of interest, the samples drawn for the study are taken from a population of buildings found in the selected city for the study, São Carlos, in the state of São Paulo, Brazil. As for the temporal scope, the study will be conducted during an entire year, that is, it will encompass all four seasons. Therefore, the findings of this study will be restricted to mixed-mode offices in a high-altitude tropical climate for summer, spring, winter and fall.

2.6.3 (a) Buildings' data collection and Pre-test

Buildings' data collection: Sampling

As stated by Shipworth e Huebner (2018), there is a wide range of sampling strategies that can be used. The "gold standard", as the authors name it, is pure random sampling. However, it is not always possible to attain the ideal case, and other sampling strategies can be applied. In this study, a *purposive sampling* was used, in which "population members are recruited based on certain characteristics considered useful to the study" (SHIPWORTH; HUEBNER, 2018).

In this work, the population members can be understood as the mixed-mode offices in the city of São Carlos, SP. A data collection was performed to create a database with potential multistory buildings and houses, where the rooms were adapted to become offices, that would meet the criteria and provide the necessary type of offices to be studied. The initial data collection was performed using the work of Carrières (2007), which listed office buildings in the city of São Carlos, SP. From this starting point, the main criteria for this study was established, that is, a range for the floor area (30m^2 to 50m^2), and the existence of operable windows and air conditioning unit. As for the control of the operable windows and the AC, the criteria was that users were free to operare either, and there were no automation systems nor any indication that could inform the user's decision as to which action to take. Therefore, When analyzing the data collection made by Carrières (2007), some buildings were excluded for not meeting the above-mentioned criteria. With the remaining buildings, the specific criteria for this study was created, as shown in Table 3.

The specific criteria guaranteed the presence of operable windows as well as an AC

Questions	Expected Answers
Is there an AC unit?	Yes
Are there operable windows?	Yes
Does the user stay all day?	Yes
Does the user operate the window(s)?	Yes
Are the windows unobstructed?	Yes
Type of office	Not medical
Activity	Sedentary
Main equipment	Computers and printers
Number of occupants	1 - 5

Table 3: Specific criteria for building selection

unit in each office. The operable windows had to be unobstructed and operated by users, therefore they were asked if they alternated using windows and the AC unit. Although some offices did have unobstructed windows, the users reported that such windows were never used, only the AC unit, and such units were not included in this study. As for presence, the criteria questioned if the users remained all day in the office, that is, if the users occupied the office during most of the reported working hours, from 9am to 12pm and from 2pm to 6pm. Because there was no equipment to monitor presence, units where users did not remain for the most part of the commonly reported working hours, were also excluded from the database.

The common activity performed in the selected offices was sedentary and mainly using a computer. Medical offices and alike were excluded, due to the difference in activities performed, fluctuation on the number of users during the day and difference in equipment. The offices selected only use computers and printers, which account for a specific load that can be estimated when simulating. The number of occupants varied from 1 to 5, given the difficulty to select all offices with the same amount of occupants. The number of occupants in each office can influence the way users behave, and this will have to be taken into consideration when building the model. Another factor that will have to be accounted for when creating the algorithm is the way the sampling was conducted. Because it could not be performed using the "golden standard", it might have an influence in the algorithm's performance.

Pre-test

The pre-test was designed as a prior step to the actual monitoring campaign, with the objectives of (a) determining how best to measure the selected constructs (operationalizing constructs (SHIPWORTH; HUEBNER, 2018)) and; (b) testing the selected equipment (Table 4) and learning how to set up each one of them. The location for the equipment was also tested, and details, such as positioning on the window, type of tape to use and how to fix the equipment on the AC unit were all verified and tested, so there were as few errors as possible during the measuring periods. The software for each equipment was also verified and updated, and all the cables for downloading and uploading data were verified and tested. The pre-test also allowed to test for equipment malfunction, thus contributing to minimizing errors during the measuring campaign period. The variables monitored by each equipment are further detailed in Item 2.6.4 on Table 6.

Quantity	**Equipment**	**Variable**	**Model**	**Brand**
03	Air Temp. + RH	AC monitoring	HOBO H08-003-02	Onset
03	Air Temp. + RH	Indoor environment	175H1	Testo
03	State data logger	Window monitoring	HOBO UX90-001	Onset

Table 4: Equipment for measuring indoor variables

The temporal sampling established in the pre-test to measure indoor temperature and relative humidity was set at a 10-minute intervals, based on previous studies (ANDERSEN et al., 2013; JONES et al., 2017; RIJAL; HUMPHREYS; NICOL, 2014). The AC temperature was initially also set at a 10-minute interval, then tested at 5-minute intervals. The 10-minute interval was then established, since the temperature difference recorded between the 5-minute intervals was not significantly different from the ones recorded on the 10-minute interval trial. Also, because the other indoor variables being monitored were established at 10-minute intervals, standardizing all intervals was best for posterior data treatment.

The windows were not monitored based on time intervals; a state logger was used to record the changes in state. The equipment continually logged every event (date and time) when there was a change in state. The pre-test allowed a better comprehension of how sensitive this equipment is to displacement. The state logger is composed of a sensor and a magnet; when the sensor is close to the magnet, it records as closed, and when it is away from the magnet, as open. The office room where the pre-test was conducted had top-hung windows, and the sensor was attached to the fixed window frame with a velcro band, while the magnet was attached to the movable part with a tape (Figure 6a). The data from the pre-test showed that the windows remained open the entire time, while the users reported that the common routine was that they opened the windows upon arrival, closed when using the AC and always closed at departure. It was possible to conclude that the sensor displaced by very little, and thus the minimal distance between the sensor and the magnet affected the recording of the closed periods, showing as always open. These details were all taken into consideration and attended to when the measuring campaign began, to minimize errors.

The positioning of the equipment on the AC was done by attaching the equipment on the AC's flap using a plastic clamp (Figure 6b), and the equipment monitoring the indoor air temperature and relative humidity was positioned away from heat sources (windows and computers) at approximately 1.6m high (Figure 6c). Figure 7 shows the floor plan of the office monitored during the pre-test, the equipment location within the unit and number of occupants. Figure 8 shows the location of the monitored building and the meteorological station. The approximate distance between the two locations is of 5Km.

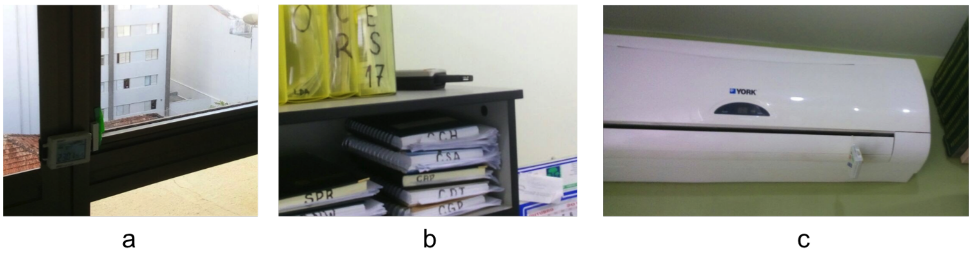

Figure 6: Equipment positioning in monitored office

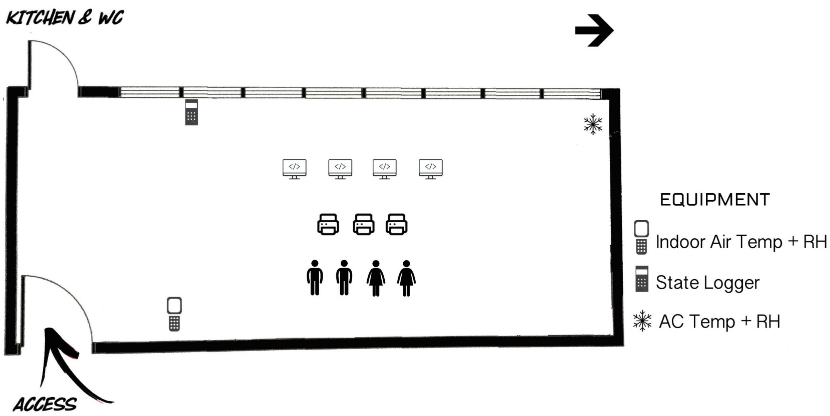

Figure 7: Floor plan of monitored office. No scale.

Figure 8: Location of monitored building and meteorological Station. Google Maps. No scale.

2.6.4 (b) In situ measurements and Data Analysis

A descriptive, or correlational design, is the basis of studies on the impact of occupant behavior in building energy consumption. It is when data is gathered using sensors, be they installed or virtual, or if the data are gathered for other purposes and possibly enriched with paper or electronically surveys, by use of smart-phones or computers (SHIPWORTH; HUEBNER, 2018). Once the data are collected, they are analyzed in search of correlations between the variables. This type of study allows researchers to understand the relationships in the data, but not state that a change in one variable is the cause for a change in another. It is common to relate, for example, window opening behavior to high indoor temperature, or to control the indoor air quality. However, as described by Fabi et al. (2012), there are different types of driving factors, which can be alternative reasons for users to take actions, such as hour of day, routine, lifestyle or safety, to name a few.

There are many descriptive research designs; the one adopted for this specific work was the cross-sectional design. As described by Shipworth and Huebner (2018), this design is one that collects data at a specific point in time covering a range of units of analysis, such as occupants and buildings, for example. This type of design can be conducted once or several times at different moments, thus creating a repeat cross-sectional design. This design differs from the longitudinal survey in the sense that in the latter, the same people are measured repeatedly through time, as opposed to the cross-sectional, where a new representative sample from the population is generated each time the survey is conducted.

In Situ Measurements

The measuring campaign for this study is scheduled to last 12 months, from November/2017 to October/2018. The intention is to measure during all four seasons, thus broadening its applicability scope. As for the location of the study, measurements are being conducted in the city of São Carlos, in the state of São Paulo, Brazil (Figure 9). According to the Koppen climate classification, São Carlos is a city of a high-altitude tropical climate, located at latitude 22°02' South at 863 meters (Cwa, for the Koppen classification; (CEPAGRI, 2018)), characterized by a generally non-rigorous dry winter and moderately rainy and hot summer.

According to the Brazilian Standard 15 220-3 (ABNT, 2005), Brazil is divided into eight bioclimatic zones, and São Carlos is located in Zone 04, representing an intermediate climate. Table 5 presents specific monthly characteristics for the city of São Carlos regarding dry bulb temperature, relative humidity and wind speed using the weather data provided by Roriz (2012).

Because there were no equipment to monitor presence, during the Pre-test, users informed their working hours and reported when unusual activities or occupancy occurred.

Figure 9: Brazilian national territory and São Carlos' location within the state of São Paulo.

Month	DBT (°C)	RH (%)	Wind Speed (m/s)
January	21	79	2
February	22	77	2
March	21	75	2
April	20	78	1
May	17	73	1
June	17	74	2
July	17	54	2
August	19	59	2
September	19	59	2
October	22	67	2
November	22	70	2
December	21	73	2

Table 5: Climatic characteristics for São Carlos, SP. Adapted from *Climate Consultant*.

This policy was also established for the remainder of the measuring period. If and when there are any unusual activities or if a user works during the weekend or after hours, for example, one of the occupants was designated as a point of contact in each office to report such occasions to be included in the data collection. If there are no uncommon activities, it is assumed that the occupied period is from Monday to Friday, from 9 am to 12 pm and from 2 pm to 6 pm. The measurements' schedule was designed intentionally avoiding national holidays, as to minimize the gaps in the data collection.

Because all the equipment and measuring intervals were previously tested, as stated in Pre-test (Item 2.6.3), the variables being measured in this study were established and are listed in Table 6 with their respective units.

These variables were selected based on other field studies in the literature (RIJAL; HUMPHREYS; NICOL, 2014; HALDI; ROBINSON, 2009; ZHANG; BARRETT, 2012).

The variables that show greater influence on occupants' actions, are indoor and outdoor temperatures and relative humidity, and therefore are always monitored. This study followed this pattern, not including wind speed and CO_2, variables that are also recurring but not included in all studies. Neves et al. (2018) performed a field monitoring in São Paulo, SP, Brazil, and reported very low wind speed rates even when windows were open (maximum registered value of 0.17 m/s). From the observations during this study, the authors concluded that such low values were a consequence of the offices being unilaterally ventilated, as is the case of the monitored offices in the present research. Vecchi et al. (2017) reported very similar results when performing a study for the same type of building in Florianópolis, Brazil. Also, Haldi e Robinson (2009) stated that window operation was correlated with outdoor air temperature, and not wind speed.

As for the CO_2 monitoring, it is mostly monitored in residencies (ANDERSEN et al., 2013; CALÌ et al., 2016a), since its levels can be higher within this type of building due to the activities performed in it, such as cooking, for instance. The higher levels of CO_2 occasioned by the activities associated with the type of building can be a driver to occupants taking actions, which may not be the case in offices. Also, because this study focuses on mixed-mode buildings with a maximum of five occupants in each unit, it is unlikely that CO_2 levels become high enough to trigger a response in users.

The outdoor variables were taken from a meteorological station in the city of São Carlos, with a maximum distance of 7 Km from the measured buildings, except for one unit that is more distant from the perimeter containing most buildings (Figure 10). This building is approximately 10 Km away from the meteorological station.

Variables	**Units**
Indoor	
Temperature	°C
Relative Humidity	%
Window opening	-
AC Activation	°C
Outdoor [1]	
Temperature	°C
Global Solar Radiation (vertical)	kJ/m^2
Air speed	m/s
Relative Humidity	%
Rainfall Index	mm

[1] Hourly measurements at Meteorological station A711 OMM Code: 86845 (www.inmet.gov.br/sonabra)

Table 6: Measured Indoor and Outdoor Variables

The study targeted to measure a total of 10 units in each period, repeating the measurements in the same 10 units during each designated period, though occupants in these offices may not be the same at all times. There is the possibility that the monitored

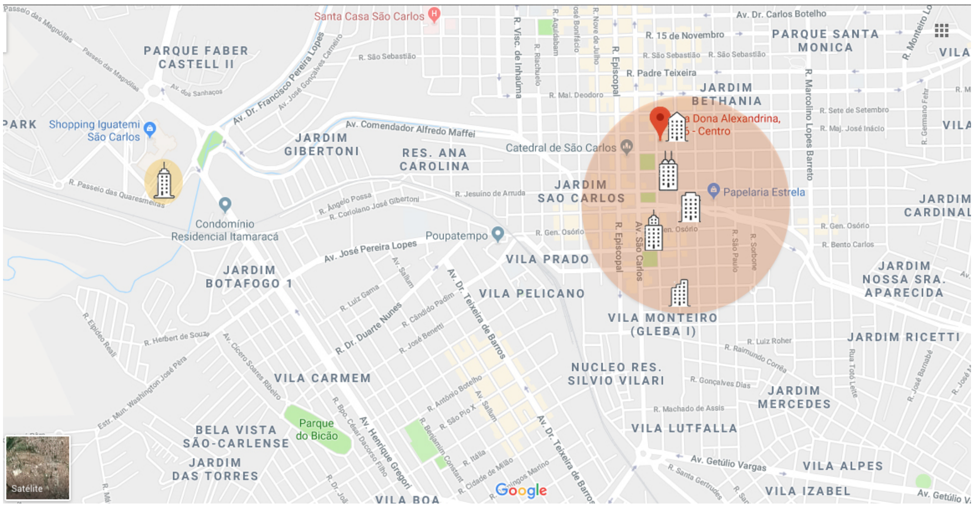

Figure 10: Monitored buildings' location within the city of São Carlos, SP. Google Maps.

offices are also not the same. If one or more units become unavailable during one of the monitoring periods, other offices will be included and the total amount of 10 units will be maintained. For the summer period, a total of 6 buildings was selected, and in some of the buildings more than one unit was monitored. Table 7 lists all the buildings, with the amount of units measured in each one and their locations.

Number of units	Building's Name	Address
02	Bandeirantes	R. Conde do Pinhal, 2185
01	Rotary Club	R. Conde do Pinhal, 2265
01	Luciano Zanollo	R.D. Alexandrina, 966
02	House	R. José Rodrigues Sampaio, 47
03	Racz Center	Av. São Carlos, 2205
01	Tríade	Passeio dos Flamboyants, 60

Table 7: Buildings locations and amount of units measured within them.

Some of the measured variables record at different time intervals than others, due to the specifications of each equipment. The window state logger and the meteorological station record variables at different time intervals than the other equipment being used. Because of this difference, some data are treated so that the entire set follows the established 10-minute interval.

Window opening and AC activation are the two main actions being monitored and observed in this study. The equipment recording window opening and closing is a state logger that registers when one of these events occur. As established in the Pre-test section, this equipment was not programmed to measure at given time intervals, but rather when there was a change in state. The equipment is binary and programmed to register an opening event as zero (0) and a closing event as one (1). When reading the collected data, the interpretation for such is that when there is a date and time with a given event, zero for example, it is understood that the window was opened, and that state only changes when the next entry records it. Consequently, the next state will read one (1) and that is read as closed, and so on for the entire monitored period. Because the other indoor variables are being monitored at 10-minute intervals, the window state data has to be treated to fill the 10-minute interval rows respective to the readings on the other equipment, as shown in Figure 11, so it shows the entire period when the window remained open or close.

Entry #	Date	Time	State
1	3/28/18	03h0min0s	0
2	3/29/18	05h53min3s	1
3	4/2/18	07h49min55s	0
4	4/2/18	02h0min16s	1
5	4/2/18	05h44min32s	0
6	4/2/18	05h44min41s	1
7	4/3/18	07h40min19s	0
8	4/3/18	01h20min32s	1
9	4/3/18	03h32min55s	0
10	4/3/18	05h52min39s	1
11	4/4/18	08h20min7s	0
12	4/5/18	07h47min0s	1

log#	DATE	TIME	Window State	%rH	°C	AC Temp °C	AC RH %
1	28/03/2018	15:00:00	0	44.9	27.2	26.73	38.1
2	28/03/2018	15:10:00	0	44.4	27.2	26.73	38.2
3	28/03/2018	15:20:00	0	44.8	27.1	26.73	37.8
4	28/03/2018	15:30:00	0	44.3	27	26.73	38.1
5	28/03/2018	15:40:00	0	44.7	27	26.73	38.1
6	28/03/2018	15:50:00	0	45.2	27	26.73	38.2
7	28/03/2018	16:00:00	0	44.2	27.1	26.73	37.7
160	29/03/2018	17:30:00	0	54.3	27.1	26.73	47
161	29/03/2018	17:40:00	0	54.6	27.1	26.73	47.8
162	29/03/2018	17:50:00	1	55.1	27.1	26.73	48.2
163	29/03/2018	18:00:00	1	55.1	27.1	26.73	48
164	29/03/2018	18:10:00	1	53.5	27	26.73	48.2
165	29/03/2018	18:20:00	1	49.8	26.9	26.73	47.7
166	29/03/2018	18:30:00	1	48.3	26.8	26.34	46.1
167	29/03/2018	18:40:00	1	47.2	26.7	26.34	45.8
168	29/03/2018	18:50:00	1	47.6	26.6	26.34	45.5
169	29/03/2018	19:00:00	1	47.2	26.6	26.34	44.8
170	29/03/2018	19:10:00	1	48.1	26.6	26.34	41.8
171	29/03/2018	19:20:00	1	50.1	26.7	26.34	43.3
172	29/03/2018	19:30:00	1	51.7	26.7	26.34	44.2
173	29/03/2018	19:40:00	1	54.8	26.7	26.34	46.7
174	29/03/2018	19:50:00	1	58.5	26.5	26.34	50.2
175	29/03/2018	20:00:00	1	59.9	26.5	26.34	51.9

Figure 11: Data treatment: Adapting to different intervals

The equipment registering the AC temperature follows the 10-minute interval specified in the Pre-test. Although there is no need to treat these data to fit the required interval, it is necessary to establish a guideline for its interpretation. Because the equipment registers temperature and not the date and time when the AC unit was activated or deactivated, it is necessary to analyze the data set for the measured period and identify when temperature drops occurred, thus indicating AC activation.

Figure 12 depicts an excerpt from the spreadsheet with the data collected from one of the monitored units. The portion highlighted in blue shows when the temperature is stable and close to the indoor temperature recorded, and thus interpreted as Air Conditioning Deactivated (AC/OFF). When the temperature begins to drop and oscillate within lower values (darker gray highlighted portion), it can be read as Air Conditioning Activated (AC/ON). And when there is an increase in temperature and it begins to stabilize again (lighter gray highlight), one can interpret it as the AC/OFF again, with stable temperature readings in the blue portion. It can also be seen that the AC was activated during some of the warmest hours of the day, given it is a set of data taken from the readings from the end of November, which is very close to summer and already with high temperatures. It is also possible to see that the AC was deactivated at the end of the day, possibly when the users (or the last user) left the office.

Because there is a large amount of data, it is not viable to identify such periods only by looking at the collected data on spreadsheets. In an effort to identify the occurrence of

Date	Time	Temp (˚C)	RH (%)
11/28/17 14:35:00.0	25.17	32.5
11/28/17 14:45:00.0	25.17	31.6
11/28/17 14:55:00.0	25.17	31.3
11/28/17 15:05:00.0	25.17	31
11/28/17 15:15:00.0	25.17	30.6
11/28/17 15:25:00.0	24.4	30.5
11/28/17 15:35:00.0	23.63	39
11/28/17 15:45:00.0	25.56	33
11/28/17 15:55:00.0	21.33	51.6
11/28/17 16:05:00.0	21.71	31.1
11/28/17 16:15:00.0	22.48	51.5
11/28/17 16:25:00.0	18.28	57
11/28/17 16:35:00.0	20.57	38.2
11/28/17 16:45:00.0	22.48	53.5
11/28/17 16:55:00.0	16.76	49.6
11/28/17 17:05:00.0	15.62	59.6
11/28/17 17:15:00.0	17.14	54
11/28/17 17:25:00.0	15.23	55.1
11/28/17 17:35:00.0	17.52	51.8
11/28/17 17:45:00.0	15.23	53
11/28/17 17:55:00.0	17.14	56.3
11/28/17 18:05:00.0	15.23	55.5
11/28/17 18:15:00.0	16.76	52.7
11/28/17 18:25:00.0	17.9	78.5
11/28/17 18:35:00.0	16.38	51.5
11/28/17 18:45:00.0	17.9	56.1
11/28/17 18:55:00.0	16.38	54.4
11/28/17 19:05:00.0	21.71	60.8
11/28/17 19:15:00.0	24.79	45.8
11/28/17 19:25:00.0	25.17	42.3
11/28/17 19:35:00.0	25.56	42.9
11/28/17 19:45:00.0	25.56	41.7
11/28/17 19:55:00.0	25.56	41.9
11/28/17 20:05:00.0	25.56	42.2
11/28/17 20:15:00.0	25.56	41.5
11/28/17 20:25:00.0	25.56	41.9

Figure 12: Excerpt from Air Conditioning spreadsheet data

the above-mentioned situation and the periods when the AC remained ON or OFF, the following equation was applied to the data set pertaining AC entries:

$$(T_n - T(n-1))/10 \tag{2.1}$$

Where T_n is the n^{th} temperature in a set of temperatures, regarding the equipment positioned on the AC flap, divided by 10 (given the established 10-minute interval). If the module of this value is greater than 0.3, it means that the AC was operated. It is important to highlight that this procedure identifies when the AC was operated, and not necessarily activated. That is, in most cases, when the AC was operated was to activate it, according to the cross referencing of the data. However, there are cases that indicate operation within the period when the AC is already activated, and those are read as solely operation and not activation.

As for the outdoor variables, the meteorological station is set by the National Meteorology Institute (INMET), and provides the hourly values for each variable. For some of them, such as temperature and relative humidity, the equipment records an instantaneous measurement for each hour, for example at 9:00, and several measurements within that given hour, the amount varying depending on the equipment being used. The data provided by the institute for each variable are then, the instantaneous value, the maximum and the minimum. Once again, these data need to be treated to be used in this study, because of the established time interval for the remaining variables. The criteria applied to this was to use the instantaneous value and linearly decrease or increase it (at 10-minute intervals) to match the next hour's instantaneous value, thus providing the same measuring interval as the other variables being recorded in the study.

Data Analysis

The data collection is divided into four main measuring periods, corresponding to each season. Two transition periods are scheduled to be monitored; from summer to fall (May) and from winter to spring (August). During the 12-month measuring period, when a data subset is collected, one entire season, for example, a preliminary data analysis will be conducted on such subset. The objective of this preliminary analysis of each data set is to identify which of the measured and observed variables are influencing occupant behavior, related to window opening and AC activation, and possibly how they are influencing it. By analyzing the data, the intention is to relate the driving factors identified in the Literature Review to the actions being studied in this research.

The first step to this analysis is to characterize each of the monitored offices, describing its key features as listed on Table 8, as well as presenting their respective floor plans. To aid in this analysis, a graph combining indoor, outdoor and AC temperatures, and window opening/closing periods is presented for each room. In addition, histograms portraying the frequency of window opening and AC activation by indoor temperature and hour of day are also presented.

By combining the information from the room's characterization and the graphs, it is possible to create a general overview of how each of the measured rooms perform differently and how users respond to the building's characteristics, in combination with their personal preferences and routine. The following step on the data analysis is to consider how the observed factors (those not measured), such as unobstructed view and privacy, can influence occupant behavior related to window opening and AC activation. The graphs aid in the analysis of the measured variables and enables further analysis, allowing to infer

Items observed for office characterization
Number of windows
Number of occupants
Type of window
Blinds
External/Internal wall
View
AC position
Window facade facing N,S,E,W
Unilateral or Cross ventilation
Office's area
Multistory Buildings (and storey) or House

Table 8: Office rooms' characterization items

how routine and hour of day, for example, influence users' actions. The factors that are not monitored nor observed, will be taken into account when the measuring campaign is over.

Once the 12-month period finishes, questionnaires will be applied in an effort to better understand occupants' behavior. The objective of the questionnaires is to obtain information that can further explain behaviors observed in the collected data that are not following patterns (reacting to indoor or outdoor temperature, for example), and cannot be explained by the observed variables either. Inactions, such as not activating the AC when indoor and/or outdoor temperatures are high, cannot be explained by solely analyzing the collected data, hence the use of questionnaires post measuring period. The following questions are options to be included in the questionnaire, and user's can rate each given option with 0 (not influential), 1 (somewhat influential), 2 (influential) and 3 (highly influential).

How influential are the following items on your decision to:				
	Open Window	Close Window	Activate AC	Deactivate AC
Noise				
Pollution				
Odour				
Glare (blinds up)				
Window position				
AC position				
Wind speed				
Health				

Table 9: Possible questionnaire to be applied post-monitoring period

By analyzing the data subsets during the 12-month period, it is possible to better understand the common driving factors among most users during each season, as well as to identify the different behaviors that users may show that can affect energy consumption.

Also, the analysis enables the identification of different actions under similar circumstances, portraying different user profiles.

The characterization of each office room combined with the analysis of occupants' behavior and the collected data, allows some suggestions to improve the spaces. For instance, it enables to identify if an office could benefit from a different envelope material, or if the AC unit seems insufficient for the room, or even if nocturnal ventilation is recommended. All of which can also be explanations for some of the observed behaviors.

The data analysis of each period and identifying the factors the most influence or drive users to certain actions will provide a better understanding of the complete data set once the measuring campaign ends. The data analysis conducted on the subsets will provide insight to the actions presenting a higher probability of leading to window opening or AC activation, which can be helpful when analyzing the entire data set.

2.6.5 (c) Statistical Methods' Application and Creation of algorithm

The definition of the statistical method, or a combination of them, to be applied to create the algorithm, can only be defined once the data set is complete. Because the data is still being collected, several methods that are commonly used in this type of study have been presented in the Literature Review (item 2.5.4) as viable options for this research.

2.6.6 (d) Algorithm's validation and test

Validation

Validation and verification are procedures employed to determine a realistic and confidence expectations (YAN et al., 2018). For this research area, specifically, Yan et al. (2015) describe that validation can include a careful collection and preparation of sufficient and representative data, and a systematic separation of subsets to (a) generate a model and (b) to evaluate the model and generate a clear discussion of its limitations based on statistical significance and application.

The validation method applied to each study can vary according to the model obtained after applying the selected statistical method. Because the model in this study has not yet been created, the preliminary validation method selected is a comparison between the observed (in situ measurements) and simulated data, regarding window opening and AC activation, as employed in previous similar studies (FABI; ANDERSEN; CORGNATI, 2015).

For this comparison, two simulations will be run on EnergyPlus using a mixed-mode office and the same input data, except for occupant behavior. The output data will be energy consumption for both runs. A specific scenario will be chosen, where details such as season, number of occupants and occupation schedule, for example, will be set and kept for both. *Simulation (a)* will use the measured occupant behavior data as input, and *Simulation (b)* will use the algorithm. Because the output data selected will be the same, it will possible to compare the results and assess the algorithm's accuracy in identifying the most probable actions taken by users given the set of variables considered and how that impacts energy consumption as opposed to the actual measured data.

EnergyPlus

EnergyPlus is an open source program that models heating, ventilation, cooling, lighting, water use and renewable energy generation among other building energy flows it is supported by the Department of Energy (DOE) of the United States and validated by ASHRAE. The program includes some capabilities that can be considered innovative, such as sub-hourly time-steps, natural ventilation and thermal comfort.

It is a reliable program, since its heat balance approach has the potential to be the most accurate method to solve the heating and cooling loads, because it accounts for all energy flows in their most fundamental form and does not make simplifications to its solution technique (WANG; JOHN, 2016). Interfaces and modules were created to make the program easier to use in engineering.

Test

Once the algorithm is validated and its reliability established, a test will be conducted to use the algorithm to study the impact of different users within the same scenario. As stated by Shi e Zhao (2016), user behavior can vary from one country to another.

The test will be divided into four distinct simulations, all using the same mixed-mode office model and the same constructive materials of a standard mixed-mode office, as the ones where the data collection took place. The model and its constructive characteristics will be maintained the same in all simulations. The input data that will vary in this test will be the weather files and the algorithms for user behavior. The weather files to be used as input data will be from; (a) São Carlos, SP, Brazil and; (b) City to be determined. The algorithms will be; (a) Brazilian user behavior developed in this study and; (b) Foreign user behavior (matching the country from which the weather file will be used). Table 10 lists the data combinations configured to enable comparing the results and relate them to energy consumption in mixed-mode office buildings.

Simulation #	**Weather file**	**Algorithm**	**Mixed-mode office**
1	São Carlos, SP	BR Algorithm	Kept the same for all simulations
2	São Carlos, SP	Foreign Algorithm	
3	To be determined	BR Algorithm	
4	To be determined	Foreign Algorithm	

Table 10: Input data combination for EnergyPlus simulations

The output data from simulations 1 and 4 will be the basis for comparison for simulations 2 and 3, respectively. This test intends to observe the different impacts that users from different countries can have in the same building. That is, the foreign occupant behavior will be analyzed within a Brazilian climate context and vice versa.

2.7 Partial Results

The observations made in this section pertain a period of summer, from November/2017 to March/2018 and one week measured in April, which could be considered a transition period, though temperatures during the day were still high. Table 11 lists the offices and their respective measuring periods. In this section, there is a characterization of each monitored office, a general graph combining indoor, outdoor and AC temperatures and window operation over the measured period. In addition, three histograms are presented for each unit showing; (1) frequency of window opening and AC activation in relation to indoor temperature, (2) frequency of window opening and AC activation in relation to outdoor temperature and; (3) frequency of opened window and activated AC for each half-hour period during the working hours.

The equipment shown on the floor plans indicate their location during the measured period.

	Measuring Period					
	2017		**2018**			
Office #	Nov	Dec	Jan	Feb	Mar	Apr
01	From 27	To 08				
02	From 27	To 08				
03	From 27	To 08				
04		11 to 15	17 to 25			
05			17 to 25		From 28	To 06
06		11 to 22				
07			From 25	To 08		
08			From 25	To 08		
09		11 to 22				
10					06 to 21	

Table 11: Measuring period of each office (Summer)

Office 1

This unit is in the building farthest from the meteorological station, counts with the largest area of the monitored offices and it is on the 9th floor, which is the last floor on the building. The space is subdivided into a director's office, meeting area and an area for the workstations, however there are no doors fully closing off any of these spaces, there are only walls dividing them. Because there is a meeting room integrated with the workstations' area, the number of users in the office may vary sporadically. There are six windows in this unit, and the state logger was placed on the window next to the icon as indicated in Figure 13.

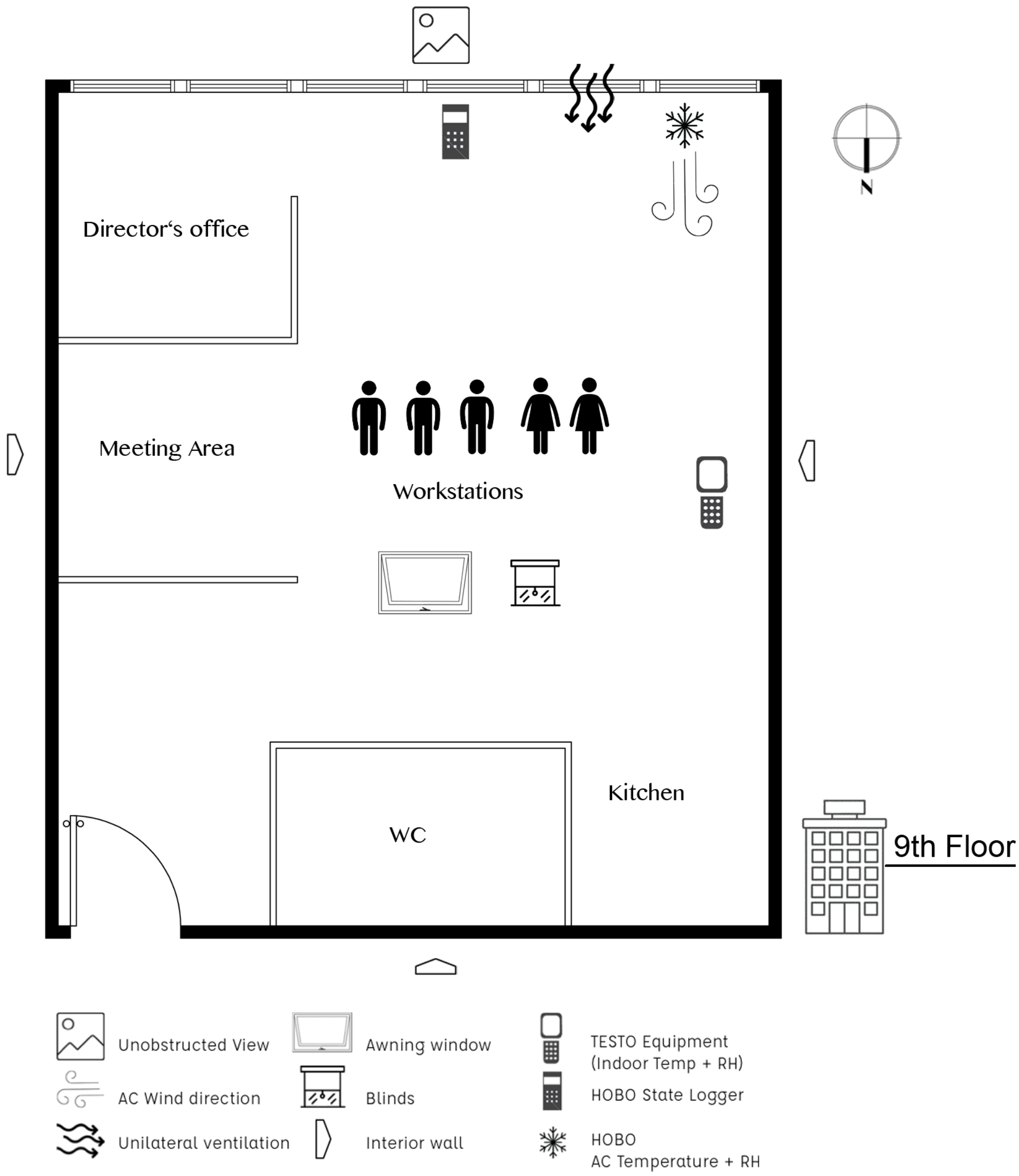

Figure 13: Office 1 floor plan. No scale.

AC Operation

Figure 14 shows that the AC was activated during most of the working hours, with brief periods of open windows, during which it was deactivated. For the most part, the indoor temperature was higher than the outdoor temperature, and it did not significantly decrease even when the AC was activated. There were periods when the outdoor temperature exceeded the indoor temperature, and that event was combined with the AC being activated and remaining in that state until the end of the working hours.

Figure 14: Office 1: Monitored data

Window Operation

Windows were mostly opened when the outdoor temperature was lower than the indoor temperature. They remained in that state while the outdoor temperature remained at least 5°C lower than the indoor temperature. Once the outdoor temperature began to rise and got close to, or exceed the indoor temperature, windows were closed, combined with AC activation. Figure 17 shows that the highest frequency of a period of open windows was around 9:30 am to 10 am, when the outdoor temperature was still increasing, and met, most times exceeding, the indoor temperature around noon, when windows were then closed.

Indoor and Outdoor Temperatures

Figure 15 presents the frequency of the studied actions by indoor temperature. It

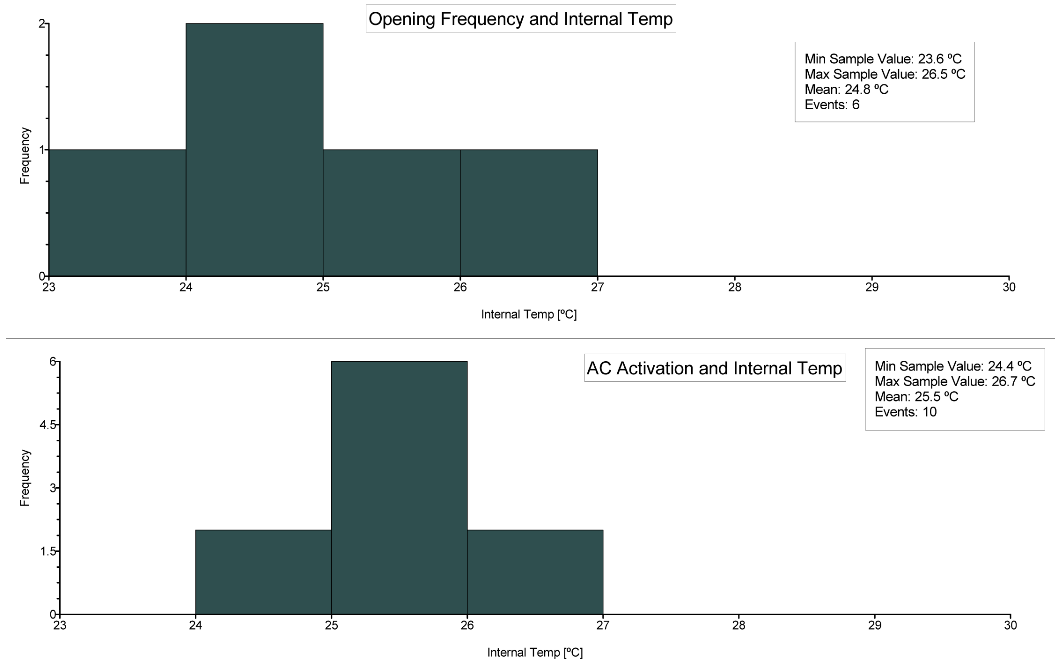

Figure 15: Office 1: Histogram 1 - Frequency of actions by indoor temperature

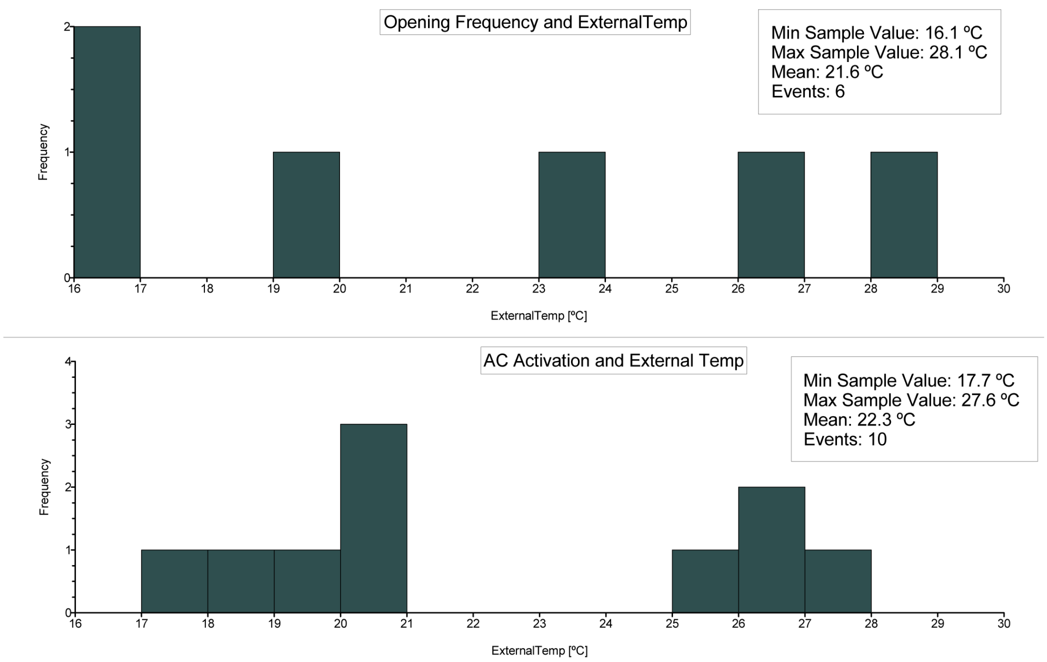

Figure 16: Office 1: Histogram 2- Frequency of actions by outdoor temperature

can be seen that in this office, occupants made use of natural ventilation when the indoor temperature was at 23°C. As it increased and reached 24.5°C, the AC was activated. As for the AC, its highest activation frequencies were at 25 and 26°C, mostly combined with one or zero window opening event. Figure 16 plots actions' frequency and outdoor temperature. As previously stated, when the outdoor temperature was low, 16 to 19.5°C, windows were opened. As it reached 20°C, the AC was activated with a high frequency, as opposed to no

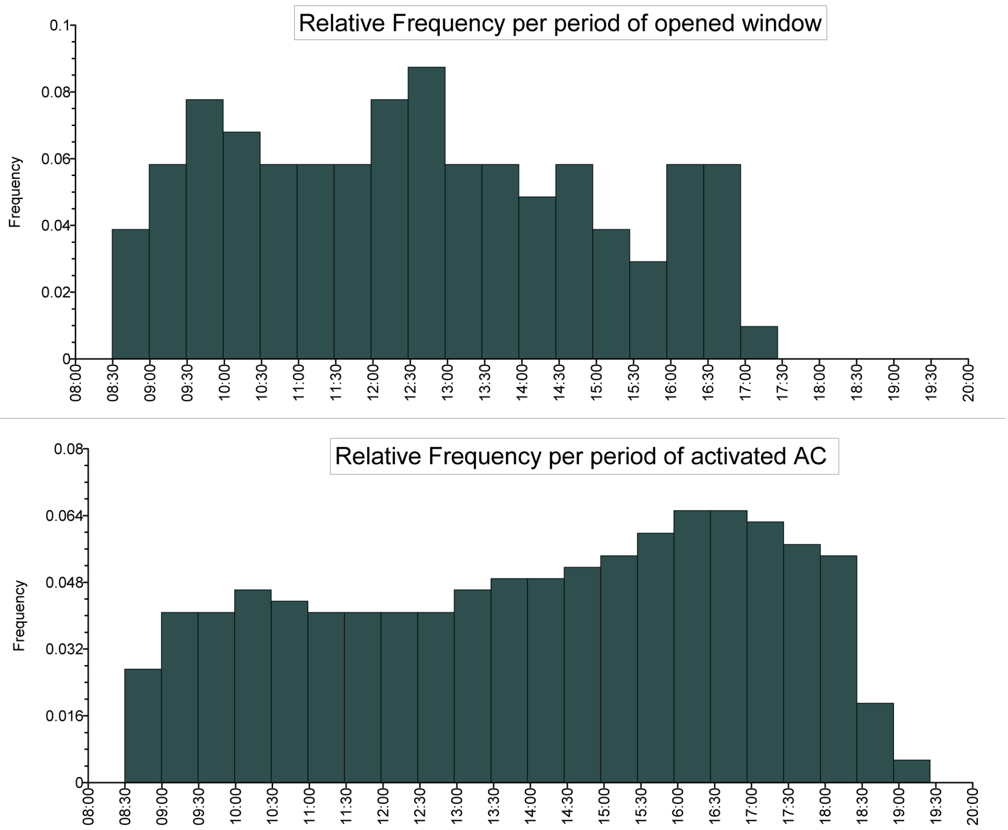

Figure 17: Office 1: Histogram 3 - Relative frequency of actions by period

window opening at this temperature. Higher frequency of AC activation can also be seen when the outdoor temperature reached close to 25°C, although there was some window opening action, however at a lower frequency.

Office 2

Office 2 is occupied by two female users, one of which stays all day and the other occupies the room some days during the week. The office counts with a sliding window that gives access to a small balcony, and the glass on the window is covered with a gray reflexive glass film. The exterior wall indicated on this unit is white.

AC Operation

Figure 19 shows that in this unit the AC was activated when the outdoor temperature met or exceeded the indoor temperature. It is also possible to notice the AC was activated several times while the window was open. Another phenomenon that can be noticed in this figure is that when the AC was activated, even when the windows remained open, there was a significant decrease in the indoor temperature. The Ac's efficiency in cooling the room can be better noticed on December 5, when the window was open and the AC was activated, causing the indoor temperature to decrease. After a period of activated AC, it was deactivated and the indoor temperature quickly increased, due to the

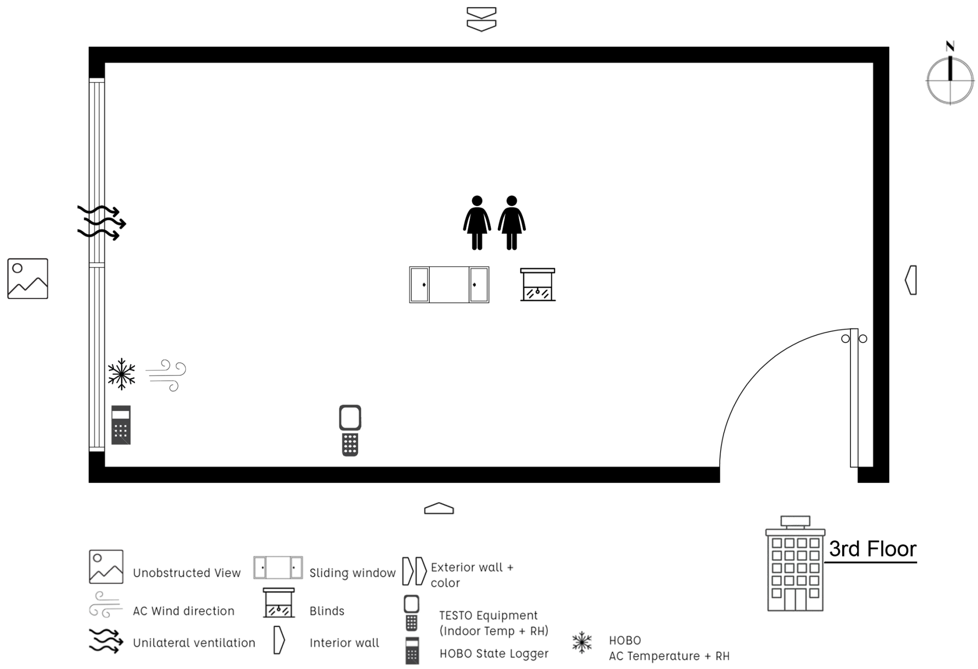

Figure 18: Office 2 floor plan. No scale.

elevated outdoor temperature combined with the open window. Shortly after the quick indoor temperature increase, the user activated the AC once again, probably at a slightly higher temperature, causing the indoor temperature to decrease once more. Most likely, this scenario remained until the end of the working hours, when the AC was deactivated and the window closed.

Window Operation

This unit shows long periods of open window, however, some of these periods coincide with the AC being activated. Only during some of the activated AC periods the window was closed. On December 6, the window was closed during the period when the AC was activated, which coincides with the outdoor temperature rising (Figure 19). By closing the window, the indoor temperature decreased, and the window remained closed until the end of the working hours.

Indoor and Outdoor Temperatures

Figure 20 shows that there was a higher frequency of window opening when the indoor temperature was around 24 and 24.6°C, at which point there was only one AC activation. The AC was mostly activated when the indoor temperature exceeded 24.6°C and then again when it reached between 26°C and 27°C. Figure 21 depicts the ideal behavior in relation to the outdoor temperature, except for one window opening event. The highest window opening frequencies were displayed between 16 to 23°C, making use

Figure 19: Office 2: Monitored data

of natural ventilation when the outdoor temperature was lower than the indoor. When the temperature rose above 23°C, the frequency of window opening was zero (except for one event), and the frequency of AC activation increased, showing the influence of outdoor temperature in users in this office. As for the periods when each action was taken, they coincide with lower (morning) and higher (afternoon) temperatures, using natural ventilation and AC, respectively (Figure 22).

Office 3

Office 3 is occupied by one female user. There is a small waiting area integrated to it, and at times there may be one or more occupants in the space for a short period. The user is positioned with her back to the window, facing the door to the elevators' hall.

AC Operation

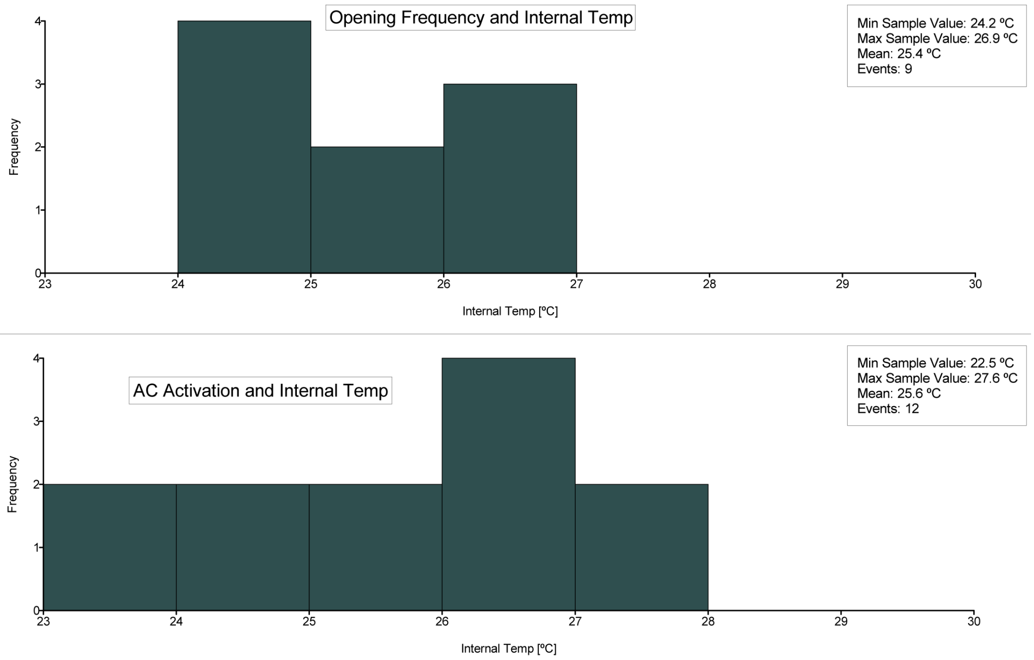

Figure 20: Office 2: Histogram 1 - Frequency of actions by indoor temperature

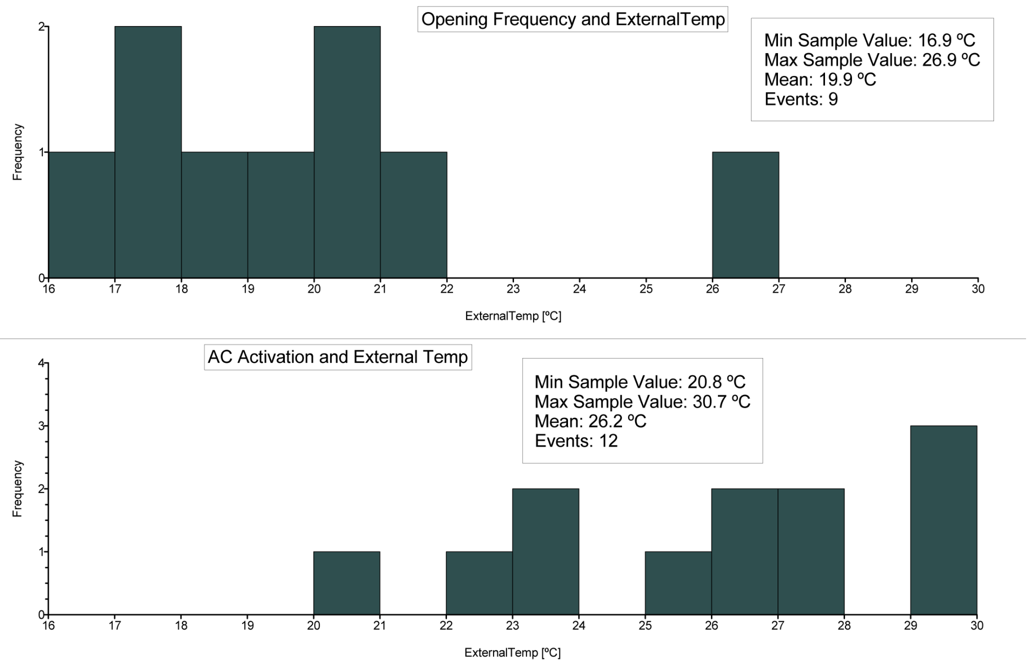

Figure 21: Office 2: Histogram 2- Frequency of actions by outdoor temperature

Figure 24 shows that there was no AC activation in this office during the entire monitored period. The AC remained deactivated even when the indoor temperature reached 25°C, or above, and the outdoor temperature was registered close to, or exceeding, 30°C.

Window Operation

In this unit there was only window operation. Almost every morning during the

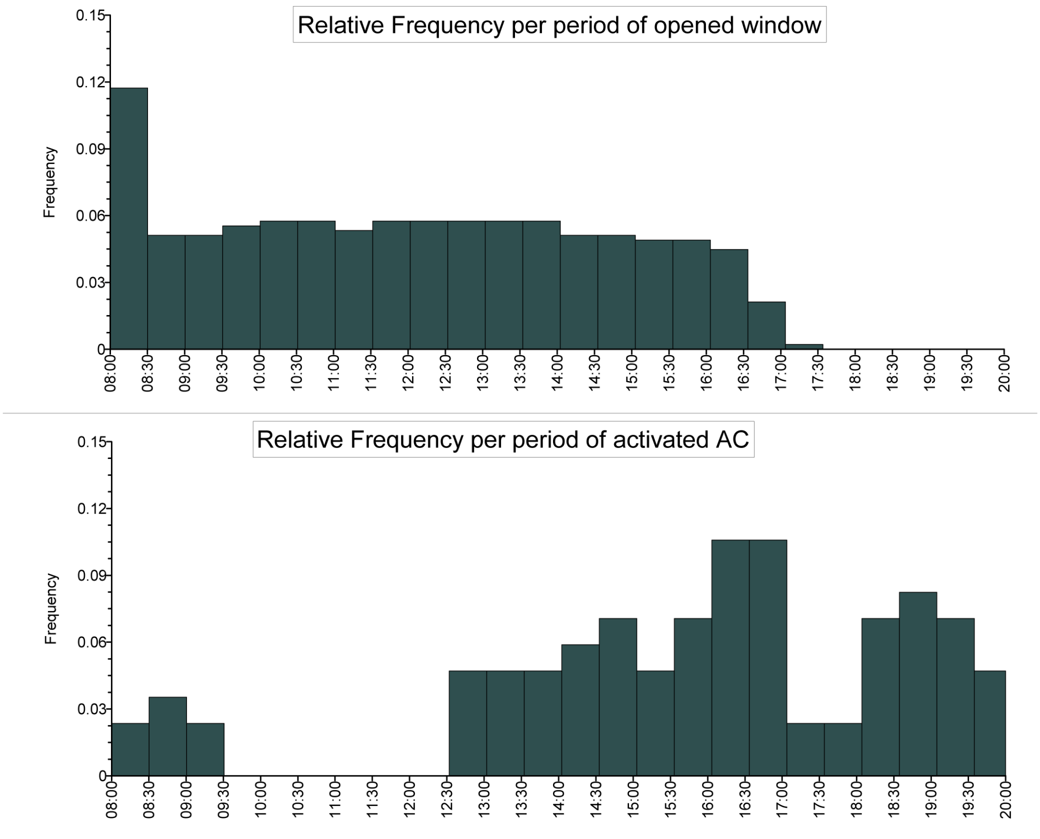

Figure 22: Office 2: Histogram 3 - Relative frequency of actions by period

monitored period the window was opened around 8 am, remaining in that state all morning, and at times until the end of the day (Figure 24). In the morning, when the window was opened, the outdoor temperature was around 17°C. It gradually increased during the morning and reached the indoor temperature at about 25°C around noon. Within the prolonged open window periods, there were very brief periods of closed window. This can be exemplified by looking at December 4, when the window was opened at 8 am and remained open until almost 6 pm, except for 20 minutes, from 2:20 pm to 2:40 pm. This behavior was repeated a few other times over the monitored period, and some reasons for such behavior could be that it rained, given the season, or that the wind speed was high.

Indoor and Outdoor Temperatures

Because there was no AC activation during the monitored period, all histograms present the frequency of window operation only. This unit exemplifies the difference in user preference for indoor temperature; the occupant used solely natural ventilation at all times, showing a higher frequency of window opening when the indoor temperature reached 24.5°C (Figure 25, which is coincidental with a higher AC activation frequency in most units. The second highest window opening frequency was around 26°C, depicting this user's tolerance for higher temperatures.

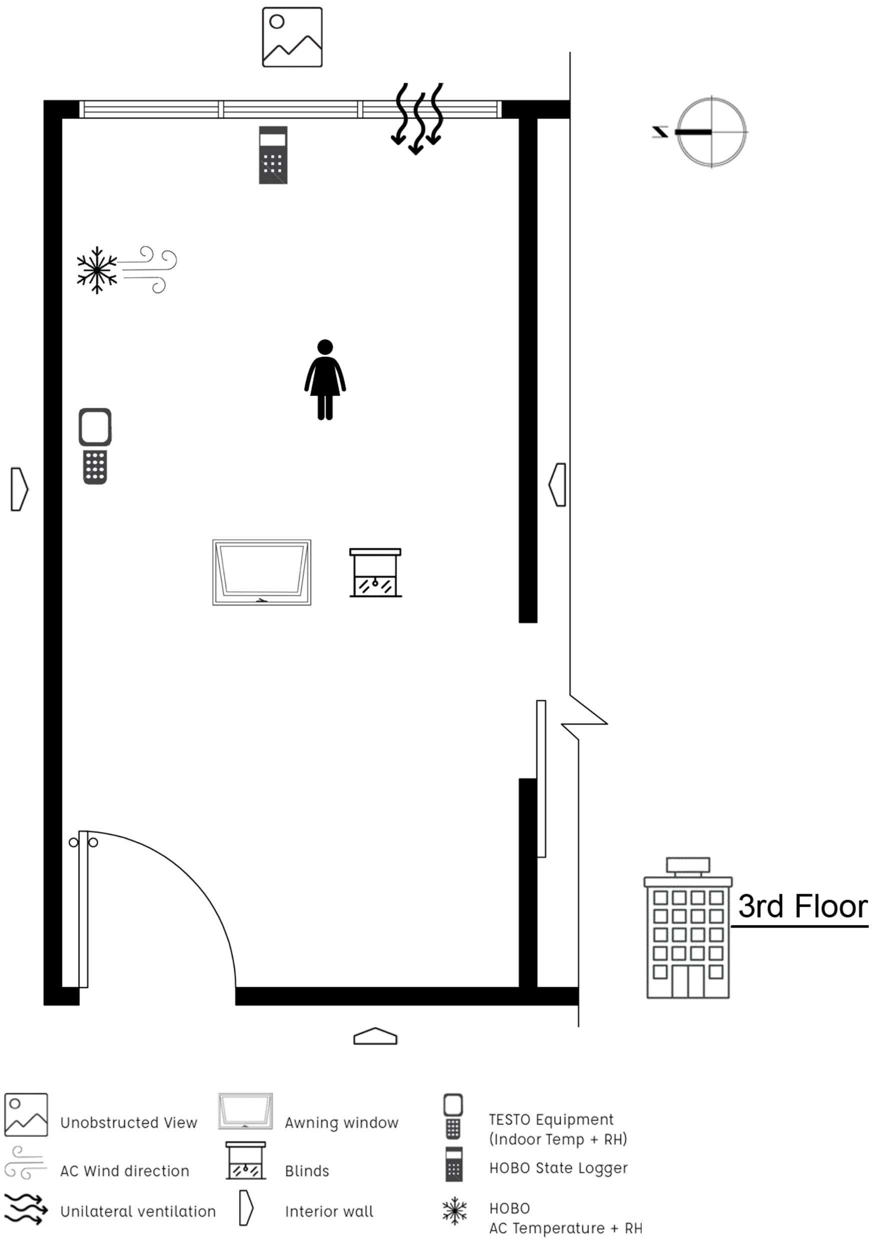

Figure 23: Office 3 floor plan. No scale.

As shown in Figure 24, the highest outdoor temperatures were during the afternoon, and Figure 27 identifies that the period with a higher frequency of open window was the afternoon, confirming that the user kept the window open mostly when the outdoor temperature was elevated, and the indoor temperature around 25°C.

Office 4

Offices 4 and 5 are in the same building, a detached ground floor house, where there are three offices in total, each occupied by one user. The house was adapted for the bedrooms and living/dining rooms to become offices. The waiting room is separated from

Figure 24: Office 3: Monitored data

this office, however its door remains open to such room. As indicated in Figure 28, this room was classified as having its view partially obstructed. That is because the house is surrounded by walls, and even thought it allows to ventilate the rooms, the view can be considered somewhat obstructed by the wall.

The measuring period for offices 4 and 5 was broken down into two separate weeks, as opposed to two continuous weekas, as the other offices.

AC Operation

Figures 29 and 30 shows that the AC was activated when the outdoor temperature was at or above 25°C. However, it is possible to see that the AC was probably not activated at a very low temperature, since the registered temperatures on the equipment positioned on the AC flap did not present a drastic temperature decrease, but rather a very slight

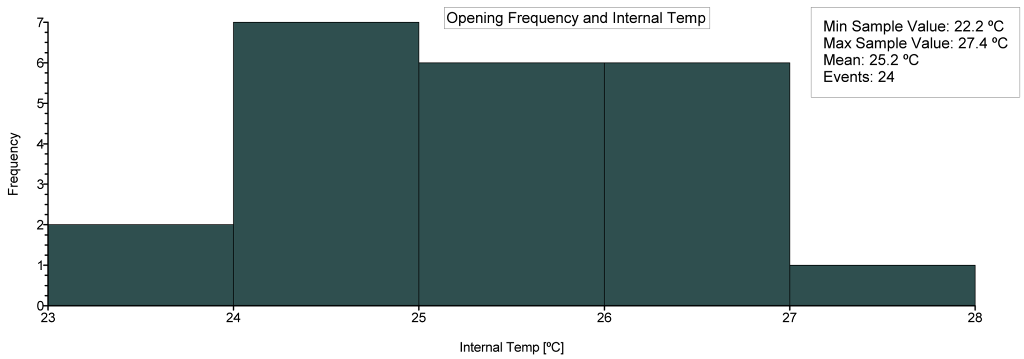

Figure 25: Office 3: Histogram 1 - Frequency of actions by indoor temperature

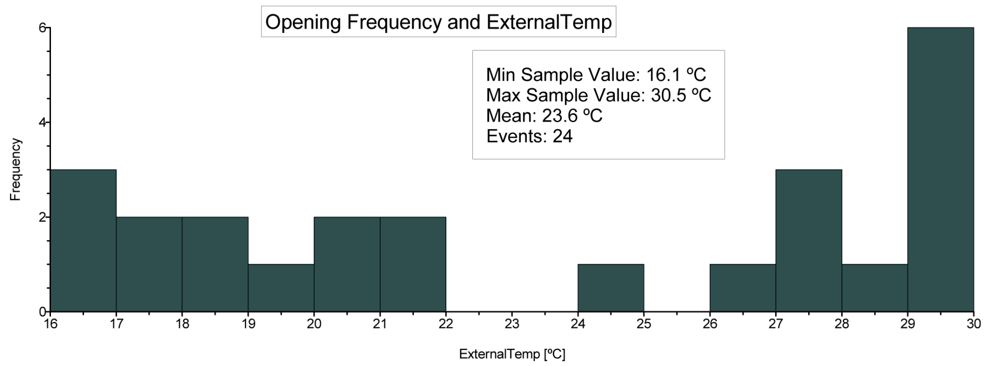

Figure 26: Office 3: Histogram 2- Frequency of actions by outdoor temperature

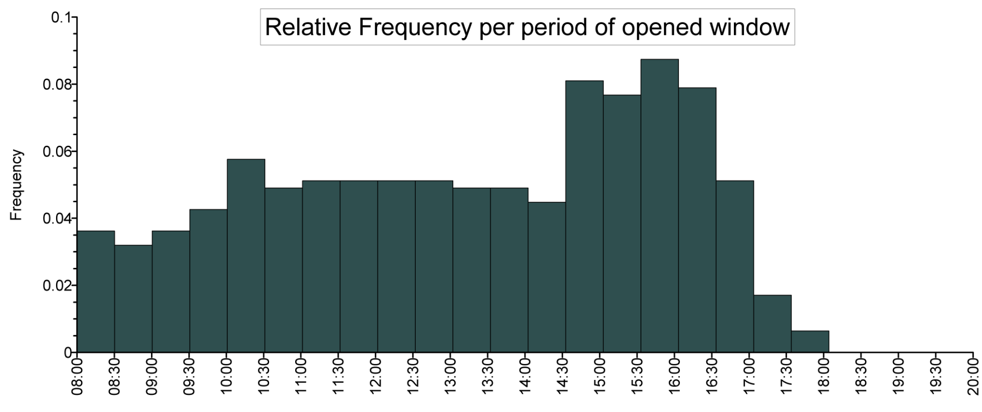

Figure 27: Office 3: Histogram 3 - Relative frequency of actions by period

one, accompanied by a decrease on the indoor temperature as well. On the other hand, the deactivation could be identified at the end of the working hours, around 5:30 pm, when there was an increase in both temperatures (AC and indoor). One event, on December 11, suggests that the AC was activated at a much lower temperature than the other registered events, since the AC temperature in Figure 29 for this day at about 10 am significantly decreased, consequently decreasing the indoor temperature to 25°C. About 20 minutes

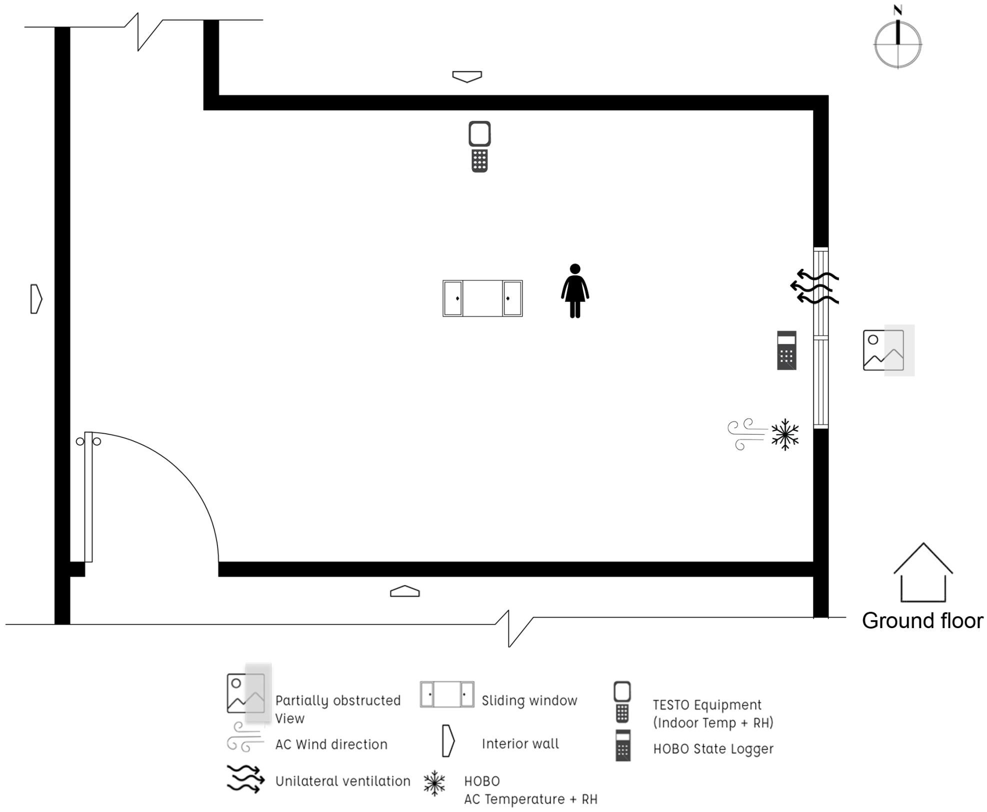

Figure 28: Office 4 floor plan. No scale.

after the AC was activated, the window was closed, and the AC and indoor temperatures increased, suggesting that the user changed the temperature on the AC unit to maintain the indoor temperature around 25°C.

Window Operation

This user alternated between the use of natural ventilation and air conditioning. The window was always opened in the morning around 8 am, which combines arrival and outdoor temperature about 5°C lower than indoor temperature. Once the window was opened in the morning, it remained in this state during this period, and was closed around noon, when the outdoor and indoor temperatures increased. There were some events, such as on January 22, when the window was opened in the afternoon and remained in this state until the end of the working hours, even though the outdoor temperature reached 30°C and the indoor was above 25°C.

Indoor and Outdoor Temperatures

As shown in Figures 31 and 32, the occupant made use of natural ventilation when indoor and outdoor temperatures were lower in relation to the values within the measured period, that being between 24 and 26°C and 17 and 23°C, respectively. As for AC activation, it was complementary to the window opening behavior, as the user activated

Figure 29: Office 4: Monitored data (December 11 to 15)

the AC when indoor temperatures were between 27 and 29°C and outdoor between 22 and 30°C, with higher frequencies observed between 22-23°C and 28-29°C. The lower temperatures occurred in the morning, whereas the higher ones, in the afternoon, as can be seen in Figure 33, where the frequency period of opened window is greater in the morning, and for the AC in the afternoon.

<u>Office 5</u>

Office 5 is in the same house as office 4. However, there are sliding external blinds on the window in this unit. This feature caused some incongruence on the window state logger readings, because the user closed the blinds and not the glazed portion of the window, where the equipment was positioned. Therefore, the window was registered as open overnight from April 4 to 5 (Figure 36), even though the external blinds were closed

Figure 30: Office 4: Monitored data (January 17 to 25)

and the office unoccupied. Another unusual activity reported in this unit is that a co-worker worked on a Saturday and used this office; opened the window but did not close the glazed portion. Therefore, once again, the equipment registered an open window over the weekend (January 20 and 21 - Figure 35), when in fact it was open only during a small portion of Saturday.

There were two measuring periods (one week each) for this unit as well, one of them being in April.

AC Operation

Figures 35 and 36 show that the AC was mostly activated in the afternoon, when the outdoor temperature was close to or exceed 30°C, or when the outdoor temperature reached values close to the indoor temperature. Unlike the other user in the same house,

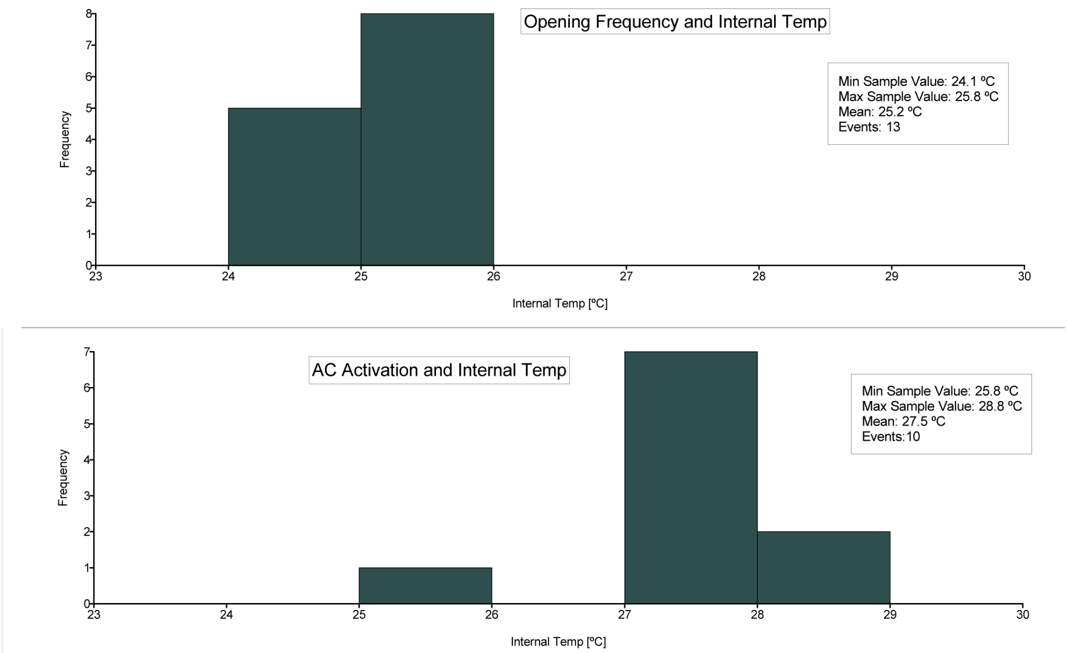

Figure 31: Office 4: Histogram 1 - Frequency of actions by indoor temperature

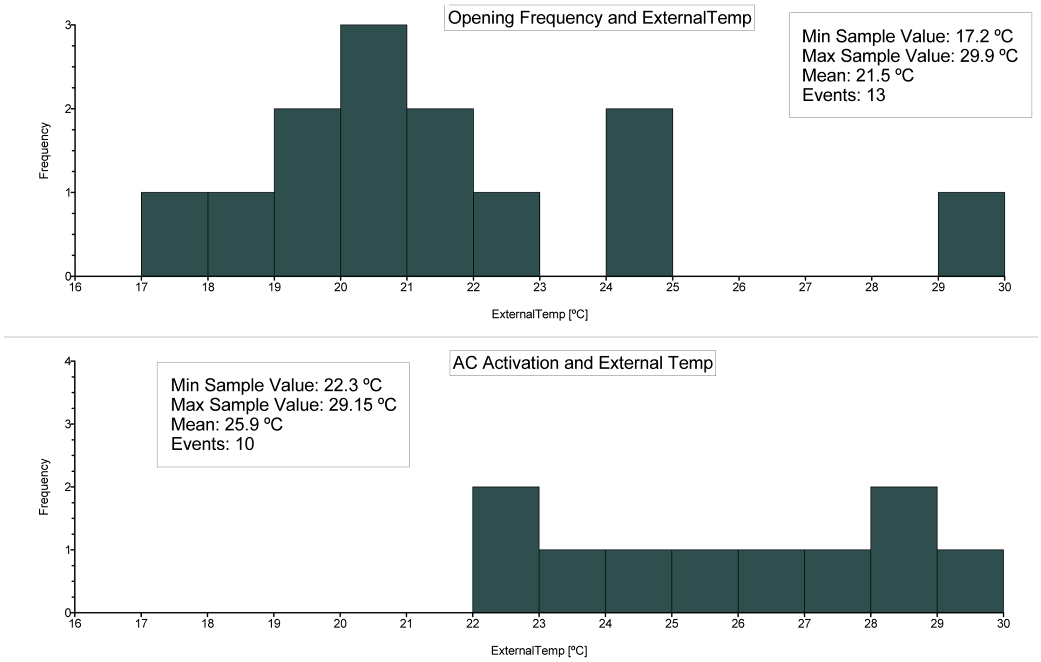

Figure 32: Office 4: Histogram 2- Frequency of actions by outdoor temperature

the data suggests that this user activated the AC at a lower temperature than the one used in Office 4. The AC was mostly activated when the windows were closed, but there was an afternoon period (January 24 - Figure 35) that shows the air conditioning being used while the window was open. This specific AC activation presented very low temperatures registered on the AC unit, combined with very high outdoor temperature (close to 30°C).

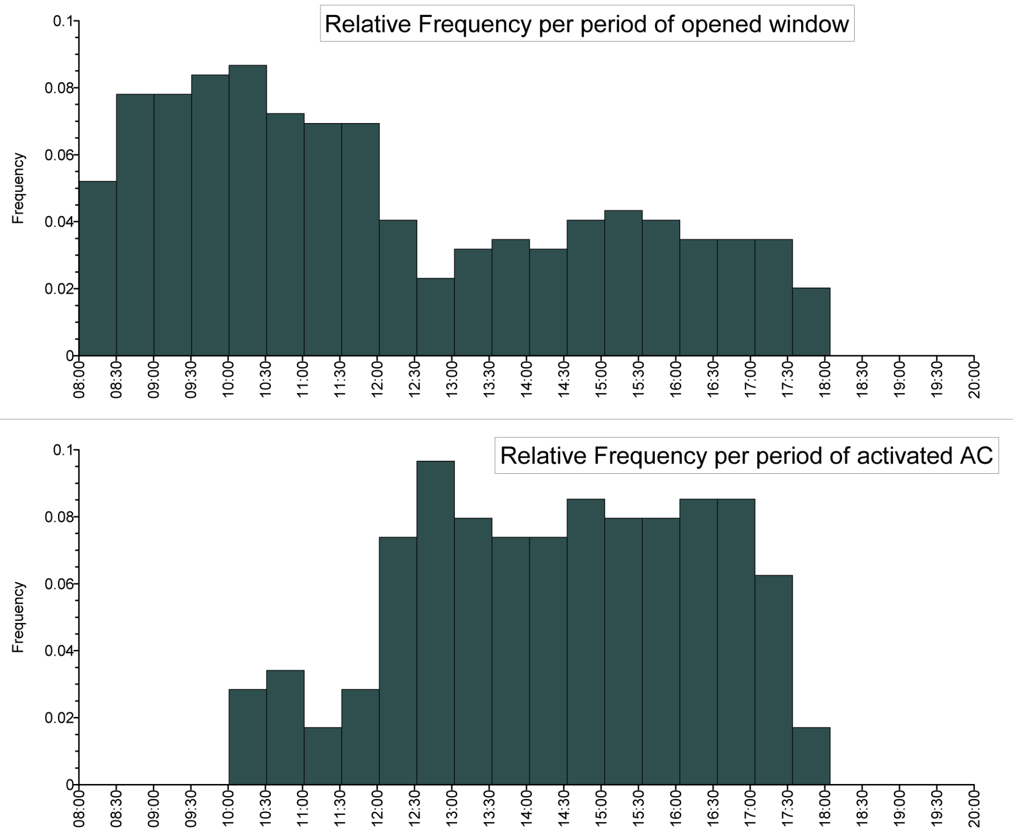

Figure 33: Office 4: Histogram 3 - Relative frequency of actions by period

Window Operation

Window operation in this unit followed the same pattern as the one identified for the previous units. The user opened the window in the morning, while the outdoor temperature was around 5°C lower than the indoor temperature, at 20°C and 25°C, respectively, likely coinciding with arrival. As the outdoor temperature rose and its value reached that of the indoor temperature or exceeded it, the window was closed and the AC activated. However, Figure 36 shows, on April 5, that when the outdoor temperature was about 10°C below the indoor temperature, the window was closed and the AC remained deactivated. Later on that same day the outdoor temperature increase about 10°C, causing the indoor temperature to also increase, however at a much lower rate, and the window remained closed and the AC deactivated.

Indoor and Outdoor Temperatures

The second week that composed the measuring period for this office was during April, when temperatures during the day reached 25°C and sometimes exceeded it by one or two degrees, differing from January, when the outdoor temperature during the afternoon reached 30°C, and sometimes exceeded it. As a consequence, during the first measured period (Figure 35), the user activated the AC more than on the second period

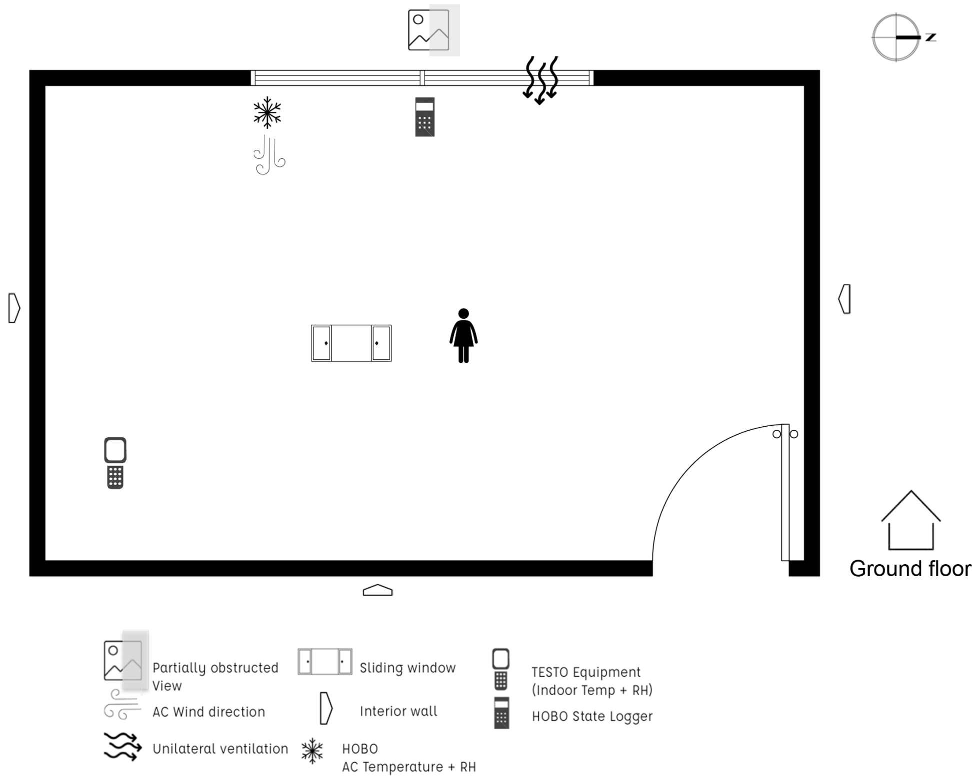

Figure 34: Office 5 floor plan. No scale.

(Figure 36). On the latter, there were days when only natural ventilation was used.

The histograms for this unit combined the data for both periods. As shown in Figure 39, the AC was activated on the afternoon period with more frequency, which is in accordance with the higher outdoor temperatures in January for this time of the day. As for the window operation, it shows a slightly different frequency distribution than the other units, since it presents some low frequency of opened windows during the entire day. The highest window opening frequency period is between 8 and 8:30 am, which is coincidental with arrival, and it is likely to have happened on most days. The lowest frequencies throughout the entire day are likely to refer to the April period of monitoring, since the outdoor temperature remained around 25°C and the window remained open during all day (Figure 36).

It can be inferred that this user operates the AC in response to outdoor temperature, since it is possible to see in Figures 35 and 36 that the indoor temperature accompanies the fluctuations on the outdoor temperature.

Office 6

This and the following two offices, 7 and 8, are in the same building. Each being located at a different position within the building and some on different floors. The windows' facade of this particular unit faces the building's open parking lot.

Figure 35: Office 5: Monitored data (January 17 to 25)

AC Operation

Figure 41 shows the combination of the registered data, evidencing that the AC is mostly activated when the outdoor temperature is above 25°C, and the indoor temperature around 30°C, usually during the afternoon. However, there were two AC activations that occurred in the morning, after the office remained closed and unoccupied for a prolonged period, such as the weekend. On Monday December 18, it is possible to see that the AC was activated in the morning, unlike most days, even though the outdoor temperature was close to 20°C. However, the indoor temperature on this same date and time, was around 30°C, resulting in AC activation instead of window opening in this case.

Window Operation

As a counterpoint to the above mentioned situation, on Tuesday December 19, the

Figure 36: Office 5: Monitored data (March 28 to April 06)

indoor and outdoor temperatures were about the same as the previous day, 30°C and 20°C, respectively. However, users opened the windows instead of activating the AC, clearly depicting that for the same scenario, different actions can be taken. As for the remainder of the monitored period, it is possible to see that there were long periods of open windows, usually starting in the morning and lasting until the beginning of the afternoon, around 2 pm, when the outdoor temperature began to increase and reached values close to the indoor temperature (Figure 41).

Indoor and Outdoor Temperatures

In general the indoor temperature in this office remained constant, though high (over 25°C). This temperature was maintained even overnight, when the outdoor temperature significantly decreased, given it reached close to or exceeded 30°C during the day and

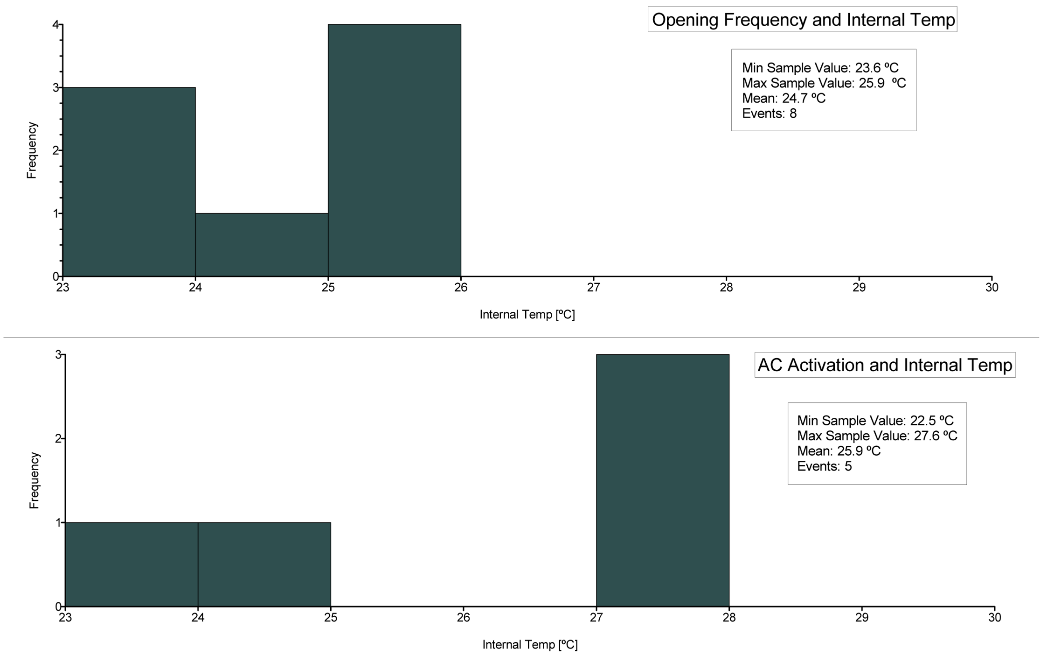

Figure 37: Office 5: Histogram 1 - Frequency of actions by indoor temperature

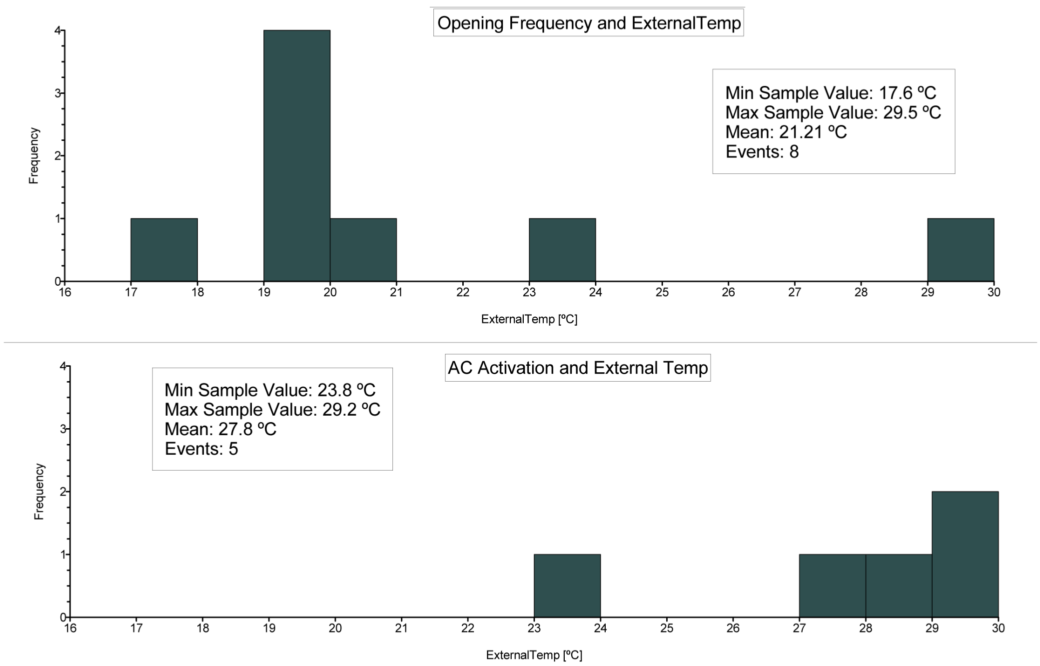

Figure 38: Office 5: Histogram 2- Frequency of actions by outdoor temperature

reached close to or below 20°C between 2 am and 6 am. Because the indoor temperature was constantly high, Figure 42 illustrates that both actions took place more frequently when the indoor temperature was between 26 and 30°C.

As in response to the outdoor temperature (Figure 43), the events were less frequent. Except for window opening between 19 and 20°C, which showed the highest frequency

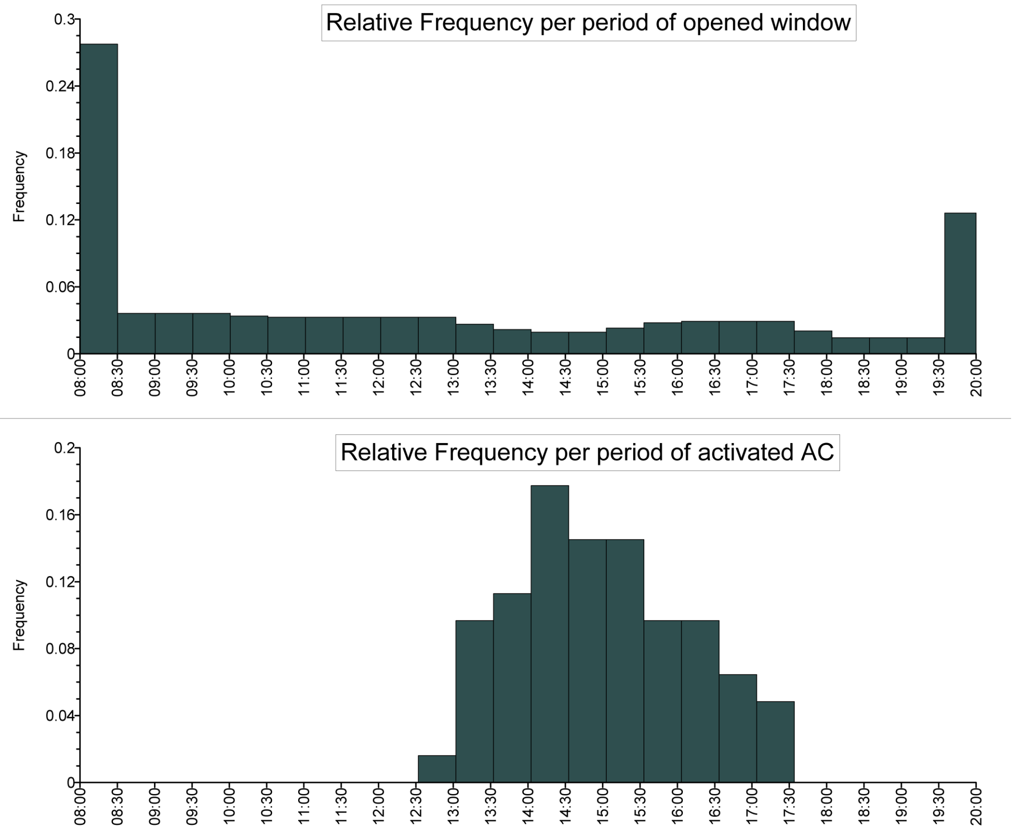

Figure 39: Office 5: Histogram 3 - Relative frequency of actions by period

and is likely to be in the morning, as observed in Figure 44. This illustrates that windows remained open in the morning and the AC was activated in the afternoon, a behavior that was observed in several of the monitored rooms.

Office 7

Offices 7 and 8 were monitored during the same period. There was a malfunction on the equipment monitoring the AC on both units, therefore the AC activation in these units was observed according to the relative humidity (RH) recorded with the indoor temperature. It is possible to identify when the AC was activated, though the time precision is not as accurate as on the other monitored units. There are two occupants in this office and at times this number increases, as clients come in for meetings. There is a small hall with a sliding glass door that is always kept closed.

AC Operation

Figure 46 shows that AC operation in this office follows the same general pattern as the other monitored offices in the study. During the morning, when the outdoor temperature was close to 20°C, the AC remained deactivated. As the outdoor temperature rose, reaching higher values in the beginning of the afternoon, the AC was activated, which can be identified by significant decreases in RH values and a small decrease on the indoor

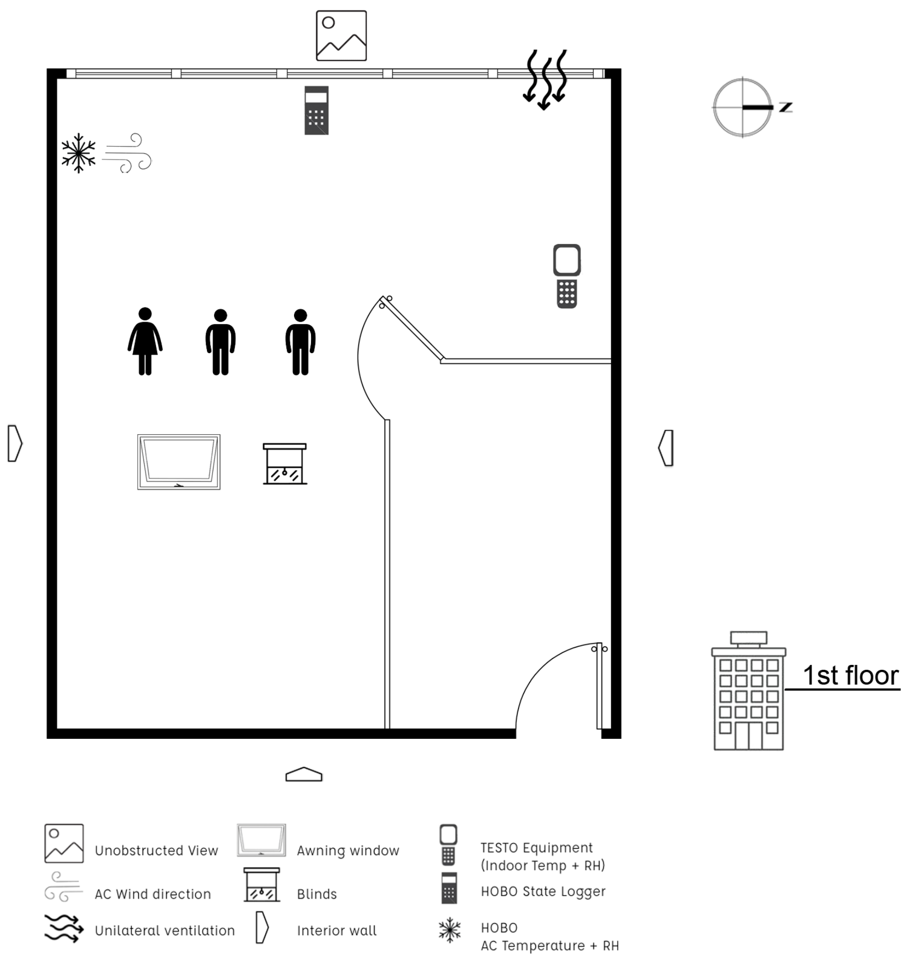

Figure 40: Office 6 floor plan. No scale.

temperature.

Window Operation

Occupants in this office always kept the windows closed when the AC was activated, alternating well between the two actions. Therefore, windows were mostly opened in the morning, while the outdoor temperature was around 20°C, and closed around midday, when the temperature rose.

Indoor and Outdoor Temperatures

Although offices 7 and 8 are in the same building, their positioning within the building differs, and each office performs differently. Office 7 is located between two other offices on the 10th floor, with no external walls other then the windows' facade. As it can be observed in Figure 46, the indoor temperature was constant throughout the entire measuring period, with slight decreases when the AC was activated. Although the outdoor temperature fluctuates and decreases several degrees during the night, the indoor temperature did not vary much. Therefore, it is possible to infer that users in this unit react, to some degree, in response to indoor temperature.

Figure 41: Office 6: Monitored data

In Figure 47 it is possible to see that users activated the AC with a higher frequency when the indoor temperature was above 25°C, but mainly when it exceeded 26°C. As shown in Figure 48, users alternated well between opening windows and activating the AC, being that the change in the action taken was around 21°C. This can be reaffirmed when looking at Figure 49, as it shows well the period with higher window opening frequency was the morning, and AC activation in the afternoon. As observed in other offices, as the outdoor temperature increases, users tend to close the window and activate the AC, configuring a greater use of natural ventilation in the morning and air conditioning in the afternoon.

Office 8

Office 8 is a corner office, meaning there is an exterior wall, which is green. This

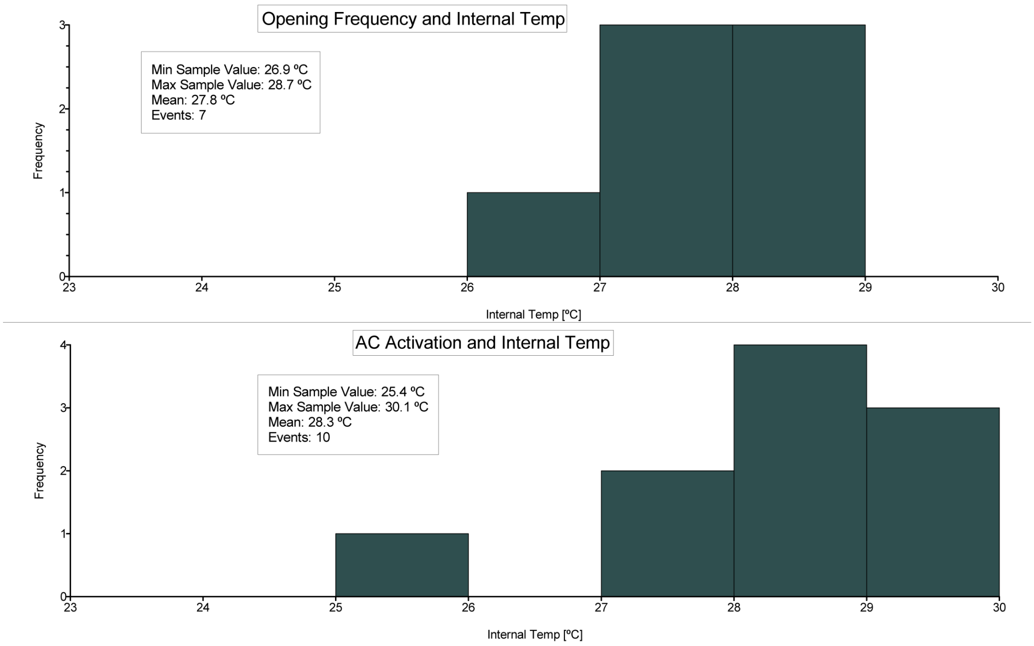

Figure 42: Office 6: Histogram 1 - Frequency of actions by indoor temperature

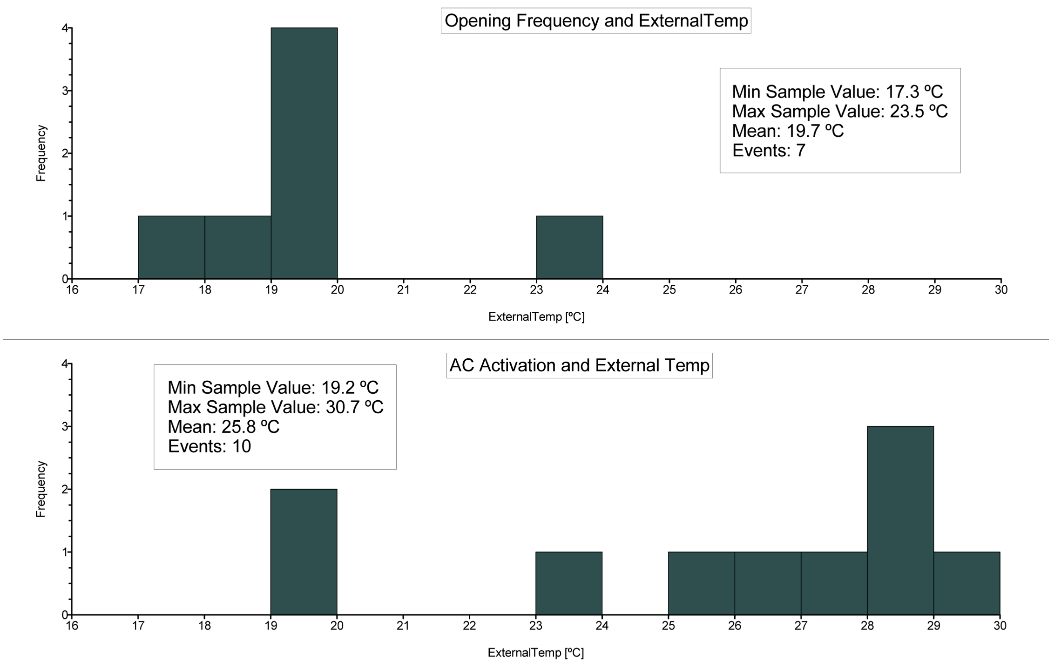

Figure 43: Office 6: Histogram 2- Frequency of actions by outdoor temperature

office is subdivided into 2 offices (Figure 50), one for the director and another where there is an open space with several workstations and a storage area. The director's office is fully separated, with its own AC unit. The space monitored in this campaign was the area where the workstations are located, and where several users occupy.

AC Operation

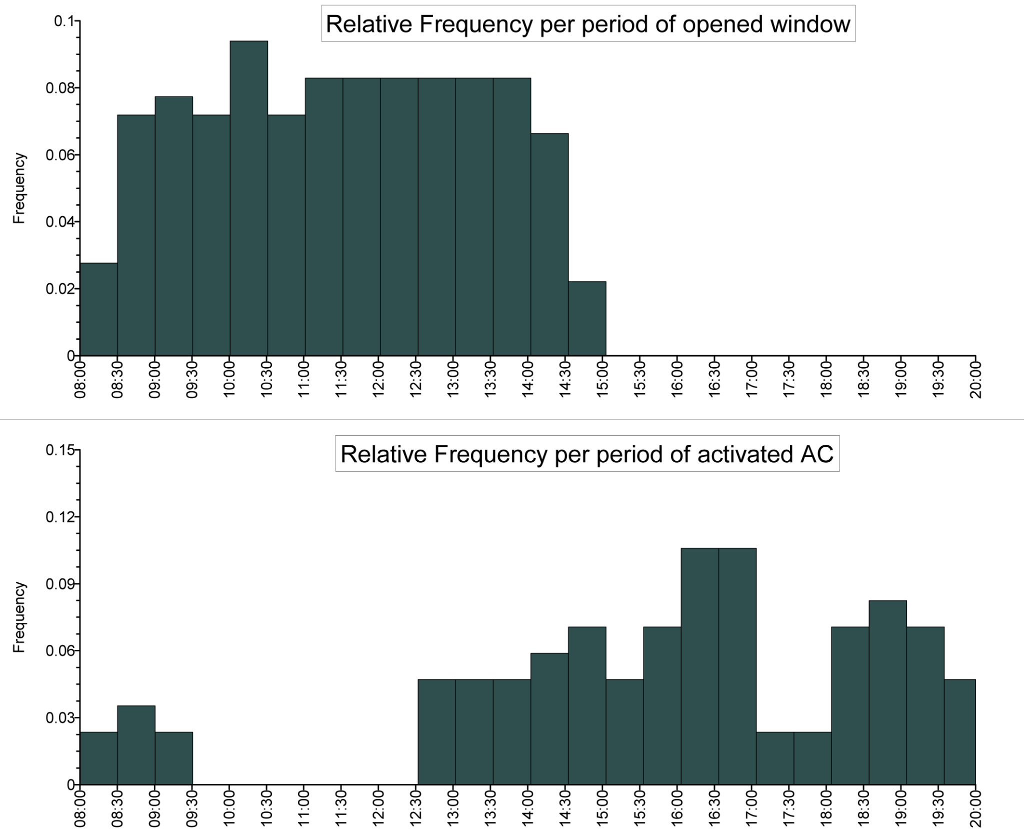

Figure 44: Office 6: Histogram 3 - Relative frequency of actions by period

The AC was activated several times while the window was open. As previously identified in other units, users in this office activated the AC when the outdoor temperature rose, between 1 pm and 2 pm. As for the indoor temperature, it showed a greater influence in this unit, given its values reached 30°C, triggering AC activation.

Window Operation

There were short periods of open window in this office, as the indoor temperature quickly increased during such periods, causing windows to be closed and the AC activated. On the morning of January 30, it is possible to see that there was greater window operation, which can be explained by looking at complementary data, that between 9 and 10 am it rained.

Indoor and Outdoor Temperatures

As above mentioned, this unit presented very high indoor temperatures during the monitored period. Figure 52 shows that both actions were taken when the indoor temperature was above 25°C, the average value for both being 28.3°C. As for the outdoor temperature, actions were taken at an average value of 21°C (Figure 53), which can lead to infer that the indoor temperature had more impact on actions in this unit. Differing from office 7, which is in the same building, users in this office did not present one behavior

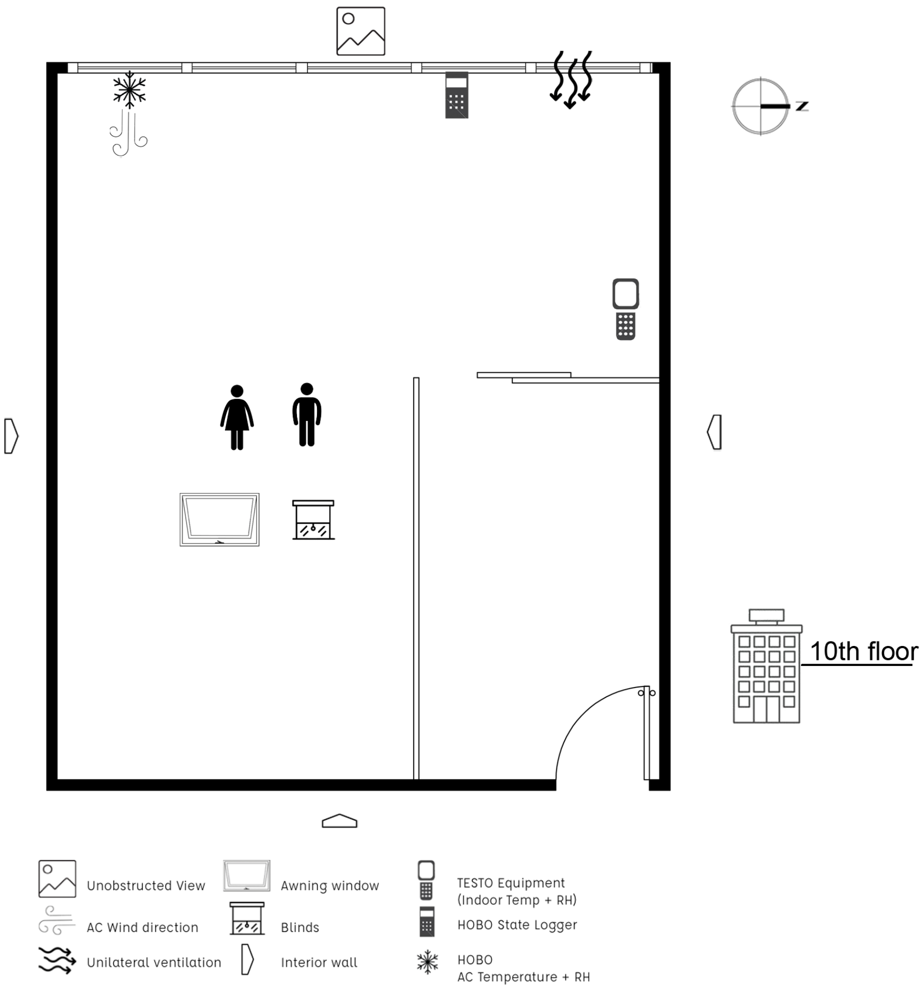

Figure 45: Office 7 floor plan. No scale.

in the morning (window opening) and another in the afternoon (AC activation), which could be related to the rising outdoor temperature. Figure 54 shows that the AC was activated with high frequencies almost all day long, reinforcing the information that indoor temperatures were constantly high and users responded to it mostly by activating the air conditioning.

Office 9

Offices 9 and 10 are in the same building, though monitored during different periods during the summer. There are four occupants in this office, however one of them is mostly present after the lunch break. The office is subdivided into two rooms, though the partitions to create this subdivision are not from floor to ceiling, and do not obstruct the AC unit, therefore it was not included in Figure 55.

AC Operation

Occupants in this office activated the AC several times and for long periods, sometimes during all working hours, always at very low temperatures (Figure 56). However, even

Figure 46: Office 7: Monitored data

though the AC equipment registered such low temperatures, the indoor temperature did not decrease much, and stabilized at 25 and 26°C. This unit presented indoor temperatures always above 25°C, remaining constant around that value throughout the monitored period. It is possible to see that when the AC was activated, it worked mostly to prevent the indoor temperature from rising as the outdoor temperature rose, instead of decreasing it.

Window Operation

There were few window opening events, given the AC was active for the most part of the monitored period. Windows remained closed when the AC was on, and most days it remained that way for the entire period. It is possible to see in Figure 56 that windows were mostly opened when the outdoor temperature was around 20°C. As it rose, windows were closed and the AC was activated.

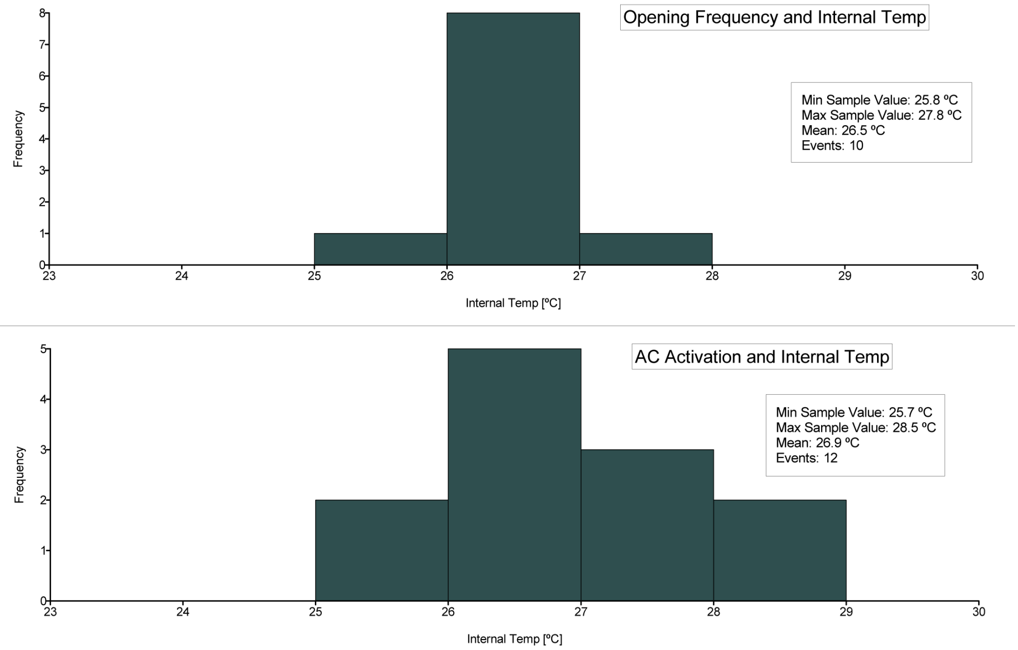

Figure 47: Office 7: Histogram 1 - Frequency of actions by indoor temperature

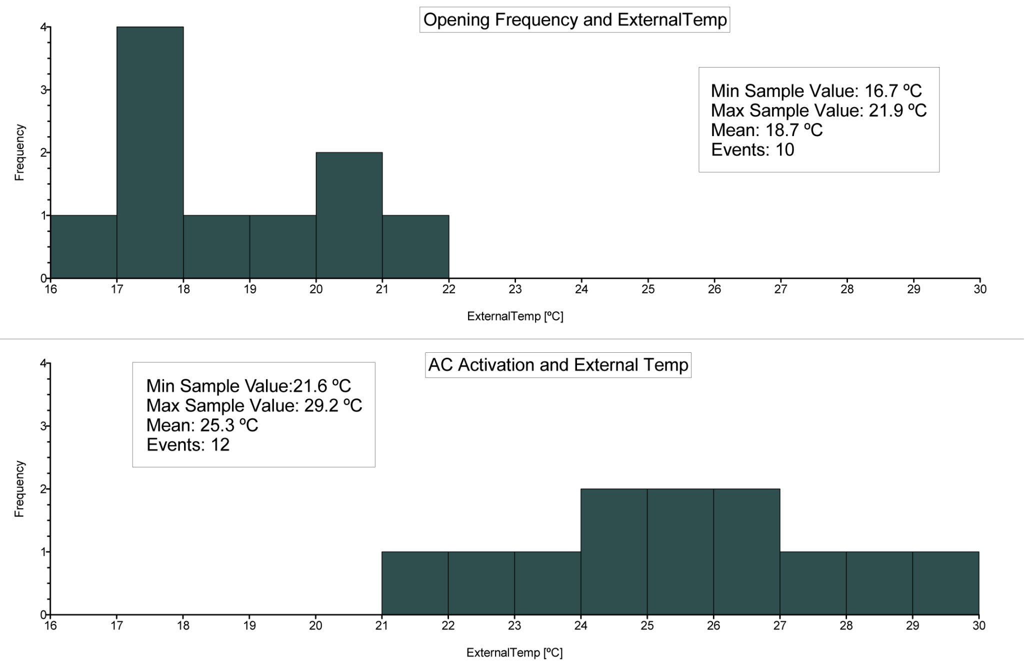

Figure 48: Office 7: Histogram 2- Frequency of actions by outdoor temperature

Indoor and Outdoor Temperatures

As observed in other monitored units, the indoor temperature in this office was constant and mainly around 26°C. Figure 57 shows that the mean value for the indoor temperature regarding window opening frequency was 26.3°C, which is the minimum value for AC activation. Therefore, it can be said that in this office, when the indoor temperature

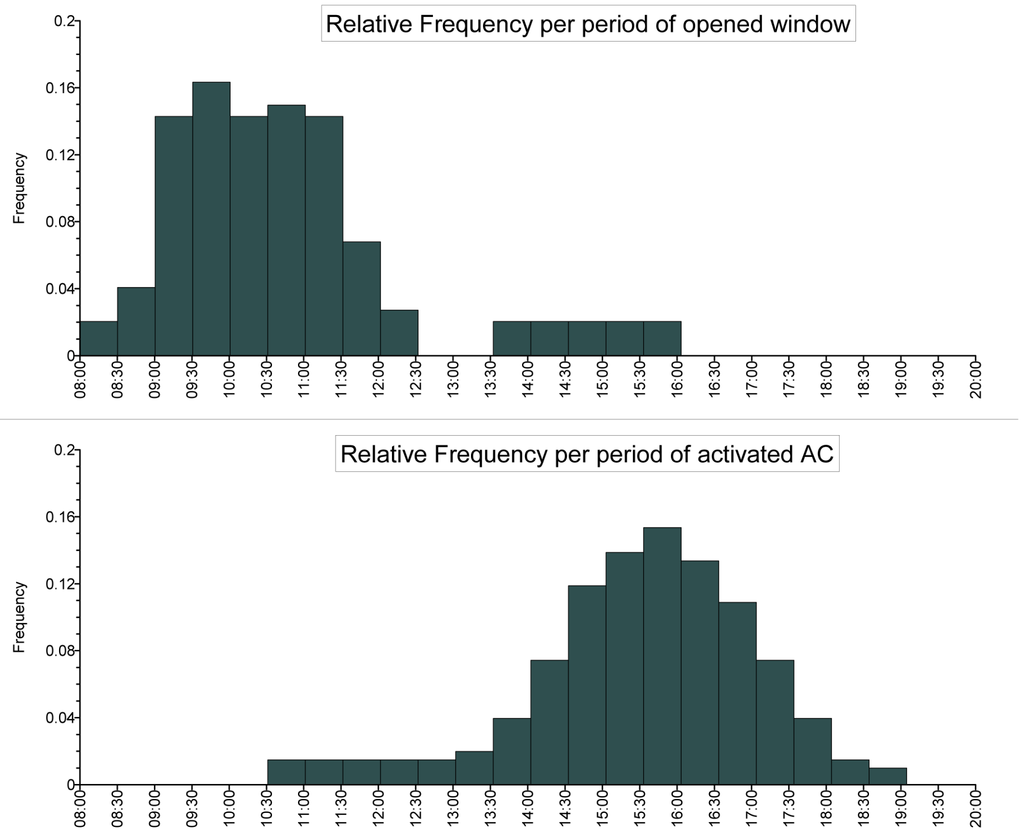

Figure 49: Office 7: Histogram 3 - Relative frequency of actions by period

was around 26°C, it triggered a change in occupant's actions, which also confirms the use of AC more frequently than the use of open windows. Figure 58 presents how the AC was more frequently activated when the outdoor temperature was 23°C and above, and Figure 59 allows to confirm that higher outdoor temperatures occurred in the afternoon, when the remained AC mostly active.

Office 10

This office is in the same building as office 9. However, there are subdivisions on this unit, and Office 10 is one of the subdivisions within a greater office. Unlike office 9, the subdivisions in this space create fully enclosed rooms, each with its own AC unit. The monitored office within this set of rooms is occupied by one female user, who eventually leaves the office due to the nature of the business in this space.

AC Operation

The AC was activated every day during the measuring period, most events while the windows were closed. There were two occasions when the AC was active and the windows were open, though brief periods. As observed in the other office within the same building, the AC in office 10 was also activated at a very low temperature. However, unlike in office 9, when the AC was activated, the indoor temperature quickly decreased,

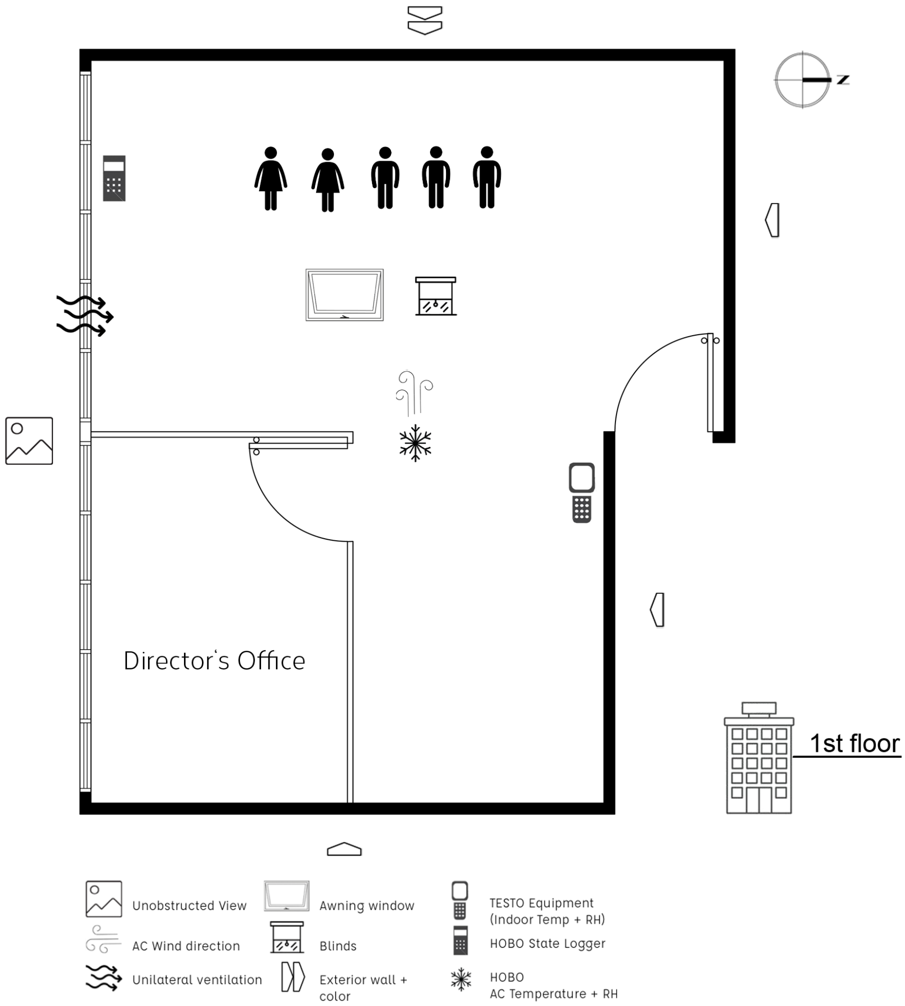

Figure 50: Office 8 floor plan. No scale.

accompanying the AC temperature and sometimes remaining at around 25°C and at other times around 20°C.

Window Operation

The window was opened every morning during the monitored period. Figure 61 shows that when the window was opened, the outdoor temperature was 5°C (or more) below the indoor temperature, which were at about 20 and 25°C, respectively. On March 15, this temperature difference was even more evident, displaying a difference of 8°C between them, showing that the occupant kept the window open for a longer period of time, since it took longer for the outdoor temperature to reach values close to the indoor temperature (about 30°C on this specific day). Windows were closed most days during the afternoon, when the outdoor temperature increased, even though the indoor temperature remained almost the same as in the morning.

Indoor and Outdoor Temperatures

Figure 51: Office 8: Monitored data

Figure 62 shows that the user took one of the observed actions mostly when the indoor temperature was above 25°C. The exceptions being that there was no window opening, only AC activation, when it was above 29°C, and no AC activation, only window opening, when it was below 25°C. In relation to the outdoor temperature, Figure 63 shows that there was a higher frequency of window opening between 18 and 23°C, and of AC activation between 25 and 30°C, although there was some AC activation, though at a lower frequency, when outdoor temperature was between 18 and 22°C.

Figure 64 shows that the user kept the window opened mostly in the morning, with its frequency gradually decreasing as the day went by, which coincides with the outdoor temperature increasing, leading to the AC activation period frequency also increasing. The periods of activated AC displayed in the morning are likely to coincide with the AC being activated at lower outdoor temperatures (Figure 63), which are observed in the morning

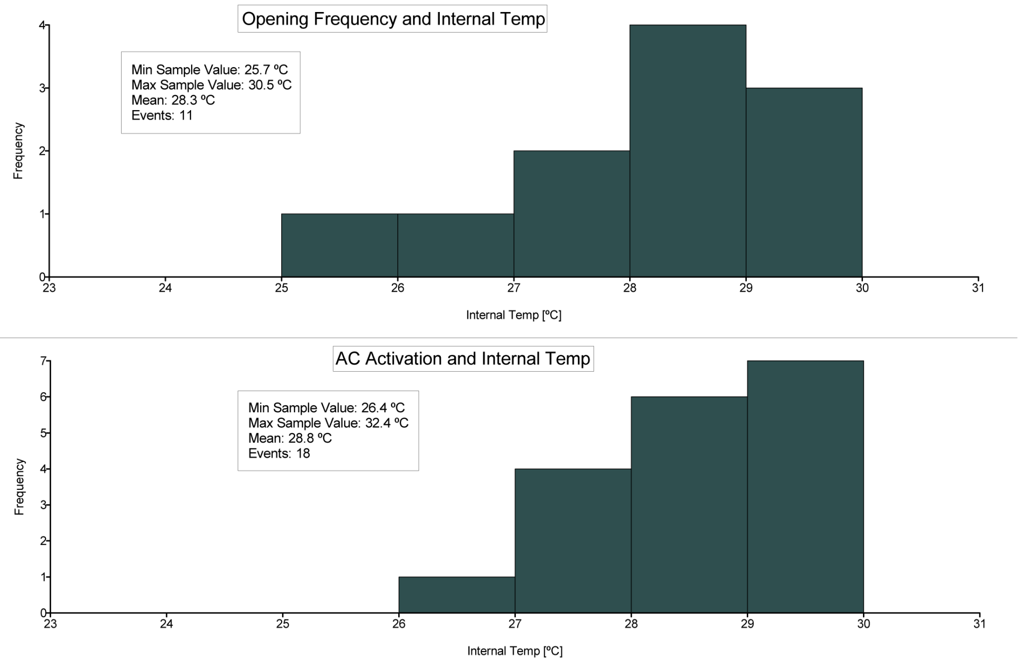

Figure 52: Office 8: Histogram 1 - Frequency of actions by indoor temperature

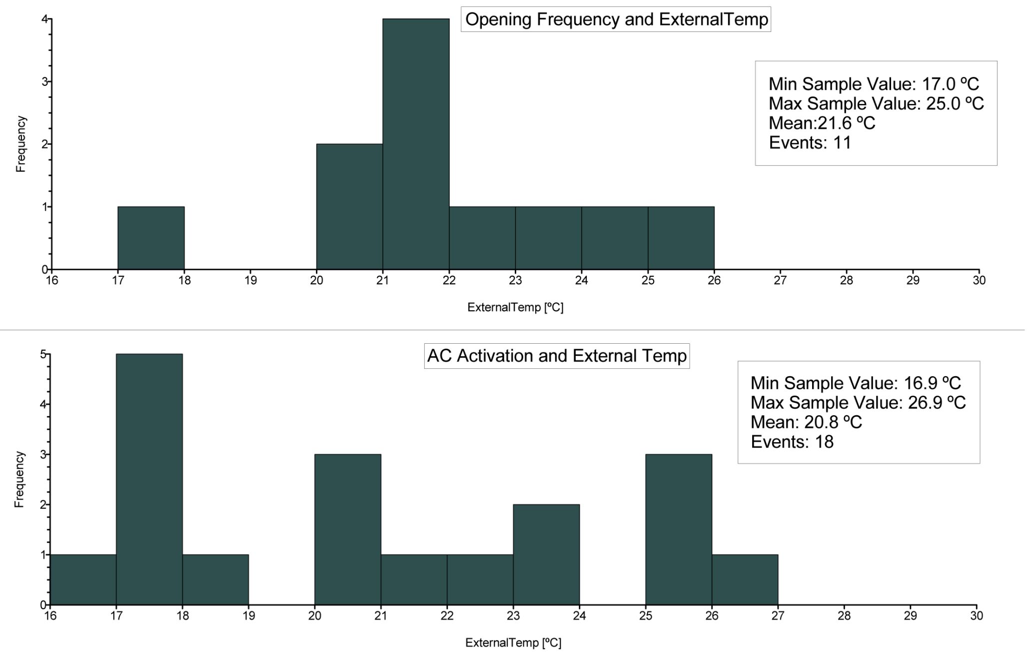

Figure 53: Office 8: Histogram 2- Frequency of actions by outdoor temperature

(Figure 61).

2.7.1 General Considerations

The characterization and analysis of each room for the summer period allowed some general considerations to be made regarding behaviors that were common in several

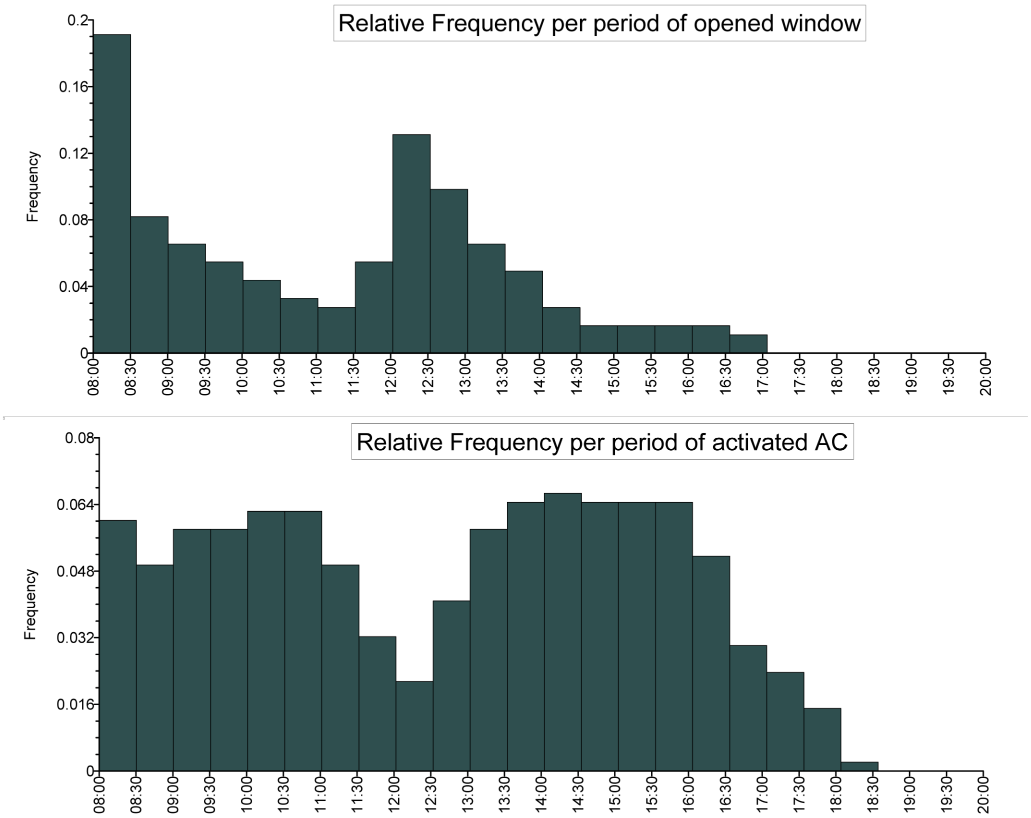

Figure 54: Office 8: Histogram 3 - Relative frequency of actions by period

offices. Brief considerations in relation to a building's thermal performance and positioning of the AC unit could also be drawn from this analysis.

Temperatures

a. When the outdoor temperature was 5°C or more lower than the indoor temperature, approximately 20 and 25°C respectively, the windows were open and the AC was off. This coincided mostly with early mornings, between 7 and 9 am, which is also the time of arrival in offices.

b. When the outdoor temperature values reached and/or exceed the indoor values, around 25°C and above, the windows were closed and the AC was activated. As the outdoor temperature progressively increased during the day, reaching its maximum values around midday, windows were closed and the AC activated. The average observed temperature for AC activation was about 25°C.

c. Periods of open windows and activated AC mostly coincided with lower and higher outdoor temperatures, generally showing morning and afternoon, respectively.

d. Offices where the indoor temperature reached very high values, close to 30°C, windows were closed and the AC activated, even if the outdoor temperature was around 20°C.

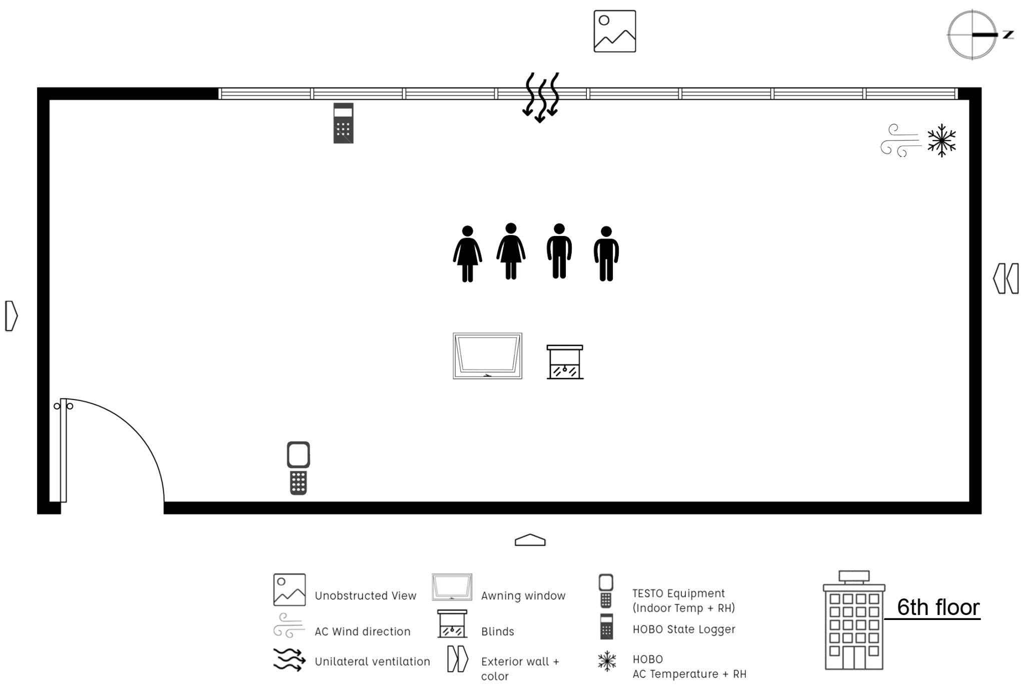

Figure 55: Office 9: floor plan. No scale.

Specifics

Office 1: AC was activated every day and remained in that state for long periods of time. Indoor temperature did not decrease, occupants operated the AC while it was already on (Figure 14), probably in an effort to decrease the temperature even more. AC unit is possibly not well dimensioned for the space and number of users, and/or not well positioned. The unit is on the last floor of the building, which needs to be taken into account, due to heat gain from the roof.

Office 3: AC was not activated during the monitored period. Possible unusual occupant preference, AC unit location, health conditions, etc. Example of unit where questionnaires will aid in explaining occupant behavior.

Offices 6, 7 and 8: Offices within the same building. Office 8 displays an external wall, and therefore also the highest indoor temperatures, close to, and sometimes exceeding, 30°C. At times, even during the periods when the AC was active, indoor temperature remained close to 30 °C. The other two offices, 6 and 7, also presented high indoor temperatures. However, in these units, when the AC was activated, indoor temperature quickly decreased.

Office 9: Constant indoor temperature (around 26°C), and AC was activated every day. Some days there was only AC operation and windows were not opened. AC always activated at a very low temperature, but indoor temperature did not decrease much. Possibly location of AC unit is not favorable to cooling down the entire office. Current

Figure 56: Office 9: Monitored data

location probably chosen due to window proximity and installation viability.

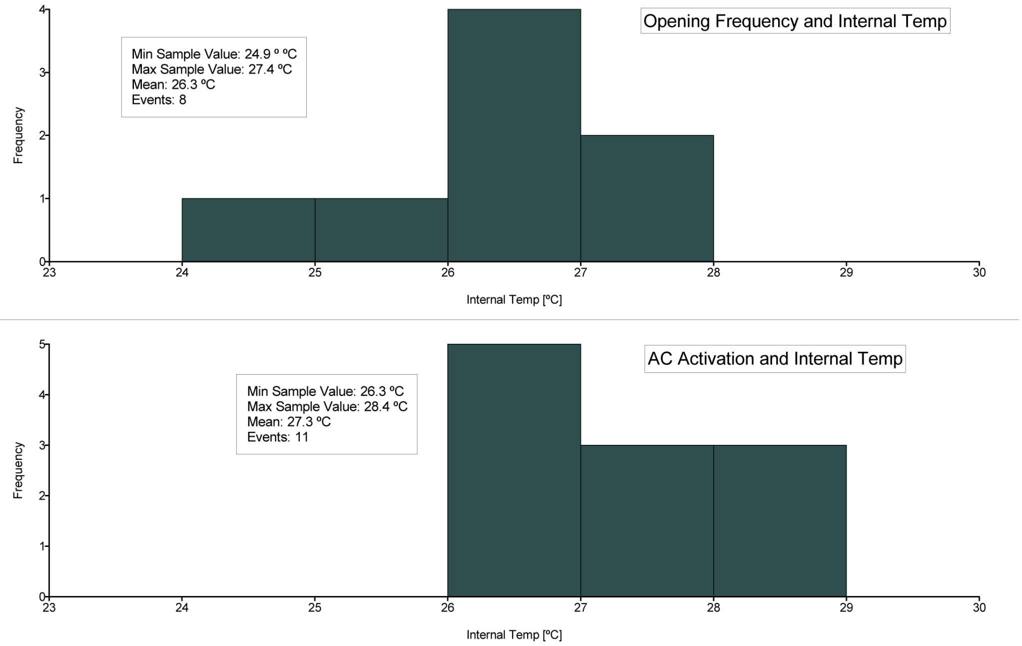

Figure 57: Office 9: Histogram 1 - Frequency of actions by indoor temperature

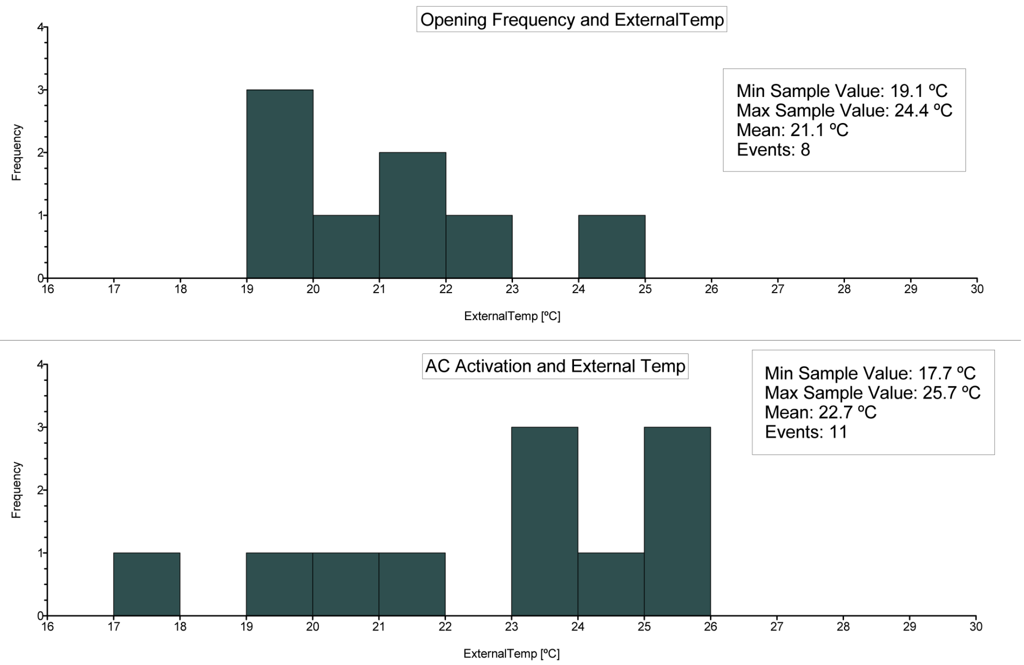

Figure 58: Office 9: Histogram 2- Frequency of actions by outdoor temperature

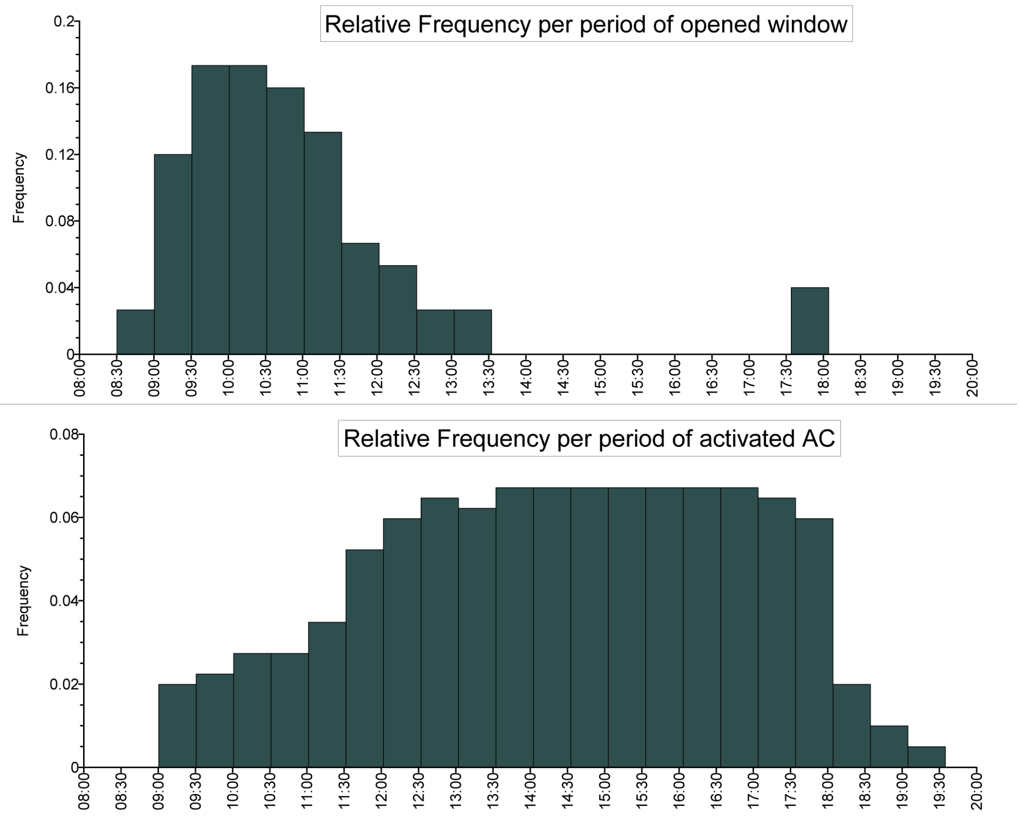

Figure 59: Office 9: Histogram 3 - Relative frequency of actions by period

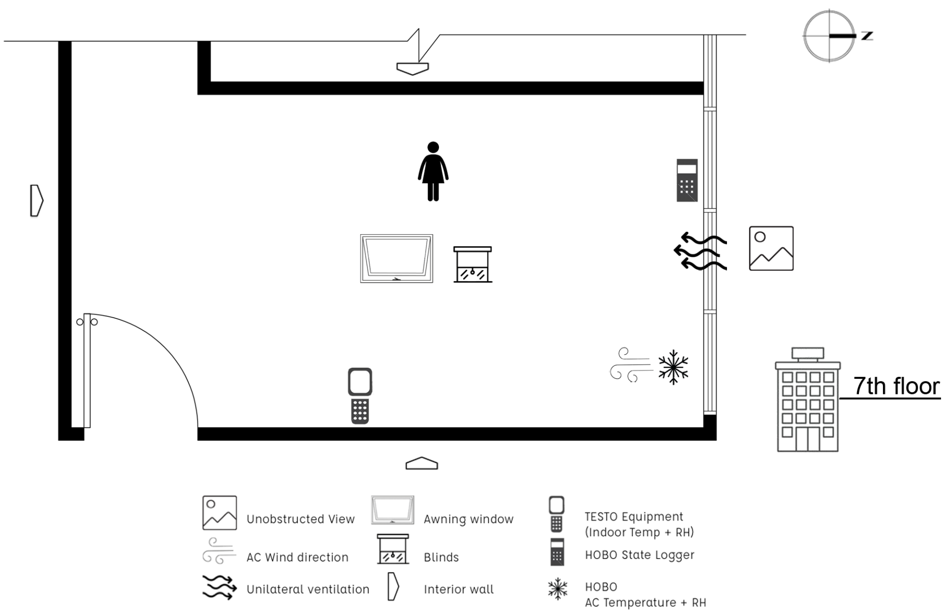

Figure 60: Office 10 floor plan. No scale.

Figure 61: Office 10: Monitored data

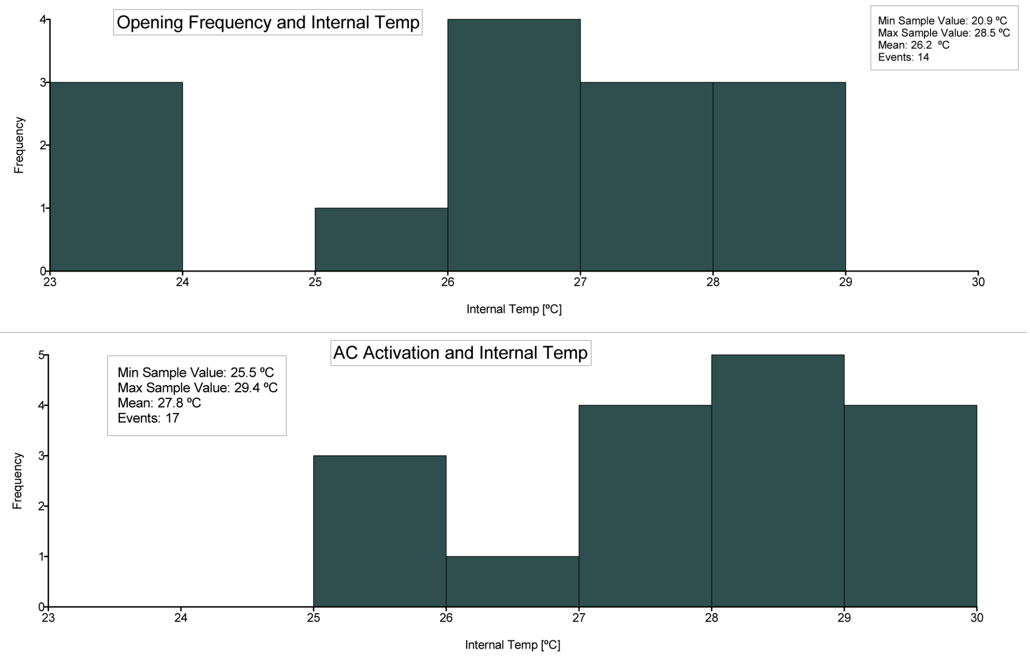

Figure 62: Office 10: Histogram 1 - Frequency of actions by indoor temperature

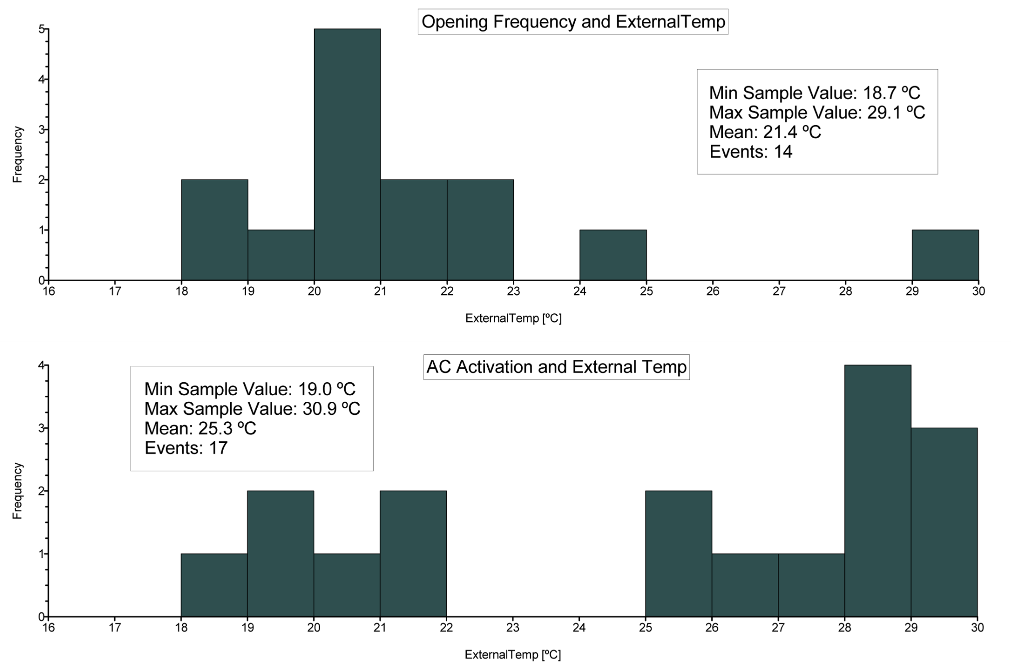

Figure 63: Office 10: Histogram 2- Frequency of actions by outdoor temperature

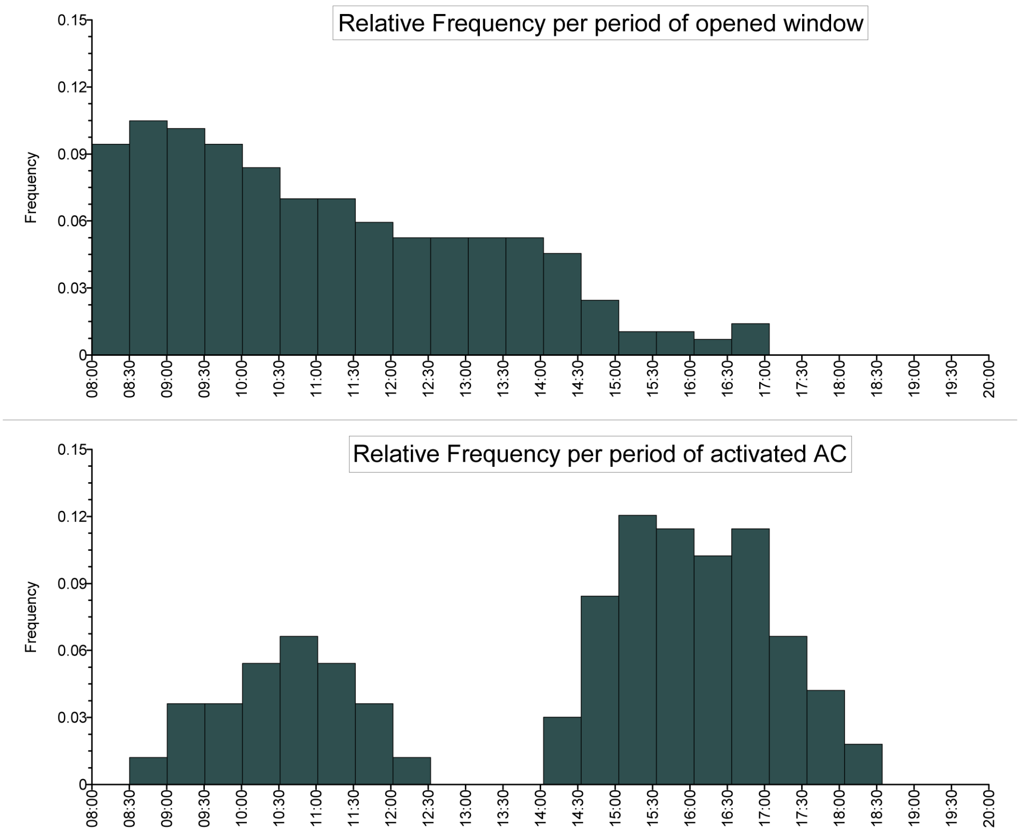

Figure 64: Office 10: Histogram 3 - Relative frequency of actions by period

3 FUTURE ACTIVITIES

This section presents the activities to be developed in this research as a means to achieve its objectives. The schedule for such activities is also presented, including the stages that have already been completed.

3.1 Method

This research counts with a period of internship at the Karlsruhe Institute of Technology (KIT), Germany, where stages (c) and (d) are scheduled to be developed.

3.1.1 (b) In situ measurements and Data Analysis

This stage is ongoing and scheduled to be concluded in October/2018. The summer monitoring was concluded and its data treated and analyzed. The following monitoring periods, fall, winter and spring, will follow the same procedure and method.

3.1.2 (c) Statistical methods' application and Algorithm's creation

At this stage the data set will be complete, and it will provide the necessary information to adequately choose the most appropriate statistical method to be applied, and thus create the algorithm.

3.1.3 (d) Algorithm's validation and test

After the algorithm is created, it will be validated to verify its accuracy in predicting occupant behavior within a mixed-mode office. Once it is validated, it will then be tested to demonstrate its application.

3.2 Thesis Structure

The following structure is a suggestion to be used in the final thesis, as it differs from the structure used in this volume.

- Abstract
- Introduction
- Literature Review
- Method
  - Development of Theoretical Model

  - Units of analysis, population and scope
  - (a) Buildings' data collection and Pre-test
  - (b) In situ measurements and Data Analysis
  - (c) Statistical methods' application and Algorithm's creation
  - (d) Algorithm's validation and test

- Results
  - Analysis of Complete Data set
  - Behavior characterization according to season
  - Algorithm's Validation
  - Test

- Conclusions
- Suggestions for Future Work
- References

3.3 Schedule

Activities		Months											
	Year	1	2	3	4	5	6	7	8	9	10	11	12
	2016												
Class Credits			x	x	x	x	x						
Literature review		x	x	x	x	x	x	x	x	x	x	x	x
	2017												
Literature review		x	x	x	x	x	x	x	x	x	x	x	x
Teaching Internship Program			x	x	x	x	x						
Foreign Language Prof.Exam			x										
Data collection and initial visits									x	x	x		
Pre-test											x	x	
Data Collection												x	x
	2018												
Data Collection		x	x	x	x	x	x	x	x	x	x		
Qualifying Exam						x							
Windsor Conference					x								
Partial data processing		x	x	x	x	x	x	x	x	x	x		
Internship at KIT												x	x
	2019												
Internship at KIT		x	x	x	x	x	x	x	x	x	x	x	x
Healthy Buildings Europe								x					
	2020												
Thesis writing and defense panel		x	x	x	x	x	x	x	x				

Table 12: Activities Schedule

BIBLIOGRAPHY

ABNT. **ASSOCIAÇÃO BRASILEIRA DE NORMAS TÉCNICAS. NBR 15220: Desempenho Térmico de edificações**. Rio de Janeiro: [s.n.], 2005.

ANDERSEN, R. et al. Window opening behaviour modelled from measurements in Danish dwellings. **Building and Environment**, v. 69, p. 101–113, 2013. ISSN 03601323. Disponível em: <http://www.sciencedirect.com/science/article/pii/S0360132313001960>.

ANDERSEN, R. K.; FABI, V.; CORGNATI, S. P. Predicted and actual indoor environmental quality: Verification of occupants' behaviour models in residential buildings. **Energy and Buildings**, Elsevier B.V., v. 127, p. 105–115, 2016. ISSN 03787788. Disponível em: <http://dx.doi.org/10.1016/j.enbuild.2016.05.074>.

AUGENBROE, G. Trends in building simulation. **Building and Environment**, v. 37, n. 8-9, p. 891–902, 8 2002. ISSN 03601323. Disponível em: <http://linkinghub.elsevier.com/retrieve/pii/S0360132302000410>.

BAKER, N.; STANDEVEN, M. Thermal comfort for free-running buildings. **Energy and Buildings**, v. 23, n. 3, p. 175–182, 3 1996. ISSN 03787788. Disponível em: <http://linkinghub.elsevier.com/retrieve/pii/0378778895009426>.

BEN. **Balanço Energético Nacional 2016: Ano base 2015**. Rio de Janeiro, 2016. 292 p. Disponível em: <www.epe.gov.br>.

BLUYSSEN, P. M. **The Indoor Environment Handbook**. London: Earthscan, 2012. v. 165. 234–234 p. ISSN 1478-4629. ISBN 9781844077878.

BOROVKOV, K. **Elements of Stochastic Modelling**. 2nd. ed. Singapore: World Scientific, 2014. 482 p.

BUONOMANO, A.; SHERMAN, M. H. Analysis of residential hybrid ventilation performance in US climates. **30th AIVC Conference**, n. October, p. 1–6, 2009.

BURNHAM, K. P.; ANDERSON, D. R. Multimodel inference: Understanding AIC and BIC in model selection. **Sociological Methods and Research**, v. 33, n. 2, p. 261–304, 2004. ISSN 00491241.

CABANAC, M. Physiological Role of Pleasure. **Science**, v. 173, n. 4002, p. 1103–1107, 1971. ISSN 0036-8075. Disponível em: <http://www.sciencemag.org/cgi/doi/10.1126/science.173.4002.1103>.

CALÌ, D. et al. Analysis of occupants' behavior related to the use of windows in German households. **Building and Environment**, v. 103, p. 54–69, 2016. ISSN 03601323. Disponível em: <http://www.sciencedirect.com/science/article/pii/S036013231630107X>.

______. Energy performance gap in refurbished German dwellings: Lesson learned from a field test. **Energy and Buildings**, Elsevier, v. 127, p. 1146–1158, 9 2016. ISSN 0378-7788. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0378778816303814?via%3Dihub>.

CARPENTER, J.; WOODBURY, K. A.; O'NEILL, Z. Using change-point and Gaussian process models to create baseline energy models in industrial facilities: A comparison. **Applied Energy**, Elsevier, v. 213, p. 415–425, 3 2018. ISSN 0306-2619. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0306261918300448>.

CARRIÈRES, K. **Desempenho Térmico e Consumo Energético de Edifícios de Escritórios em São Carlos , SP**. 2007. Tese (Doutorado) — Universidade Estadual de Campinas, UNICAMP, 2007.

CBE. **Center for the Built Environment (CBE), About Mixed-Mode[Online]. Available: http://www.cbe.berkeley.edu/mixedmode/aboutmm.html, 2017 (accessed: 31.05.17).** 2013.

CEPAGRI. **CENTRO DE PESQUISAS METEOROLÓGICAS E CLIMÁTICAS APLICADAS A AGRICULTURA**. 2018. Disponível em: <http://www.cpa.unicamp.br/outras-informacoes/clima-dos-municipios-paulistas.html>.

CHEN, S. et al. Definition of occupant behavior in residential buildings and its application to behavior analysis in case studies. **Energy and Buildings**, Elsevier, v. 104, p. 1–13, 10 2015. ISSN 0378-7788. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0378778815301146>.

DAR, U. I. et al. Influence of occupant's behavior on heating needs and energy system performance: A case of well-insulated detached houses in cold climates. **Building Simulation**, v. 8, n. 5, p. 499–513, 2015. ISSN 1996-3599. Disponível em: <http://link.springer.com/10.1007/s12273-015-0230-y>.

DAVIS, B. R. A. Gaussian Process : Theory. **Encyclopedia of Environmetrics**, 2006.

DELZENDEH, E. et al. The impact of occupants' behaviours on building energy analysis: A research review. **Renewable and Sustainable Energy Reviews**, Pergamon, v. 80, p. 1061–1071, 12 2017. ISSN 1364-0321. Disponível em: <https://www.sciencedirect.com/science/article/pii/S1364032117309061?via%3Dihub>.

DEUBLE, M. P.; DEAR, R. J. de. Mixed-mode buildings: A double standard in occupants' comfort expectations. **Building and Environment**, Pergamon, v. 54, p. 53–60, 8 2012. ISSN 03601323. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0360132312000364>.

D'OCA, S. et al. Effect of thermostat and window opening occupant behavior models on energy use in homes. **Building Simulation**, v. 7, n. 6, p. 683–694, 12 2014. ISSN 19968744. Disponível em: <http://link.springer.com/10.1007/s12273-014-0191-6>.

Eletrobrás. **Avaliação do mercado de eficiência energética do Brasil**. Rio de Janeiro, 2009.

Energy Information Administration. **International Energy Outlook**. [s.n.], 2016. v. 0484(2016). 1–2 p. ISSN 0163660X. ISBN 2025866135. Disponível em: <www.eia.gov/forecasts/ieo/pdf/0484(2016).pdf>.

FABI, V.; ANDERSEN, R. K.; CORGNATI, S. Verification of stochastic behavioural models of occupants' interactions with windows in residential buildings. **Building and Environment**, Elsevier Ltd, v. 94, n. P1, p. 371–383, 2015. ISSN 03601323. Disponível em: <http://dx.doi.org/10.1016/j.buildenv.2015.08.016>.

FABI, V. et al. Occupants' window opening behaviour: A literature review of factors influencing occupant behaviour and models. **Building and Environment**, v. 58, p. 188–198, 2012. ISSN 03601323.

______. A methodology for modelling energy-related human behaviour: Application to window opening behaviour in residential buildings. **Building Simulation**, v. 6, n. 4, p. 415–427, 2013. ISSN 19963599.

FRITSCH, R. et al. A Stochastic Model of User Regarding Ventilation Behaviour. **Building and Environment**, v. 25, n. 2, p. 173–181, 1990. ISSN 03601323.

GAMERMAN, D.; LOPES, H. **Markov Chain Monte Carlo: Stochastic simulation for Bayesian Inference**. 2nd. ed. Boca Raton: Chapman & Hall/CRC Taylor & Francis Group, 2006. 323 p.

GRAY, F. M.; SCHMIDT, M. A hybrid approach to thermal building modelling using a combination of Gaussian processes and grey-box models. **Energy and Buildings**, Elsevier, v. 165, p. 56–63, 4 2018. ISSN 0378-7788. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0378778817332942#bib0010>.

HALDI, F. et al. Modelling diversity in building occupant behaviour: a novel statistical approach. **Journal of Building Performance Simulation**, v. 1493, n. January, p. 1–18, 2016. ISSN 1940-1493. Disponível em: <https://www.tandfonline.com/doi/full/10.1080/19401493.2016.1269245>.

HALDI, F.; ROBINSON, D. Interactions with window openings by office occupants. **Building and Environment**, Elsevier Ltd, v. 44, n. 12, p. 2378–2395, 2009. ISSN 03601323. Disponível em: <http://dx.doi.org/10.1016/j.buildenv.2009.03.025>.

HOES, P. et al. User behavior in whole building simulation. **Energy and Buildings**, v. 41, n. 3, p. 295–302, 3 2009. ISSN 03787788. Disponível em: <http://linkinghub.elsevier.com/retrieve/pii/S0378778808002168>.

HOLMES, M. J.; HACKER, J. N. Climate change, thermal comfort and energy: Meeting the design challenges of the 21st century. **Energy and Buildings**, v. 39, n. 7, p. 802–814, 2007. ISSN 03787788. Disponível em: <http://www.sciencedirect.com/science/article/pii/S0378778807000424>.

HONG, T. et al. An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema. **Building and Environment**, Elsevier Ltd, v. 94, n. P1, p. 196–205, 2015. ISSN 03601323. Disponível em: <http://dx.doi.org/10.1016/j.buildenv.2015.08.006>.

______. Ten questions concerning occupant behavior in buildings: The big picture. **Building and Environment**, v. 114, p. 518–530, 2017. ISSN 03601323. Disponível em: <http://www.sciencedirect.com/science/article/pii/S0360132316304851>.

HOSMER, D. W.; LEMESHOW, S. **Applied Logistic Regression**. [S.l.]: John Wiley & Sons, 1989. 307 p. ISBN 0471615536.

IPCC. **Climate Change 2014: Mitigation of Climate Change.** Cambridge, United Kingdom, 2014. 1454 p.

ITÔ, K. **Translations of Mathematical Monographs: Essentials of Stochastic Processes**. Providence, Rhode Island: American Mathematical Society, 2006.

JAMES, G. et al. **An Introduction to Statistical Learning with Applications in R**. [s.n.], 2007. v. 64. 856–875 p. ISSN 01665316. ISBN 9780387781884. Disponível em: <http://books.google.com/books?id=9tv0taI8l6YC>.

JANDA, K. B. Buildings don't use energy: People do. **Architectural Science Review**, v. 54, n. 1, p. 15–22, 2011. ISSN 00038628.

JONES, R. V. et al. Stochastic behavioural models of occupants' main bedroom window operation for UK residential buildings. **Building and Environment**, v. 118, p. 144–158, 2017. ISSN 03601323. Disponível em: <http://www.sciencedirect.com/science/article/pii/S0360132317301312>.

KRAUSSE, B.; COOK, M.; LOMAS, K. Environmental performance of a naturally ventilated city centre library. **Energy and Buildings**, v. 39, n. 7, p. 792–801, 2007. ISSN 03787788. Disponível em: <http://www.sciencedirect.com/science/article/pii/S0378778807000515>.

KUSS, M. **Gaussian process models for robust regression, classification, and reinforcement learning**. 2006. Tese (Doutorado), 2006. Disponível em: <http://tuprints.ulb.tu-darmstadt.de/674/>.

LI, N. et al. Probability of occupant operation of windows during transition seasons in office buildings. **Renewable Energy**, v. 73, p. 84–91, 2015. ISSN 09601481. Disponível em: <http://www.sciencedirect.com/science/article/pii/S0960148114003401>.

MACKAY, D. J. C. Gaussian processes - a replacement for supervised neural networks? **Advanced Lectures on Machine Learning**, p. 63–71, 1997. ISSN 1549-960X. Disponível em: <http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.47.9170>.

MARKUS, K. A. Constructs, Concepts and the Worlds of Possibility: Connecting the Measurement, Manipulation, and Meaning of Variables. **Measurement: Interdisciplinary Research & Perspective**, v. 6, n. 1-2, p. 54–77, 2008. ISSN 1536-6367. Disponível em: <http://www.tandfonline.com/doi/abs/10.1080/15366360802035513>.

MARTINAITIS, V. et al. Importance of occupancy information when simulating energy demand of energy efficient house: A case study. **Energy and Buildings**, Elsevier, v. 101, p. 64–75, 8 2015. ISSN 0378-7788. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0378778815003308?via%3Dihub>.

NEVES, L. D. O. et al. Developing user profiles for mixed-mode office buildings operation based on occupant behaviour evaluation. In: **Windsor Conference - Rethinking Comfort**. Windsor, UK: [s.n.], 2018.

NICOL, J. Characterising occupant behavior in buildings: Towards a stochastic model of occupant use of windows, lights, blinds heaters and fans. **Seventh International IBPSA Conference**, p. 1073–1078, 2001. ISSN 00012491.

NICOL, J.; HUMPHREYS, M. Adaptive thermal comfort and sustainable thermal standards for buildings. **Energy and Buildings**, Elsevier, v. 34, n. 6, p. 563–572, 7 2002. ISSN 0378-7788. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0378778802000063?via%3Dihub>.

PAGE, J. et al. A generalised stochastic model for the simulation of occupant presence. **Energy and Buildings**, v. 40, n. 2, p. 83–98, 2008. ISSN 03787788.

PARK, J.; KIM, H. A field study of occupant behavior and energy consumption in apartments with mechanical ventilation. **Energy and Buildings**, Elsevier, v. 50, p. 19–25, 7 2012. ISSN 0378-7788. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0378778812001636?via%3Dihub>.

PENG, C. et al. Quantitative description and simulation of human behavior in residential buildings. **Building Simulation**, v. 5, n. 2, p. 85–94, 6 2012. ISSN 1996-3599. Disponível em: <http://link.springer.com/10.1007/s12273-011-0049-0>.

PISELLO, A. L. et al. How peers' personal attitudes affect indoor microclimate and energy need in an institutional building: Results from a continuous monitoring campaign in summer and winter conditions. **Energy and Buildings**, Elsevier B.V., v. 126, p. 485–497, 2016. ISSN 03787788. Disponível em: <http://dx.doi.org/10.1016/j.enbuild.2016.05.053>.

RASMUSSEN, C. E.; WILLIAMS, C. K. I. Regression. In: **Gaussian Processes for Machine Learning**. [S.l.]: MIT Press, 2006. cap. 2. ISBN 026218253X.

RICHARDSON, I.; THOMSON, M.; INFIELD, D. A high-resolution domestic building occupancy model for energy demand simulations A high-resolution domestic building occupancy model for energy demand simula- tions. Energy and. **Buildings**, v. 40, n. 8, p. 1560–1566, 2008. Disponível em: <www.elsevier.com/locate/enbuild%0Ahttp://hdl.handle.net/2134/3112%0Ahttps://dspace.lboro.ac.uk/2134/4757>.

RIJAL, H.; HUMPHREYS, M.; NICOL, F. Adaptive Thermal Comfort in Japanese Houses during the Summer Season: Behavioral Adaptation and the Effect of Humidity. **Buildings**, v. 5, n. 3, p. 1037–1054, 2015. ISSN 2075-5309. Disponível em: <http://www.mdpi.com/2075-5309/5/3/1037/>.

RIJAL, H. et al. Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings. **Energy and Buildings**, v. 39, n. 7, p. 823–836, 7 2007. ISSN 03787788. Disponível em: <http://linkinghub.elsevier.com/retrieve/pii/S0378778807000400>.

RIJAL, H. B.; HUMPHREYS, M. A.; NICOL, J. F. Development of a Window Opening Algorithm to Predict Occupant Behavior in Japanese Houses. **PLEA 2014 - 30th INTERNATIONAL PLEA CONFERENCE**, v. 2013, n. December, p. 90–97, 2014.

RIJAL, H. B.; STEVENSON, F. Thermal comfort in UK housing to avoid overheating: lessons from a 'Zero Carbon' case study. **Proceedings of Conference: Adapting to Change: New Thinkingon Comfort Cumberland Lodge, Windsor, UK, 9-11 April 2010. London: Network for Comfort and Energy Use in Buildings, http://nceub.org.uk**, n. April, p. 9–11, 2010.

RIJAL, H. B. et al. An algorithm to represent occupant use of windows and fans including situation-specific motivations and constraints. **Building Simulation**, v. 4, n. 2, p. 117–134, 2011. ISSN 19963599.

RORIZ, M. Arquivos Climáticos de Municípios Brasileiros. **ANTAC – Associação Nacional de Tecnologia do Ambiente Construído. Grupo de Trabalho sobre Conforto e Eficiência Energética de Edificações**, 2012.

SALCIDO, J. C.; RAHEEM, A. A.; ISSA, R. R. From simulation to monitoring: Evaluating the potential of mixed-mode ventilation (MMV) systems for integrating natural ventilation in office buildings through a comprehensive literature review. **Energy and Buildings**, v. 127, p. 1008–1018, 2016. ISSN 03787788.

SCHAKIB-EKBATAN, K. et al. Does the occupant behavior match the energy concept of the building? – Analysis of a German naturally ventilated office building. **Building and Environment**, v. 84, p. 142–150, 1 2015. ISSN 03601323. Disponível em: <http://www.sciencedirect.com/science/article/pii/S0360132314003394>.

SCHWEIKER, M. Occupant Behaviour and the Related Reference Levels for Heating and Cooling. **Indoor Air**, n. JANUARY 2010, 2010.

SCHWEIKER, M.; SHUKUYA, M. Comparison of theoretical and statistical models of air-conditioning-unit usage behaviour in a residential setting under Japanese climatic conditions. **Building and Environment**, v. 44, n. 10, p. 2137–2149, 2009. ISSN 03601323. Disponível em: <http://www.sciencedirect.com/science/article/pii/S0360132309000687>.

SCHWEIKER, M.; WAGNER, A. The effect of occupancy on perceived control, neutral temperature, and behavioral patterns. **Energy and Buildings**, v. 117, p. 246–259, 2016. ISSN 03787788.

SHI, S.; ZHAO, B. Occupants interactions with windows in 8 residential apartments in Beijing and Nanjing, China. **Building Simulation**, v. 9, n. 2, p. 221–231, 2016. ISSN 19968744.

SHIPWORTH, D.; HUEBNER, G. M. Designing Research. In: WAGNER, A.; O'BRIEN, W.; DONG, B. (Ed.). **Exploring Occupant Behavior in Buildings. Methids and Challenges**. Cham, Switzerland: Springer, 2018. cap. 3, p. 333. ISBN 978-3-319-61463-2.

STAZI, F.; NASPI, F.; D'ORAZIO, M. **A literature review on driving factors and contextual events influencing occupants' behaviours in buildings**. Pergamon, 2017. 40–66 p. Disponível em: <http://www.sciencedirect.com/science/article/pii/S0360132317301191?_rdoc=1&_fmt=high&_origin=gateway&_docanchor=&md5=b8429449ccfc9c30159a5f9aeaa92ffb&dgcid=raven_sd_recommender_email>.

_____. Modelling window status in school classrooms. Results from a case study in Italy. 2017. Disponível em: <http://www.sciencedirect.com/science/article/pii/S036013231630405X>.

STULP, F.; SIGAUD, O. Many regression algorithms, one unified model: A review. **Neural Networks**, Pergamon, v. 69, p. 60–79, 9 2015. ISSN 0893-6080. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0893608015001185?via%3Dihub>.

TAYLOR, H. M.; KARLIN, S. **An introduction to stochastic modeling**. [S.l.: s.n.], 1994. 566 p. ISBN 9780126848854.

VANGTOOK, P.; CHIRARATTANANON, S. Application of radiant cooling as a passive cooling option in hot humid climate. **Building and Environment**, v. 42, n. 2, p. 543–556, 2007. ISSN 03601323. Disponível em: <http://www.sciencedirect.com/science/article/pii/S0360132305004002>.

VECCHI, R. D. et al. Thermal comfort in office buildings: Findings from a field study in mixed-mode and fully-air conditioning environments under humid subtropical conditions. **Building and Environment**, Pergamon, v. 123, p. 672–683, 10 2017. ISSN 0360-1323. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0360132317303281?via%3Dihub>.

WANG, H.; JOHN, Z. Advances in building simulation and computational techniques : A review between 1987 and 2014. **Energy & Buildings**, Elsevier B.V., v. 128, p. 319–335, 2016. ISSN 0378-7788. Disponível em: <http://dx.doi.org/10.1016/j.enbuild.2016.06.080>.

YAN, D. et al. Occupant behavior modeling for building performance simulation: current state and future challenges. **Energy and Buildings**, v. 107, p. 264–278, 8 2015. ISSN 03787788. Disponível em: <http://www.sciencedirect.com/science/article/pii/S0378778815302164>.

_____. Validation and Ground Truths. In: WAGNER, A.; O'BRIEN, W.; DONG, B. (Ed.). **Exploring Occupant Behavior in Buildings. Methids and Challenges**. Cham, Switzerland: Springer, 2018. cap. 9, p. 333.

YOON, Y. R.; MOON, H. J. Energy consumption model with energy use factors of tenants in commercial buildings using Gaussian process regression. **Energy and Buildings**, Elsevier, v. 168, p. 215–224, 6 2018. ISSN 0378-7788. Disponível em: <https://www.sciencedirect.com/science/article/pii/S0378778817329201>.

YOSHINO, H. **Total energy use in buildings Analysis and evaluation methods**. [S.l.], 2013. 132 p. Disponível em: <http://www.iea-ebc.org/fileadmin/user_upload/images/Pictures/EBC_Annex_53_Main_Report.pdf>.

YUN, G. Y.; STEEMERS, K. Time-dependent occupant behaviour models of window control in summer. **Building and Environment**, v. 43, n. 9, p. 1471–1482, 2008. ISSN 03601323.

ZHANG, Y.; BARRETT, P. Factors influencing the occupants' window opening behaviour in a naturally ventilated office building. **Building and Environment**, v. 50, p. 125–134, 2012. ISSN 03601323.