A Contribution to Artificial Intelligence-based Thermal Comfort Control with Dynamic Modeling for Smart Buildings

Résumé : Différents facteurs, tels que le confort thermique, la qualité de l'air intérieur, la ventilation, l'humidité et les conditions acoustiques, ont des effets combinés importants sur l'acceptabilité et la qualité des activités réalisées par les occupants des bâtiments qui passent une grande partie de leur temps à l'intérieur. Parmi les facteurs cités, le confort thermique, qui contribue au bien-être humain en raison de son lien avec la thermorégulation du corps humain. Par ailleurs, la relation entre l'occupant et son environnement ainsi que l'ensemble du bâtiment est complexe et interdépendante, et elle a un impact significatif sur l'efficacité énergétique. Par conséquent, le développement d'environnements thermiquement confortables et énergétiquement efficaces joue un rôle important dans la conception des bâtiments et ainsi des systèmes de chauffage, de ventilation et de climatisation. À cet égard, diverses études ont été menées, depuis des décennies, y compris des enquêtes et des expérimentations afin d'établir des normes pour évaluer le confort et les facteurs thermiques, ainsi que les paramètres de réglage des systèmes CVC. Cependant, la plupart des travaux de recherche rapportés dans la littérature traitent uniquement des paramètres qui ne sont pas suivis dynamiquement. Pour surmonter cette lacune, cette thèse présente une approche axée sur les données pour développer un modèle de confort personnalisé en utilisant des caractéristiques liées a l'homme telles que des paramètres anthropométriques comme la morphologie du corps traduite par l'indice de masse corporelle, et des variables environnementales pour prédire des indicateurs de confort thermique. Une large base de données contenant des données expérimentales sur le confort humain au sein des plusieurs bâtiments réels est utilisée, ici, pour estimer la probabilité de sensation, d'acceptabilité et de préférence thermique individuelle. Le modèle développé sera mis en œuvre a l'intérieur des bâtiments pour configurer les systèmes CVC, où les occupants pourront être identifiés de manière non-intrusive. Cela permettra de modifier dynamiquement les réglages de température et donc d'atteindre le niveau du confort attendu.

Mots clés : Bâtiments intelligents, Occupants, Contrôle, Confort thermique, Apprentissage Automatique, Efficacité énergétique, Économies d'énergie, Systèmes CVC.

Abstract: Different factors such as thermal comfort, indoor air quality, ventilation, humidity and acoustic conditions, have significant combined effects on the acceptability and quality of the activities performed by the buildings' occupants who spend a great part of their times indoors. Among the factors cited, thermal comfort, which contributes to the human well-being because of its connection with the thermoregulation of the human body. Besides, the relationship between the occupant and his surrounding environment as well as the entire building is complex and interdependent, and has a significant impact on the energy efficiency. Therefore, the development of thermally comfortable and energy efficient environments is of great importance in the design of the buildings and hence the heating, ventilation and air-conditioning systems. In this regard, various studies have been conducted, for decades, including surveys and experimentations in order to establish standards to evaluate thermal comfort and factors, and setting-up parameters for HVAC systems. However, to the best of our knowledge, most of the research work reported in the literature deal only with parameters that are not dynamically tracked. To address this gap, this thesis presents a data-driven approach for developing a personalized comfort model that uses human-related features such as anthropometric parameters such as the body shape translated by the individual body mass index, and environmental variables to predict personalized thermal comfort indicators. Here, a large database containing experimental occupant comfort data from real office and classroom buildings is used to estimate the probability of individual thermal sensation, acceptability, and preference for multiple building types. The developed model will be implemented inside the buildings to setup HVAC systems, in which the occupants could be identified through a non-intrusive way. This allows to dynamically change the temperature settings and hence, meeting the expected comfort level.

Keywords: Smart buildings, Occupants, Control, Thermal Comfort, Machine Learning, Energy-Efficiency, Energy savings, HVAC Systems.

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THÈSE DE DOCTORAT

A CONTRIBUTION TO ARTIFICIAL INTELLIGENCE-BASED THERMAL COMFORT CONTROL WITH DYNAMIC MODELING FOR SMART BUILDINGS

Présentée par

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To my dearest mother, father, brothers and sister, for all their love and support.

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LIST OF ABBREVIATIONS

ABM	Agent-Based Model
ACMV	Air-Conditioning and Mechanical Ventilation
AI	Artificial Intelligence
ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Networks
ARX	Autoregressive Exogenous
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
BCM	Bayesian Comfort Model
BEM	Building Energy Management
BEMS	Building Energy Management System
BN	Bayesian Network
BRITE	Berkeley Retrofitted and Inexpensive HVAC Testbed
CA	Context-Awareness
CAC	Comfort Air-Conditioning
CFD	Computational Fluid Dynamics
CHP	Combined Heat and Power
CI	Computational Intelligence
CIBSE	Chartered Institution of Building Services Engineers
CL	Cooling Load
CTR	Comfort Time Ratio
DAI	Distributed Artificial Intelligence
DCC	Demand-driven Cooling Control
DID	Degree of Individual Dissatisfaction
DL	Load Demand
DNN	Deep Neural Networks
DRL	Reinforcement Learning
DT	Decision Tree
EACRA	Energy Aware Context Recognition Algorithm
EDA	Epistemic-Deontic-Axiologic
eJAL	Extended Joint Action Learning
FACT	Fuzzy Adaptive Comfort Temperature
FCM	Fuzzy Cognitive Map
FDM	Fused Deposition Modeling
FIS	Fuzzy Inference System
FLC	Fuzzy Logic Control
FRB	Fuzzy Rule Base
GA	Genetic Algorithm
gARTMAP	Gaussian Adaptive Resonance Theory Map
HABIT	Human and Building Interaction Toolkit
HIYW	Have-It-Your-Way
HL	Heating Load
HMM	Hidden Markov Model
HVAC	Heating, Ventilation, and Air-Conditioning
HVAC & R	Heating, Ventilation and Air-Conditioning and Refrigeration
iBEMS	Intelligent Building Energy Management Systems
ICT	Information and Communication Technologies
IEA	International Energy Agency
IEEMS	Indoor Environment Energy Management System
IEQ	Indoor Environmental Quality
IHMS	Intelligent Heat Management System
IoT	Internet of Things

KBS	Knowledge-Based System
kNN	k-Nearest Neighbor
LBMPC	Learning-Based Model Predictive Control
LR	Logistic regression
LRLC	Linear Reinforcement Learning Controller
LSTM	Long Short-Term Memory
MACES	Multi-Agent Comfort and Energy System
MAS	Multi-Agent Systems
MBPC	Model-Based Predictive Control
MISO	Multi-Input, Single-Output
ML	Machine Learning
MLR	Multivariate Linear Regression
MOABC	Multi-Objective Artificial Bee Colony
MOGA	multi-objective genetic algorithm
MOPSO	Multi-Objective Particle Swarm Optimization
MRA	Multiple Regression Analysis
MSE	Mean Squared Error
NARX	Nonlinear Autoregressive Exogenous
NFQ	Neural Fitted Q-iteration
NIST	National Institute of Standards and Technology
NSGA	Nondominated Sorting Genetic Algorithm II
OMG	Occupant Mobile Gateway
OSHA	Occupational Safety and Health Administration
PAR	Peak to Average Ratio
PID	Proportional-Integral-Derivative
PMV	Predicted Mean Vote
PPD	Predicted Percentage of Dissatisfied
PPV	Predicted Personal Vote
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
PSO	Particle Swarm Optimization
RBF	Rule Base Function
RBF	Radial Basis Function
RF	Random Forest
RL	Reinforcement Learning
RMSE	Root-Mean-Square Deviation
RNN	Recurrent Neural Network
SBSA	State-Based Sensitivity Analysis
SQP	Sequential Quadratic Programming
SVM	Support Vector Machine
TPI	Thermal Perception Index
VAV	Variable Air Volume
WSN	Wireless Sensor Networks

ABSTRACT

Different factors such as thermal comfort, indoor air quality, ventilation, humidity, acoustic conditions, and so forth, have significant combined effects on the acceptability and quality of the activities performed by the occupants of the buildings who spend a great part of their time indoors. Among the factors cited, thermal comfort, which contributes to human well-being because of its connection with the thermoregulation of the human body. Moreover, the relationship between the occupant and his surrounding environment as well as the entire building is complex and interdependent and has a significant impact on energy-efficiency. Therefore, the development of thermally comfortable and energy-efficient environments is of great importance in the design of the buildings and hence the heating, ventilation, and air-conditioning systems. In this regard, various studies have been conducted, for decades, including surveys and experimentations in order to establish standards to evaluate thermal comfort and factors, and setting up parameters for HVAC systems. However, to our best of knowledge, most of the research work reported in the literature deal only with parameters that are not dynamically tracked.

In order to address this gap, this thesis presents a data-driven approach for developing a personalized comfort model that uses human-related features such as anthropometric parameters such as the body shape translated by the individual body mass index and environmental variables to predict personalized thermal comfort indicators. Here, a large database containing experimental occupant comfort data from real office and classroom buildings is used to estimate the probability of individual thermal sensation, acceptability, and preference for multiple building types.

The developed model will be implemented inside the buildings to set up HVAC systems, in which the occupants could be identified in a non-intrusive way. This will allow to dynamically change the temperature settings and hence, meeting the expected comfort level. Finally, the developed model will pave the way to develop systems that can dynamically adjust the environment to the users' preferences. Besides, the system can take advantage of this information to consider more energy efficiency opportunities. For instance, currently, the HVAC system set up the environment statically assuming an average user comfort level. With the current model, HVAC systems will be able to dynamically change the temperature setting and save energy.

Keywords: Smart buildings, Occupants, Control, Thermal comfort, Machine Learning, Energy-Efficiency, Energy savings, HVAC Systems.

1 INTRODUCTION

Discussion of the environmental impact of buildings has been gaining weight in the agendas of several cities and countries around the world. Indeed, approximately 38% of the final energy consumption growth between 2015 and 2050 in the world is correlated to the use and occupation of buildings. In this regard, the building sector was identified as a world pioneer in CO_2 in the fifth report produced by the International Panel of Climate Change (IPCC) [1]. However, the same report also has identified this sector as the one with the greatest potential for reducing CO_2 emissions, due to the design opportunities, technological advances, and user behavior.

Proportionally, climate change, the increased frequency, and the severity of warmer periods during the year has made a large part of the world's population dependent on artificial conditioning, which further drives peak demand during the summer [2]–[4]. Figure (1-1) shows the penetration of HVAC systems in households in some countries around the world. HVAC penetration will impact peak power demand which is extreme in countries such as Japan, the United States, and Korea. On the other hand, countries with low HVAC penetration are expected to have their peak electricity load increase by around 45% by 2050, according to the International Energy Agency (IEA) [5]. This significant consumption has been generating concern about the management and energy efficiency of these devices taking into account the thermal comfort of the buildings' occupants. Research in this area shows how difficult it is to balance the two main objectives in question: thermal comfort and energy savings.

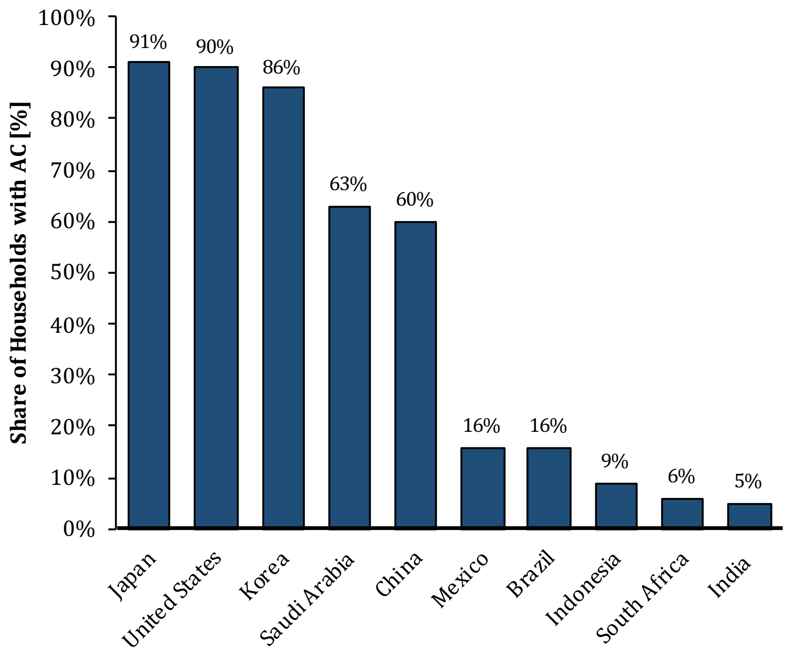


Figure 1-1. Percentage of households equipped with AC in selected countries, 2018, (Source: Adapted from IEA [5]).

Currently, thermal comfort is a recognized and justified demand in buildings because of its impact on the indoor environmental quality (IEQ), the health and productivity of the occupants spending three-quarters of their time indoors. This demand is supported by standards and regulations that ensure the conformity of indoor environments to the requirements of thermal comfort. Moreover, understanding the concept of thermal comfort, as well as the search for ways to predict whether a given situation represents comfort or discomfort has been the object of study for more than 50 years. In general, they are polarized on two fronts: the *static* (or *analytical*) perspective and the *adaptive* one, both brought the main thermal comfort standards into use today.

Evaluating thermal comfort in indoor environments is fundamental for the establishment of environmental and energy performance regulations in buildings, and which is mainly performed according to the American Society of Heating, Refrigerating and Air-Conditioning Engineers – ASHRAE 55 standard [6]. However, the analytical models adopted by this standard require the knowledge of several parameters whose measurement is complex, and can therefore be distorted, as they are based on a set of hypotheses that lead to defining an approximate comfort. Studies have shown that in the case of naturally ventilated buildings, these models fail to determine comfort situations: in reality, the comfort ranges are wider than those provided [7]. This situation is mainly due to the greater freedom of occupants. also, the implementation of these models in the current commercial buildings is static and does not take into consideration the variability of thermal perceptions amongst the occupants. Also, the parameters used by these models cannot be dynamically evaluated by the buildings to change their settings. Such gap has been addressed through this thesis by developing a personalized thermal comfort model as a function of variables that are dynamically updated, e.g., the individual body mass index, allowing to infer the adequate individual thermal comfort.

This thesis also focuses on comfort in office buildings, for a few reasons. First, within the context of offices, the human cost represents a hundred times more than the energy cost of buildings, which makes the performance of people in their work significantly important to improve the productivity factor in organizations as a whole [8]. Second, in the offices, the air temperature is influenced by multiple heat sources such as lighting, poorly insulated windows, machines (photocopiers, computers, other machines in operation). Finally, space insulation conditions affect comfort (e.g., thermal bridge, airflow, the temperature difference between workspaces…).

Moreover, in order to adjust the indoor climate conditions, many technological solutions have been proposed. However, achieving a comfortable and energy-efficient environment, the occupant is supposed to become an *expert* on these technologies that can challenge his daily habits. Given the complexity of these technologies, the user could choose the solution of the smart buildings equipped with sensors to adjust everything (temperature, ventilation, opening/closing windows) to promote energy savings and comfort. Moreover, we might think that building automation makes it possible to reach comfort and reduce energy consumption, but studies have shown that when the user can act on his environment, he sets up the conditions allowing him to achieve his optimal comfort. Thus, the occupant must interact with his surrounding environment to achieve the expected savings, since the human being is always the final sensitive sensor, i.e., he is an actor of comfort and can act to meet the conditions that are favorable to the risk of going against the social or technical practices designed to reduce energy consumption or to improve comfort.

In their study, J. Nicol and M. Humphreys [7] have shown that the individual is more tolerant towards comfort situations if he can act (by himself) on the regulation of systems. For example, in buildings where the control is centralized, the occupants must adapt to a certain temperature that may make them feel uncomfortable. Thus, according to them, when the occupants have the access to control of the temperature changes, they find the atmosphere more comfortable.

In the same context, research has recently been directed towards more advanced control structures that take multiple inputs (temperature, humidity, comfort sensation, and so forth) and uses, and developing individual comfort models based on personal characteristics of the users within given environments [9]–[15]. One study [9] proposed a decision support system for a real-time individual's thermal comfort prediction dedicated especially to senior citizens, and using environmental, psychological, and physiological features. Results showed significant prediction accuracy improvement (76.7%) compared to the conventional Fanger's model (35.4%) by including two new factors: the age and outdoor temperature that are not considered in the Fanger's model. Other suggested personalized models dealing with both thermal comfort and energy savings, by investigating the "human-in-the-loop" approach that allows HVAC adjustments adaptable to the users' preferences [10], [11].

Otherwise, several types of research have studied the influence of different contextual variables, such as gender, age, body composition, and thermal history on thermal comfort. They have concluded that:

- **Gender:** women are more sensitive to temperature variations than men, as they prefer warmer conditions, and report more frequently being in thermal discomfort [16]–[22].
- **Age:** elderly people are more sensitive to temperature variations compared to young adults [23], [24].
- **Body Composition:** overweight people prefer cooler thermal conditions than underweight people [24]–[26]. In field studies, this variable is usually investigated through the Body Mass Index (BMI) that relates the weight and height.
- **Thermal History**[1]**:** people previously exposed (to field studies and in the climatic chamber) to: (1) higher temperature conditions expressed thermal sensations tending more to the negative (cold) side of the seventh scale of thermal sensation than people previously exposed to lower temperatures [27],

[1] According to the theory of adaptive comfort, thermal comfort can also be influenced by people's thermal history (the thermal conditions in which people were recently submitted, besides the conditions at the time of application of thermal comfort questionnaires).

[28]; (2) environments with air-conditioning (cooling) felt more heated [27] and preferred to be colder than people not exposed to air-conditioning [3].

However, despite the studies indicating differences in thermal comfort perception among different groups of people, the impact of different contextual variables on the temperature limits of the thermal comfort zone still needs to be investigated taking into account field studies.

1.1 RESEARCH ITEMS

This chapter contributes addressing the gaps discussed previously (cf. Chapter 1) and proposing a dynamic interaction between the subject and his environment through answering the following questions:

- Does the temperature preference of people represent the actual comfort level?
- Which model can be used to correlate between the temperature preference of the occupants and their anthropometric parameters?
- How can we develop a dynamic model that can change the comfort level using the anthropometric parameters (e.g., BMI, weight, height, or waist)?

Hence, this chapter seeks to examine items that are not covered by previous studies:

- Identifying the conditions of comfort and the acceptability of the thermal environment without trying to understand the mechanism involved.
- Evaluating the impact of the anthropometric parameters (age, gender, body shape, and weight) and the ambient variables (air temperature and relative humidity) on a variable presenting multiclass singularities (thermal sensation vote and perception).

1.2 THESIS ROADMAP

The thesis content is presented in six stages, each assigned its own chapter:

Chapter 1 has an introductory character, presenting the justifications of the work, the general and the specific objectives as well as the structure of the thesis.

Chapter 2 reviews existing literature on thermal comfort in buildings with three objectives: (1) Investigating the relevant aspects of the history and scientific evolution in the field of thermal comfort, then describing existing approaches for assessing comfort, reaching the current situation: the inexistence of methods that take into consideration the diversity of comfort perceptions among the occupants; (2) Presenting a general review on the importance of environmental building control linked with the human behavior; and (3) Introducing a point in which the anthropometric characteristics of the human body and the possible implications on the sensation and preference of thermal comfort are discussed, as well as a discussion on the lack of studies focusing on the influence of these characteristics on the thermal satisfaction.

Chapter 3 depicts a systematic literature review results of the application of the artificial intelligence-based tools in buildings environmental control, which is related to one or more of the objectives of the thesis. In this review, several characteristics were considered and have found a lack of existing reviews, by insisting on the AI techniques for both thermal comfort and energy control in buildings, whilst including individual interactions into the comfort-energy control loop. This enables a holistic view of (1) the complexities of delivering thermal comfort to users inside buildings in an energy-efficient way, and (2) the associated bibliographic material to assist researchers and experts in the field in tackling such a challenge. Chapter 3 references a paper published in the **Renewable and Sustainable Energy Reviews** journal under the title "Intelligent building control systems for thermal comfort and Energy-Efficiency: A systematic review of Artificial Intelligence-assisted techniques".

Chapter 4 deals with the method of research, through the characterization of the research, sample data, criteria, etc. while **Chapter 5** develops a model of individual-level thermal comfort. The chapter describes the results acquired through the tabulation and analysis of data obtained in the field, the main mathematical models identified, as well as the influence of anthropometric characteristics on the thermal sensation. These chapters refer to an article published by the author in the **Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering** under the title "A Dynamic model for human thermal comfort for smart building applications" [29]. An earlier version of this paper was presented in the **International Conference on Smart Digital Environment (ICSDE)** under the title "Measuring human comfort for smart building application: Experimental set-up using WSN" [13].

Finally, **Chapter 6** refers to the general conclusions of the thesis, the final considerations about the research, the limitations of the study, and proposals for future developments.

2 HUMAN THERMAL COMFORT IN THE BUILT ENVIRONMENT

To formulate the research problem, it was necessary to investigate relevant aspects of the history and scientific evolution in the area of thermal comfort. In this chapter, some comments and quotations have been crucial to underlying the discussions and the results of the sample-based analysis. Various researchers have stated that thermal comfort is the result of the influence of thermal adaptation, Alliesthesia, thermal experience, and thermal expectation. These concepts are discussed in this chapter together with a brief analysis on the predictive indices of thermal comfort, the control strategies, and their relationship with the occupant's behavior, finally this impact of the human variability on thermal comfort.

2.1 EVALUATING THERMAL COMFORT: FROM THE LAST 50 YEARS TO THE STATE OF THE ART

2.1.1 The Logic of Thermal Comfort, Relevant Definitions and Considerations

Through standardized experiments performed in thermally controlled environments, researcher Fanger created extensive diagrams that would be able to predict comfort in any environment [30]. His studies were focused on the relationship between the human body's physiological awareness and physical theories of thermodynamics based on heat balance. The heat balance refers to the heat exchange between the human body and the environment, i.e., the difference between the heat generated in the metabolism and that converted into work with the heat exchanges occurring through the skin and respiratory system, and a possible balance.

In 1995, M. Humphreys published an article entitled *Thermal comfort temperatures and the habits of Hobbits* [31]. Comically, although academic, he explains how research should be performed in the field of thermal comfort using the Middle Earth *Hobbits*, as an illustration. In its roadmap, the research begins with an investigation of the population's habits, followed by the application of questionnaires with simultaneous measurements of environmental variables in real situations, rejecting methods with intrusive measurements and complicated experimental routines. The author criticizes, in an incisive way, the necessity of thermal physiology or heat balance theory for the study of comfort, whose knowledge would be merely interesting for certain quantitative and theoretical explanations.

Although the two lines of reasoning described are divergent in theory and practice, both coexist mutually in standards such as ASHRAE 55-2017 [6] and EN15251-2007 [32], and usually referred to as *Static model* (also called *Analytical*, it refers to experiments carried out in climate chambers, thermally controlled environments, in which the researcher has control over the thermal conditions, such as the Fanger tests) and *Adaptive* (refers to experiments performed in real situations, so that the researcher interferes as little as possible in the interviewee's daily life and that he is free to adapt to the thermal conditions of the environment).

The first time that the adaptive and analytical concepts have been convened was in 1972, at the *First International Conference on Thermal Comfort* [33]. Since then, there is a dispute between researchers about which predictive method of thermal comfort is more effective, being commonly the Fanger's model considered the best for artificially conditioned (AC) environments, and the adaptive one for naturally ventilated (NV) (as observed in the indications of the ASHRAE 55-2017 standard).

Identifying which predictive index of thermal comfort achieves the best result in a given context is one of the many gaps existing in the academic area. Another primary problem is the definition of terms, since, according to A. Auliciems [34], such terms have imprecise semantic use, with inconsistencies in basic concepts such as thermal comfort, thermal neutrality, and localized discomfort.

According to ASHRAE 55-2017[2], thermal comfort is "the state of mind that expresses thermal satisfaction with the environment". O. Fanger [30] complemented this definition by stating that the person should also be in thermal neutrality, as well as presenting the skin temperature and the rate of secretion within certain intervals without there being asymmetrical heat loss. R. de Dear et al. [35] used the ASHRAE definition and added that thermal comfort can be assumed to mean that there are no thermal changes in the environment. Although these last two definitions use the more comprehensive concept found in ASHRAE 55-2017, conceptual complementation leads to disparate results, and incorrect use of thermal neutrality as a synonym for thermal comfort is not uncommon.

In contrast to the ASHRAE definition of thermal comfort and the way that predictive models are commonly approached, J. Nicol and S. Roaf [36] raised an interesting question: If comfort is a state of mind, a complex psychological construction referring to a state of mind, would it be coherent to affirm that something so abstruse can be measured through a single linear scale?

The term "Thermal Neutrality" was defined by O. Fanger [30] as neither colder nor warmer (it is observed that this is the complementation of the concept of thermal comfort presented in the work of R. de Dear et al. [35]. Hey [37] has interpreted it as the balance resulting from the conditions of thermal equilibrium (i.e., heat balance equation equal to zero). R. de Dear et al. [35] and ASHRAE 55-2010[3] [38] defined it as the neutral thermal sensation, i.e., not feeling cold or warm. The association of thermal neutrality, either as a synonym or as a necessary condition to achieve comfort, arises, according to Auliciems [34], from the idea that feelings of warmth are equivalent to the feelings of comfort. Such a pragmatic idea removes the subjective aspect of the comfort definition and prescribes it in thermal terms.

The research work of M. Humphreys and J. Nicol [39] points to a tendency of the link between sensations and non-neutral preferences and comfort, the individual's thermal history, and the external temperature. Although comfort and thermal neutrality were not correlated, R. de Dear et al. [35] suggested that much of what was considered climate adaptation was the optimal temperature (preference), emphasizing the semantic discrepancy between neutrality and preferred temperature (consequently, optimal

[2] Although ASHRAE 55-2017 is cited, it is a fact that, in previous versions of the American standard, this same concept was already used, which is why Fanger's work published in 1973 used the concept of the standard as a reference.
[3] The version of standard 55-2013 removes the term "thermal neutrality" from its definitions.

comfort), especially in artificially air-conditioned environments. The terms "thermally optimal", "optimal comfort" and "very comfortable" are usually found when one wants to indicates that the person is in his/her preferred thermal state.

Another conceptual incongruity lies in localized discomfort, which is usually seen as asymmetry of thermal radiation, the existence of draughts, difference in air temperature in the vertical direction, and heating or cooling of floors [30], [40]. The inconsistency in this concept is generated by the specific term "discomfort" which, due to its etymology, refers to the absence of comfort. In this way, it contradicts itself with two principles: Personal Environmental Control (PEC) and Alliesthesia, since both asymmetrically use heat losses or gains to promote comfort and satisfaction.

According to R. de Dear [41], more efficient than homogeneous, isothermal, and stationary environments, which are listed as neutral and comfortable, are asymmetric, non-uniform, and transient environments, where "very comfortable" levels of perception are found. In this respect, L. Webb [42] claimed that the thermal experience is never neutral because thermal diversity implies in the intuitive fact that we are subjected daily to a full set of thermal stimuli.

According to H. Zhang et al. [43], the PEC, formerly known as TAC (task-ambient conditioning), consists of devices and systems that allow the user to control the thermal conditions that surround him directly and, although the literature has not reached a consensus on whether comfort is achieved due to the perception of personal control or heat transfer, it is a fact that some authors consider it an improved version of conventional means of mechanical environmental conditioning [44]. H. Zhang et al. [45] predicted that the general condition of comfort is strongly influenced by the hands, feet, and face and, through experiments carried out in air-conditioned chambers, have proven that, in addition to energy efficiency, it is possible to achieve comfort in temperature ranges considered uncomfortable through the PEC, i.e., losing or gaining heat in a generally asymmetrical way[4].

The PEC was based on the term Alliesthesia, coined in 1971 by M. Cabanac in his work called *Physiological Role of Pleasure* [46]. This term comes from the Greek 'aísthēsis' and 'allós', which mean change and sensation, respectively. This notion consists not in

[4] Prediction models, such as the adaptive and the PMV of Fanger, because they are based on average environmental characteristics, are not able to predict comfort in situations with considerable asymmetries. The multi-node models are the most adequate to evaluate this type of situation. However, they will not be addressed in this research.

the study of thermal comfort, but of pleasure with the temperature that is only acquired when a body in a state of discomfort receives a stimulus that tries to re-establish the internal thermal balance; therefore, it is submitted to different and simultaneous thermal conditions.

An example could be found in the work of R. de Dear [41], who made an analogy between thermal comfort and nutritional needs. According to the author, the thermal environment is essential for life, as well as nutrition. Thus, although it is possible to survive only with a few pills and injections, one cannot ignore all the customs and sensations that are associated with a good meal. In parallel, it also makes an analogy with the thermal environment: if the state of satisfaction of the strictly nutritional need can be contrasted with a thermally neutral environment, the maximum potential for pleasure could only be achieved with a good meal, which exists only beyond a thermally neutral world.

The usual methods of prediction, as well as the proper definition of the terms found in the literature, diverge from each other or do not cover in their entirety the possibilities of comfort, mainly because they exclude in their definition the adaptation. As listed by A. Auliciems and S. Szokolay [47], the comfort specifications need to be understood beyond the boundaries of thermal ambiance, by assuming a spatial and temporal dimension. In this sense, M. Humphreys et al. [48], who have described discomfort as the result of restrictions placed on the process of choice and adjustment, while thermal comfort is not an equation of physiology and heat regulation, but a broad and intelligent behavioral response to the climate. Psychological, sociological, and external factors can influence perception, sensation, and thermal comfort itself; however, when not subjected to such pressures, the sensation of thermal well-being is strongly influenced by adaptation.

2.1.2 Thermal Comfort Models

Realizing the importance of the impact of thermal comfort on human health and productivity, much research has been conducted in this field since the beginning of the last century. Such studies are carried out in climatic chambers or in situ, on mannequins or with human beings. They seek to identify the conditions for comfort and acceptability of thermal environments without trying to understand the mechanisms involved. As a result, several thermal comfort indices have been developed based on thermal comfort models, which are of different natures. There are physical models which are often measuring instruments whose physical responses to the thermal environment are similar to those of the human body. There are also thermal mannequins often used for determining the thermal characteristics of clothing. Finally, there are empirical models and rational models. Empirical models establish, through experiments (in climatic chambers or in situ), a statistical regression by combining the effects of two or more physical and/or physiological variables into a single variable. Rational models are based on estimates of the different forms of heat exchange between the human body and thermal environments, as well as the heat balance and the resulting physiological stress.

2.1.2.1 Environmental Indices

2.1.2.1.1 Operative Temperature – T_{op}

The operative temperature is a comfort index integrating the effect of convection and radiation (t_a and t_r). It is defined as the temperature of an isothermal enclosure in which, through radiation and convection, an occupant exchanges the same amount of heat as in the enclosure in which it is located. It can be written as follows:

$$T_{op} = \alpha . t_a + (1 - \alpha) t_{mrt} \tag{2-1}$$

Whereas, t_a is the air temperature; t_{mrt} is the mean radiant temperature while α is a parameter depending exclusively on the air speed (often around 0.5).

This index is assumed to be equal to the temperature measured inside a black globe whose diameter is determined so that heat exchanges by convection and radiation are in the same proportions as for the human body. For natural convection with a low air speed (between 0.1 and 0.15 m/s), a 40 mm diameter globe is sufficient. Moreover, it has a faster response time compared to the 150 mm globe traditionally used [49].

2.1.2.1.2 Equivalent Temperature – t_{eq}

The equivalent temperature is defined as the temperature of an isothermal enclosure with zero air speed, in which a subject would exchange the same amount of sensible heat, by convection and radiation, as in the actual enclosure in which it is located. It takes into account the effects of air temperature, radiation and air speed (t_a, t_r, and v_a). It can be calculated from the temperature inside a heated globe.

*2.1.2.1.3 Effective Temperature – ET**

The effective temperature is defined as the equivalent dry temperature of an isothermal enclosure at 50% relative humidity, in which a subject would exchange the same amount of heat and even skin wetness as in the actual enclosure in which it is located. The ET* index takes into account the effects of temperature and humidity (t_a, t_r, and p_a), and to calculate it, it is necessary to know the skin wetness and the water vapor permeability index of the clothing (i_m). ASHRAE has developed comfort scales based on this index for subjects with low activity (1 Met), 0.6 Clo clothing, and a quiet environment (v_a< 0.2 m/s).

2.1.2.2 Analytical Models

Numerous analytical models have been developed to predict the thermal and physiological responses of the human body as a function of environmental conditions, under stationary or transient conditions. In the simplest models, the body is treated as a single block. More complex models divide the body into several segments and allow the dynamics of physiological responses to be simulated. At this point, the focus of this work is not to make a literature review of how these models emerged or the mathematical models that generated them, but rather to present the most commonly used.

2.1.2.2.1 Fanger's Model: PMV & PDD

In the 1970s the Danish O. Fanger [50] derived a general equation for thermal comfort. Fanger's model, which is the most recognized for evaluating thermal comfort, also known as the static method, since the studies were conducted within a completely controlled environment, taking into consideration the combination of some physical environmental variables such as air temperature, mean radiant temperature, humidity, and air velocity. Besides these environmental variables, the metabolic rate and clothing insulation are also considered to measure the individual sensation of thermal comfort. Through his experimental work and the equations developed, Fanger obtained the Predicted Mean Vote (PMV), which consists of a numerical value that demonstrates human sensitivity to cold and heat. From these studies, the concept of Predicted Percentage of Dissatisfied (PPD) also emerged. Its equations and methods are still used worldwide and have served as a basis for the elaboration of important international standards such as ISO 7730-1994 and ANSI/ASHRAE 55-1992, both already updated.

Currently, ISO 7730-2005 and ASHRAE 55-2017 adopt the O. Fanger surveys and determine the PMV as an index that predicts the average value of votes of a large group of people on the seventh scale of thermal sensation, (cf. Table (2-1)), based on the balance of the human body heat.

Table 2-1. The seven-point thermal sensation scale (Source: Adopted from ISO 7730-2005).

Sensation	Cold	Cool	Slightly Cool	Neutral	Slightly Warm	Warm	Hot
Vote	-3	-2	-1	0	+1	+2	+3

For the calculation of the PMV (Equation (2-2)), the ISO 7730-2005 standard presents four equations that should be used, Equations (2-3), (2-4), and (2-5):

$$PMV = (0.303 \cdot \exp(-0.036 \cdot M) + 0.028) \cdot \begin{cases} (M - W) - 3.05 \cdot 10^{-3} \cdot (5733 - 6.99 \cdot (M - W) - p_a) \\ -0.42 \cdot \left((M - W) - 58.15\right) - 1.7 \cdot 10^{-5} \cdot M \cdot (5867 - p_a) \\ -0.0014 \cdot M \cdot (34 - t_a) - 3.96 \cdot 10^{-8} \cdot f_{cl} \cdot ((t_{cl} + 273)^4 \\ \quad -(\overline{t_r} + 273)^4) - f_{cl} \cdot h_c \cdot (t_{cl} - t_a) \end{cases} \tag{2-2}$$

$$t_{cl} = 35.7 - 0.028 \cdot (M - W) - I_{cl} \cdot [3.96 \cdot 10^{-8} \cdot f_{cl} \cdot ((t_{cl} + 273)^4 - (\overline{t_r} + 273)^4) - f_{cl} \cdot h_c \cdot (t_{cl} - t_a)] \tag{2-3}$$

$$h_C = \begin{cases} 2.38 \cdot |t_{cl} - t_a|^{0,25} & for\ 2.38 \cdot |t_{cl} - t_a|^{0,25} > 12.1 \cdot \sqrt{v_{ar}} \\ 12.1 \cdot \sqrt{v_{ar}} & for\ 2.38 \cdot |t_{cl} - t_a|^{0,25} < 12.1 \cdot \sqrt{v_{ar}} \end{cases} \tag{2-4}$$

$$f_{cl} = \begin{cases} 1.00 + 1.290 I_{cl} & if\ I_{cl} \leq 0.078 m^2 \cdot K/W \\ 1.05 + 0.645 I_{cl} & if\ I_{cl} > 0.078 m^2 \cdot K/W \end{cases} \tag{2-5}$$

Whereas, M is the metabolic rate; W is the effective mechanical power, which is 0 for most indoor activities; I_{cl} is the clothing insulation factor; f_{cl} is the clothing surface area factor; $\overline{t_r}$ is the mean radiant temperature; v_{ar} is the air velocity; p_a is the partial pressure of water; h_C is the convective heat transfer coefficient; while t_{cl} is the clothing surface temperature; and t_a is the air temperature.

The standard also describes, through Equation (2-6), how to calculate the index of people thermally dissatisfied with the environment (PPD), which is the percentage of people who would like the environment to be warmer or less hot (colder) and correlates, through Figure (2-1), the PMV and PPD indices.

$$PPD = 100 - 95 \cdot \exp\left(-0.03353 \cdot PMV^4 - 0.2179 \cdot PMV^2\right) \tag{2-6}$$

Both ISO 7730-2005 and ASHRAE 55-2017, in their analytical method for determining comfort zones, recommend that in thermally moderate spaces of human occupation, the PPD index should be less than 10%, which corresponds to a PMV range of -0.5 to +0.5.

The use of Fanger's PMV/PPD as a universal model has been widely discussed by researchers who adopt the recommendations of these standards in field study analysis. Research to assess thermal comfort in thermally conditioned environments that are not fully controlled or even research in warmer regions with environments without artificial conditioning, such as those naturally ventilated, are the ones that present more disagreements with the premises of the PMV/PPD method, where the model generally overestimates the real thermal sensation of the occupants of the environment, i.e., occupants end up tolerating a wider range of temperatures than the foreseen by the method [51]–[53].

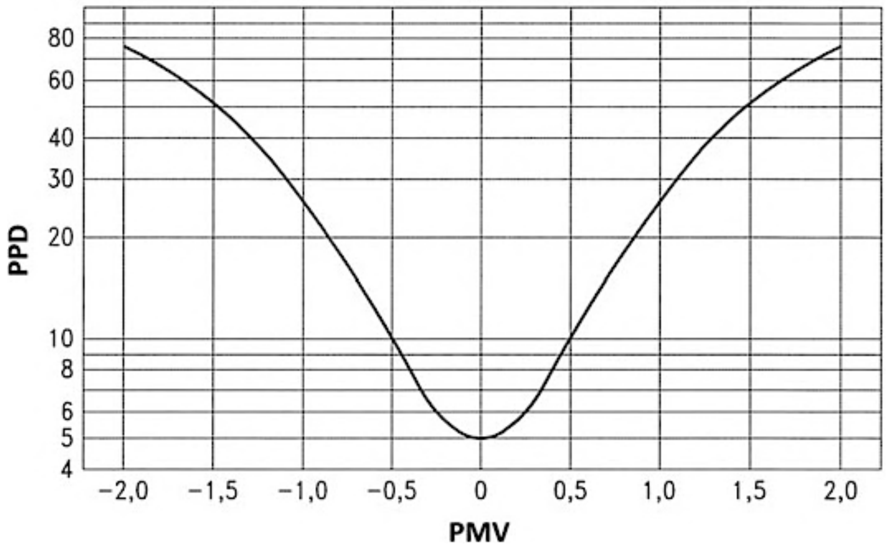


Figure 2-1. The Predicted Percentage of Dissatisfied (PPD) as a function of Predicted Mean Vote (PMV) (Source: Adopted from ASHRAE 55-2017).

2.1.2.2.2 Gagge's Two Node Model: ET, SET & PMV**

A. Gagge has developed a simplified dynamic model of thermoregulation. This model represents the human body in two concentric nodes representing the center of the body and the skin [6]. The exchanges between the two components considered isothermal are modeled as tissue conduction and blood convection. Unlike Fanger's model, this model allows the calculation of physiological variables (skin and internal temperatures, skin wetness) under transient conditions. Skin temperature, skin wetness, and skin heat flow are used to calculate the ET* index (new effective temperature). The ET* index depends on the clothing and activity level of the subject. To standardize the calculation, a new index, the "SET" (standard effective temperature) has been defined. SET represents the equivalent dry temperature of an isothermal enclosure at 50% relative humidity, in which a subject, wearing clothing standardized to his activity, would exchange the same amount of heat and have the same skin wetness as in the actual enclosure in which he is located. Standardized clothing is calculated according to Equation (2-7) [54].

$$I_{cls[clo]} = \frac{1.33}{(M_{[Met]} - W_{[Met]} + 0.74)} - 0.095 \tag{2-7}$$

The SET is a thermal comfort index integrating the effect of the six basic parameters, and applicable in hot, moderate, or cold transient conditions. Thermal sensations can be deduced from the different SET values from Table (1-2) [49].

Furthermore, A. Gagge suggested replacing the operative temperature with the effective temperature in the calculation of the PMV. The PMV calculated, in this way, is noted as PMV*, which makes it possible to better take into account the effects of humidity in hot areas [54].

Table 2-2. Relationship between standard effective temperature (SET) index levels and thermal sensation (Source: Adopted from [49]).

SET (ºC)	Sensation	Physiology State of Sedentary Person
>37.5	Very hot, very uncomfortable	Failure of regulation
34.5 – 37.5	Hot, very unacceptable	Profuse sweating
30.0 – 34.5	Warm, uncomfortable, unacceptable	Sweating
25.6 – 30.0	Slightly warm, slightly unacceptable	Slight sweating, vasodilation
22.2 – 25.6	Comfortable and acceptable	Neutrality
17.5 – 22.2	Slightly cool, slightly unacceptable	Vasoconstriction
14.5 – 17.5	Cool and unacceptable	Slow body cooling
10.0 – 14.5	Cold, very unacceptable	Shivering

Finally, ASHRAE proposes two other empirical indices TSENS (thermal sensation) and DISC (thermal discomfort). These two indices are calculated from the average body temperature which is a weighted average of the internal and skin temperature. The TSENS determines the thermal sensation on the ASHRAE scale by adding two extreme degrees (±4 for extremely hot/cold and ±5 for intolerably hot/cold), while DISC determines the level of thermal discomfort on a 6-point scale ranging from comfortable (DISC=0) to intolerable (DISC=5) [6].

2.1.2.2.3 Local Thermal Discomfort

The overall thermal comfort does not guarantee the individual well-being, since only one part of the body is warmer or cooler to create a situation of thermal discomfort [30]. The incidence of local thermal discomfort is higher in people with slightly cooler overall thermal sensation (PMV=-1) and with sedentary activity (1.2 met) [55]. The reasons behind local thermal discomfort are related to drafts, vertical air thermal difference, floor surface temperature, and radiant temperature asymmetry [56].

The phenomenon of convection, due to the existence of drafts, reduces the temperature of the skin by removing heat from the skin's surface, which, depending on the person's general thermal sensation, can cause discomfort. The Draft Rating (DR) can be determined through Equation (2-8) [56].

$$DR = (34 - t_{a,l}) \cdot (v_{a,l} - 0.05)^{0.62} \cdot (0.37\, v_{a,l} \cdot T_u + 3.14) \tag{2-8}$$

Whereas, $t_{a,l}$ is the local air temperature (ºC); $v_{a,l}$ is the local mean air speed (m/s); while T_u is the local turbulence intensity (%).

On the other hand, the vertical thermal amplitude causes differences in temperature between the ankles and the occupant's head, causing discomfort proportional to the amplitude of the temperature range. The percentage of dissatisfied people can be determined by equation (1-9), applicable only to situations with a temperature range below 8ºC [56].

$$PD = 100/(1 + \exp\,(5.76 - 0.856 \cdot \Delta t_{a,v})) \tag{2-9}$$

Whereas, $\Delta t_{a,v}$ is the difference in vertical thermal between head and feet (ºC).

A warm or cool floor provides thermal discomfort in the feet as they are permanently in contact, especially in sedentary activities. Figure (2-2) relates the percentage of dissatisfied people to the floor temperature.

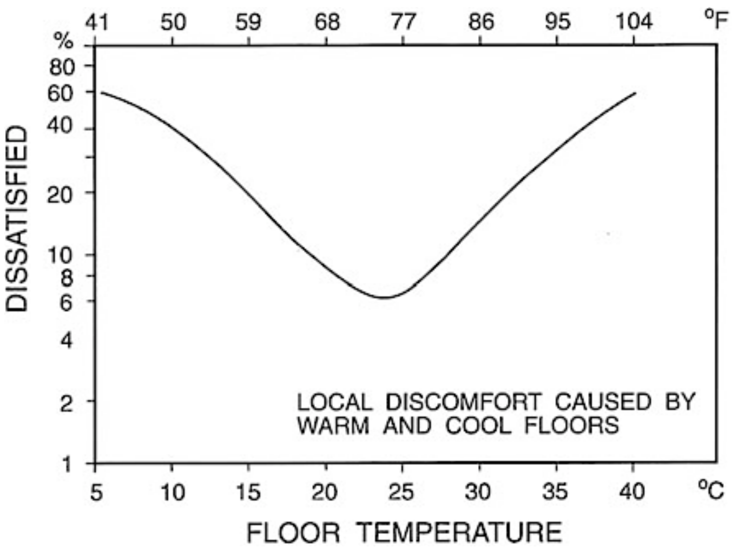


Figure 2-2. Local discomfort caused by warm and cool floors (Source: Adopted from [6]).

On the other hand, the asymmetry of the radiant temperature causes oscillation of the body's thermal sensation, which results from the thermal radiation emitted unequally by warm, cool surfaces or direct solar radiation. Local thermal discomfort is easily detected in places with warm ceilings or cool walls [56]. The influence of radiant thermal asymmetry on comfort in various situations can be analyzed in Figure (2-3).

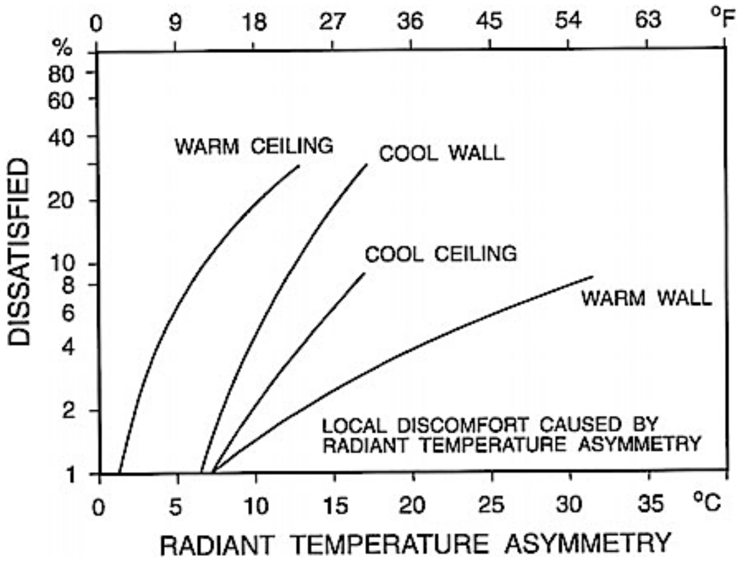


Figure 2-3. Local thermal discomfort caused by radiant temperature asymmetry (Source: Adopted from [6]).

2.1.2.3 The Effect of Inter-Individual Diversity

The calculation of thermal comfort is essentially based on the six basic parameters (air temperature, radiation temperature, air humidity, air speed, and subject activity and clothing). However, given its subjective aspect, it is normal that thermal comfort is influenced by factors related to the subjects and their living conditions: age, gender, ethnic origin, geographical region (climate), physiological acclimatization, circadian or seasonal rhythm, diet, and so forth. Numerous studies have been carried out to determine the influence of these factors on thermal comfort conditions. These studies often aim to evaluate or validate the PMV, which is the index proposed by the international standard ISO 7730. This index was developed from studies conducted in climatic chambers with North American and European subjects, leaving doubts about its applicability to other populations with different living conditions in other geographical regions.

Most of the studies carried out have shown that the influence of these factors is of a small magnitude and that the six basic parameters are sufficient to calculate thermal comfort conditions [49]. Although inter-individual remains, they are often expressed by the activity and clothing of the subjects, which are among the six basic parameters. The preference for slightly warmer environments by the elderly people is due to their sedentary activities [57]. The sensitivity of women to the cold is due to their clothing, which is generally lighter than men. People sometimes tend to prefer a slightly warm atmosphere before lunch, but without having a significant effect on thermal comfort [6]. Regarding physiological acclimatization, studies conducted with people acclimatized to hot or cold show that it does not affect acceptability and thermal discomfort for typical conditions encountered in homes or offices. Hence, the PMV (or SET) takes these factors into account indirectly through clothing and activity.

On the other hand, surveys and in-situ studies on thermal comfort revealed a discrepancy between the subjective responses evaluated and those predicted by analytical models (PMV) especially in non-air-conditioned buildings (with natural ventilation) during the summer period, with a tendency to overestimate the sensation of warmth [51], [58]. This has led the researchers to multiply in situ experiments on thermal comfort, paving the way for a new approach that consists in determining thermal comfort conditions from the results of surveys and in situ studies. This approach, known as the adaptive approach (cf. Section 2.1.2.4).

2.1.2.4 Adaptive Model

According to J. Nicol and M. Humphreys [7], people have a natural tendency to adapt to the environment, which is mainly related to seasonal fluctuations in external temperature. From this statement, it is possible to conclude that thermal comfort temperatures are dynamic and can change constantly according to the local climate [35]. R. de Dear and G. Brager [59] stated in their studies that, when adapted to the current condition of the environment, the occupants accept and even prefer the thermal variability of naturally ventilated buildings, and such results have already been confirmed several times in other studies that evaluated commercial environments [51], [60]–[62].

The acceptance of the adaptive model in international thermal comfort standards has allowed passive strategies such as natural ventilation to become viable worldwide [51], [63]–[65]. Thus, adaptation, whether physiological or psychological, certainly contributes to user satisfaction; which, by logical extension, also contributes to the reduction of energy demand necessary for the operation of air-conditioning systems in commercial buildings [66]. The expansion of thermal comfort temperature limits proposed by the adaptive model has resulted in energy rationing initiatives in artificially conditioned buildings around the world through setpoint temperature adjustments, such as Cool Biz and Setsuden in Japan (setpoint temperature adjustments close to 28°C) [67]. According to R. de Dear [68], at each degree of expansion in the comfort zone provided by the adaptive model, it is possible to save around 10% of final electric energy consumption.

Initially, the first equations from the adaptive model appeared to define a temperature that represents thermal neutrality as a function of the external temperature. M.

Humphreys has developed two equations for neutral temperature prediction (Equations (2-10) and (2-11)) [69]. The first one in the function of the internal temperature, and the second one in function of the external temperature; A. Auliciems and R. de Dear [70] developed equations to predict the neutral temperature of a group, relating means of internal and external temperature (Equations (2-12), (2-13), and (2-14)); while Nicol and Roaf [71] presented an equation for naturally ventilated buildings (Equation (2-15)) as a function of external temperature. Based on equations (2-12), (2-13), and (2-14), equation (2-16) was developed, which determines the thermal comfort temperature based on the external air temperature, and can be found in the American standard ASHRAE 55.

$$T_{n,i} = 2.6 + 0.831\,T_i \tag{2-10}$$

$$T_{n,o} = 11.9 + 0.534\,T_o \tag{2-11}$$

$$T_{n,i} = 5.41 + 0.731\,T_i \tag{2-12}$$

$$T_{n,o} = 17.6 + 0.31\,T_o \tag{2-13}$$

$$T_{n,i,o} = 9.22 + 0.48\,T_i + 0.48\,T_o \tag{2-14}$$

$$T_{n,o} = 17.0 + 0.38\,T_o \tag{2-15}$$

$$T_c = 0.31 + 17.8 \tag{2-16}$$

Whereas T_c is the comfort temperature; T_o is the outdoor air temperature; T_i is the average indoor air temperature; $T_{n,i}$ is the neutral temperature, based on the average values of the indoor air temperature; while $T_{n,o}$ is the neutral temperature based on the average values of the outdoor air temperature; and $T_{n,i,o}$ is the neutral temperature based on the average values of indoor and outdoor air temperatures.

Subsequently, ASHRAE presented an updated version of the equation for the prediction of neutral temperature in naturally ventilated indoor environments, which is based on a prevailing average external air temperature value and determines the minimum and maximum limits of a thermal acceptability zone. In this method, the average temperature of the prevailing outside air can be calculated from an arithmetic mean of the daily average values of the outside air temperature, considering no less than seven days and no more than 30 sequential days before the day in question. However, the prevailing temperature can also be calculated using an exponentially weighted average of daily average values of the external air temperature of the last days before the day in question, with a weighting factor that can vary between 0.6 and 0.9; in this second method, there is no upper limit of days to be considered for the calculation. When climate data are not available, the standard allows the use of average monthly temperature data published by local weather stations. Equations (2-17) and (2-18) present, respectively, the equation referring to the upper limit of the zone of thermal acceptability of the adaptive model employed by the standard, and the equation referring to the lower limit of this same zone.

$$t_{upper\ limit} = 0.31\ \overline{t_{pma(out)}} + 21.3 \tag{2-17}$$

$$t_{lower\ limit} = 0.31\ \overline{t_{pma(out)}} + 14.3 \tag{2-18}$$

Whereas $\overline{t_{mpa(out)}}$ is the prevailing mean external air temperature.

Based on Fanger's model and adaptive concepts, Yao et al. [72] developed a model called adaptive Predict Mean Vote (aPMV), noting that only a combination of the characteristics of static and adaptive models would be able to explain all the environmental influences that occur in occupant responses in a real environment. In this model, the authors considered a coefficient of adaptation that when derived in zero, results in the same equation of the PMV of the Fanger's model [50]. Such principle is similar to the expectation factor proposed by Fanger and Toftum [73], if both methods are considered as a correction factor directly applicable in the PMV index.

It is also important to note that the adaptive model was incorporated into ASHRAE 55 in 2004, and since then it has been undergoing substantial updates, which can be seen in the last publication of the standard in 2017. Research works in this field since the adaptive model was incorporated to ASHRAE 55-2004, suggest that the method indicated by the graph of the model's 80% and 90% thermal acceptability zones (cf. Figure (2-4)) can be extended to other applications, such as artificially conditioned environments, correctly characterizing the thermal comfort of occupants in these spaces, especially when there is environmental control.

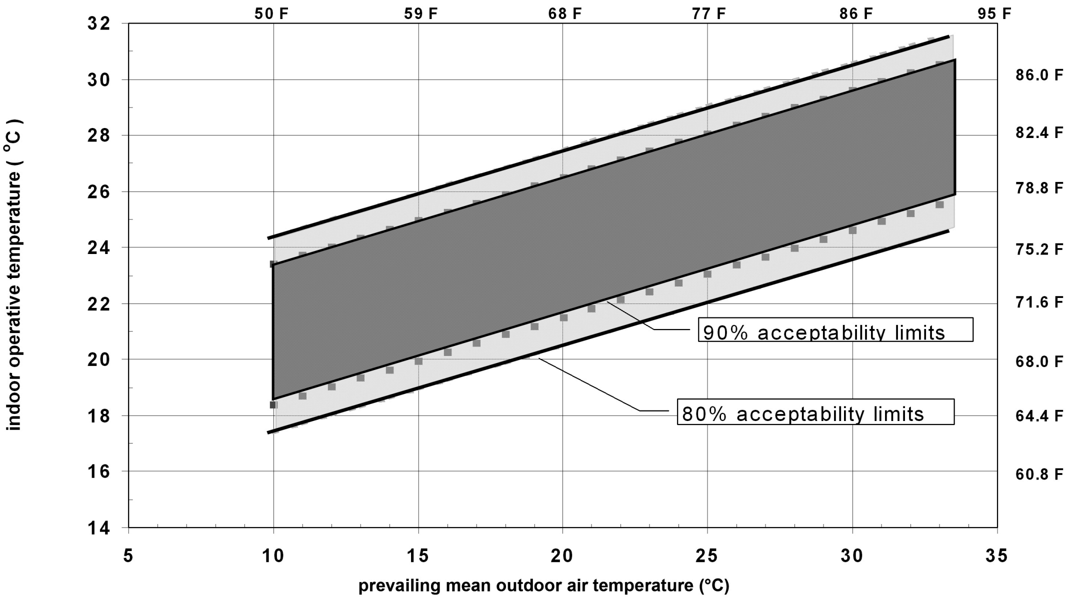


Figure 2-4. Acceptable operative temperature ranges for naturally conditioned environments (Source: Adopted from ASHRAE 55-2013 [40]).

2.1.3 Thermal Comfort Standards and the Current Gap

Currently, the evaluation of thermal comfort in indoor environments is made mainly according to the American standard ASHRAE 55 (last revision published in 2017), which deals only with environmental thermal conditions for human occupation (ASHRAE 55 - Thermal environmental conditions for human occupancy). Other standards are also in action, such as the most recent revision of ISO 7730 of 2005, focused mainly on the Fanger's model [50] and the calculation of PMV/PPD (ISO 7730 - *Moderate thermal environments - calculation of the PMV and PPD indices*) and the updated European standard EN 15251 of 2012, which in addition to thermal comfort, also deals with internal air quality, lighting, and acoustics (EN 15251 - *Indoor environmental input parameters for design and assessment of energy performance of buildings: addressing indoor air quality, thermal environment, lighting, and acoustics*). In the first versions of these standards, the PMV/PPD model was the only one considered for thermal comfort evaluation, and in environments with uniform temperature conditions. Over time, and with updates in assessment methods, the PMV/PPD has continued to be effective for the evaluation of thermal comfort in conditioned environments. However, some of these standards have also started to incorporate the adaptive model method, intended for naturally ventilated buildings. Among the three standards cited, ISO 7730 remains today with a superficial version of the concept of adaptation, with no updates since the last revision of 2005, while ASHRAE 55 and EN 15251 have adopted versions of the model based on results of extensive differentiated field studies. The model and equations that generated the comfort limits of the European standard EN 15251 [32] are based on the results of a European Union (EU) study, known as *Smart Controls and Thermal Comfort* (SCATs), aimed at reducing the energy consumption of air-conditioning systems by adjusting the setpoint temperature according to the external climatic conditions and the adaptive algorithm [74]. The American standard ASHRAE 55 method was based on the results of the research report known as ASHRAE RP-884, which analyzed a dataset of more than 20,000 microclimate variable inputs measured simultaneously to occupant sensation, preference, and thermal acceptability responses. The use of data with great climatic variability, collected in several countries, made ASHRAE 55 [6] to be used globally.

Although ASHRAE 55 is considered a worldwide standard for the evaluation of thermal comfort in indoor environments, there are a number of issues to be discussed that involve the scientific community. The main one is that the comfort models existing in this standard are considered valid for anyone, i.e., even though the models indicate thermal comfort zones for 80% or 90% of thermal comfort/acceptability, they do not discriminate which users' group would not be in comfort or would not be accepting the thermal conditions. However, different groups of people may have different thermal perceptions. In addition, the parameters used by these models cannot be dynamically evaluated by buildings to change their settings.

2.2 NON-THERMAL PARAMETERS INFLUENCING THERMAL COMFORT: LINKING COMFORT & ENERGY USE

Apart from the role of physical and physiological parameters in thermal comfort, the adaptive approach recognizes the role of other psychological and behavioral parameters. They are actively involved in the regulation of thermal conditions and contribute to the acceptability of certain environments that are qualified as unsatisfactory from a physical and physiological point of view. A comparison of the predictions of analytical indices with in-situ comfort votes showed a discrepancy between them, especially in naturally ventilated (NV) buildings with a tendency to overestimate discomfort during hot periods. These indices take into account only the physical and physiological parameters and infer the role of other psychological and behavioral parameters in the perceived comfort in these buildings.

2.2.1 Control Strategies and User's Behavior

The thermo-energetic performance of a building is influenced by factors such as climate, orientation, and the architectural characteristics of the envelope, in addition to lighting systems, air-conditioning, and electronic equipment. Besides these factors, the user's behavior and local culture, which play a fundamental role in energy consumption, also have an important role in the emission of CO_2 and greenhouse gases. An active user, who participates in the environmental control of a building and, especially when considering mixed/naturally ventilated buildings, does so by opening windows, maintaining shading elements, switching on/off cooling, heating, and artificial lighting systems [75].

According to S. Borgeson and G. Brager [76], occupants generally appreciate the opportunity to control the environment and usually prefer to have access to fresh air, wind breeze, and the open-air environment. In buildings that operate passively, local air speed control, or so-called Personal Control Systems (PCS) directly influence thermal satisfaction and acceptability, which allows the occupants to tolerate temperature conditions above those usual [77]–[79]. From the logic of G. Brager et al. [79], if people feel more comfortable in a wider range of environmental conditions provided by naturally ventilated, occupant-controlled buildings, then a significant amount of energy could be saved if there were greater flexibility in thermal comfort standards. H. Zhang et al. [43], stated that personal comfort systems represent a powerful tool for individual thermal satisfaction, focusing on occupants of different age groups, genders, body mass, clothing habits, metabolic rate, and thermal adaptation.

Environmental control is thus a viable strategy, considered by a number of studies as a form of adaptation, which allows the users to modify the environment to meet their preferences, including the temporal variation of their personal preferences [80]. In this context, G. Brager et al. [79] conducted field experiments in naturally ventilated offices, where the occupants had different degrees of environmental control. In their study, the authors performed continuous environmental measurements in the occupant's workspace and used online questionnaires that evaluated the physical conditions of the environments. The results showed that different levels of control strongly influence the responses of the occupants, even in some cases where the clothing (Clo) and metabolic activity (Met) were identical.

It is in this scenario that some studies explain that, although environmental control is pointed out with a viable energy-saving strategy, it is important to consider that users change the environment according to their preferences, and these preferences, besides being convenient and subjective, do not necessarily result in significantly higher levels of energy efficiency [76], [81]. According to B. Bordass et al. [82], the occupants can respond in unexpected ways to uncomfortable situations, which must be observed and considered in analyses involving energy consumption.

2.2.2 Human Behavior Investigation

The analysis of human behavior is mainly done by two techniques. The first consists in carrying out *sociological surveys*, which can be quantitative or qualitative, and which most often lead to statistical studies. However, there may be a discrepancy between the statements and the actions that are actually taken, which is a common bias in the field of sociology. The second technique consists of *in situ instrumentation* in the residential or workplace environments of persons volunteering for the study. These in situ measurements thus reveal a real behavior insofar as the measuring instrument does not interfere with the daily practice of the occupants. Some studies combine the two survey methods, which gives an explanation of the practices by the occupants themselves.

Human behavior is frequently discussed to explain the differences in energy consumption between simulations and in situ measurements. However, modeling human behavior is complicated. In a period, with no simulation time, several adaptive behaviors may have taken place. In this regard, Vorger [83], in his work, outlined three approaches for modeling human behavior: the deterministic approach, the agent-oriented approach based on thermal comfort, and the stochastic approach.

The deterministic approach is typically the one adopted in dynamic thermal software, in which the designer determines a set of scenarios defining room occupancy, internal contributions, ventilation rates, setpoint temperatures, occlusion closure rate, and so forth. He traces, on an hourly basis, a predefined behavior over a week and then over the whole year.

Other more complex models rely on the potential of computing and programming to determine individual behavior. In [84], the author has developed a dynamic model of thermal comfort. Based on the individual thermal state, feedback loops are allowed to define a list of actions (corresponding to adaptive opportunities) the events that will be accomplished. While [85] is based on experimental designs to show the importance of taking into account the behavior of individuals in dynamic thermal simulations. Then he proposed modeling of the behavior through an artificial intelligence algorithm. The system is subject to a thermal environment. Based on the calculated thermal sensation, if discomfort is found, a reaction is triggered. After a learning phase, the system can determine the actions that will be effective in achieving comfort. Finally, J. Langevin et al. [86] adopted the agent-oriented approach based on thermal sensation to define occupant behavior. This method models a system composed of autonomous agents (i.e., in their case the occupants). Agents are autonomous software with defined characteristics (clothing, metabolism, behavioral habits, an acceptable level of thermal sensation...) that can interact with each other. They have one goal: maintaining an acceptable thermal sensation, and they evolve in an environment: a building whose specificities allow to define adaptive opportunities and indoor climatic conditions.

The stochastic approach is based on statistics to determine the situations in which the individual has a high probability of operating his window, shutter... to restore his comfort. Time-use surveys and population census statistics can be used to determine the adaptive behavior of individuals. By developing several stochastic models, on openings, thermostats, lightings, etc., in this way, it is possible to determine behavioral scenarios that can then be added to dynamic thermal simulation software.

2.3 CHARACTERISTICS AND IMPLICATIONS IN THERMAL COMFORT STUDIES

The vast majority of studies and evaluations involving physiology and thermal comfort are based on a thermal neutrality zone, also known as the "Thermoneutral Zone" (TNZ). The thermal neutrality zone is defined as the temperature range in an environment where no thermoregulatory change occurs in the human body: neither heat production by metabolism (involuntary and often imperceptible attitudes seeking to keep the body temperature constant), nor heat loss by evaporation (e.g., perspiration) [22]. Factors such as body composition (weight or Body Mass Index (BMI)), clothing, energy expenditure, age, and gender directly influence the thermal neutrality zone of the human body and are potential drivers of erroneous results in studies of various areas.

O. Fanger was one of the precursors in thermal comfort analyses, which considered other parameters besides the six basic ones already known worldwide (such as gender, age, number of people in the same environment, etc.) and concluded that none of them had an effect of significant enough magnitude to be taken into account [50]. His results were considered by some authors as controversial, which led to several other studies that presented different results.

Despite their importance, anthropometric characteristics and their impact on thermal comfort studies are usually treated in an individualized way, as a modifying agent of the users' responses (sensation, satisfaction, and thermal acceptability). Thus, the following items will introduce the anthropometric aspects to be investigated based on the results of the experiment in this study, seeking to discuss studies dealing with the influence of age, gender, and body composition on thermal perception. However, the relationship of such anthropometric characteristics in the user's behavior, and consequent influence on the operation of buildings with the user's control strategies, constitutes a gap in this area, being therefore on the specific objectives of this work.

2.3.1 Age

Although there is a lot of controversy amongst studies of different authors, it is known that age is a factor that can directly influence the body temperature and metabolic rate, which is consequently reflected in the response to the thermal environment if considered occupants of different age groups. Fanger conducted experiments in an air-conditioned chamber considering two different groups: the first one with 128 people of advanced age (average of 68 years), and the second one with 128 students (average of 23 years), exposed to exactly the same thermal conditions during a period of 3 hours, and with standardized clothing of 0.6 clo [50]. According to the results, the comfort temperature preferred by older people and younger people was quite similar, close to 25.7ºC. O. Fanger also stated that the reason for the preference for higher temperatures of elderly people found in other studies is related to the low metabolism, and concluded that for this reason, the PMV/PPD is an approximate index for all age groups, since the metabolic rate is one of the main factors considered in its calculation. Following the publication of the results of O. Fanger [50], a series of studies pointed out results similar to those found by the author [87]–[90]. However, another stream of studies found that such differences exist, especially when considering the thermal neutrality zone, the preference and thermal acceptability in other age groups not analyzed until then.

In their work, E. Hey and G. Katz [90] focused on maternal age groups and defined ideal temperature conditions for undressed newborns through a study of the magnitude of environmental factors affecting thermal equilibrium. According to the authors, the thermal neutrality zone varies according to the weight of babies at birth, and can be between 34.5°C and 33.8°C for babies weighing approximately two kilograms in the first five days of age, and change rapidly until the same baby reaches one month of age, moving to 32°C and 33°C.

B. Kingma et al. [24] also confirmed in their results that the thermal neutrality zone changes with age. According to the authors, at about one month of age, the thermal neutrality zone varies from 32ºC to 34ºC and decreases to the range of 28.5 to 32.0ºC in early adulthood (according to the authors, around 20 years of age). This is mainly due to the metabolism and the amount of lean mass and fat mass, which increases with age[5]. For M. Indraganti and K. D. Rao [91], it is evident that the level of expectation regarding the thermal environment will also change and vary according to the individuality of each age group, affecting the thermal sensation. Besides, R. de Dear et al. [92] found preferred temperatures in groups of school-age children lower than those expected for groups of adults under the same indoor thermal conditions (22.5ºC), although the range of acceptability found was from 19.5ºC to 26.6ºC.

Although international thermal comfort standards such as ASHRAE 55 and ISO 7730 assume that the requirements for obtaining thermal comfort are universal and common for all age groups, R.-L. Hwang and C.-P. Chen [93] reaffirm that people over 60 have unique physiological and psychological characteristics, and therefore have different requirements concerning the indoor microclimate when compared to younger occupants. According to the authors, few studies have been carried out in this area in order to establish or modify the existing comfort parameters, and also adapt them to the specific needs of people in different age groups.

2.3.2 Gender

One of the main anthropometric differences observed in the vote of thermal sensation, and which generates discussions since the first thermal comfort experiments published until today, is related to the human gender. In his studies, O. Fanger [50] observed that although the neutral temperature of a group is a parameter independent of age, gender, weight, time of the day, race, or geographical location, women have greater sensitivity to temperature fluctuations when compared to men. Still, according to the results of Fanger, women tend to prefer an internal temperature slightly higher than that preferred by men (0.3°C).

Some authors believe that this difference may be directly related to the way female and male users dress [74]. However, L. Webb and K. Parsons [94] and K. Parsons [49] discarded the hypothesis of the differences being related to clothing by performing a

[5] The difference between the metabolism of a young adult and an elderly person is approximately $4.7\ W/m^2$.

comparison between groups of different genders using identical clothing and physical activities. The authors found that in a cold situation (PMV=-2.0), women tend to complain significantly more than men. In addition, women usually have a thermal sensation vote much closer to the PMV value calculated when compared to male results. Even though the authors also concluded that women are more sensitive to cold, no significant differences between genders were found when the environment presents temperature conditions that lead to thermal neutrality or in a slightly warm situation. Moreover, S. Karjalainen [21] found that women are on average 74% more likely to complain about the thermal environment than men. In his literature review, the author did not find any study where women had a higher level of thermal satisfaction when compared to men.

In terms of physiology, H. Kaciuba-Uscilko and R. Grucza [95] explained that such differences between genders are evidenced by the body characteristics and the endocrine system. Women usually have a larger body lining surface than men and are more susceptible to heat loss. On the other hand, women have a higher amount of subcutaneous fat, which increases the heat insulation of the body in some specific parts such as the hips and waist [96].

The issue of differences in thermal perception between men and women was recently discussed by B. Kingma and W. van Marken Lichtenbelt [97]. The authors stated that the greatest difference between men and women is related to the metabolic rate, and therefore, this is the main gap coming from thermal comfort assessment models such as O. Fanger [50], as the accuracy of the two main variables of the model inputs – clothing and metabolic rate – were, in general, poorly defined [49], [95]–[98]. Such a problem has directly impacted the methods proposed by the current standards, and consequently on the energy consumption of the spaces shared by men and women, which present different demands for indoor cooling and heating set-points. According to J. Van Hoof [99], gender inequalities are increasingly reported. For this reason, the author stated that a large-scale re-evaluation of field studies focused on these differences is imperative, bringing together material large enough to convince not only the real estate sector but also the global standards committees and professionals in the building sector that a review of all existing thermal comfort practices and requirements is extremely necessary.

2.3.3 Physical Conditions and Weight

According to O. Fanger, there is a widespread and popular theory that obese people prefer cooler environments when compared to thin people [50]. In this regard, in [100] the authors explained that subcutaneous fat and skin surface create a kind of thermal resistance that directly influences heat conductivity and blood flow. Although O. Fanger [50], and more recently T. H. Karyono [101], have investigated this issue in their studies without, however, finding significant differences relating weight to the thermal comfort condition. Other authors have stated that individuals with higher amounts of body fat (both subcutaneous fat and the general percentage of body fat) are able to tolerate lower temperatures, without having to increase their internal heat production [102], [103]. M. O. Fadeyi [26] found that the thermal sensation of overweight occupants was warmer than the thermal sensation of normal-weight occupants, even after a long period of occupancy in the same space, as well as the thermal acceptability levels, which were also lower. Thus, overweight people have a certain tendency to prefer lower operating temperatures than those preferred by thinner people, both in winter and summer. The influence of weight on the thermal comfort sensation can also be related to age, considering the body composition as something that changes over the years [104].

Few published studies have investigated the influence of weight and body mass on sensation, preference, thermal acceptability, and environmental control of the occupants in indoor spaces. However, with the advent of the so-called "obesity epidemic", differences between the physical condition and body mass of occupants in the same space in which environmental control is a current practice may become common and even recurring. Although there is a lack of studies focusing on this issue, on the other hand, human physiology researchers have often related the continuous exposure of the body in static environments to the increase in the number of obese people in the world [102], [105]–[107]. F. Johnson et al. [108] explained that prolonged exposure of the body to a thermal neutrality zone can significantly contribute to body weight gain. Thus, considering the people who spend 90% of their working time in indoor spaces with artificial air-conditioning such as cars, shopping malls, offices and supermarkets, it is reasonable to conclude that the energy expenditure related to the metabolism in daily life has been significantly reduced. In addition to the use of artificial air-conditioning and prolonged stay in thermal neutrality zone, being considered two contributors to the obesity epidemic, Wijers et al. [85] went further and explained that obese people spend less energy on metabolism compared to thinner people, even when they are outside the thermal neutrality zone.

2.4 WAYS TO CAPTURE THE HUMAN VARIABILITY

Capturing the anthropometric parameters of human beings is necessary for performing ergonomic studies which allow the evaluation and the design in different fields that are related to the people characteristics especially building automation applications (in the context of thermal comfort and energy control). Otherwise, the body dimensions are of two types: *Structural* and *Functional*. The static or structural anthropometry is concerned by the measurement of static dimensions, i.e., those that are taken with the body in a fixed and determined position. However, human beings are usually in motion, hence dynamic or functional anthropometry has been developed with a purpose to measure the dynamic dimensions that are those measurements made from the movement associated with certain activities [32].

The knowledge of the static dimensions is basic for the design of the workstations and allows the establishment the necessary distances between the body and its surrounding. Besides the dynamic or functional dimensions, as previously mentioned, are those that are taken from the work positions resulting from the movement associated with certain activities, i.e., it considers the study of the joints, providing knowledge of the function and possible movements of them and allowing to evaluate the capacity of the joint dynamics [109]. In this regard, several methods and sensors are used to capture dynamically the dimensions with a relatively high degree of precision and they can be classified according to the used technologies into:

- **Electromagnetic motion capture systems**, there is a collection of electromagnetic sensors that measure the spatial relationship with a nearby transmitter. The sensors are placed on the body and connected to a central electronic unit; they are constituted by three orthogonal turns that measure the magnetic flux, determining the position and orientation of the sensor [110].
- **Inertial motion capture systems**, inertial sensors are placed in different parts of the body. Accurate data are obtained from the individual's orientation and acceleration [111].
- **The ultrasonic sensors-based systems**, where the sensors are composed of a transmitter and a receiver and use the ultrasound telemetry method to

calculate the distance between the transmitter and a remote object (e.g., the human body). This method consists of measuring the time taken by an ultrasonic impulse to reach the object and return by reflection to its starting point [112].

2.5 FINAL CONSIDERATIONS

The assessment of thermal comfort is currently done in different ways, considering the various parts of the world and their climatic and cultural characteristics. Given the broad variety of existing models, approaches, and applications for thermal comfort evaluation, it is important to understand that the use of any of these models should be carefully considered and restricted to the conditions for which they are intended. The opportunity to adapt and control environmental conditions has opened space for occupants to experience more thermally comfortable environments, which can provide a significantly higher level of overall satisfaction; in addition to a better thermal and energy performance of the building. Although there are several models and equations intended for evaluation in artificially conditioned environments (static models such as PMV and PPD) or naturally ventilated (adaptive models), when the subject involves environments with mixed conditioning systems, there is still a significant gap in the field.

During thermal comfort experiments, it is important to point out that the occupants can react in different ways under the same environmental conditions. Therefore, it is correct to assume that anthropometric or psychosocial factors, besides the parameters already considered by the current models, directly influence the thermal perception and the quality of the internal environment supplied to the occupants. Anthropometric parameters such as age, weight, and height contribute actively to thermal perception, and when combined, may produce unproven effects. According to the studies discussed in the review, there is little evidence of the influence of such characteristics on the operation of air-conditioners; but in general, female occupants are generally known to be sensitive to lower temperatures, while older people may prefer temperatures higher than those preferred by younger people. Obese people are more inclined to heat, which can make these users prefer cooler environments. Although prominent in a few studies, such results require further investigation.

In the following chapter, we will present the integration of the various computer resources, in terms of artificial intelligence applied for energy management and thermal comfort in buildings.

3 Artificial Intelligence in Building Control: Linking Comfort & Energy Use

Reducing energy consumption while maintaining comfortable conditions in buildings turned out to have conflicting objectives and has accelerated the development of new systems for energy and thermal comfort optimization. For instance, reducing the inside temperature of a building in a hot area in order to make it comfortable will make the consumption of energy higher. Over the last decade, different methodologies based on Artificial Intelligence (AI) techniques have been applied to find the sweet spot between the energy consumption of HVAC systems and the acceptable comfort level of occupants. The application of AI and Machine Learning (ML) in optimizing energy efficiency while maintaining an acceptable comfort level of the occupant is a promising area of research and still an ongoing endeavor. Accordingly, this chapter develops a systematic review of AI-based techniques for building control and investigating their abilities to improve the energy-efficiency while maintaining personalized thermal comfort. Hence, this provides a holistic view of the complexities of delivering comfort conditions to users inside buildings in an energy-efficient way; and broadening the state-of-the-art by evaluating and categorizing all current literature and presenting materials relevant to AI-assisted buildings environmental management tools when recognizing complex activity within the comfort-subject-energy control loop.

3.1 BACKGROUND

Initial efforts to apply AI for building control began in the 1990s. Intelligent controllers have been optimized using evolutionary algorithms designed to control smart building subsystems. Synergy between neural networks, fuzzy logic, and evolutionary algorithms, or more broadly computational intelligence (CI) techniques, has been applied to buildings. To overcome non-linear functions of thermal comfort indices, time delay, and system uncertainty, certain advanced control algorithms have also integrated adaptive fuzzy control for optimal comfort control. In this context, a direct neural network controller, using a *back-propagation* algorithm, was developed and successfully deployed in Japanese air-conditioning installations and electrical fans for commercial applications. For example, a system incorporating two neural networks has been integrated into an air-conditioning in order to ensure that the equipment is adapted to customer preferences [113].

Although the use of AI-based technologies for building management has lasted over two decades, the performance of such techniques for building environmental control using these techniques is not yet fully satisfactory. Based on [114], the personal environmental comfort model could save about 20-30% of cooling and heating energy while maintaining acceptable comfort for the occupants. Nevertheless, based on the current study, from 1993 to 2020, the application of AI-based techniques and customized comfort models was able to achieve an average of between 21.81% and 44.36% of energy savings and an average of between 21.67% and 85.77% of comfort improvement.

The principles of the different artificial intelligence techniques used to design building controllers will be defined. In this regard, we will present the most employed ones – based on the analysis – to control both thermal comfort and energy use.

3.2 BUILDINGS CONTROL

Building climate control is a multi-parameter problem with no single solution, especially in sustainable buildings. Specifically, the objectives of an intelligent energy and comfort management system are as follows:

- **High comfort level:** Learning the comfort zone from the user's preferences, ensuring a high level of comfort (thermal, acoustic, air quality, and lighting) and improved dynamic performance.
- **Energy Saving:** Combining the control of comfort conditions with an energy-saving strategy.

- **Air quality control:** Providing a ventilation control system (CO_2 concentration control).

User interactions always have a direct effect on the system under examination to give the user the impression that he/she is in control of his/her environment. Users of an electric lighting system can change the state of the lighting, or choose its level. Users of the heating system may adjust the temperature set-point. An increase in this threshold immediately triggers the heating system until the interior temperature is below this set-point. Additionally, people using blinds can choose any dark position they prefer.

The combined control process for the above systems requires the optimal performance of all subsystems, under the basic assumption that they are operating properly, in order to avoid conflicts that arise between user preferences and the simultaneous operations of these control subsystems. Such example in [115], when the authors developed effective cost control strategies to achieve optimal energy and acceptable comfort conditions.

The different approaches to the design of control systems for indoor environments of buildings can be classified into (1) Classical methods, and (2) Artificial Intelligence techniques.

3.2.1 Classic PID Controllers

Initially, the purpose of the development of control systems for buildings was primarily to reduce energy consumption, while thermostats were used to control temperature feedback. In order to prevent frequent changes between the two states of a thermostat, thermostats with a dead zone have been implemented and used, and this type of control is called bang-bang control with a dead zone. However, controlled temperature excesses have not been avoided, resulting in increased energy consumption. To solve the problem, the designers used PID (Proportional-Integrate-Derivative) controllers.

A PID controller allows a closed-loop control (a system is said to be in a closed-loop when the output of the process is taken into account to calculate the input) of a physical quantity of a system. In other words, the goal is to reduce the error between set-point and measurement. Therefore, it generates a control signal from the difference between the set-point and the measurement. The PID corrector acts in three ways:

- **Proportional action:** the error is multiplied by a gain, G.
- **Integral action:** the error is integrated and divided by a gain, T_i.

- **Derivative action:** the error is divided and multiplied by a gain, T_d.

There are several possible architectures to combine the three effects (serial, parallel or mixed), and here we present a parallel architecture:

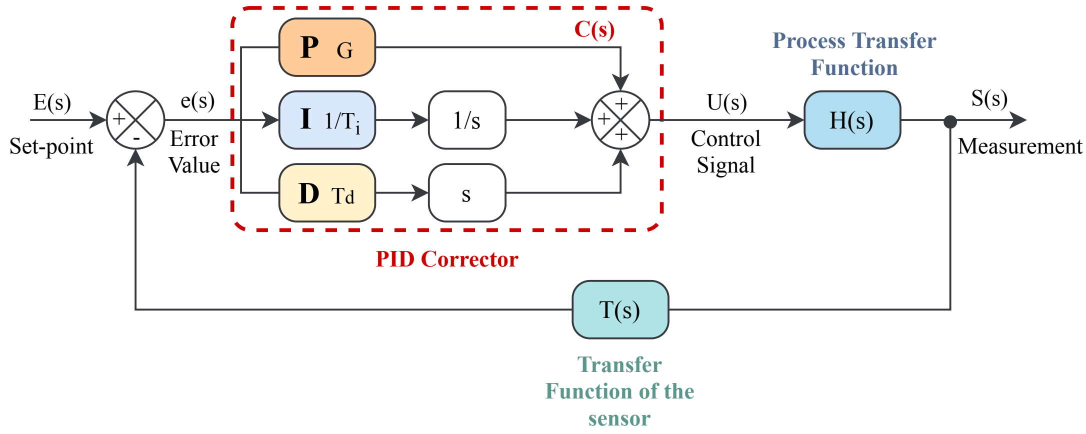


Figure 3-1. Block-diagram of PID controller.

The transfer function id given by:

$$C(p) = G\left(1 + \frac{1}{T_i \times p} + T_d \times p\right) \tag{3-1}$$

Whereas, T_i and T_d are time constants and G is the gain of the proportional part.

The different parameters to be determined are G, T_i, and T_d to control the physical process variable with the transfer function $H(s)$. there are a number of methods to find these parameters, which is generally referred to as *synthesis*. Additionally, for these three parameters, setting a too high threshold has the effect of causing the increasing system oscillation, leading to instability.

Analyzing the PID system is very simple, but its design can be challenging, even difficult, as there is no single method to solve this problem. Compromises have to be found, as there is no perfect controller. In general, specifications are set for the robustness, the overrun, and the time for the establishment of the stationary regime. The most commonly used tuning methods, in theory, are the Ziegler-Nichols methods (open and closed-loop), the P. Naslin method (normal polynomials with adjustable damping), and the inverse Nyquist locus method (uses the Nyquist diagram). In the context of buildings, the controller's parameters adapt to the system's behavior, which can be effective when installing hardware. The non-linearity of different types of HVAC equipment is another disadvantage of self-tuning. Thus, taking into account the special knowledge of thermal equipment used in buildings, a higher degree of control is required, which can no longer be synthesized in the form of a simple PID controller. The main additional knowledge that can be used are: the description of a thermal comfort zone, the occupancy profile, weather forecast, energy prices, thermal connections between rooms, as well as different types of constraints (maximum available power). In order to make the best use of them, research work has been oriented towards more advanced control systems, based on artificial intelligence or optimized approaches, which are presented in the following section.

3.2.2 Developed AI-based Techniques for Comfort and Energy-Efficiency Control

AI is a field of expertise that offers decision support and control models based on real facts and empirical and theoretical knowledge. In this sense, one of the main objectives of AI is related to the development of systems capable of solving problems that only the capacity of human beings reasoning allows due to their ability to learn and make decisions correctly (i.e., intelligence). AI has the challenge of developing problem-solving systems that can be converted into mathematical models and programs for use in computers or controllers. In this section, the principles of the different AI techniques used to design building controllers in the reviewed works will be defined first, we will highlight in particular the most used and well-known tools. In the second part of this section, we will introduce the optimization functions, as a fundamental key in the building control system component.

Numerous AI-based solutions were developed for controlling energy and thermal comfort inside buildings. We performed a thorough analysis of all existing works on the use of AI in buildings' control, which are recorded in Tables (3-1) to (3-7). Based on this analysis, almost 20 AI techniques were employed to control both thermal comfort and energy consumption.

3.2.2.1 Artificial Neural Networks

Artificial Neural Networks (**ANN**) or **Neural Networks** (**NN**), including **Recurrent Neural Networks** (**RNN**), **Deep Neural Networks** (**DNN**), and **Feedforward-ANNs**, are among the most well-known tools (cf. Table 3-1). First introduced by McCulloch and Pitts in 1943, ANNs are now widely used methods for obtaining efficient results in many domains, in supervised or unsupervised classifications. Although it dates back to the 1950s (then called a perceptron and composed of a single neuron) [116], [117], ANN was later developed with the introduction of new types of ANN [118], and new learning methods [119], [120]. Deep learning has continued to be refined thereafter [121], [122], yet has above all revealed its potential through the provision of powerful computational tools (such as graphics processors) to leverage the potential of ANN.

An artificial neuron (or formal neuron) is inspired by a biological neuron to which it gives mathematical inspiration as shown in Figure (3-2).

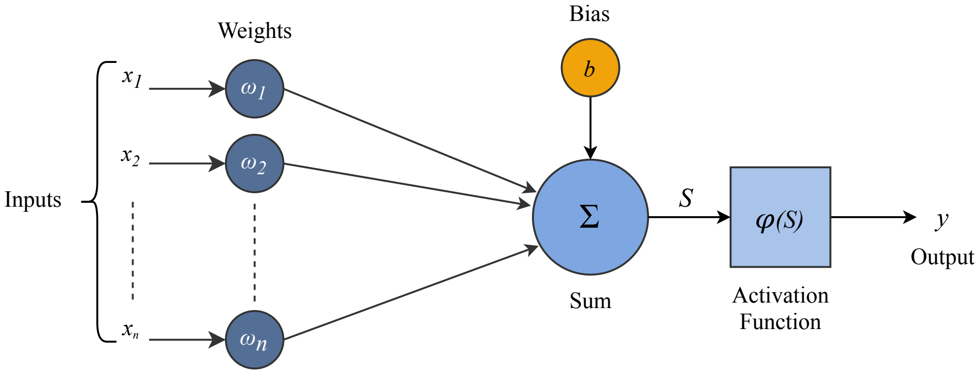


Figure 3-2. Mathematical model of a biological neuron.

In a formal neuron, we observe:

- **Inputs** $(X = x_1, \dots, x_n)$ to which are associated weights $(W = \omega_1, \dots, \omega_n)$ relating to the importance of the information conveyed;
- A **bias** (b) constituting the weight of a constant input allowing to add flexibility to the network by acting on the position of the decision boundary;
- An **activation function** (φ) applied to inputs and bias, such as:
    - Sigmoid: $\varphi(Z) = 1/1 + e^{-Z}$
    - Hyperbolic tangent (tanh): $\varphi(Z) = (1 - e^{-Z})/(1 + e^{-Z})$
    - ReLu (Rectified linear unit): $\varphi(Z) = max(0, Z)$
    - Identity: $\varphi(Z) = Z$
- An **output** (y) that can be used as the input of other neurons, such as:

$$y = \varphi(W.X + b) \tag{3-2}$$

An ANN is then the association of several neurons grouped in layers linked by weighted connections.

The ANN architecture determines the way neurons are ordered and connected within the same network. In general, the ANN consists of several successive layers of neurons: the inputs, the hidden layers (which are not accessible outside the network) up to the output layer(s). The depth of the ANN is estimated by the number of hidden layers.

In the field of thermal building, ANNs are used to solve various problems. Direct neural network controllers were applied for thermal comfort monitoring [123] and HVAC control systems [10], [124], [125]. Such controllers are simple and do not need a building recognition model, unlike indirect neural network controllers.

Figure (3-3) shows the configuration of a neural network controller, which is dual-layer, multi-input, single-output (MISO) [123]. There are two inputs and one output for this controller: e is an error between the PMV setting and the feedback value, $\dot{e}$ is a differential error, and u is a building control signal.

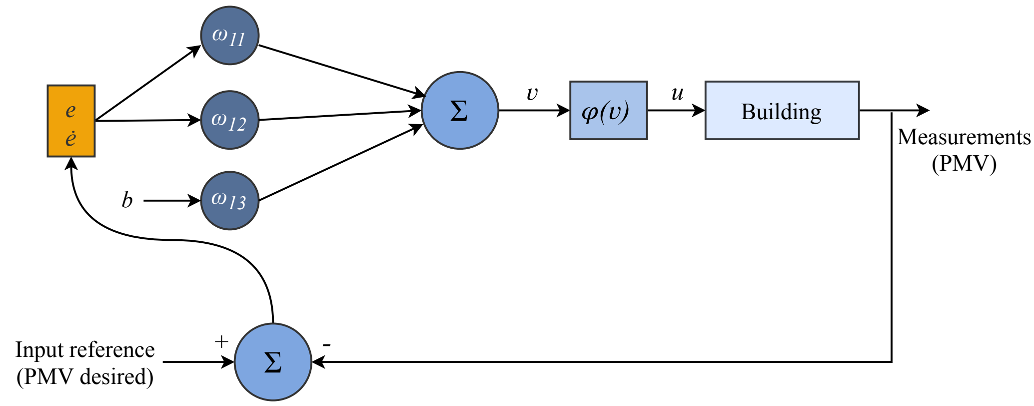


Figure 3-3. A Direct Neural Network controller (Source: figure adopted from [126]).

The equations describing this controller are as follow [126]:

$$v = w_{11}e + w_{12}\dot{e} + w_{13}b \tag{3-3}$$

$$u = \varphi(v) = 1/(1 + e^{-v^2}) \tag{3-4}$$

$$\Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} = -\eta \frac{\partial E}{\partial PMV} \frac{\partial PMV}{\partial u} \frac{\partial u}{\partial w_{ij}} = \pm\eta^* \frac{\partial E}{\partial PMV} \frac{\partial u}{\partial w_{ij}} \tag{3-5}$$

Whereas v in the input of the output layer of neural network; ω_{11} and ω_{12} are the synaptic weights; ω_{13} is the synaptic weight of the fixed input $b = 1$; $\varphi(v)$ is the activation function (unipolar sigmoid function); u is the output of the output layer; and η^* is the learning rate parameter.

Learning an ANN is, in essence, the adjustment of these weight coefficients to optimize the cost functions. The weight of interconnections between neurons is based on the gradient descent algorithm. Initially, this algorithm sets random values to the weights of the network, obtains the two input signals of the controller, and calculates the output. Afterward, the algorithm adjusts both the weights and the output signal.

Table 3-1. Summary of the works focusing on intelligent management of thermal comfort and energy in buildings using Artificial Neural Networks (ANN).

YEAR	STUDY CASE	UNDERLYING AL/ML TOOLS	AI APPLICATION SCENARIO	THERMAL COMFORT METHOD	OPTIMIZATION OBJECTIVE	OUTCOMES & KEY RESULTS	REF.
2005	NN-based control development for individual thermal comfort optimization, and energy saving by combining a thermal space model for VAV&HVAC application.	Direct neural network	Optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, HVAC, Temperature, Humidity), Energy/Load	The controller showed high comfort level (by maintaining the comfort zone between -0.5 and +0.5) while conserving energy. But, still some limitations in practice.	[123]
2008	Intelligent comfort control system (ICCS) design by combining the human learning and minimum energy consumption strategies for HVAC system application.	Deep neural networks	Optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Humidity, VAV), Energy/Load	More energy saving and higher comfort level (by applying VAV control), compared to conventional temperature controller by maintaining the PMV within the comfort zone	[126]
2009	Developing an inferential sensor based on the adaptive neuro-fuzzy modeling to estimate the average temperature in space heating systems.	Adaptive neuro-fuzzy model	Adaptive neuro fuzzy inference system	Average air temperature estimation (based on To, QSQL, and Fire)	Comfort parameters (Temperature, Hot/Cold water), Energy/Load	The average air temperature estimated by ANFIS control model are very close to experimental results, with a highest possible RMSE = 0.5782ºC.	[127]
2009	Predicting fan speed based on ANFIS for energy saving purpose in HVAC system	Adaptive neuro-fuzzy model	Predictive control	Desired temperature by controlling the damper	Comfort parameters (Temperature), Energy/Load	Simulation results showed that the ANFIS model is more effective and can be used as an alternative for HVAC control system.	[128]
2010	Multi-objective optimization methodology used to optimize thermal comfort and energy consumption in a residential building	ANN combined with NSGA-II	Optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Heating/Cooling, Humidity, Temperature), Energy/Load	Optimization results showed significant improvement in thermal comfort (average PMV<4%), more saving in total energy (relative error<1%) and reduction in simulation time compared to conventional optimization methods.	[129]
2011	AI-based thermal control of a typical residential building in USA	Adaptive neuro-fuzzy model	Adaptive neuro fuzzy inference system (ANFIS)	Defined comfort ranges	Comfort parameters (Temperature, Hot/cold water), Energy/load	ANFIS could save 0.3% more energy than ANN. Both methods satisfied thermal comfort (~98% in winter/100% in summer), and reduction in Std. dev. of air temperature from setpoint temperature (under 0.3ºC).	[130]
2014	Dynamic and automatic fuzzy controller for indoor for indoor thermal comfort requirements	Neural network-based ARX	Predictive control	Defined Temperature ranges (based on personal thermal preferences)	Comfort parameters (Temperature, Humidity), Energy/Load	The proposed control system allowed to achieve efficient use of energy and bringing the room temperature to the maximum value of personal comfort.	[131]
2014	Radiator-based heating system optimization to maintain indoor thermal comfort and minimize energy consumption for residential building	Random neural network (RNN)	Predictive control & optimized setting	PMV-based setpoint[6] ($PMV = a \cdot t + b \cdot p_v - c$)	Comfort parameters (PMV, Temperature, Hot/cold water), Energy/load	The proposed model accuracy is of MSE=38.87% for PSO less than GA; MSE=21.19% for PSO less than SQP. RNN with GA allowed to maintain comfortable comfort conditions with the minimum energy consumption (400.6 MWH), compared to MPC model.	[115]

[6] Defined by the Institute for Environmental Research at KSU under ASHRAE contract.

Table 3-1. (Continued).

Year	Study Case	Underlying AL/ML Tools	AI Application Scenario	Thermal Comfort Method	Optimization Objective	Outcomes & Key Results	Ref.
2014	Control logic for thermally comfortable and energy-efficient environments in buildings with double skin envelopes	Rule-base & ANN-based control	Predictive & adaptive control	Comfort range (built from the cavity and indoor temperature conditions)	Comfort parameters (Temperature, heating/cooling), Energy/load	ANN-based logic showed significant results in reducing over/undershoots out of the comfort range. Simplest rule-base control logic use allowed to save cooling energy.	[132]
2015	Developing and testing an NN-based smart controller for maintaining a comfortable environment, and saving energy using a single zone test chamber	Recurrent neural networks (RNN)	Predictive control & optimized setting	User recommendations; PMV-based setpoints (Fanger's model)	Comfort parameters (PMV, Temperature, CO_2 Concentration/Air quality/ heating/cooling), Energy load	The proposed controller has learned the human preferences with an accuracy of 94.87% for heating, 98.39% for cooling and 99.27% for ventilation. The occupancy estimation using RNN is about 83.08%.	[133]
2015	Predictive-based controller development for multizone HVAC systems management in non-residential buildings	Low-order ANN-based model	Predictive control & optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Heating/ cooling), Time efficiency, Energy/load	The proposed strategy could optimize operation time of HVAC subsystems, reducing energy consumption and improving thermal comfort for cooling/heating modes.	[134]
2015	AI-theory-based optimal control for improving the indoor temperature conditions and heating energy efficiency of the building with double-skin	ANN & ANN coupled with FLC	AI-based optimal control	Defined comfort temperature range	Comfort parameters (Temperature, Heating/ cooling), Energy/load	FLC, ANFIS-1 inputs and ANFIS-2 input models increased significantly the comfortable condition period by 2.92%, 2.61% and 2.73% respectively (compared to the rule-based algorithm).	[135]
2015	Automatic air-conditioning control development for indoor thermal comfort based on PMV and energy saving	Adaptive neuro-fuzzy based model	Predictive control based on Inverse-PMV mode	Inverse-PMV model (based on desired PMV and measured variables)	Comfort parameters (PMV, Humidity, Temperature), Energy/load	The proposed control method performed better than conventional method by effectively maintaining the PMV within a range ±0.5 and up to 30% of energy saving.	[136]
2016	ANN-based algorithms development for optimal application of the setback moment during heating season.	ANN-based model	Predictive control & optimized setting	Defined setpoint temperature for occupied periods	Comfort parameters (Temperature), Energy/load	The optimized ANN model showed a promising prediction accuracy (R^2 up to 99.99%). ANN-based algorithms are much better in thermal comfort improvement (97.73% by Algorithm (1)); energy saving (14.04% by Algorithm (2)), compared to the conventional algorithm.	[137]
2016	ANN-based control algorithm development for improving thermal comfort and building energy efficiency of accommodation buildings during the cooling season.	ANN-based algorithms	Predictive & adaptive controls	Fixed setpoint/setback temperatures for occupied/ unoccupied periods	Comfort parameters (Temperature), Energy/load	ANN models gave accurate prediction results with acceptable error for comfort and energy improvement: 1st model: Average difference = 17.07%/MBE = 17.66%, 2nd model: Average difference = 20.87%/MBE = 21.90%.	[138]
2016	A personalized energy management system (PEMS) development for HVAC systems in residential buildings.	Adaptive neuro-fuzzy based model	Predictive control	Personalized comfort bands	Comfort parameters (Temperature), Energy/load, Cost	About 9.7% to 25% reduction in energy consumption and the cost, from 8.2% to 18.2%.	[139]
2017	Proposing an AI-based heating and cooling energy supply model, responding to abnormal/ abrupt indoor situations, to enhance thermal comfort and energy consumption reduction.	Decision making based ANN model	Optimized setting	PMV-PPD (Fanger's model)	Comfort parameters (PMV/PPD, Temperature, Humidity, Heating/ cooling), Energy/load	Thermal comfort improvement: 2.5% for office building, and ~10.2% for residential building. annual energy consumption reduction: 17.4% for office building and 25.7% for residential buildings.	[140]

Table 3-1. (Continued).

Year	Study Case	Underlying AL/ML Tools	AI Application Scenario	Thermal Comfort Method	Optimization Objective	Outcomes & Key Results	Ref.
2017	A low-cost, high-quality decision-making mechanism (DMM) targeting smart thermostats in a smart building environment.	ANN and fuzzy inference system (FIS)	Neural-Fuzzy control	PPD (Fanger's model)	Comfort parameters (PPD, Temperature, Humidity), Energy/load	The proposed framework allowed to reach a higher thermal comfort while reducing energy consumption by an average between 18% and 40%. The use of FL by considering the dynamic behavior of the world allowed to improve the total cost by 7%–19% on average.	[141]
2017	Designing and implementing a smart controller by integrating the internet of things (IoT) with cloud computing for HVAC within an environment chamber.	Random neural network	Occupancy estimation & optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, HVAC, CO_2 concentration/Air quality), Energy/load	Results showed that the hybrid RNN-based occupancy estimation algorithm was accurate by 88%. ~27.12% reduction in energy consumption with the smart controller, compared to the simple rule-based controllers.	[142]
2017	RNN-based smart controller development for HVAC by integrating IoT with cloud computing and web services.	RNN trained with PSO-SQP	Occupancy estimation & optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Humidity, CO_2 concentration/Air quality, HVAC), Energy/load	Energy consumption was 4.4% less than Case-1 and 19.23% less than Case-2. The RNN HVAC controller could maintain the user defined set-points and accurate temperature for PMV set-points.	[143]
2017	Implementing a predictive control strategy in a commercial BEMS for boilers in buildings.	ANN-based model	Predictive control	Predefined temperature (according to daytime)	Comfort parameters (Temperature, Hot/cold water), Energy/load	The predictive strategy allowed to reduce ~20% of energy required to heat the building without compromising the user's comfort, compared to scheduled ON/OFF control.	[144]
2017	A smart heating set-point scheduler development for an office building control.	ANN coupled with MOGA	Optimized setting & predictive control	PPD (Fanger's model)	Comfort parameters (PPD, Temperature, Humidity), Energy /load	4.93% energy savings whilst improving thermal comfort by reducing the PPD by an average of 0.76%.	[145]
2017	A hybrid rule-based energy saving approach development using ANN and GA in buildings.	ANN-based model	Optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Heating/cooling), Energy/load	Validation results showed an average 25% energy savings while satisfying occupants' (elderly people) comfort conditions ($-1 \leq PMV \leq +1$).	[146]
2017	Deploying ML techniques to balance energy consumption and thermal comfort in ACMV systems through computational intelligence techniques in optimizations.	ANN with Extreme learning machine	Optimized setting & predictive control	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Humidity), Energy/load	Maximum energy saving rate prediction ~31% and maintaining thermal comfort within pre-established comfort zone ($PMV \approx 0$)	[147]
2017	Machine learning-based thermal environment control development	ANN-based model	Predictive control	Individual's thermal preference/feedback	Comfort parameters (Temperature, Humidity), Energy/load	A total of up to 45% more energy savings and 44.3% better thermal comfort performance than the PMV model.	[148]
2018	A novel real-time automated HVAC control system built on top of an Internet of Things (IoT).	ANN MPL-based predictive model	Optimized setting & predictive control	Personal dissatisfaction level expressed by users (thermal comfort is a function of temperature)	Comfort parameters (Temperature, Humidity, CO_2 concentration/Air quality), Energy/load	Between 20% and 40% energy savings were achieved while maintaining temperature within the comfort range (except the pre-peak cooling hour).	[149]

Table 3-1. (Continued).

Year	Study Case	Underlying AL/ML Tools	AI Application Scenario	Thermal Comfort Method	Optimization Objective	Outcomes & Key Results	Ref.
2019	An indoor-climate framework development for air-conditioning and mechanical ventilation (ACMV) systems control in buildings	Self-layered feedforward-ANN	Predictive control & optimized setting	Thermal sensation index based on ASHRAE 7-point sensation scale	Comfort parameters (ACMV, Temperature, Humidity), Energy/load	An average of 36.5% energy saving was ensured, and 25ºC was found as the ideal comfort temperature with a minimum energy use.	[150]
2019	A novel optimization framework using a deep learning-based control for building thermal load.	Recurrent neural network (RNN)	Load prediction & optimized setting	Defined temperature setpoints	Comfort parameters (Temperature), Energy/load	Up to 12.8% cost savings compared with a rule-based strategy, while maintaining the users' thermal comfort during the occupied periods.	[151]
2019	A learning-based optimization framework development for HVAC systems in smart buildings	Deep neural networks	Predictive control & optimized setting	Predicted thermal comfort by time slot: $M_t = \Phi(T_t^{in}, H_t^{in})$	Comfort parameters (Temperature, Humidity), Energy/load	DDPG allowed to achieve higher degree of thermal comfort with an average value closer to the preset threshold of 0.5. As it could save 6% more energy than the baseline methods.	[152]
2020	Hybrid data-driven approaches development for predicting building indoor temperature response in VAV systems.	MLR and ANN trained by Bayesian Regulation	Predictive control	Defined comfort zones	Comfort parameters (Temperature, VAV system, Heating/cooling), Energy/load	The proposed model allowed to improve the control and optimization of buildings space cooling	[153]
2020	A network-based deterministic model development to respond the ever-changing users' fickle taste that can deteriorate thermal comfort and energy efficiency in building spaces.	Fuzzy inference system (FIS), ANN	Thermostat on/off, ANN, ANN + FDM	PMV (Fanger's model)	Comfort parameters (PMV, Humidity), Energy/load	ANN-FDM showed significant results by improving thermal comfort by up to 4.3% rather than thermostat model and up to 44.1% of energy efficiency rather than ANN model.	[154]
2020	ANN-based prognostic models' development for load demand (LD) prediction for a Greek island by capturing three different forecasting horizons: medium, short and very short-terms	Multilayer Perception ANN	Predictive control	Biometeorological human thermal comfort-discomfort index	Comfort parameters (Humidity, Heating/cooling), Energy/load	Both medium and short-term prognoses showed significant ability to predict LD by errors around 7.9% and 7.2% respectively.	[155]
2020	An intelligent-based ML model to predict the energy performances in heating loads (HL) and cooling loads (CL) of residential buildings.	ANN, Deep neural networks	Predictive control	Maintaining defined comfort conditions	Comfort parameters (Temperature, Humidity, Heating/cooling), Energy/load	Deep NN showed better results compared to ANN (i.e., HL and CL prediction), by applying state-based sensitivity analysis (SBSA) technique allowing to improve the model by selecting the most significant variables.	[156]
2020	A novel personal thermal comfort prediction method using less physiological parameters.	ANN-based model	Predictive control	Modified thermal sensation vote scale {cold, cool, neutral, warm, hot}.	Comfort parameters (Temperature, Humidity, HVAC), Energy/load	the proposed model showed good prediction accuracy and stability by an average of 89.2% and a standard deviation around 2.0%.	[157]
2020	Investigating the performances and comparative analyses of combined on-demand and predictive models for thermal conditions control in buildings.	ANN combined with FIS	On-demand & predictive controls	PMV/PPD (Fanger's model)	Comfort parameters (PMV/PPD, Temperature), Energy/load	combining the predictive and on-demand algorithms improved the energy efficiency from 13.1% to 44.4% and reduced the thermal dissatisfaction by 20% to 33.6%, compared to each independent model.	[158]
2020	A building intelligent thermal comfort control and energy prediction based on the IoT and artificial intelligence.	Back-propagation (BP) neural networks	Predictive control & optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Humidity), Energy/load	The system performed better than traditional control on comfort and energy savings. Limitations: ~3% error between expected and actual values.	[159]

3.2.2.2 Fuzzy Logic Control

Fuzzy Logic Control (FLC) is an appropriate tool for imitating the behavior of building users and developing linguistic descriptions of the thermal comfort sensation that approach the PMV model and facilitate the calculation of the control system (cf. Table (3-2). Unlike conventional control methods, FLC is more widely used in poorly specified, complicated procedures that can be managed by a professional human agent without a deep understanding of their underlying mechanisms. The basic idea behind FLCs is to integrate the "expert knowledge" of a human agent into the regulation of a mechanism whose input-output association is defined as a collection of fuzzy control rules (e.g., IF-THEN), which involve linguistic variables rather than a complex dynamic model. The use of linguistic variables, fuzzy rules, and rough set reasoning offers a way of integrating the human expert experience into the design of the controller. The typical FLC architecture is shown in Figure (3-4), comprising four main elements: a **Fuzzifier**, a **Fuzzy Rule Base** (**FRB**), an **Inference Engine**, and a **Defuzzifier**.

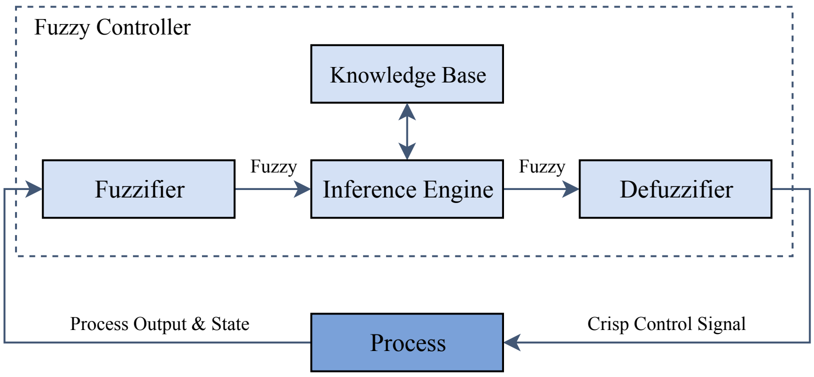


Figure 3-4. Schematic of fuzzy logic controller.

i. **Fuzzification:** is the operation that consists of assigning a degree of membership to each fuzzy subset for each physical input. In other words, it is the operation that allows the transition from numerical (physical) to symbolic (fuzzy) variables.

ii. **The knowledge Base:** includes knowledge of the field of application and the objectives of the planned control. It includes:

   - The basis of fuzzy rules for storing empirical knowledge of how the process works by experts in the field.

- The rule base is a set of linguistic expressions structured around expert knowledge and represented in the form of rules, such as:

IF <condition> THEN < consequence>

iii. **Defuzzification:** this is the inverse fuzzification operation, which consists of converting the fuzzy number B into the numerical quantity, y_0.

iv. **Fuzzy inference rules**: the inference engine is the core of the FLC, and has the ability to simulate human decision-making by performing rough reasoning to achieve the desired control strategy.

In the context of building control systems, the application of FL control methods for HVAC systems is efficient as this technique is well suited for non-linear systems [160]. These methods can uniformly approximate a non-linear function to any degree of accuracy and also provide fast operation. In [161], the use of Fuzzy-PID, Fuzzy-PD, and adaptive Fuzzy-PD methods to control thermal comfort and indoor air quality is described. One of the main objectives of this work was to reduce energy consumption. The lowest values were obtained with the adaptive Fuzzy-PD controller. Moreover, T. Bernard T. and H-B. Kuntze [162] proposed a fuzzy logic supervisory system, which allows the monitoring of the thermal environment inside a building where the customer could follow a compromise solution (through a weighting factor) between efficiency and comfort. M. Hamdi M. and G. Lachiver [163], studied in this direction and developed a concept of comfort conditions based on human sensitivity, without maintaining a constant internal temperature, but rather a constant indoor comfort. The results showed that it was possible to combine the comfort of the occupants while saving resources.

Table 3-2. Summary of the works focusing on intelligent management of thermal comfort and energy in buildings using Fuzzy Logic Control (FLC).

Year	Study Case	Underlying AL/ML Tools	AI Application Scenario	Thermal Comfort Method	Optimization Objective	Outcomes & Key Results	Ref.
1998	Fuzzy controller development for improving thermal comfort and energy saving of HVAC systems.	Fuzzy logic control (FLC)	Fuzzy control	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Humidity, HVAC), Energy/load, cost	20% energy saving, and better comfort level at the lower cost (than provided by thermostatic techniques)	[163]
1999	Multi-objective supervisory control of building climate and energy.	Fuzzy logic control (FLC)	Optimized setting	Pre-defined (standardized) temperature	Comfort parameters (Temperature, Humidity, CO_2 concentration/Air quality	The proposed system allows the user to compromise solution (comfort requirements /energy saving)	[162]
2001	PMV-based fuzzy logic controller for energy conservation and indoor thermal requirements and of a heating system in a building space.	Fuzzy logic control (FLC)	Fuzzy control	PMV/PPD (Fanger's model)	Comfort parameters (PMV/PPD, Temperature, Humidity, Heating/ cooling), Energy/load	By maintaining PMV index at 0 and PPD with a maximum threshold of 5%, fuzzy controller had better performance with a heating energy of 20% (compared to tuned PID control).	[164]
2001	Developing fuzzy controller for energy saving and occupants' thermal-visual comfort and IAQ requirements.	Fuzzy logic control (FLC)	Fuzzy control	PMV (Fanger's model)	Comfort parameters (PMV, CO_2 concentration/Air quality, Lighting), Energy/load	Adaptive fuzzy PD showed better performance for energy consumption (up to 25-30%) and the PMV/CO2 responses, for visual comfort, the non-adaptive fuzzy PD was sufficient.	[161]
2003	Fuzzy controller for indoor environment management.	Fuzzy logic control (FLC)	Fuzzy control	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, CO_2 concentration, Lighting, Heating/cooling), Energy/load	Up to 20.1% heating and cooling energy saving using P-controller by maintaining PMV between 0 and 0.1 and CO2 concentration less than 20 ppm.	[165]
2003	Fuzzy control for indoor environmental quality, energy and cost efficiencies.	Fuzzy logic control (FLC)	Fuzzy control	Defined ranges/ Preferred set-points variables	Comfort parameters (Temperature, Humidity, CO_2 concentration/Air quality), Energy/load, Cost	Fuzzy approach showed its ability to deal with multivariate problems by collaborating expert knowledge for decision making at complex level.	[166]
2005	Integrated indoor environment energy management system (IEEMS) implementation for buildings application	Fuzzy logic control (FLC)	Fuzzy control	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, CO_2 concentration, Lighting), Energy/load	Up to 38% energy conservation in both buildings without compromising the indoor comfort requirements.	[167]
2005	Dynamic illumination and temperature response control in real time conditions.	Fuzzy logic control (FLC)	Fuzzy control	Temperature preference set-point (by the user)	Comfort parameters (Temperature, Lighting, Heating/cooling), Energy/load, Cost	Adjusting automatically roller blind position and window geometry according to external weather enables to get closer to thermal-visual preferences, contributing to lower energy consumption for lighting, heating/cooling and cost-saving enhancement.	[168]
2005	Controller development to improve energy conservation with a constraint on the individual dissatisfactions of indoor environment.	FLC based on kNN approximations	Gradient-based optimization	Degree of individual dissatisfaction (DID) $DID(vote) = (1 + \tanh(2\|vote\| - 3)/2$	Comfort parameters (DID, Temperature), Energy/load	Optimized HIYW presented better performance than OFSA (PPD exceeding 20% for ~15% of population and 50% for ~5%) to minimize the energy consumption.	[169]
2006	Adaptive fuzzy control strategy for comfort air-conditioning (CAC) system performance	Fuzzy logic control (FLC)	Indirect fuzzy adaptive control	PMV (Fanger's model)	Comfort parameters (PMV, HVAC), Energy/load	The adaptive fuzzy controller could save almost 18.9% of energy, compared to PID controller.	[170]

Table 3-2. (Continued).

Year	Study Case	Underlying AL/ML Tools	AI Application Scenario	Thermal Comfort Method	Optimization Objective	Outcomes & Key Results	Ref.
2007	Fuzzy controller development for improving indoor environmental conditions while reducing energy requirements for building energy management system	Fuzzy logic control (FLC)	Fuzzy control	PMV (Fanger's model)	Comfort parameters (PMV, Lighting, CO_2 concentration /Air quality), Energy/load	Using a suitable cost function for BEMS allowed to save energy at a level lower than recommended by the literature. Also, users were satisfied by adopting the fuzzy controller	[171]
2011	Fuzzy adaptive comfort temperature (FACT) model development for intelligent control of smart building.	Fuzzy adaptive control	Fuzzy control and optimized setting	Adaptive comfort model	Comfort parameters (Temperature), Energy/load	Using the FACT model with grey predictor in agent-based control system of a smart building, provided reasonable comfort temperature with less energy consumption to the customers	[172]
2013	Fuzzy method-based data-driven to model and optimize thermal conditions of smart buildings applications.	Fuzzy logic control (FLC)	Fuzzy control	Comfort temperature ranges (defined by the users).	Comfort parameters (Temperature), Energy/load	The type-2 fuzzy model performs better, with RMSE=12.55 compared to the linear regression model where the RMSE=17.64.	[173]
2013	Identifying building behaviors related to energy efficiency and comfort for an office building in the Pacific Northwest.	Fuzzy knowledge base	Fuzzy rule base & optimized setting	Comfort levels based on average zone temperature	Comfort parameters (Temperature), Energy/load	The developed framework was able to identify and extract complex building behavior, which improve the building energy management systems (BEMSs) by eliminating the low efficiency and low comfort behavior	[174]
2014	Deploying and evaluating a user-led thermal comfort driven HVAC control framework in office building on University of Southern California	Fuzzy predictive model	Predictive control	Personalized comfort profiles based on a thermal preference (TPI) scale	Comfort parameters (Temperature, Humidity, Lighting, CO_2 concentration /Air quality, HVAC), Energy/load	The developed framework showed promising results for energy saving and comfort improvement. 39% reduction in daily average airflow rates.	[175]
2015	Fuzzy logic-based advanced on–off control for maintaining thermal comfort in residential buildings	Fuzzy logic control (FLC)	Fuzzy control	Defined (desired) room temperature	Comfort parameters (Temperature), Energy/load	Compared to the conventional on–off controller, the proposed system had better control performance and saved energy.	[176]
2018	Combining a Comfort Eye sensor with a sub-zonal heating system control for building climate management	Fuzzy logic control (FLC)	Fuzzy PID-PMV control	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Humidity, Heating/cooling), Energy/load	Up to 17% energy savings with respect to the standard ON/OFF mono-zone control, thermal comfort has been slightly improved with a minimum deviation from the neutral condition (PMV=0)	[177]

3.2.2.3 Distributed Artificial Intelligence & Multi-Agent Systems

Distributed Artificial Intelligence (DAI) and Multi-Agent Systems (MAS) (cf. Table (3-3)). MAS are derived from Distributed AI, a branch of artificial intelligence. The DAI has structured around three axes:

- **Distributed problem solving**, allows the problem to be divided into a set of sub-problems supported by distributed and collaborating entities and studies on how to share problem knowledge to find a solution.
- **Parallel AI**, develops parallel languages and algorithms to improve computer system performance.
- **Multi-agent systems**, promote a decentralized modeling approach and emphasize the collective aspects of systems.

The MAS approach, which has evolved considerably over the last twenty years, makes it possible to apprehend, model, and simulate complex systems, i.e., systems involving multiple components that interact dynamically with each other and with the outside world. It looks at how to coordinate a set of entities called agents so that they can collectively solve a global problem. Otherwise, the concept of agent refers to an autonomous entity evolving in interaction with its environment, which is often dynamic and unforecastable. The modeling and interactions of these agents were inspired by the observation of complex biological systems (e.g., organized animal societies such as ant colonies, bird swarms [178], or fish schooling [179]). MAS are therefore a privileged approach to addressing complex systems. Their entirely decentralized nature makes them particularly suitable for this type of system. MAS make it possible to work on the overall functioning of the system by looking at the entities that make it up and their interactions. MAS have been developed in a variety of areas including image processing, robotics, simulation, among others.

In the building sector, the usage of agent-based and distributed intelligent energy-saving systems while maintaining a satisfactory indoor environment has been adopted in several works. For example, L. Klein et al. [180] proposed a multi-agent comfort and energy system (MACES) to coordinate equipment and occupants within a building. Also, P. Davidsson and M. Boman [181] presented a MAS for energy control in tertiary sector buildings. The purpose of this system is to provide three services: lighting, heating, and ventilation, as well as minimizing office energy consumption. Also, Z. Mo [182] built an agent-based platform for individual users and buildings occupants in order to negotiate their control activities. A. I. Dounis and C. Caraiscos [183] suggested the use of an intelligent supervisor to arrange the optimal collaboration of local controller-agents. Consequently, overall control is reached, the occupants' preferences are met, disagreements are avoided and the energy consumption is reduced on a conditional basis. Another agent-based system control developed by M. Barakat and H. Khoury [184], which examines multi-comfort (visual, thermal and acoustic) level control designed to reduce energy consumption. In [185], an agent-based model was introduced to simulate the effect of occupant's behavior on comfort and energy usage in a residential building. The developed model showed a realistic estimation of the energy consumption levels.

3.2.2.4 Reinforcement Learning & Deep Reinforcement Learning

Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) have been used in building control (cf. Table (3-4)). Reinforcement learning is a type of machine learning through which an intelligent agent learns based on rewards (or reinforcements) that may be positive or negative depending on how the action is taken by the agent brings it closer to its goal [186]. In RL, the agent interacts with the environment and receives information from this interaction that helps to manage the environment better over time. In each interaction, the agent is in a state s, from a set of all possible S $(s \in S)$ states, and performs an action a, from a set of all possible A $(a \in A)$ actions. After performing the action, the agent goes to a new state s' and receives a reward r from the environment. This process can be shown in Figure (3-5).

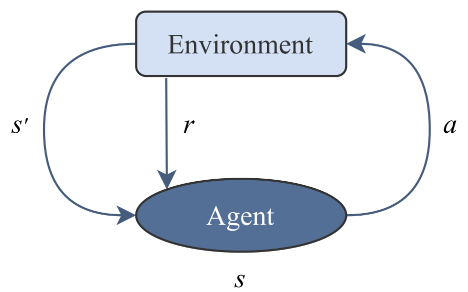


Figure 3-5. Illustration of the general framework of reinforcement learning.

The agent must carry out those actions that increase the total amount of received rewards, i.e., it is necessary to locate a movement policy that optimizes the accumulated reinforcement over the long term. A policy π is a mapping of states to actions that determines the probability $\pi(a|s)$ of an action being performed in a state s. This map is updated on the basis of the experience acquired by the agent during training.

Table 3-3. Summary of the works focusing on intelligent management of thermal comfort and energy in buildings using distributed AI (DAI) & Multi-agent systems (MASs).

Year	Study Case	Underlying AL/ML Tools	AI Application Scenario	Thermal Comfort Method	Optimization Objective	Outcomes & Key Results	Ref.
2005	Decentralized system development for controlling and monitoring an office building.	Agent-based approach	Distributed AI	Personal comfort based on individual preferences	Comfort parameters (Temperature, Lighting), Energy/load	MAS approach allowed to save up to 40% energy, compared to thermostat approach, and ~12% compared to timer-based approach. Reactive approach is more energy consuming than pro-active, ensuring 100% of thermal satisfaction.	[181]
2006	Centralized HVAC with multi-agent structure.	Agent- based approach	Distributed AI and optimized setting	PMV (Fanger's model)	Comfort parameters (Temperature, Humidity, HVAC), Energy/load	The control accuracy goes around 89% to 92.5%. which means that the thermal comfort is predicted by 7.5% to 11% of error rate.	[187]
2011	Multi-agent simulation for building system energy and occupants' comfort optimization	Multi-agent system (MAS)	Distributed AI	PMV (Fanger's model)	Comfort parameters (PMV, Temperature), Energy/load	17% energy savings while maintaining high comfort level, approximately 85% occupants' satisfaction.	[188]
2011	Developing a MAS combined with an intelligent optimizer for intelligent building control.	Multi-agent system (MAS)	Optimized setting	Temperature set-point control	Comfort parameters (Temperature, Lighting, CO_2 concentration/Air quality), Energy/load	Implementing PSO optimizer allowed to maintain a high-level of overall comfort, i.e., mainly around 1.0, when the total energy supply was in shortage.	[189]
2012	Coordinating occupants' behaviors for thermal comfort improvement and energy conservation of an HVAC system.	Agent-based approach	Distributed AI	PMV (Fanger's model)	Comfort parameters (PMV, HVAC), Energy/load	Reducing 12% of energy consumption while maintaining 70%–75% occupant satisfaction for both proactive and proactive-MDP.	[180]
2012	Distributed AI control with information fusion-based Indoor energy and comfort management for smart building application.	Multi-agent approach	Distributed AI & optimized setting	Defined comfort range	Comfort parameters (Temperature, Lighting, CO_2 concentration/Air quality), Energy/load	All case studies showed the effectiveness of the system of the developed system in different operating scenarios.	[190]
2013	Intelligent management system development for energy efficient and comfort in building environments.	Agent-based approach	Distributed AI	Individual thermal comfort based on the indoor temperature	Comfort parameters (PMV, Temperature, Lighting, CO_2 concentration), Energy/load	Case studies simulation results showed that the developed MAS could manage comfort needs and reducing energy consumption simultaneously (PMV was kept around 0.61).	[191]
2014	A human and building interaction toolkit (HABIT) development for building performance simulation	Agent-based model (ABM)	Distributed AI	Individual comfort distribution based on PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Heating/cooling), Energy/load	Up to 32% reduction of total energy use in all zones in summer without significant increase in winter are expected, and a promising decrease in thermal discomfort in all zones in both seasons.	[192]
2014	NN-based approach with a MAS infrastructure to improve energy efficiency, while maintaining acceptable thermal comfort level for occupants of an academic building	MAS combined with gARTMAP	Distributed AI	Learning the user's thermal preferences	Comfort parameters (Temperature, Hot/cold water), Energy/Load	The proposed gARTMAP-MAS IHMS might use less heat to achieve the desired indoor temperature, compared to the existing rule-base BMS and fuzzy ARTMAP IHMS	[193]
2015	Multi-agent control architecture for cooling and heating processes in smart residential building.	Multi-agent system + ML algorithms	ML & distributed AI	Desired temperature based on occupant's behavior	Comfort parameters (Temperature, Heating/cooling), Energy/load	The proposed system allowed to significantly improve the occupants comfort with a slight increase in energy consumption, with respect to 'sense behavior' (compared to simple strategies)	[194]

Table 3-4. Summary of the works focusing on intelligent management of thermal comfort and energy in buildings using Reinforcement Learning (RL) & Deep-RL.

Year	Study Case	Underlying AL/ML Tools	AI Application Scenario	Thermal Comfort Method	Optimization Objective	Outcomes & Key Results	Ref.
2007	Linear reinforcement learning controller (LRLC) for energy saving while sustaining comfort requirements.	Linear reinforcement learning	Machine Learning (ML)	PMV-PPD (Fanger's model)	Comfort parameters (PMV/PPD, Temperature, Humidity, CO_2 level /Air quality), Energy/load	Over a period of 4 years, training the LRLC, the energy consumption has been increased from 4.77Mwh to 4.85Mwh, however the PPD index has been decreased from 13.4% to 12.1%.	[195]
2014	Reinforcement learning for tenant comfort and energy use optimization in HVAC systems.	Q-learning based supervisory approach	Optimized setting	Occupant's comfort is learnt from the tenant preferences and occupancy patterns	Comfort parameters (Temperature, HVAC), Energy/load	Learning to adjust/schedule, appropriately, thermostat temperature setpoints for energy efficiency while keeping the tenant comfortable.	[196]
2015	Implementing and evaluating a multi-grid reinforcement learning method for energy conservation and comfort control of HVAC systems in buildings.	Multi-grid methods for Q-learning	Optimized setting	PPD-PMV (Fanger's model)	Comfort parameters (PMV/PPD, Temperature, Humidity, HVAC), Energy/load	The proposed multi-grid approach helped to accelerate the convergence of Q-learning, and performed better on energy saving and comfort than the constant grid versions.	[197]
2017	A deep reinforcement learning based data–driven approach development for building HVAC control.	Deep reinforcement learning (DRL)	Optimized setting	Desired temperature range based on ASHRAE standard	Comfort parameters (Temperature), Energy/load, Cost	Up to 20%-70% energy cost reduction while meeting the room temperature requirements, compared to a conventional rule-based approach.	[124]
2017	A reinforcement learning-based thermostat schedule controller development using long–short–term memory recurrent neural network for an office HVAC system.	Actor-critic RL + LSTM-RNN	Optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature), Energy/load	An average 2.5% energy savings was achieved while improving thermal comfort by an average of 15%, compared to other control baselines (Ideal PMV & Control Variable).	[198]
2018	A novel type of decentralized and cooperative method development for decision-making strategies in the buildings' context, based on reinforcement learning.	Extended joint action learning (eJAL)	Distributed AI	Thermal comfort index as a function of indoor temperature	Comfort parameters (Temperature, Humidity, Lighting), Energy/load	The long-term learning analysis showed that Q-learning and eJAL gave acceptable comfort losses ($\Delta C \leq 0.4$), for demand/response balance, eJAL (Median=1.67) was slightly better than Q-learning (Median=2.21)	[199]
2018	Plug & play solution of an HVAC thermostat's set-point scheduling inspired by reinforcement learning technique	Neural Fitted Q-iteration (NFQ)-RL	RL-based control	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Humidity, HVAC), Energy/load	With energy/comfort trade-off balance, an average up to 32.4% energy savings and up to 27.4% comfort improvements in average.	[12]
2018	A whole BEM-DRL framework development for HVAC optimal control in a real office building	Deep reinforcement learning (DRL)	Optimized setting	PPD (Fanger's model)	Comfort parameters (PPD, Hot/cold water), Energy	About 15% heating energy savings with similar comfort conditions as the base-case	[200]
2019	AI-based agent development for indoor environment control while optimizing energy use of air-conditioning and ventilation fans in a classroom and a laboratory	Deep RL (double Q-learning)	Optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, HVAC, CO_2 concentration/Air quality), Energy/load	AI-agent has successfully managed the indoor environment within an acceptable PMV values between -0.1 and +0.07, and 10% lower CO_2 levels, reducing energy consumption by 4% to 5%.	[201]
2020	An event-triggered paradigm based on RL approach for smart learning and autonomous micro-climate control in buildings.	Stochastic/deterministic policy gradient RL	Optimized setting & event-trigged control	Discomfort rate derived from desired temperature	Comfort parameters (Temperature, Heating/ cooling), Energy/load	the proposed algorithms learn the optimal policy in an appropriate time, i.e., optimal thresholds were found $T_{ON}^{th} = 12.5°C$ and $T_{OFF}^{th} = 17.5°C$ resulting an optimal rewards rate.	[202]
2020	A framework development for optimal control over AHUs by combining DRL methods and long-short-term-memory networks (LSTM).	Deep reinforcement learning (DRL)	Predictive control & optimized setting	PMV (Fanger's model)	Comfort parameters (PPD, Temperature, CO_2 concentration/Air quality), Energy/load	27% to 30% lower energy consumption compared to rule-based control, while maintaining the average PPD at 10%.	[203]

3.2.2.5 Advanced Predictive Control

Advanced predictive control, including predictive functions of ANN and model-based predictive control (MPC) (cf. Table (3-5)), is a widely recognized comfort control technique using a model (system, noise, and disturbance) to predict the future output. These predictions are integrated into the cost function of closed-loop action and control activity, which is reduced with regard to the sequence of anticipated signals, taking into account the problem constraints. Finally, a rolling-horizon strategy is implemented, applying at time k the control signal calculated for that time and repeating the calculations for the next sampling period. Many variants of these techniques have emerged and, within the context of this paper, we consider the most relevant in the field of comfort and energy management in built environments, such as **Linear MPC**, **Non-Linear MPC**, **Distributed MPC**.

3.2.2.6 Hybrid Methods & Other AI-based Tools

Hybrid methods, resulting from a combination of intelligent techniques and classical or advanced techniques, such as **FLC** and **Genetic Algorithm** (**GA**) [204]–[209], **MAS** and **FLC** [210], [211], **ANN** and **GA** [212]–[214], among others [215]–[220]. Hybrid controllers are useful since this incorporation can solve problems that the single controller cannot solve. Nevertheless, the design of the "intelligent" component involves the expertise of the user and a large amount of training data, while the "classic" or "advanced" part is difficult to adjust (tuning), particularly for HVAC systems, which is a constraint on the control system.

In addition, there are other AI-based methods including: **Genetic Algorithm** (**GA**) method [221]–[225], **Knowledge-Based System** (**KBS**) [226], [227] for reasoning and resolving complex problems, **Autoregressive Exogenous** (**ARX**) technique [228], [229], **Bayesian Network** (**BN**) [10], [230], **Decision Tree** (**DT**) [231], **Multi-Objective Artificial Bee Colony** (**MOABC**) and **Multi-Objective Particle Swarm Optimization** (**MOPSO**) [232], [233] for multi-objective optimizing control strategies, **Radial Basis Function** (**RBF**) [212], [234], **Support Vector Machine** (**SVM/C-SVC**) [219], [235], **Logistic Regression** (**LR**) [236], **Random Forest** (**RF**) [219], [237] , and **k-Nearest Neighbor** (**kNN**) [238] for classification purpose, **k-Means** algorithm for clustering [239], and the **Hidden Markov Model** (**HMM**) for modeling [138], while the **Bayesian Inference** (**BI**) which is useful to quantify the uncertainty in the estimated parameters of a given model [240].

Table 3-5. Summary of the works focusing on intelligent management of thermal comfort and energy in buildings using advanced predictive control methods.

Year	Study Case	Underlying AL/ML Tools	AI Application Scenario	Thermal Comfort Method	Optimization Objective	Outcomes & Key Results	Ref.
2012	Improving the energy efficiency in an AC by reducing transient and steady-state electricity consumption on BRITE platform.	Learning-based model predictive control	Predictive control	Comfort specifications based on OSHA guidelines	Comfort parameters (Temperature, HVAC), Energy/load	30%–70% reduction in energy consumption while maintaining comfortable room temperature by keeping temperature close to the specified comfort middle (22ºC)	[241]
2012	Model-based predictive control development for thermal comfort improvement with auction of available energy of a limited shared energy resource in three houses.	Distributed model predictive control	Predictive control	Defined comfort temperature bounds	Comfort parameters (Temperature), Cost, Energy/load,	The developed system is flexible, allowing the customer to shift between comfort and lower cost.	[242]
2012	A discrete model-based predictive control for thermal comfort and energy conservation in an academic building.	MBPC based (RBF) ANN	Discrete models-based predictive control	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Humidity), Energy/load	Up to 50% energy savings are achieved by using the MBPC, which provided good coverage of the thermal sensation scale, when used with radial basis function-NN models.	[234]
2013	Model-based predictive control development for optimal personalized comfort and energy consumption management in an office workplace	Learning-based model predictive control	Predictive control & optimized setting	PPV function defined as an affine transform of PMV index	Comfort parameters (PPV-PMV, Temperature), Energy/load	About 60% energy savings when compared with fixed temperature set-point, and discomfort reduction from 0.36 to 0.02 compared to baseline methods.	[238]
2014	Predicting an integrated building heating and cooling control based on weather forecasting and occupancy behavior detection in the Solar House test-bed in real-time located in Pittsburgh.	Nonlinear model predictive control	Predictive control & optimized setting	Personalized thermal comfort (based on occupancy and weather)	Comfort parameters (Temperature, Humidity, HVAC, Lighting, CO_2 concentration), Energy/load	30.1% of energy reduction in the heating season, besides 17.8% in the cooling season. NMPC allowed reducing time not met comfort (from 4.8% to 1.2% in heating season, and from 2.5% to 1.2% for cooling season).	[243]
2015	Hybrid predictive control model development for energy and cost savings in a commercial building (Adelaide airport).	Linear MPC combined with ANN	Hybrid predictive control	Defined comfort range based on ASHRAE	Comfort parameters (Temperature, Hot/cold water), cost, Energy/load	About 13% of energy cost saving was achieved and up to 41% of energy saving, compared to the baseline control.	[244]
2016	Simulation-based MPC procedure for multi-objective optimization of HVAC system performance and thermal comfort, applied to a multi-zone residential building in Naples.	Model-based predictive control	Predictive control & optimized setting	PPD^{MAX}: the maximum hourly value of PPD (Fanger's model)	Comfort parameters (PPD, HVAC), cost, Energy/load	Up to 56% operating cost reduction and improvement in thermal comfort, compared to the standard control strategy.	[245]
2020	A novel MPC relied on artificial intelligence-based approach development for institutional and commercial buildings control.	MPC relied on AI-based approach	Predictive control & optimized setting	Pre-defined set-point ramps (temperature) profiles	Comfort parameters (Temperature, Heating), Time efficiency, Energy/load	Reduction of the natural gas consumption and the building heating demand by 22.2% and 4.3% resp. Improving thermal comfort, while minimizing the required amount of time and information, compared with *business-as-usual* control strategies.	[246]
2020	A neural network-based approach for energy management and climate control optimization of buildings (applied to two-story building in Italy).	MPC with ANN-based models	Predictive control & optimized setting	Constant set-point temperature (defined as $T_{ref} = 25°C$) for each zone.	Comfort parameters (Temperature, Humidity), Energy/load	The proposed model showed significant results in energy savings (5.7% energy reduction of one zone) and better comfort compared to the baseline controller.	[247]

Table 3-6. Summary of the works focusing on intelligent management of thermal comfort and energy in buildings using the Hybrid methods.

Year	Study Case	Underlying AL/ML Tools	AI Application Scenario	Thermal Comfort Method	Optimization Objective	Outcomes & Key Results	Ref.
2002	Controller development for indoor environmental conditions management for users' satisfaction while minimizing energy consumption inside a building.	GA-based fuzzy control	Optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, lighting, CO_2 concentration/Air quality, Humidity)/ Energy/load	Overall energy saving up to 35%, with a steady-state error of 0.5 for PMV, ~ 80ppm for CO_2, and ~80 lx for illuminance (after applying GA).	[204]
2003	Developing controller for HVAC system to improve indoor comfort requirements and energy performance in two real sites.	GA-based fuzzy control	Optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, CO_2 concentration/Air quality), Energy/load	While maintaining a steady-state indoor conditions, the developed controller showed best experimentation results in the real test cells, with up to 30% energy saving for CNRS–ENTPE case and 12.5% for ATC (anonymous enterprise).	[205]
2005	Development of fuzzy rule-based controller using GA for HVAC system	GA-based fuzzy control	Optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, HVAC, CO_2 concentration/Air quality), Energy/load	By considering the rule weights and rule selection, results showed that FLC controller presented improvement by 14% in energy saving and about 16.5% in system stability.	[206]
2007	Development of an intelligent coordinator of fuzzy controller-agents (FCA) for indoor environmental control conditions using 3-D fuzzy comfort model	Agent-based FLC	Intelligent system-based fuzzy control	PMV (Fanger's model)	Comfort parameters (PMV, Lighting, CO_2 concentration /Air quality), Energy/load	The combined controller showed significant results by maintaining the controlled variables in acceptable ranges (PMV between -0.5 and +0.6) besides up to 30% of energy savings	[210]
2011	Intelligent control system development to optimize comfort and energy savings using soft computing techniques for building application	GA-based fuzzy control	Optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Lighting, CO_2 concentration /Air quality), Energy/load	The proposed system has successfully managed the user's preferences for comfort requirements and energy consumption (while maintaining PPD < 10%).	[207]
2011	Controller development for a heating and cooling energy system	GA-based fuzzy control	Predictive control	Fixed set-point temperature for the thermal zone (24ºC)	Comfort parameters (Temperature, Heating/ cooling), cost, Energy/load	The proposed methodologies allowed to achieve higher energy efficiency and comfort requirements by lowering equipment initial and operating costs up to 35%, and comfort costs up to 45%.	[208]
2013	Intelligent control system deployment for energy and comfort management in commercial buildings	MAS & FLC	Distributed AI & Fuzzy control	User preferences (temperature setpoint)	Comfort parameters (Temperature, Lighting), Energy/load	Up to 0.9 is achieved by comfort factors, i.e., the customers satisfaction is ensured. The GA-based optimization allowed to minimize the energy consumption	[211]
2014	Improving the fuzzy controller's performance for comfort energy saving in HVAC system	GA-based fuzzy control	Fuzzy control & optimized setting	Individual comfort classes: ISO 7730 based on PMV/PPD (Fanger's model)	Comfort parameters (PMV/PPD, HVAC), Energy/load	The overall energy consumption is decreased by 16.1% in case of cooling and 18.1% in case of heating. Also, the PMV is reduced from -0.3735 to -0.3075 compared to EnergyPlus.	[209]
2014	Stochastic optimized controller development to improve the energy consumption and indoor environmental comfort in smart buildings	MAS + GA	Distributed AI and optimized setting	User preferences (temperature setpoint)	Comfort parameters (Temperature, Lighting, CO_2 concentration), Energy/load	Overall occupant comfort with GA was kept between 0.97 and 0.99, and the error between setpoints and the sensor data became smaller with GA. A significant reduction in the overall energy consumption (~20% compared to system without GA)	[215]

Table 3-6. (Continuous).

Year	Study Case	Underlying AL/ML Tools	AI Application Scenario	Thermal Comfort Method	Optimization Objective	Outcomes & Key Results	Ref.
2015	Agent-based particle swarm optimization development for inter-operation of Smart Grid-BEMS framework	Agent-based approach	Distributed AI & optimized setting	Comfort was modeled as a temperature Gaussian function	Comfort parameters (Temperature, Humidity, CO_2 concentration), Energy/load	The proposed system could effectively improve the voltage profile of the feeder, while ensuring acceptable comfort levels.	[216]
2016	Deploying an intelligent MBPC solution for HVAC systems in a University building	MOGA framework + RBF-NN	Predictive control	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Humidity, HVAC), Cost, Energy/load	The IBMPC HVAC showed significant results in reducing energy cost and maintaining thermal comfort level during the whole occupation period.	[212]
2018	Optimizing the passive design of newly-built residential buildings in hot summer and cold winter region of China	NSGA-II combined with ANN	Optimized setting	Annual indoor thermal indices: CTR and DTR	Comfort parameters (Comfort indices: CTR/DTR), Energy/load	The annual thermal comfort hours were extended by 516.8–560.6 hours, and the annual building energy demand was reduced by 27.86–33.29% compared to base-case design	[213]
2018	A demand-driven cooling control (DCC) based on machine learning techniques for HVAC systems in office buildings.	k-means clustering & kNN	ML & predictive control	Predefined comfort conditions (temperature setpoints)	Comfort parameters (HVAC, Temperature, Humidity, CO_2 concentration/Air quality), Energy/load	Between 7% and 52% energy savings were ensured compared to the conventionally-scheduled cooling systems (by maintaining temperature deviations means less than 0.1ºC)	[217]
2020	Comfort and energy management of daily and seasonally used appliances for smart buildings application in hottest areas.	Binary-PSO + FLC (BPSOFMAM, BPSOFSUG)	Fuzzy logic and optimization setting	Fanger's PMV method	Comfort parameters (PMV, Temperature), Energy/load	Simulation results showed that the BPSOFSUG controller outperformed the BPSOFMAM in terms of energy efficiency by 16%, while comfort computation, via PMV, was kept in satisfactory range.	[248]
2020	A multi-objective optimization method for a passive house (PH) design by considering energy demand, thermal comfort and cost.	Combining: RDA, GBDT and NSGA-II	Optimized setting	The annual cumulative comfort ratio (CTR)-based adaptive model	Comfort parameters (CTR index), Cost, Energy/load	the optimization results showed around 88.2% energy savings rate and improvement in thermal comfort by 37.7% compared to base-case building.	[218]
2020	A predictive model for thermal energy by integrating IoT architecture based on *Edge* Computing and classifier ensemble techniques for smart buildings application.	Combining: SVM, LR and RF	Predictive control	Indoor temperature set by the user or by the learning algorithm	Comfort parameters (Temperature, Humidity, CO_2 concentration/Air quality, lighting), Energy/load	Simulation results showed that the proposed approach presented the highest accuracy, by 91.526% compared to neural networks, ensemble RF and SVM.	[219]
2020	A novel optimization method for building environment design by integrating a GA, an ANN, MRA and an FLC based on the results of computational fluid dynamics (CFD) analysis.	Combining GA + ANN + multivariate regression analysis (MRA) + FLC	Optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, Cost, Time efficiency, Energy/load	Integrating GA, ANN, MRA and FLC in the design process allowed to reduce the variable space and computational cost by 50% and 35.7% respectively.	[214]
2020	An energy flexibility quantification methodology based on supervised machine learning techniques for hybrid demand-side control for high-rise office building.	MLR + SVR + backpropagation NN	Predictive control	Indoor setpoint temperature	Comfort parameters (Temperature, Hot/cold water), Time efficiency, Energy/load	The hybrid controller allowed to reduce the time duration of the peak power, which was reduced by 61% of the grid importation	[220]

Table 3-7. Summary of the works focusing on intelligent management of thermal comfort and energy in buildings using other AI-assisted tools.

Year	Study Case	Underlying AL/ML Tools	AI Application Scenario	Thermal Comfort Method	Optimization Objective	Outcomes & Key Results	Ref.
1993	An intelligent operation support system (IOSS) to improve HVAC operations for IAQ control and energy saving for industrial application.	Knowledge-based system (KBS)	Optimized setting	PMV (Fanger's method)	Comfort parameters (PMV, HVAC), Time Efficiency, Energy/load	The developed system can provide real-time planning, and assisting the interaction between the operator and the HVAC process	[226]
2004	Two-objective optimization of HVAC system control with two variable air volume (VAV) systems.	Genetic Algorithm (GA)	Optimized setting	PMV-PPD (Fanger's model)	Comfort parameters (PMV/PPD, Temperature, HVAC), Energy/load	The on-line implementation of GA optimization allowed to save up to 19.5% of energy consumption while minimizing the zone airflow rates and satisfying thermal comfort	[221]
2007	Modelling indoor temperature using autoregressive models for intelligent building application.	Autoregressive exogenous (ARX)	Predictive control	Black-box model to predict indoor temperature based on defined variables	Comfort parameters (Temperature, Humidity), Energy/load	Results showed that ARX model gave better temperature prediction than ARMAX model by the structure $ARX(2,3,0)$ with a coefficient of determination of 0.9457 and the $ARX(3,2,1)$ with a coefficient of determination of 0.9096.	[228]
2009	Exploring the impact of optimal control strategies of a multi-zone HVAC system on the energy consumption while maintaining thermal comfort and IAQ of a built environment.	Genetic Algorithm (GA)	Optimized setting & predictive control	PMV (Fanger's model)	Comfort parameters (PMV, Temperature, HVAC, Air quality), Cost, Energy/load	Up to 30.4% savings in energy costs when compared to conventional base strategy whilst sustaining comfort and indoor air quality	[222]
2009	Estimating occupant mental performance and energy consumption of determining acceptable thermal conditions under different scenarios.	Bayesian Networks (BN)	Predictive control	PMV (Fanger's model) and the adaptive comfort model	Comfort parameters (PMV, Temperature), Energy/load	Results concluded that determining acceptable thermal conditions with the adaptive model of comfort can result in significant energy saving with no large consequences for the mental performance of occupants.	[230]
2010	Energy consumption optimization and thermal comfort management using data mining approach in built environment	Decision tree classifier (C4.5 Algorithm)	Optimized setting & predictive control	Comfort levels based on CIBSE standard	Comfort parameters (Temperature, CO_2 concentration/Air quality, Humidity), Energy/load	Based on decision tree analysis and results relying ambient environmental conditions with user comfort, designers and facility managers can determine the optimal energy use	[231]
2014	Improving HVAC systems operations by coupling personalized thermal comfort and zone level energy consumption for selecting energy-aware and comfort-driven set-points.	Knowledge-based approach	Optimized setting	Personalized comfort profiles	Comfort parameters (Temperature), Energy/load	About 12.08% (57.6m3/h) average daily air-flow rates were reduced in three target zones, compared to operational strategy that focus on comfort only.	[227]
2016	Simulation-based multi-objective optimization for building energy efficiency and indoor thermal comfort	MOABC optimizer	Optimized setting	PPD (Fanger's model)	Comfort parameters (PPD, Temperature, Heating/cooling), Energy/load	The multi-objective optimization + TOPSIS showed that in different climates, even the energy consumption increased a bit by 2.9-11.3%, the PPD significantly reduced by 49.1-56.8%, compared to the baseline model.	[232]
2016	An operation collaborative optimization framework development for a building cluster with multiple buildings and distributed energy systems while maintaining indoor thermal comfort	Multi-objective optimization (PSO)	Optimized setting	PMV (Fanger's model)	Comfort parameters (PMV, Temperature), Cost, Energy/load	Around 12.1–58.3% of energy cost saving under different electricity pricing plans and thermal comfort requirements.	[233]

Table 3-7. (Continuous).

Year	Study Case	Underlying AL/ML Tools	AI Application Scenario	Thermal Comfort Method	Optimization Objective	Outcomes & Key Results	Ref.
2016	Multi-objective control and management for smart energy buildings	Hybrid multi-objective GA	Optimized setting	Discomfort parameter based on the user preferences	Comfort parameters (Temperature, Lighting, CO_2 concentration/Air quality), Energy/load	31.6% energy saving could be achieved for smart control building, and the comfort index was improved by 71.8%, compared to the conventional optimization methods.	[223]
2016	Real-time information-based energy management controller development for smart homes applications	Genetic Algorithm	Optimized setting	User preferences	Comfort parameters (Temperature), Cost, Energy/load	The proposed algorithms are flexible enough to maintain the user's comfort while reducing the peak to average ratio (PAR) and electricity cost up to 22.77% and 22.63% resp.	[224]
2017	A personalized thermal comfort model (BCM) development for smart HVAC systems control	Bayesian Network-based model	Optimized setting & predictive control	Personalized comfort model (combining the static and the adaptive models)	Comfort parameters (HVAC, Temperature), Energy/load	By using alternative comfort scale, the proposed model outperformed the existing approaches by 13.2%–25.8%. The heating algorithm reduced energy consumption by 6.4%-10.5%, by 15.1%-39.4% for AC, and reducing discomfort by 24.8%.	[10]
2017	A newly developed Epistemic-Deontic-Axiologic (EDA) agent-based solution supporting the energy management system (EMS) in office buildings	Support vector machine (SVM & C-SVC)	Distributed AI & ML	Personal thermal sensation model and Group-of-people-based thermal sensation model	Comfort parameters (Temperature, Humidity), Energy/load	Case studies simulations showed the abilities of the developed model in energy saving by 3.5–10%, compared to the pre-set control systems, while fulfilling the individual thermal comfort needs.	[235]
2017	Deploying a software application based mobile sensing technology (Occupant Mobile Gateway (OMG)) for occupant-aware energy management of mix of buildings in California	Logistic regression (LR)	ML & predictive control	Occupants' subjective feedbacks	Comfort parameters (Temperature, Humidity), Energy/load	Implementing occupant-driven models showed that thermal management learned by subjective feedback had the potential energy savings while maintaining acceptable levels of thermal comfort	[236]
2017	An HVAC optimization framework deployment for energy-efficient predictive control for HVAC systems in office buildings	Random Forest (RF) regression	Predictive control and optimized setting	Comfort ranges defined by Royal Decree 1826/2009.	Comfort parameters (Temperature, Humidity, HVAC), Energy/load	Next 24h-Energy framework allowed reduce energy consumption for heating (48%) and cooling (39%), without affecting the user's comfort.	[237]
2018	The benefits of including ambient intelligent systems for building's EMS control to optimize the energy/comfort trade-off	k-means algorithm	Optimized setting	Occupants' preferences	Comfort parameters (HVAC), Energy/load	The energy consumption was reduced by an average of 5KWh while maintaining the majority of the occupants within acceptable comfort levels (the comfort rate was 5% lower than the baseline).	[239]
2018	Agent-based control system for and optimized and intelligent control of the built environment	Evolutionary MOGA	Distributed AI & optimized setting	User preferences	Comfort parameters (Temperature, lighting, Humidity), Energy/load	By applying MOGA optimizer allowed to save up to 67% energy consumption and about 99.73% overall comfort improvement.	[225]
2020	Thermal comfort control relying on a smart WiFi-based thermostat deployment for residential applications	Nonlinear Autoregressive exogenous (NARX)	Linear-based predictive control	Fanger's PMV method	Comfort parameters (PMV, Heating/cooling, Temperature, Humidity), Energy/load	In both High- and low-efficiency residences, cooling energy savings were around 85% and 95% respectively, while the PMV index was maintained within the desired rang [0 – 0.5].	[229]
2020	Defining new occupant comfort ranges using Bayesian-based data-driven approach for U.S. office buildings using the ASHRAE global thermal comfort database	Bayesian Inference (BI) (Bayes Theorem)	Active learning and data-driven control	Setpoint temperatures/ Occupants' feedback	Comfort parameters (HVAC, Temperature)	Data-driven and Bayesian approach allowed to reach realistic setpoint temperature values which facilitate more building performance, load prediction, and better informing better HVAC design as well as technology selection.	[240]

3.2.3 Optimization Functions in support of AI-based control

Building designers increasingly need to use simulation tools to analyze the performance of scenarios for the purpose of understanding how strategies reduce environmental impact, ameliorate energy usage, and enhance comfort in buildings. These techniques can also be used to infer the adequate parameters to the AI-based building control. Another application of optimization functions in AI-based control is the use of co-simulators that provide the possible parameters in real-time to the AI-based controller for optimum operation. The co-simulator has a global view of the system, while the controller has a local view of the sub-system and they complement each other in the entire process of optimizing AI-based energy and thermal comfort of sustainable buildings.

The introduction of these optimization techniques to the design simulation field started in the 1980s and gained renewed interest from the 2000s [249], [250]. In [250], the authors reported an increase in the number of scientific works on building model optimization since 2005. This reflects the interest and importance given to the development and application of numerical optimization methods by the building community around the world. At this point, the focus of our work is not to make a literature review of all these methods, but rather to present the most advanced and adopted optimization techniques in AI-based applications, in particular the Genetic Algorithm (GA) [115], [129], [134], [145], [146], [204]–[207], [209], [213]–[215], [218], [221]–[225], [245] and the Particle Swarm Optimization (PSO) [133], [142], [143], [172], [190], [216], [233], [248]. Genetic Algorithms are an optimization technique that imitates the evolution of species through natural selection in a very simplified way. In genetic algorithms, a population is generated and submitted to the selection and recombination genetic operators (i.e., Crossover). These operators evaluate each individual, i.e., they use a quality feature of each individual as a solution to the problem. As a result, a process of the natural evolution of the individuals in the created population is generated, which will consequently generate an individual with features of a good solution to the addressed problem. A flowchart describing the classical GA is shown in Figure (3-6).

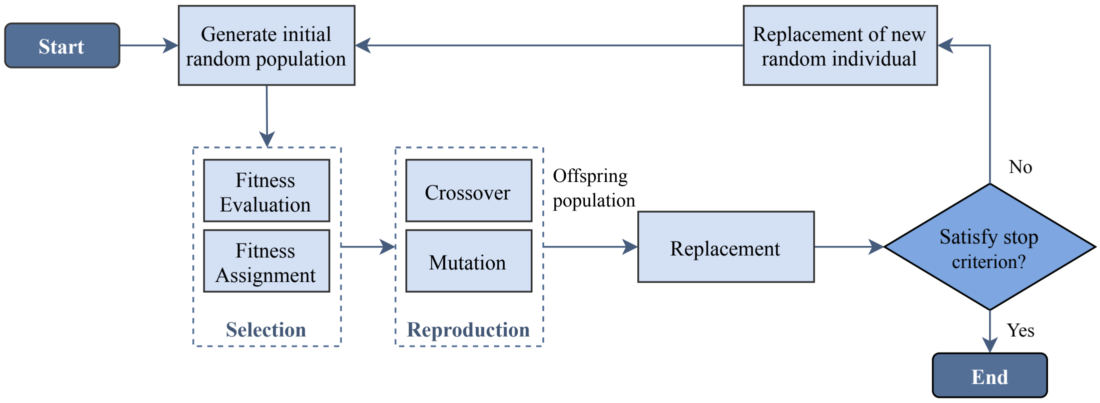


Figure 3-6. Flowchart of a classical Genetic Algorithm (GA).

Particle Swarm Optimization (PSO) is a population-based stochastic optimization technique pioneered by R. Eberhart and J. Kennedy [251]. PSO is an AI technique that seeks to imitate the social behavior of animals such as fish and birds that live in colonies. The algorithm is initialized with an initial population *candidate* to solve the problem, called *particles* [252], [253]. Similar to the GA technique, the PSO initializes a swarm with a quantity of particles i, and each particle has a dimension d representing a possible solution to the problem. This occurs in such a way that all the elements of the swarm are within the pre-established range $[x_{min}, x_{max}]$, in the same way as the best evaluation solution (global evaluation) that should guide the hyperspace search for the sub-optimal solution, i.e., solutions that have approximate values to the optimum of the function. The best individual values for each particle are stored and, therefore, the best one estimated will represent a new optimal assessment if it overlaps with that established in the previous iteration. In this way, each particle has its own velocity, which will be updated along with the iterations according to the best individual values and the global value of the swarm to then update the value of each particle, as depicted in Equations (3-6) and (3-7) [253].

$$v_i^{t+1} = w * v_i^t + c_1 * r_1\left(p_i - x_i^t\right) + c_2 * r_2(g - x_i^t) \tag{3-6}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{3-7}$$

Whereas, v_i^t and v_i^{t+1} represent the velocity vector of the particles of position v_i^{t+1} respectively at iteration t and $t+1$, w defines the coefficient of inertia, c_1 and c_2 are the positive constants, r_1 and r_2 are the arbitrary values defined in the interval $[0,1]$, while p_i and g represent, respectively, the vectors of the best solution for position i and the best global solution, and finally, x_i^t and x_i^{t+1} represent the particle vector in position i of the swarm, respectively, at iterations t and $t+1$.

A flowchart describing a typical PSO algorithm is illustrated in Figure (3-7).

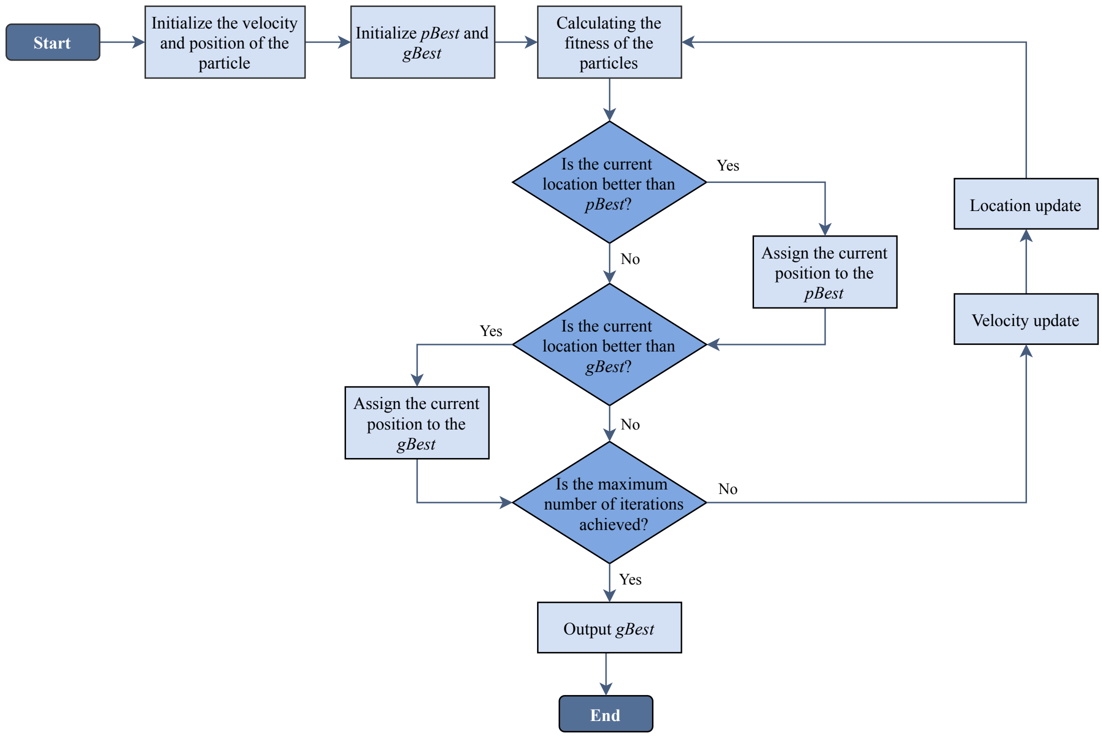


Figure 3-7. Flowchart of a classical particle swarm optimization (PSO) algorithm.

3.3 THEORETICAL ANALYSIS OF THE AI APPLIED FOR BUILDING CONTROL

Improving energy efficiency and maintaining indoor comfort conditions, while taking into account user preferences, have led researchers to develop intelligent Building Energy Management Systems (iBEMS), primarily for large-scale buildings such as hotels, offices, and commercial buildings, among others. The iBEMS are developed to be used in a wide array of applications. Such solutions are designed to track and manage the building's microclimate and to reduce energy use and operating costs. The literature includes a significant number of works on the application of AI techniques to iBEMS. The results are more persuasive than those of conventional control systems.

General advances in the development of automated control systems are the need for a mathematical model for building operation, which is a drawback of applying traditional control systems in buildings. By incorporating high-level variables that describe comfort into smart controllers, comfort could be managed without having to control lower-level variables such as temperature, humidity, and air speed. The consumer starts to get involved in specifying the ideal comfort, in these systems. Hence, through this section, the reviewed publications in which AI-assisted tools were deployed and summarized in Tables (3-1) to (3-7) are therefore extensively examined. In the first place, the case studies are discussed on the basis of the most selected inputs and their associated outputs used by the implemented models, in the second place, the control performance of the AI techniques used for energy-saving and thermal comfort optimization are quantified and, finally, the thermal comfort measurement methods are characterized and classified according to the AI tools used. In this regard, Figure (3-8) presents the block diagram of a typical structure for AI-assisted building control resulting from the reviewed articles.

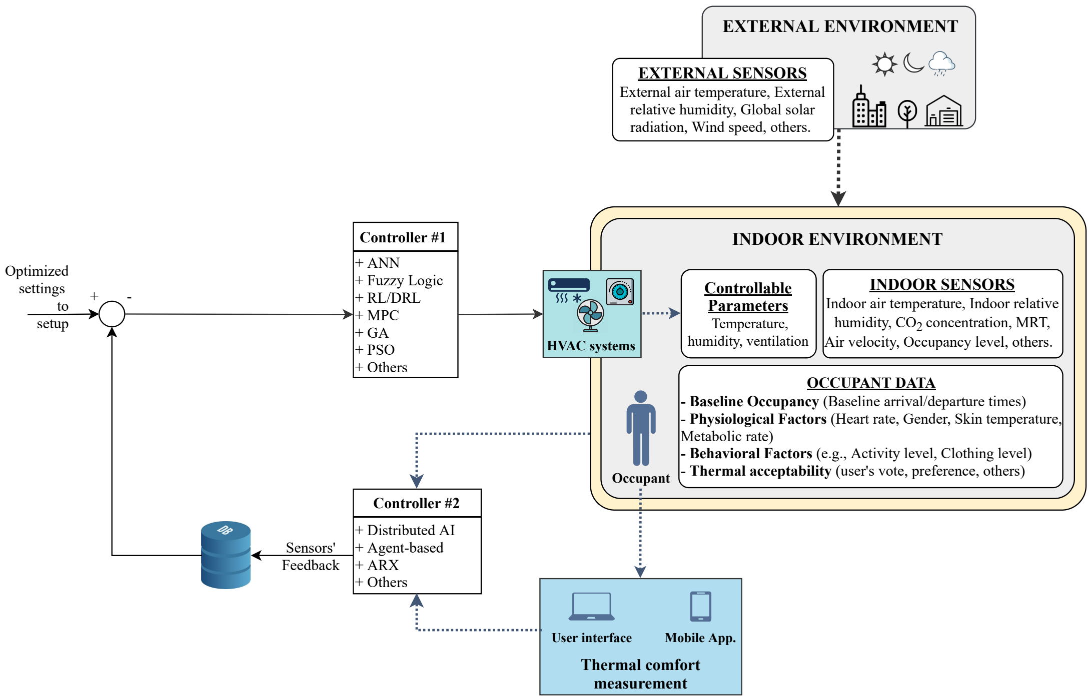


Figure 3-8. Block-diagram of the AI-assisted for HVAC and thermal comfort controls in buildings.

3.3.1 Study Cases: Inputs and Outputs

In the context of thermal comfort and energy-saving control systems, the inputs and outputs considered to generate AI-based models are closely linked. Concerning the inputs, they are mainly associated with comfort conditions and design variables as well as other indicators that could be useful for such control systems. The inputs are therefore divided into seven groups: heating, ventilation, and air conditioning (HVAC) systems, indoor and outdoor climatic conditions, occupant-related variables, building geometry, and components, among others.

Regarding the outputs, they can be categorized into four major groups: (i) **Comfort indices** (PMV, PPD, and others), (ii) **Microclimate indicators** (temperature, CO_2 concentration), (iii) **Energy/Load** (HVAC, cooling/heating, cool/hot water), and (iv)

Others (including cost and time efficiency). In this regard, the relationship between the selected inputs to describe specific outputs is illustrated in Figure (3-9).

Outputs

Inputs			Comfort Index: PMV	Comfort Index: PPD	Comfort Index: Others	Microclimate Indicators: Temperature	Microclimate Indicators: CO_2 concentration	Energy/Load: HVAC	Energy/Load: Cooling/Heating	Energy/Load: Cool/Hot Water	Energy/Load: Others	Others: Cost	Others: Time Efficiency
Space Control Devices		Component	4	1	3	8		6	4	1	7	1	2
		Component Efficiency	9	1	1	5		9	4	1	5	2	2
		Set-point temperature	8	2	5	6		20	4	3	8	3	3
		Others	4		3	6	1	7	2	2	3	2	1
Climatic Conditions	Indoor	Air temperature	29	4	16	29	2	45	12	3	15	7	3
		Relative humidity	21	3	10	12	1	26	6		9	3	1
		Air Velocity	13	2	4	2	1	11	4		4	1	
		CO_2 concentration	10	1	8	12	3	21	1		7	1	1
		MRT	9	1	2	1		5	3		3	1	
		Others	13	2	9	15	1	23	8		8	4	2
	Outdoor	Air temperature	16	4	8	17	2	24	9	4	9	1	2
		Relative humidity	4	3	3	5		7	2	1	5		
		Air Velocity	2	1		4		1	3	1	2		
		CO_2 concentration	1		1	1		2			1		
		Solar radiation	6	3	1	6		6	4	2	3	2	
		Others	2	1		6		6	3	1			
Occupant-related variables		Clothing level	10	1	3	1		4	4		5		1
		Activity level	9	1	2			4	3		3		
		Comfort Information	15	3	8	1	4	14	5		6	1	
		Preference	6	2	10	16	2	21	5	1	7	3	
		Others	2		4	1		3	1		2		
Building Component		Window	5		3	2	1	4	3		1	1	
		Wall	3	1	2	2		1	7				
		Roof	1		2			1	2				
		Floor	2			2		1	3				
		Door	2			1			2		1		
		Envelope	1		1	1			2		1		
		Others	1		1	3			5				
Building Property		Location	1		2			1	1		1		
		Geometry	3	2	2	1		3	4				
		Configuration	1		2			1	1		1		1
		Others	3	1	1			3	1				
Others		Energy Information	1		1	1		3			1	1	
		Power consumption	1			3		3			1		2
		Time/Date/Hours	3	2		7		4	5	1	4		1
		Occupancy	7	3	7	16		19	5	2	9	4	2
		Disturbances				2		2					

Figure 3-9. Heat-map of the number of times of using a given input and the corresponding output of the AI-based models.

The numbers in the heat-map represent the times when specific input is used to approximate certain outputs. For example, the air temperature was used 45 times to estimate the HVAC load. Such information is useful by highlighting the most influential and selected variables used by AI-based models as inputs to building installations/system targets (as shown in Section 3.3.2).

3.3.2 Study Cases: Energy Control

We are now turning our attention to how AI techniques have been applied to improve energy efficiency and thermal comfort. Figure (3-10) shows the diversity between the systems/installations adopted in the reviewed works, responsible for ensuring thermal comfort and suitable indoor air quality in indoor settings. It is apparent that AI techniques are relevant for implementation in different parts of the building control systems.

The most commonly used systems for research were appliances and systems used for about 78% of the total works reviewed in the current paper and used to perform space conditioning tasks in a variety of ways, such as HVAC systems, mechanical systems (or air-conditioning and mechanical ventilation (ACMV)), space heating using heaters and boilers. Building components (e.g., window, envelope, surface) and occupant factor (e.g., human behavior, occupancy estimation) were used in 6% and 8% of the studies, respectively. Building component technology is a key sustainable solution for energy savings and thermal comfort. However, its drawback is that it depends on the local weather and the outdoor air quality.

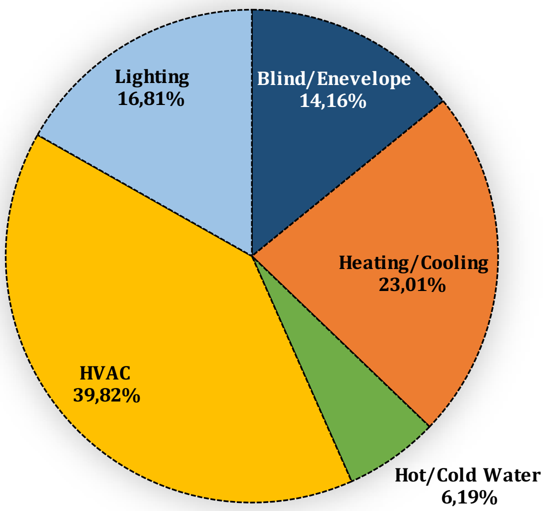


Figure 3-10. The relative distribution among the reviewed works in relation to the energy control in buildings.

3.3.3 Study Cases: Thermal Comfort Measurement

Thermal comfort assessment approaches can be categorized into two groups, according to the reviewed works: *General Comfort Models* (GCM) and *Individual Comfort Models* (ICM).

3.3.3.1 General Comfort Models

The conventional approaches focused on the thermal equilibrium between man and his surroundings allow the development of internationally recognized environmental indices, such as the Fanger PMV-PPD model, considered to be a GCM [49]. In addition, this model was statistically based on experimental studies involving 1,300 subjects in climatic chambers. Its main limitation lies in the fact that the PMV index estimates the average comfort level of the subjects, which was also determined under homogenous and stationary conditions, representing theoretical conditions rarely encountered in actual buildings.

Personal models based on the PMV model, such as the Predicted Personal Vote (PPV) model, maybe considered GCM, defined as the PMV transform affine: $ppv = f_{ppv}(pmv)$ [238]. The idea behind PPV is to assess the level of comfort within a single worker within a workplace. The inverse-PMV model may also be considered as GCM, used to calculate thermal comfort temperatures based on the desired target PMV and measured assessed air speed and humidity [136]. Apart from the Comfort Time Ratio (CTR) index, also considered as GCM, which is based on Szokolay's theory and assesses the annual indoor thermal comfort for residential buildings [213]. These comfort indices are used as inputs to the temperature control system to adjust the comfort level of the building.

Furthermore, in commercial applications, models such as conventional methods (i.e., fixed temperature settings that can be adjusted for complaints and predefined indoor conditions in accordance with standards and legislation that can be considered GCM) are adopted in order to identify comfort ranges. Among these standards: CIBSE which defines the comfort levels in office buildings between 21ºC and 23ºC [231], OSHA guidelines specifying the comfort zone between 20ºC and 24.2ºC [241], ASHRAE 55 which limits indoor temperatures between 2121.5ºC and 24ºC during occupancy hours [254], comfort margins based on Royal Decree 1826/2009 by setting indoor temperatures between 21ºC and 26ºC.

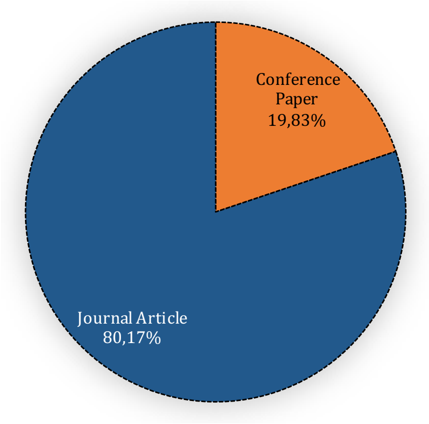
3.3.3.2 Individual Comfort Model

Although the ASHRAE 55 is considered as a global standard for assessing thermal comfort in buildings, there are a variety of drawbacks and concerns: the main issue is that the comfort models existing in this standard are considered valid for anyone (i.e., even though the models indicate thermal zones for 80% or 90% of thermal comfort/acceptability; they do not discriminate which users' group would not be in comfort or would not be accepting the thermal conditions). However, different groups of people can have different thermal perceptions. Individual comfort models (ICMs) can therefore provide individual treatment that can give better satisfaction for occupants within a given environment. ICM is a recent paradigm predicting individual-level thermal comfort and is typically based on data-driven learning algorithms. A Bayesian Comfort Model (BCM) was developed by combining a human-body-centered approach of static models with an external environment-based technique of adaptive models [10]. A data-driven thermal comfort model was also created by learning subjective feedback from the occupants in real-time through the application of the smartphone/server (OMG) and objective thermal information [236]. In addition to the personal thermal sensation model (for MET, the personal activity of the occupant) and the group-of-people-based thermal sensation model (for MET, the average activity group of people) generated by the SVM algorithm for assessing the occupants' thermal sensation [235].

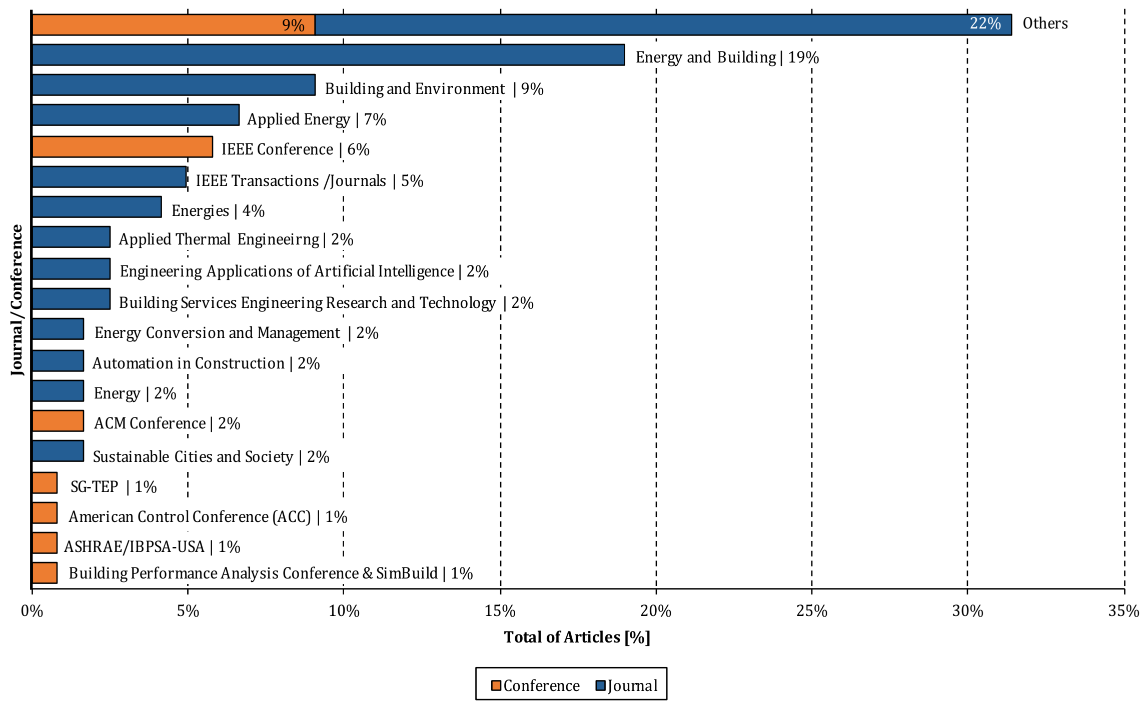
In addition, other works suggested personalized models by investigating the "human-in-the-loop" approach that allows HVAC to be adapted to user preferences. Personalized comfort profiles are established on a participatory sensing approach by embracing a Thermal Perception Index (TPI) scale (slider values) that shows thermal preferences of votes ranging from -5 to +5 [227]. The Degree of Individual Dissatisfaction (DID) index was defined as the function of the user's vote and, depending on the ambient temperature, the desired individual temperature (T_0), and the individual temperature tolerance (ΔT) [254]. A comfort-driven framework based on the scale of user preferences using the Thermal State Index (TSI) (*Cool-Discomfort/Comfort/Warm-Discomfort*) is provided in [150].

3.3.4 Trend Analysis and Discussions

The graphic detail of the studies considered in this review is displayed in Figures (3-11) – (3-19). Figure (3-11) shows the works published in various conferences and journals, and it is observed that up to 80% of the articles come from journals (cf. Figure (3-11(a))). Most of the works have been published in Building Control related journals (cf. Figure (3-11(b))), such as: *Energy and Buildings*, *Building and Environment*, *Applied Energy*, *Energy*. It has been observed that most of the academic articles published in conference proceedings are based on a fuzzy approach and that more case studies have been published in journals than in conferences.



(a)



(b)

Figure 3-11. Classification of the papers we consider by: (a) Type; (b) Journals and conferences in which the articles were published.

The percentage of published works in the field of AI-assisted tools used for energy and thermal comfort in built environments by authors from different countries is portrayed in Figure (3-12). U.S. researchers are the most prolific in developing control-related publications with more than 20% of research works conducted in the USA. Focusing on Europe, the United Kingdom, and Greece showed significant interest compared to other countries. Similarly, in developed/industrialized countries such as China, South Korea, considerable efforts have been made to solve energy and thermal comfort problems in buildings using AI techniques. However, relatively little work has emerged from underdeveloped countries, probably due to their occupation with more fundamental energy-related problems in these countries and their poorer economic standing.

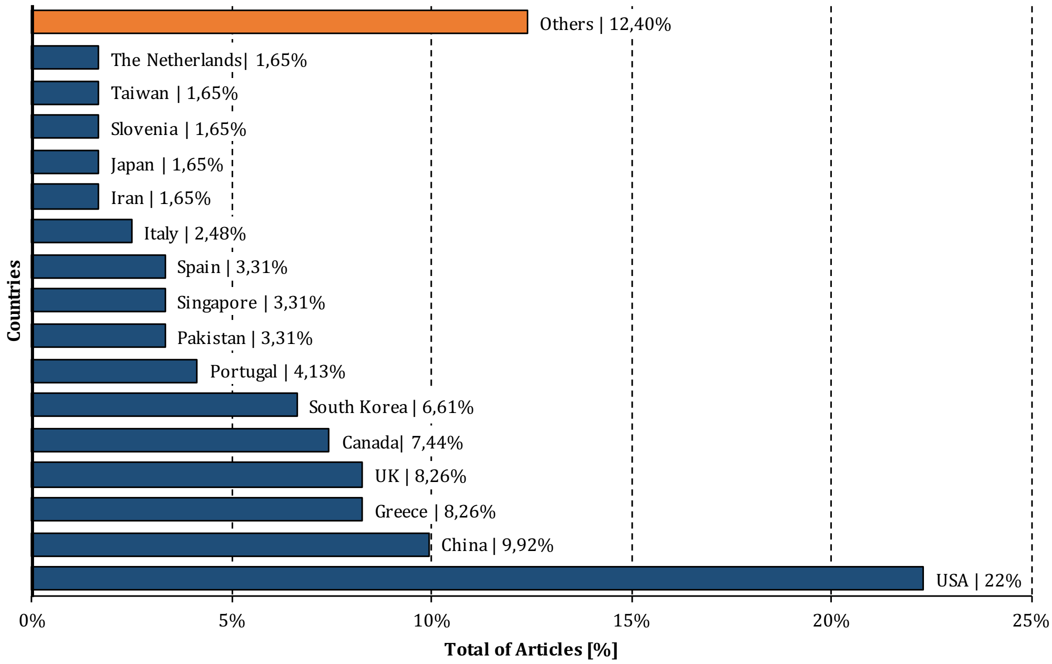


Figure 3-12. The percentage of publications by geographical origin.

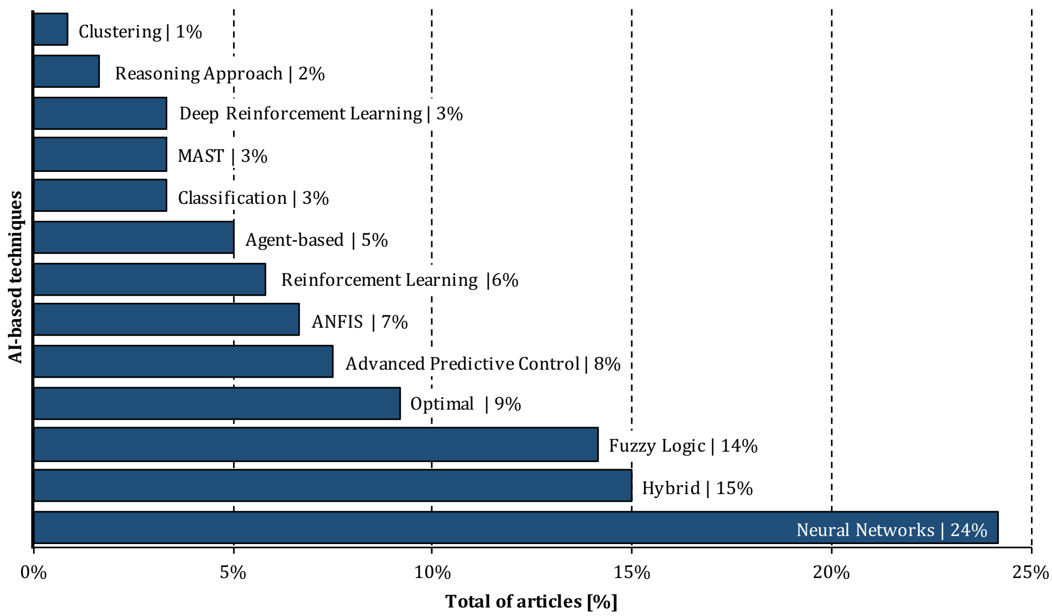


Figure 3-13. The frequency of use of the AI-based tools extracted from the reviewed publications related to the building control.

Among the various AI techniques, neural networks are the most popular approach adopted by researchers among the research papers in our study (cf. Figure (3-13)). Fuzzy logic is also widely used for energy-saving and thermal comfort improvement due to its suitability to imitate human behavior and enable linguistic descriptions of thermal comfort sensations. Hybrid methods were also preferred by combining two different techniques (e.g., FL and ANN; ANN and GA/or PSO; FL and GA/or PSO). In most cases, GA and PSO have been introduced to provide optimal solutions to building optimization problems. Although fewer works are using DAI and MAS, they have been used in complex control systems by incorporating a set of controllers instead of a single controller system.

Statistical results have shown that, from 1993 to 2020, the average energy savings in buildings by applying AI/ML techniques reached up to 31% (cf. Figure (3-14)). Maximum energy savings (~90%) were achieved by applying a Bayesian network-based model to determine acceptable thermal conditions, with the aim of estimating employee mental performance under different scenarios [230]. Moreover, advanced predictive models have shown promising results in the reduction of energy consumption, for example in [241], in which a learning-based model predictive control (LBMPC) was applied to improve energy efficiency (~50% reduction in energy consumption) in an HVAC-Testbed platform located in a room laboratory. Along the same line, a model-based predictive control of neural rule base function (RBF) networks was implemented and identified through the MOGA technique for HVAC control in large public buildings [234]. The model has shown significant results in terms of energy savings, by allowing to save more than 50% of energy while providing good coverage of the thermal sensation scale. In [238], the authors proposed a smart personalized office thermal control (SPOT+) system using the LBMPC and kNN algorithm used to estimate room occupancy and optimum room temperature within the office building. Based on the predictive model, SPOT+ identified a control schedule that allowed to save about 60% of energy use and optimized thermal comfort. Shaikh et al. [225] recently proposed an agent-based control system using an evolutionary multi-objective genetic algorithm (MOGA) for energy and comfort optimization. The developed optimizer has saved up to 67% of energy consumption in addition to about 99.73% of comfort improvement.

Furthermore, the average comfort level improvement using AI/ML-based techniques was around 50%, while the maximum comfort level reached 100% through the use of neural networks [123], [129], [131]–[133], [152], DAI and MAS [181], [189], [194], as well as GA [208] (cf. Figure (3-15)). Such comfort improvement was demonstrated in [123] by the development of an Intelligent Comfort Control System (ICCS) incorporating human learning with techniques for reduced energy usage in HVAC systems.

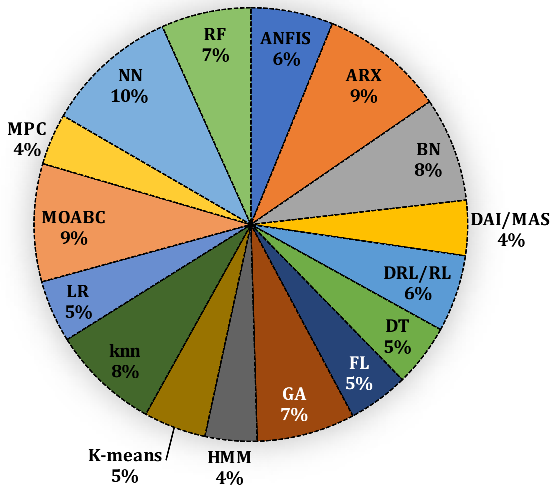


Figure 3-14. Average of key results: Implications of AI/ML techniques on 'Energy Saving'.

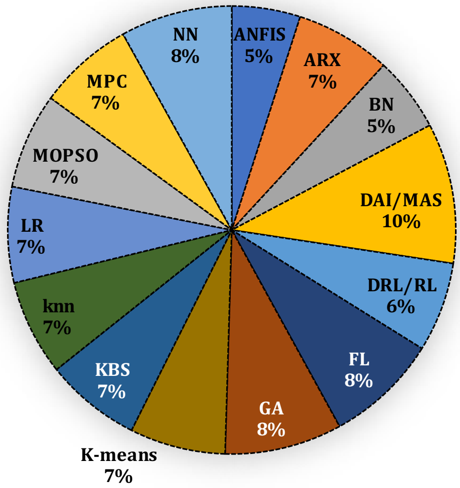


Figure 3-15. Average of key results: Implications of AI/ML techniques on 'Comfort level'.

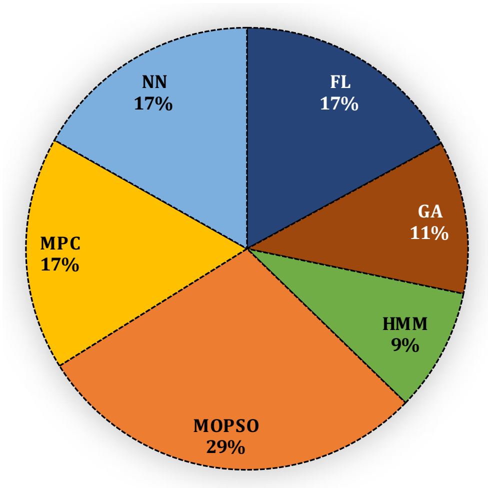


Figure 3-16. Average of key results: Implications of AI/ML techniques 'Cost'.

The system enabled to reach a higher level of comfort (100%) by keeping the PMV within the comfort zone while saving energy. The GA method has also shown its potential by achieving better energy efficiency and comfort criteria (100%) for a heating and cooling system, by lowering preliminary and operating costs by up to 35%, and decreasing the comfort cost by 45% [208]. Another objective was targeted by only 6.7% of the reviewed works (including thermal comfort and energy savings improvement), which are cost-effective, including operating costs, energy savings and electricity costs, as well as comfort costs. The average cost reduction using AI/ML methods was up to 34%, with a maximum of 58% of energy-saving costs [233] (cf. Figure (3-16)).

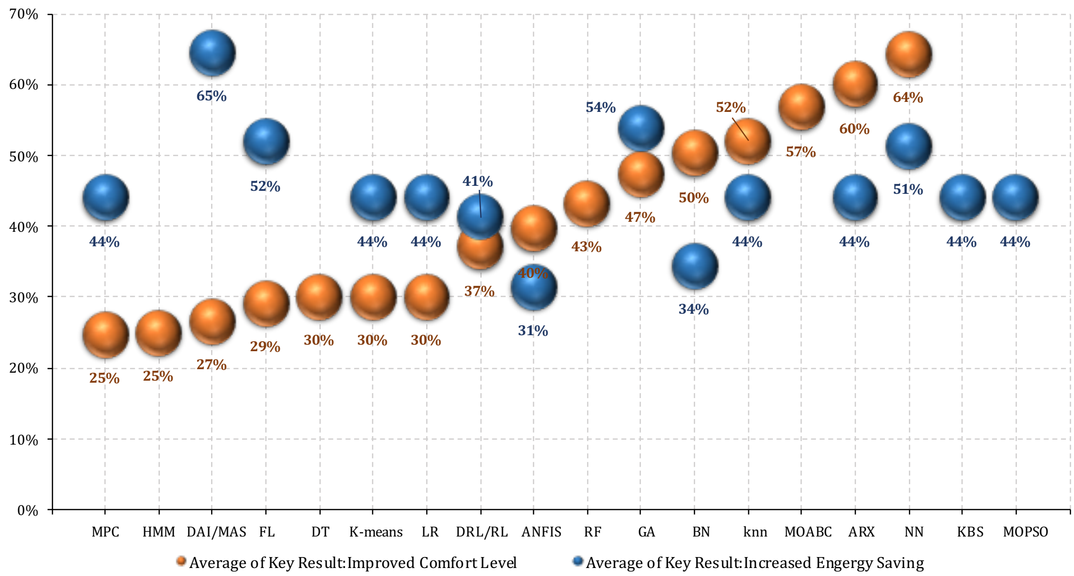


Figure 3-17. Average key result: Implications of AI/ML techniques on both energy savings and Comfort level improvements.

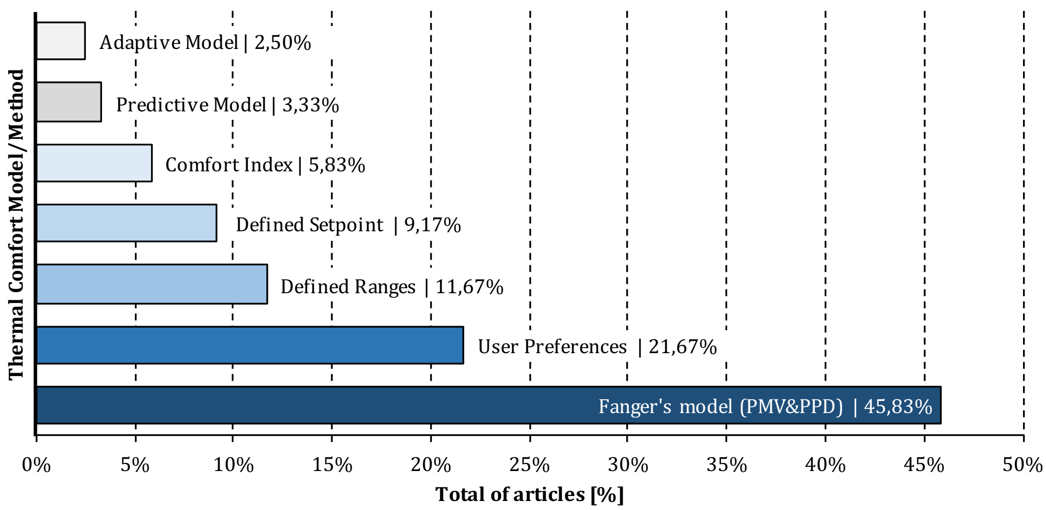


Figure 3-18. The percentage of methods used for assessing thermal comfort in the reviewed works.

Intelligent control requires no mathematical model for the configuration of the controller and is based solely on the human perception of thermal comfort. Furthermore, in thermal comfort control, which is based on the set temperature values, there is no need to keep the indoor temperature at a fixed value, although a range of these quantities is sufficient to create a situation of comfort (cf. Figure (3-18)). Reducing energy demand, and therefore energy costs, while maintaining thermal comfort indices within the permissible range, is a goal to be achieved in selecting the appropriate control technique. For example, fuzzy controllers have shown significant results in thermal building control, as they can properly imitate the behavior of building users and create linguistic descriptions of thermal comfort sensation which estimate PMV model calculations to facilitate system control (cf. Figures (3-18) and (3-19)).

In this way, the fuzzy control scheme proposed in [255] is characterized by the explicit consideration in the control law of a range of permissible values for indoor ambient temperature rather than a fixed value. Recently, several studies have been directed towards suggesting personalized models dealing with both thermal comfort and energy savings, by investigating a "human-in-the-loop" approach that allows HVAC to be adapted to the individual preferences of each user. In [10], the authors proposed a Bayesian Comfort Model (BCM) that showed significant results by giving 13.2% to 25.8% accuracy of the user's preference estimate compared to the existing method, and can save up to 13.5% of energy consumption by minimizing 24.8% of discomfort. While researchers have also shown the potential of using the smartphone/server application to generate a data-driven thermal comfort model through training, in real time, the subjective feedback from occupants in real-time [236]. The results showed that the learned settings had potential energy efficiency, while meeting standard expectations of thermal comfort, i.e., ≥ 80% of thermal satisfaction.

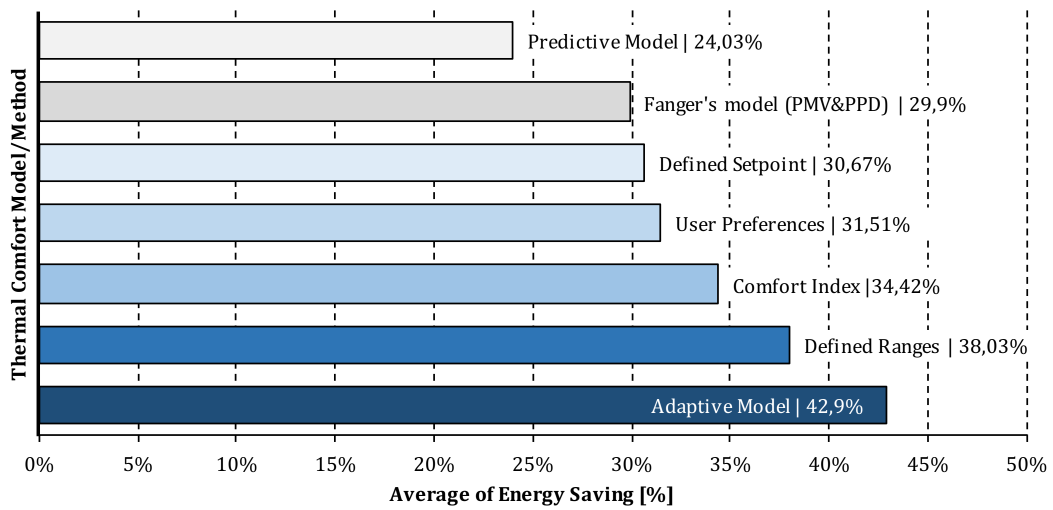


Figure 3-19. Average key result: Implications of Thermal Comfort-based model/method on energy saving.

These intelligent tools can also be used to improve existing conventional controllers, as can be found in [130], where three AI-based thermal control logics have been used to improve existing conventional controllers: (i) Fuzzy-based control; (ii) ANFIS-based control; and (iii) ANN-based control. The efficiency of each approach is examined in a two-story residential building. It is concluded that ANFIS- and ANN-based control methods are potentially better than conventional methods for maintaining indoor thermal comfort conditions (~98% in winter and 100% in summer) by setting up comfort bands for each season (20–23ºC in winter/23–26ºC in summer). However, none of the three techniques showed significantly more energy savings than the others.

Moreover, a hierarchical multi-agent system for multi-objective monitoring and maintenance of intelligent building applications was handled in [223]. The developed control system used stochastic optimization using a hybrid MOGA and saved 31.6% of energy, while the comfort index (based on user preferences) was improved by about 71.8%, compared to traditional optimization techniques. The work of P. Davidsson and M. Boman [181] is another contribution based on the MAS approach in which a decentralized framework for managing and monitoring an office building has been established. In this work, the proposed system facilitated the optimization of energy use (up to 40% of average energy savings compared to baseline) in three services: lighting, heating and ventilation, while ensuring 100% thermal satisfaction of users.

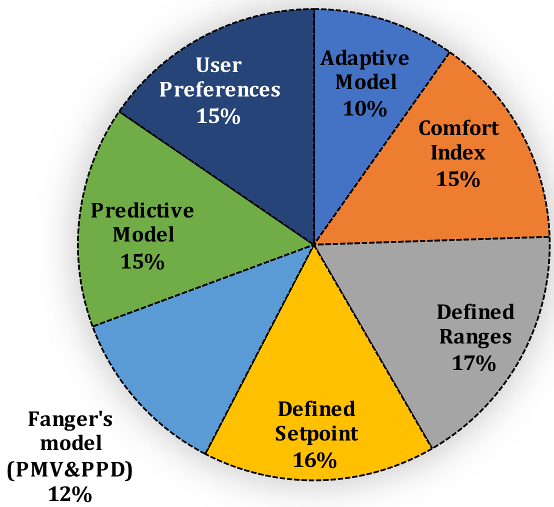


Figure 3-20. Average key result: Implications of Thermal comfort-based Model/Method on improved comfort level.

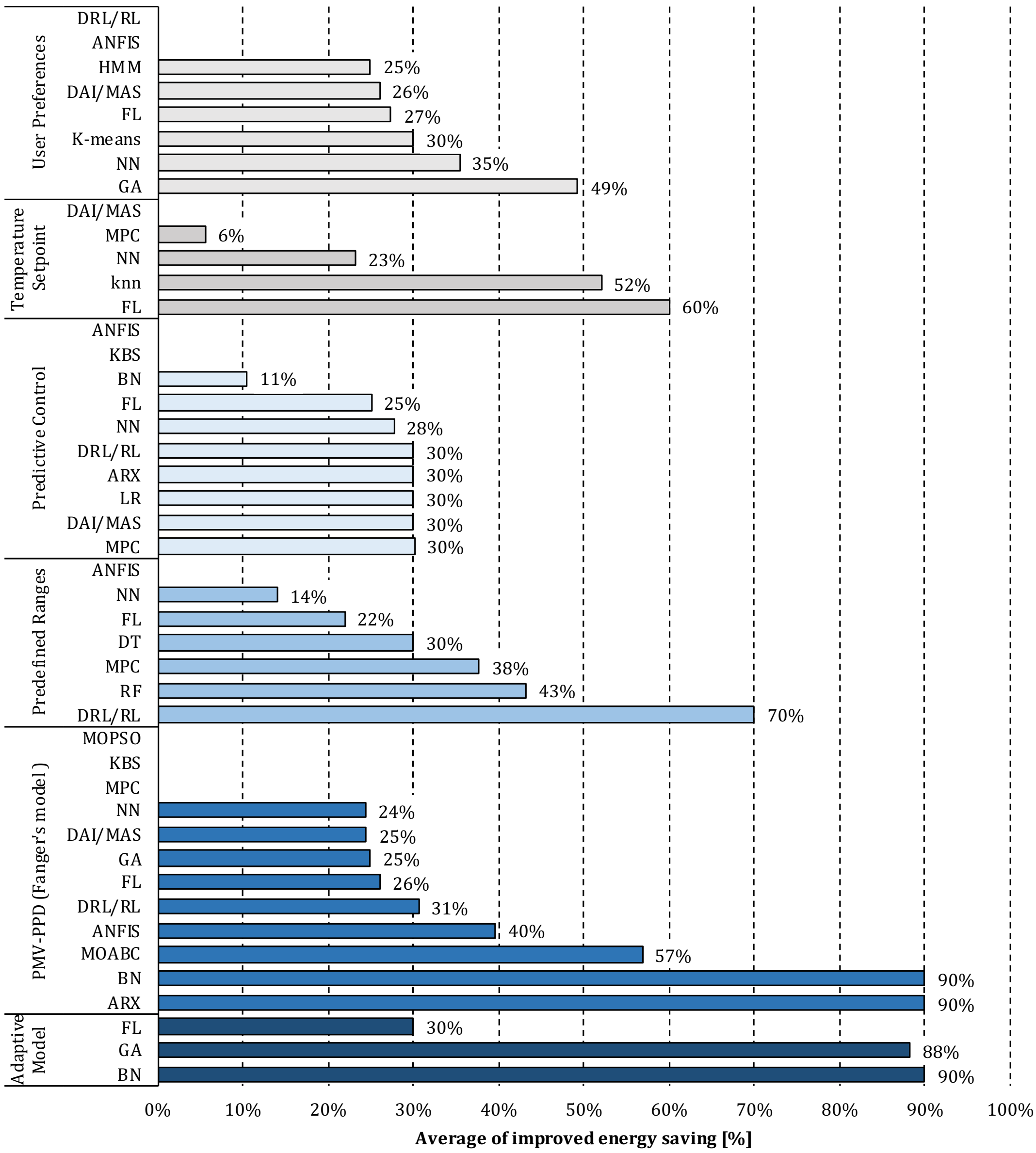


Figure 3-21. Average key result: Implications of AI/ML techniques and Thermal Comfort-based model/method on energy saving.

3.4 FINAL CONSIDERATION & CONCLUSION

In this chapter, we have presented the control systems for energy management and thermal comfort in buildings. Initially, we defined the problem as a whole, where energy, thermal comfort and control are involved. Then we presented the conventional control systems for buildings, whose development of these intelligent control systems within the framework of artificial intelligence (e.g., fuzzy logic, artificial neural networks, reinforcement learning, agent systems/distributed AI, among others) has set the basis for improving the efficiency of control systems in buildings.

4 MODELING INDIVIDUAL THERMAL COMFORT

As implicitly discussed in previous chapters, different methods were used to assess thermal comfort within buildings are based mainly, in their design, on analytical models of thermal comfort (e.g., Fanger's model). However, these models are static and do not take into consideration the different comfort sensations of the building users. In addition, the parameters used by these models cannot be dynamically evaluated by buildings to change their settings. Studies have shown that, in the case of naturally ventilated buildings, these models fail to define comfort situations, i.e., in reality, the comfort ranges are wider than those provided. This situation is mainly due to the greater freedom given to the occupants. Such gaps have led to propose dynamic interactions between the subject and his environment. Accordingly, Chapter 4 develops a holistic approach to model personalized thermal comfort by considering the human body shape to infer the adequate comfort level. Using occupant responses data from a field study, this chapter establishes thermal comfort probability distributions via Logistic Regression approach allowing to estimate parameters by addressing the research question: "Do thermal preferences of users are the actual level where they feel comfortable?" and the "is it possible to find a correlation between thermal sensation and the anthropometric indices such as age, height, weight…?".

4.1 BACKGROUND

4.1.1 Thermal Sensation and Perception: A Brief Overview

Thermal perception represents a mental process that allows the interrelation of the individual with his surroundings, occurring when the body receives and processes information from the environment. This information is internal and external stimuli responsible for the body's behavior. It is through his perception that the person captures the characteristics of the environment; and when he is in thermal discomfort, he tends to divert attention and concentration from the activities he is performing. Thermal perception covers three dimensions: sensation, acceptability, and thermal preference [35].

The thermal sensation, on the other hand, is an indication of thermal perception, i.e., it is the degree of thermal comfort or discomfort of a person when submitted to a certain environment [256]. It could be assumed that thermal sensation is a combined effect of the climatic variations with the individual variations. Among the environmental variables that influence thermal perception are: air temperature, relative humidity, and air speed.

In 1970, O. Fanger proposed a sensory scale that translated the thermal sensations reported by users according to the environment in which they were exposed. The scale presented in Table (4-1) was created to represent the users' answers to the classic question: "How do you classify this environment at this moment?", and is used in standards such as ISO 10551 and ASHRAE 55. Additionally, Table 4-2 shows the relationship between the ASHRAE scale, the Bedford scale used in 1936, and the Fanger preference scale.

Table 4-1. The Seven-point sensory scale (Source: Adopted from [50]).

Thermal Sensation	Vote
Too hot	+3
Hot	+2
Slightly hot	+1
Comfortable	0
Slightly cold	-1
Cold	-2
Too cold	-3

Table 4-2. Scales of thermal sensations (Source: Adopted from [257]).

Scale	ASHRAE	Bedford	Preference
+3	Hot	Much too warm	Much cooler
+2	Warm	Too warm	Cooler
+1	Slightly warm	Comfortably warm	Slightly cooler
0	Neutral	Comfortable	No change
-1	Slightly cool	Comfortably cool	Slightly warmer
-2	Cool	Too cool	Warmer
-3	Cold	Much too cool	Much warmer

Many are the factors the interfere in the determination of thermal sensations and, according to R. de Dear and G. Brager [51]. Finding out which of them leads to a greater influence on the sensation of individual thermal comfort is the point that most generates questions related to the subject. In order to specify these intervening factors and determine the real influence of each one of them on the performance, sensation, and thermal preference, studies all over the world have been conducted, among them those of O. Fanger [50], [258], R. de Dear et al. [35], M. Humphreys and J. Nicol [58], H. Zhang et al. [257].

4.1.2 Developed Thermal Comfort Models

The researches related to thermal comfort tend to follow two distinct lines: those based on experiments in climatic chambers, with variables controlled by the researcher and the studies done in the field, where there is the impact of the climatic characteristics of the locality in which the study was conducted.

For conditioned environments, given the thermal uniformity to which the occupants are subjected, standards such as ASHRAE 55-2017 and ISO 7730-2005 indicate the use of the methodology proposed by Fanger (i.e., PMV/PPD model) to predict and evaluate internal thermal conditions [50]. However, the use of this model with comfort parameters limited to a PMV of ±0.50, may not be as representative.

Among some contributions on the study of thermal comfort in indoor environments, we can mention the study by T. Chow et al. [16] on the thermal sensation of people in Hong Kong subjected to a higher air velocity, temperature, and humidity in an air-conditioned environment gathered about 300 people, aged between 19 and 50 years, in a controlled thermal environment. Their thermal sensation votes were gathered and the results showed that the temperature and air velocity interfered more with the occupants' thermal sensation than humidity. In this study, the interviewed women were more sensitive to the change in temperature and less to the change in air velocity than men evaluated for temperature ranges. The authors concluded that from a sustainable point of view for the building, it would be more appropriate to increase the air movement rather than reduce the temperature and humidity of the air, achieving an acceptable thermal sensation with minimal energy use.

J. Kim et al. [259] investigated the influences affecting air conditioning use decisions in households and the comfort of occupants in temperate climate regions in Australia. The field observations recorded the patterns of air conditioning use, internal and external climatic factors, perception of thermal comfort, and adaptive behaviors. In the two years of monitoring, 2105 comfort questionnaires were collected in 42 residences. The authors concluded that the users' neutral temperature was estimated at two degrees below that predicted by the adaptive model of the ASHRAE Standard 55. The findings indicated that people in their homes are more adaptable and tolerant to significantly higher temperature variations than expected.

C. -S. Kang et al. [260] evaluated the impact of environmental quality and productivity in open-plan spaces (offices, universities) in China. The study showed how office productivity is affected by layout, air quality, thermal comfort, lighting, and acoustics. The authors concluded that the layout of an office is one of the basic factors that influence the performance and the occupants' behavior. Indeed, an open plan office accommodates more people than a private office and facilitates communication between co-workers. However, the authors affirmed that this type of design and layout leads to reduce the size of the workspace of each occupant, the lack of visualization and privacy, and the increase of uncontrollable social contacts and interruptions. On the other hand, M. Luo et al. [261] evaluated environments that operate with both natural ventilation and air conditioners (mixed-mode) in China. The comparison between the stated thermal sensation votes and the predicted values of PMV for both situations indicated a failure in the index in both predictions.

Many of these studies have shown that the assessment of environmental satisfaction and subsequent relationship with their level of productivity depends on several non-measurable factors such as their psychological state, expectations, and their social position (e.g., in the workplace). In most of these studies, there are apparent discrepancies related to the comparative analysis between comfort thermal sensations reported and parameters predicted by the norms evaluated.

4.2 METHODOLOGY

4.2.1 Data Source and Structure

So far, no study has used the ASHRAE Global Thermal Comfort Database II [262] data to model field-based probability distributions of thermal comfort indicators (sensation, acceptability, preference…) for buildings' occupants. As previously mentioned, this chapter develops such probabilities to propose a data-driven approach for developing a thermal comfort model as a function of variables that are dynamically updated, such as the body shape, which reflects the individual thermal comfort. This section describes the data source from the field studies and outlines different parameters related to occupants' responses contributing to our study.

4.2.1.1 Data Source

In order to meet the objective proposed by this thesis, data are drawn from ASHRAE Thermal Comfort Global Database II ("Comfort Database"), which consists of a total of 81,846 rows of raw data of paired subjective comfort votes and objective instrumental measurements of thermal environmental parameters. The database integrates standardized data files from the ASHRAE RP-884 adaptive model project [59], which were transformed and assimilated into the new database structure. A total of 25,617 records from the RP-884 database were added to Database II, which brought the total to 107,463.

The field studies, from which the database draws, were conducted in five continents, with a broad spectrum of geographical locations[7] and different distinct Köppen climate classes [262]. Additionally, thermal comfort data were collected in Naturally Ventilated (NV), Air-Conditioned (HVAC), and Mixed Mode (MM) buildings by a research team, that classified data into five main buildings categories including offices, classrooms, multifamily houses, senior centers, and others (any other building type than the defined ones). The primary emphasis of the field studies conducted to build "Comfort Database" was to "focus on 'real' buildings occupied by *real* people doing their normal day-to-day activities…"; accordingly, key comfort determinants (Temperature, Humidity, Clothing, etc.) were allowed to vary freely, unlike in the laboratory experiments.

Table 4-3. Sensation vote binned by Ambient Temperature and PMV in "Comfort Database".

T_a (ºC)	PMV	ASHRAE Sensation Vote							N
		Cold (-3)	Cool (-2)	Slt. Cool (-1)	Neutral (0)	Slt. Warm (+1)	Warm (+2)	Hot (+3)	
13.4	-3	0	0	10	10	0	0	0	20
15.28	-2.57	2	11	43	55	3	0	0	114
17.17	-2.14	8	20	93	127	5	1	0	254
19.06	-1.71	7	18	105	259	28	6	2	425
20.94	-1.29	3	56	262	717	72	5	3	1,228
22.83	-0.86	15	188	853	1,928	399	65	11	3,459
24.72	-0.43	17	322	1,038	2,235	706	205	96	4,619
26.60	0.00	16	182	568	1,065	538	236	118	2,724
28.49	0.43	23	85	303	756	345	166	122	1,800
30.37	0.86	8	24	61	290	168	94	79	724
32.26	1.29	1	0	12	80	97	109	97	396
34.15	1.71	0	0	1	36	64	102	114	317
36.03	2.14	0	9	0	8	34	63	57	162
37.92	2.57	0	0	0	1	4	8	4	17
39.8	3	0	0	0	0	0	0	4	4

[7] The geographical locations include 23 countries: Australia, Belgium, Brazil, China, Denmark, France, Germany, Greece, India, Iran, Italy, Japan, Malaysia, Mexico, Nigeria, Philippines, Portugal, Slovakia, South Korea, Sweden, Tunisia, the United Kingdom and the United States of America.

In this regard, we generated raw data from the Comfort Database II into Table (4-3), which is translated into a short-form list of individual observations. In Table (4-3), the ambient temperature was scaled (“T_a”) to a PMV ranging from -3 to 3, with a “Neutral” PMV occurring at 26.6ºC. Note that from these data, 16,153 fields were included, after data pre-processing.

4.2.1.2 Key Variables and Ranges

Table (4-4) summarizes the key variables taken from ASHRAE Thermal Comfort Global Database II field data for the purposes of this study. It is worth noting that body mass index (BMI) data are calculated from the height and weight of the subjects, which are available in the database.

Table 4-4. Summary of key variables.

Variable	Abbreviation	Prompt	Variable Type	Value Range
Predicted Mean Vote	PMV	N/A	Continuous	-3 (Cold) to 3 (Hot)
Thermal Sensation Vote	TSV	How do feel right now?	Discrete	-3 (Cold) to 3 (Hot)
Thermal Acceptability	TSA	Acceptability of thermal environment	Discrete	1 (Unacceptable); 2 (Acceptable)
Thermal Preference	PREF	I would like to feel…	Discrete	1 (Cooler); 2 (No change); 3 (Warmer)
Season of Response	SEAS	N/A	Discrete	0 (Winter); 1 (Summer)

The seasonal variable (SEAS) (cf. Table (4-4)) is important to thermal sensation and preference distribution models, as this reflects previous observations that people may prefer cooler sensations in warm periods and warmer sensations in cold periods. The occupant thermal sensation (TSV), thermal acceptability (TSA) and thermal preference (PREF) response data are available for most of the thermal comfort studies included in the database, it is worth noting that, after data cleaning process, these three responses are only available in office and classroom buildings; besides seasons, data are only available in summer and winter (cf. Table (4-5)). This led us to consider only offices and classrooms as building types and summer and winter as seasons in our final analysis. Table (4-5) depicts the frequency of valid thermal responses classified according to seasons and building cooling strategies: Air-Conditioned (HVAC), Mixed-Mode (MM), and Naturally Ventilated (NV)).

Table 4-5. Thermal responses frequency by seasons and building types.

Building Cooling Strategy		#Valid Responses/Building Type	
		Classrooms	*Offices*
Summer	*Air-Conditioned*	-	1,807
	Mixed-Mode	455	3,699
	Naturally Ventilated	413	1,361
Winter	*Air-Conditioned*	-	1,638
	Mixed-Mode	-	5,136
	Naturally Ventilated	917	727

4.2.2 Data Analysis

Data from ASHRAE Thermal Comfort Global Database II ("Comfort Database") are translated into probability distributions of thermal sensation and acceptability as well as preferences opting a Logistic Regression model. In this section, we introduce dichotomous and multinomial logit models and describe the specific thermal sensation, acceptability, and preference distribution models that are constructed under this data analysis approach.

4.2.2.1 Data Description

Descriptive statistics procedures were used to summarize and characterize the total data, presenting the distribution of values according to the occurrence frequency and variability (maximum, minimum, mean, and standard deviation). The occupants' votes were analyzed from a crossing of information, and distributed based on the intervals of body mass index (BMI), grouping them in bars that represent the different weight classes; the results were presents in the form of graphs and tables. The thermal sensation votes, represented by the seventh scale as presented in Table (4-1) (cf. Section 4.1.1), were grouped into discomfort by cold (-3 and -2), discomfort by heat (+2 and +3), and thermal comfort (-1, 0, and +1). This grouping is based on the numerical ASHRAE scales, which states that "uncomfortable individuals are those who vote -2 (cool), -3 (cold), +2 (warm), and +3 (hot)". Hence, this work considered the concepts of reducing the seven categories in the ASHRAE standard sensation votes scale into the following three classes (cf. Figure (4-1)):

- Votes in the range of [-3, -1] are considered as *comfortably cold*;
- Votes in the central categories, i.e., in the range (-1, +1), are considered as *neutral*/or *comfortable*;
- Votes in the range of [+1, +3] are considered as *uncomfortably hot*.

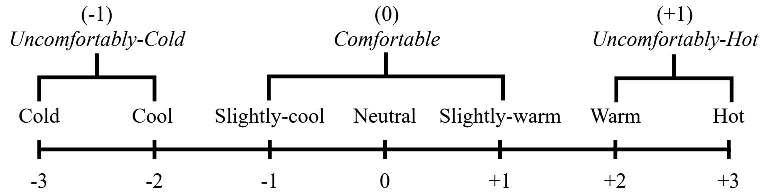


Figure 4-1. ASHRAE 7-point Thermal Sensation scale and the corresponding simplified scale for the analysis purpose.

The analyzes followed a standardized sequence of presentation: sensation, acceptability, and preference analysis and the influence of the body dimensions (cf. Section 5.2.1 & Section 5.2.2). The average behavioral graphs of the thermal sensation votes and prediction models were constructed with the help of RStudio Software as well as Microsoft Excel.

It is worth noting that the variable to be modeled TSV (Thermal Sensation Vote) has needed to go through a code conversion for the data simulations and the construction of the models, initially the seventh-point scale of the ISO7730 was used, ranging from -3 to +3 for the construction of the graphs. For the purpose of analysis, it is more suitable to reduce the number of categories into three ordered mentioned classes. Such conversion did not change the results and was only used because of the need for the Python Software for Logit model and the formulation of the statistical models.

4.2.2.2 Calculated Data Involved

4.2.2.2.1 Body Mass Index

The analyses that considered the weight of the occupants were made from the body mass index (BMI). The index is determined from the ratio of the occupant's mass (in kg) to the height square (in m) according to Equation (4-1). Although there are more complex and accurate methods for determining and evaluating body composition, few are applicable to larger groups of people, and this occurs mainly due to the high costs related to the implementation and survey of data [263]. However, this index is one of the simplest methods found, and easily promotes comparable and interpretable estimates of the bodyweight based on height, resulting in estimates of fat and body composition acceptable for the type of analysis proposed by this work.

$$BMI = \frac{Mass}{Height^2} \tag{4-1}$$

From the value found through the BMI equation, the occupants of both genders were classified according to the classes shown in Table (4-6), adapted from the pattern observed on the *World Health Organization* website[8].

Table 4-6. International classification of underweight, normal, overweight and obese adults according to Body Mass Index.

Classification	MBI Ranges
Underweight	<18.50
Normal	18.50 – 24.99
Overweight	25.0 – 29.99
Obese	>30.00

4.2.2.2.2 *Corrected Standard Effective Temperature*

The corrected standard effective temperature (SET*) index was used in all analyses presented in the results Chapter, this being a complete weighting, which considers the radiant and latent heat exchanges between the environment, the skin, and the body core, which happen every minute [54]. According to the authors, the index represents a temperature value in an imaginary uniform environment, where the ratio of relative humidity is 50%, the air velocity less than 0.10 m/s, the mean radiant temperature equals the air temperature. It was also assumed that, under these conditions, an imaginary occupant loses the same amount of heat as in a real environment when developing an activity that corresponds to 1.0 met, and clothing of 0.6 clo.

It is worth noting that the SET* index is still little used in scientific researches in the area of thermal comfort because it is a value determined in a complex way, which needs the help of software to calculate it.

4.2.2.3 Modeling Framework

This dissertation work is a case study of supervised learning, as the outcome variable is available or provided, which can guide or shape the learning process. As the objective is proposing a data-driven approach in order to predict the individual thermal comfort level based on anthropometric and ambient parameters as inputs; we have implemented a logistic regression model (or Logit model).

4.2.2.3.1 *Logistic Regression*

The logistic regression model It can be seen as a special case of the family of Generalized Linear Models (GLMs) [264], which can make it possible to establish a parametric

[8] https://www.who.int

relationship between a dichotomous variable and the vector of covariates (or explanatory variables) [264]–[266]. Then, from this generated model it is possible to calculate or predict the probability of an event occurring, given a random observation.

A logistic regression model allows to:

- Model the probability of an event occurring depending on the values of the independent variables, which can be categorical or continuous.
- Estimate the probability of an event occurring for a randomly selected observation against the probability of the event not occurring.
- Predict the effect of the set of variables on the binary dependent variable.
- Classify observations, estimating the probability of an observation being in a given category.

The dependent variable Y in logistic regression is often binary, so in these cases, it follows the Bernoulli distribution, with an unknown probability p. Remembering that Bernoulli's distribution is only a special case of the binomial distribution, where $n = 1$ (it considers conducting a single experiment).

$$Y = \begin{cases} 1, & if\ success\ occurs \\ 0, & if\ faillure\ occurs \end{cases}$$

The probability of success is $0 \leq p \leq 1$ and the probability of failure is $q = 1 - p$. In logistic regression, the unknown probability p is estimated, given a linear combination of independent variables.

♦ Dichotomous Case

Binary (or univariate) logistic regression represents cases of logistic regression where the dependent variable (DV) Y is binary or dichotomous, i.e., it has two categories and has only one independent variable. In this case, the DV Y is usually coded by the values 0 and 1, as being the absence or presence of a characteristic under study.

It is usual to make $E(Y_i|X_i) = \pi_i$, which is $P(Y_i = 1)$. The behavior of the relationship between X_i and π_i has curvilinear behavior at very small or very large values of X_i, and has an approximately linear behavior at intermediate values of X_i. This relationship can be expressed by an S-shaped curve, as shown in Figure (4-1).

The relationship between X_i and π_i is given by:

$$\pi_i(X) = \frac{e^{(\beta_0+\beta_1 X)}}{1+e^{(\beta_0+\beta_1 X)}} \tag{4-2}$$

The model that is given in Equation (4-2) meets the requirement of $0 \leq \pi_i \leq 1$. The model in terms of DV, Y, would be written as:

$$\ln\left(\frac{\pi}{1-\pi}\right) = g(x) \tag{4-3}$$

Whereas,

$$g(x) = \beta_0 + \beta_1 X \tag{4-4}$$

The above model is called the Logistic Regression Model, as it comes from a logistic transformation, also known as *logit transformation*.

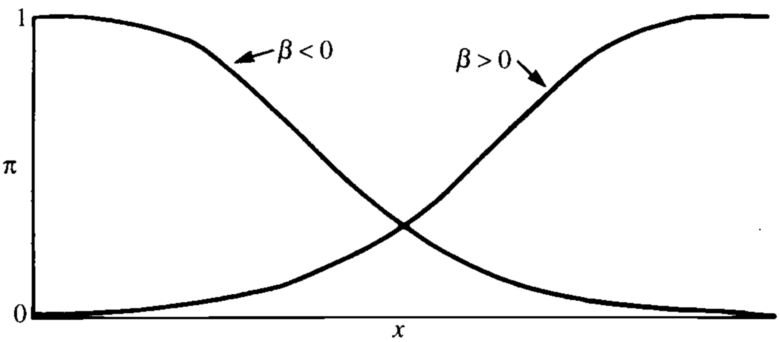


Figure 4-2. Binary regression model with complementary log-log function (Source: Adopted from [267]).

In Equation (4-2), when x tends to infinity, $\pi(X)$ tends to zero if β_1 is negative, and 1 if β_1 is positive, as illustrated in Figure (4-1). If β_1 is zero, the variable Y in independent of the variable X.

It is noticeable the absence of the term ε in the presented model, since the left side of the model is a function of $E(Y|X)$, instead of Y, which serves to remove the term error from the model.

In the case of binary logistics, ε can assume two values: if $y = 1$, then $\varepsilon = 1 - \pi(x)$ with probability $\pi(x)$, and if $y = 0$, then $\varepsilon = -\pi(x)$ with probability $1 - \pi(x)$. Thus, the random variable ε has zero average and variance $\pi(x)[1 - \pi(x)]$. This proposition indicates that regardless of whether the errors are large or small, one can expect their mean to be zero. Thus:

$$y_i = \frac{\mathrm{e}^{(gx_i)}}{1+\mathrm{e}^{(gx_i)}} + \varepsilon_i \tag{4-5}$$

Where, ε_i follows the assumptions for all i, $l = \{1, 2, \dots, n\}$

i) $E(\varepsilon_i|x_i) = 0$
ii) $Var(\varepsilon_i|x_i) = \pi(x_i)[1-\pi(x_i)]$
iii) $Cov(\varepsilon_i, \varepsilon_l) = 0$ if $i \neq l$

- **Multiple Case**

It can be seen as an extension of the simple case, where there is now instead of a predictor X, a set with p predictors. Hosmer and Lemeshow [268] establish this generalization as following: Be a set with p independent variables, denoted by $x_i^T = (x_{i0}, x_{i1}, \dots, x_{ip})$, the vector of the i[th] line of the matrix (X) of the explanatory variables; denoted by $\beta = (\beta_1, \beta_2, \dots, \beta_p)^T$, the vector of unknown parameters and β_j the j[th] parameter associated with the explanatory variable x_1. In the multiple regression model, the probability of success is given by:

$$\pi_i(x_i) = P(Y_i = 1|X = x_i) = \frac{e^{(\beta_0+\beta_1 x_{i1}+\cdots+\beta_p x_{ip})}}{1+e^{(\beta_0+\beta_1 x_{i1}+\cdots+\beta_p x_{ip})}} \tag{4-6}$$

$$= \frac{e^{(x_i^T\beta)}}{1+e^{(x_i^T\beta)}} \tag{4-7}$$

And the probability of failure becomes:

$$1-\pi_i(x_i) = P(Y_i = 0|X = x_i) = \frac{1}{1+e^{(\beta_0+\beta_1 x_{i1}+\cdots+\beta_p x_{ip})}} \tag{4-8}$$

Thus, the $g(\cdot)$ function takes the form:

$$g(x) = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p \tag{4-9}$$

The errors follow the same assumptions as the simple case. The multiple logistic model's given by:

$$\mathrm{y}_i = \frac{e^{g_i}}{1+e^{g_i}} + \varepsilon_i \tag{4-10}$$

Whereas,

$$g_i(x) = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_n x_{ip} \tag{4-11}$$

It is worth noting that in the model presented above, it is possible to have several discrete variables, of the nominal scale type, whose various numbers are used to represent levels of these scales and have no numerical meaning. These are the *dummies* variables. In this case, we have:

$$g(x) = \beta_0 + \beta_1 x_1 + \cdots + \sum_{l=1}^{k_j-1} \beta_{jl} x_{jl} + \beta_p x_p \tag{4-12}$$

When we have a variable in the nominal scale with possible k values. We introduced $k-1$ *dummies* variables, where the j[th] variable is on the nominal scale with k_j levels; each of the $k_j - 1$ *dummies* variables are denoted by x_{jl} and its coefficient β_{jl}, with $1 = \{1, \dots, k_j - 1\}$.

♦ **Multinomial Responses**

In the process given so far, the DV always assumes two values. The generalization of this situation models categorical responses with more than two categories. According to Agresti [267], multi-category logit models use all category pairs to specify the "odds" that the output falls on one category in relation to another. In this type of modeling, the order between categories is considered irrelevant.

Among the DV categories, one is elected to be the reference category. Thus, if the last category (J) of the DV is used for this purpose, the logit for this modeling is:

$$\ln\left(\frac{\pi_j}{\pi_J}\right), j = 1, \dots, J-1 \tag{4-13}$$

For example, if $J = 3$, for the modeling in this case, $\log(\pi_1/\pi_3)$ and $\log(\pi_2/\pi_3)$are calculated, since in this model, either the answer lies in $j, j = 1, 2$ or in $J, J = 3$.

$$\ln\left(\frac{\pi_j}{\pi_J}\right) = \alpha_j + \beta_j x \,, j = 1, \dots, J-1 \tag{4-14}$$

This model presents $J - 1$ equations, with different parameters for each one of them. When $J = 2$, this model becomes the binary logistic case. For the simplicity of notation, it is sometimes performed as:

$$\eta_j = \alpha_j + \beta x \tag{4-15}$$

Then,

$$\text{logit}\left(\frac{\pi_j}{\pi_J}\right) = \eta_j + \varepsilon \;, j = 1, \dots, J-1 \tag{4-16}$$

And the multinomial model expressed in terms of probabilities of occurrence of the DV categories, takes the form of:

$$\hat{\pi}_j = \frac{e^{\hat{\eta}_j}}{\sum_{h=1}^{J-1} e^{\hat{\eta}_h}} \quad ,j = 1, \dots, J-1 \tag{4-17}$$

For example, if $J = 3$, one would have:

$$\hat{\pi}_1 = \frac{e^{\hat{\eta}_1}}{e^{\hat{\eta}_1} + e^{\hat{\eta}_2}} \tag{4-18}$$

$$\hat{\pi}_2 = \frac{e^{\hat{\eta}_2}}{e^{\hat{\eta}_1} + e^{\hat{\eta}_2}} \tag{4-19}$$

$$\hat{\pi}_3 = \frac{1}{e^{\hat{\eta}_1} + e^{\hat{\eta}_2}} \tag{4-20}$$

Where, at $\hat{\pi}_3$, the numerator equal to 1 represents $\alpha_3 = \beta_3 = 0$ concerning the reference category.

By extending the modeling to the case of having a set of p explanatory variables, the regression model for category j becomes:

$$\text{logit}\left(\frac{\pi_j}{\pi_J}\right) = \beta_{0j} + \beta_{1j}x_1 + \dots + \beta_{pj}x_p + \varepsilon \ ,j = 1, \dots, J-1 \tag{4-21}$$

To develop the likelihood function, Hosmer and Lemeshow [268] illustrate the process for the case where the DV has three categories, with the help of three binary variables, which aim to illustrate to which category an observation belongs; known as Y_0, Y_1 and Y_2. If an observed value of the DV is in category 2, for example, then $Y_0 = 0; Y_1 = 0$ and $Y_2 = 1$ are done.

Thus, using this notation, the conditional likelihood function for a sample of n independent observations is:

$$\text{l}(\beta) = \prod_{i=0}^{n} [\pi_0(x_i)^{y_0} \pi_1(x_i)^{y_1} \pi_2(x_i)^{y_2}] \tag{4-22}$$

Taking the logarithm of the equation ( ) and using the fact that $\sum y_{ji} = 1$ for each i, the logarithm of the likelihood function is:

$$\text{l}(\beta) = \sum_{i=1}^{n} y_{1i} g_1(x_i) + y_{2i} g_2(x_i) - \ln\{1 + e^{g_1(x_i)} + e^{g_2(x_i)}\} \tag{4-23}$$

The likelihood equations are found by taking the first partial derivatives of $L(\beta)$ with respect to each unknown parameter. The general form of these equations, given by Hosmer and Lemeshow [268] is:

$$\frac{\partial L(\beta)}{\partial \beta_{jk}} = \sum_{i=1}^{n} x_{ki}(y_{ji} - \pi_{ji}) \tag{4-24}$$

For $j = 1, 2, \dots, J-1$ and $k = 0, 1, 2, \dots, p$, with $x_{0i} = 1$ for each object.

The maximum likelihood estimator $\hat{\beta}$ is obtained by setting these equations to zero and solving them for β.

The matrix of the second partial derivative is necessary to obtain the matrix of information and estimation of the covariance matrix of maximum likelihood estimators. The general shape of the elements in the matrix of the partial derivative second is:

$$\frac{\partial^2 L(\beta)}{\partial \beta_{jk} \partial \beta_{jk'}} = \sum_{i=1}^{n} x_{k'i} x_{ki} \pi_{ji}(1 - \pi_{ji}) \tag{4-25}$$

And

$$\frac{\partial^2 L(\beta)}{\partial \beta_{jk} \partial \beta_{jk'}} = \sum_{i=1}^{n} x_{k'i} x_{ki} \pi_{ji} \pi_{j'i} \tag{4-26}$$

For j and $j' = 1, 2, \dots, J-1$ and k and $k' = 0, 1, 2, \dots, p$. The observed information matrix is matrix $2(p+1)$ by $2(p+1)$whose elements are the negative values of the found Equations (4-25) and (2-26), evaluated in $\hat{\beta}$. The covariance matrix estimator of maximum likelihood estimators is the inverse of the observed information matrix.

The "Odds ratio" of a multinomial model, assuming category $Y = 0$ as the reference, is given by:

$$OR_j(a, b) = \frac{P(Y = j|x = a)/P(Y = 0|x = a)}{(Y = j|x = b)/P(Y = 0|x = b)} \tag{4-27}$$

Representing the odds ratio of the output $Y = j$ versus the output $Y = 0$, for the values of the covariable in $x = a$ versus $x = b$.

The preliminary indication of the importance of an independent variable in the model can be obtained from the Wald-test statistics. However, a likelihood ratio test should be used to evaluate significance. For example, to test the significance of an independent variable in a model, the logarithm of the likelihood of the model containing IV is compared with the logarithm of the likelihood of the model containing only the intercept. According to D. Hosmer and S. Lemeshow [268], under the null hypothesis that all regression coefficients are null in the model, the negative of the double chance in the logarithm of likelihood follows a chi-square distribution with two degrees of liberation.

- **Multinomial Ordinal Responses**

When the DV has an ordering between its categories, the use of the logistic model for ordinal responses has simpler interpretations and potentially greater power [267].

Logistic regression for ordinal responses is based on the use of accumulated Y probability. Thus, the probability considered now is that the value of Y falls in a range of interest, j, or in categories that fall in lower ranges. So, given a category j of interest:

$$P(Y \leq j) = \pi_1 + \cdots + \pi_j, \quad j = 1, \ldots, J \tag{4-28}$$

The accumulated probability reflects the ordering between the DV categories. It follows that $P(Y \leq 1) \leq P(Y \leq 2) \leq \cdots \leq P(Y \leq J) = 1$.

The logits for cumulative probability are:

$$\text{logit}\, P(Y \leq j) = \ln\left[\frac{P(Y \leq j)}{1 - P(Y \leq j)}\right] = \ln\left[\frac{\pi_1 + \cdots + \pi_j}{\pi_{j+1} + \cdots + \pi_J}\right], \quad j = 1, \ldots, J-1 \tag{4-29}$$

For $J = 3$, for example, the model uses $\text{logit}[P(Y \geq 3)] = \text{logit}[\pi_3/(\pi_2 + \pi_1)]$ and $\text{logit}[P(Y \geq 2)] = \text{logit}[(\pi_3 + \pi_2)/\pi_1]$. Thus, each cumulative logit uses all the response categories.

According to A. Agresti [267], a model for cumulative logit resembles a binary logistic regression model, in which categories 1 to j combine to form a single category and the other $j + 1$ to J form a second category.

For only one predictor x, such a cumulative logit model can be written as follows:

$$\text{logit}\, P(Y \leq j) = \beta_{0j} + \beta_1 x, \quad j = 1, \ldots, J-1 \tag{4-30}$$

In the equation above, β does not have a j index, indicating that the effect of variable x is described by only one parameter for all categories.

Figure (4-2) illustrates the case of an ordinal multinomial logistic regression model, where proportional *Odds* ownership is worth, with four categories and an explanatory variable. The curves are similar to the binomial case. In this model, the intercept is the parameter that differentiates the model for a category from another category, as we can see in the equation above the index j in the parameter β_0.

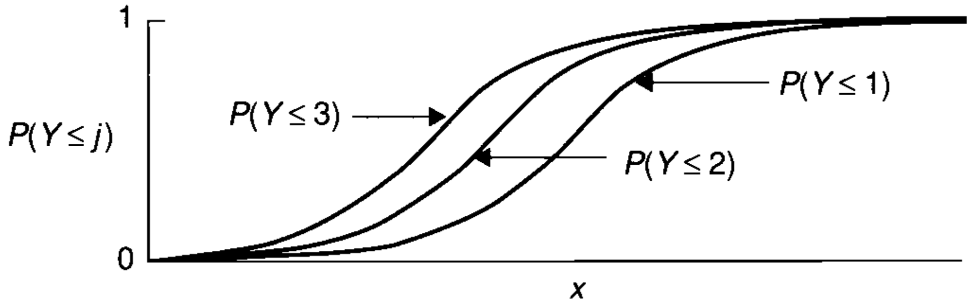


Figure 4-3. Cumulative probability in the Proportional *Odds* model (Source: Adopted from [267]).

The model is invariant when the category coding the inverted (the J[th] category becomes the first, the first becomes the J[th], the second becomes the penultimate, and so on). A. Agresti [267] states that in this case, however, the N's signs are inverted. Otherwise, there are several logistic regression models used when the response has been ordered, such as the Proportional *Odds* model (i.e., partial proportional model). Only the Proportional *Odds* model is presented here.

- **Proportional Odds Model**

We consider a multinomial Y response variable with categorical outputs, denoted by $1, 2, \dots, k$ and be x_i a p-dimensional vector of the covariates. The dependence of Y on x for the Proportional *Odds* model has the following representation:

$$\Pr\,(Y \leq y_j|x) = \frac{e^{(\alpha_j - x'\beta)}}{1 + e^{(\alpha_j - x'\beta)}}, \quad j = 1,2, \dots, k \tag{4-31}$$

Or, in the form of logit:

$$\text{logit}(\Pi_j) = \ln\left[\frac{\Pi_j}{1 - \Pi_j}\right] \tag{4-32}$$

$$\ln\frac{\Pr\,(Y \leq y_j|x)}{\Pr\,(Y > y_j)} = \alpha_j - x'\beta \tag{4-33}$$

Where $(\Pi_j) = \Pr\,(Y \leq y_j)$ is the cumulative probability of the event $Y \leq y_j$. α_j is the unknown intercept, satisfying the condition $\alpha_1 \leq \alpha_2 \leq \dots \leq \alpha_k$, and $\beta = (\beta_1, \beta_2, \dots, \beta_k)$ is a vector of the regression coefficients corresponding to the vector of the covariates, x.

It is noticeable that in this case, the terms of β do not depend on j, i.e., in the proportional odds model, no matter in which range of the DV the value is, $\beta's$ remain the same. In other words, the relationship between Y and x remains unchanged as one goes through the entire length of Y. It only changes in this case, for each range of value of the VD, the $\alpha_j's$. This premise causes this model to be called a proportional odds model, as it is assumed that there is an identical *Odds* ratio at the k cut-off points or assumption of parallel regression.

4.2.3 Model Descriptions

Using binomial and ordinal logistic regression models and the ASHRAE Thermal Comfort Global Database II, we fit field-based models of thermal comfort parameters (Acceptability, Sensation, and Preference) distributions. The models' developments are described in the next Chapter (cf. Section (5-4)). In these models, we predict the probability that an occupant would report feeling a certain ASHRAE sensation (TSV), his preferences (PREF) as well as his evaluation a given ASHRAE sensation as "Acceptable" or "Unacceptable" (TSA) for 16,153 occupant responses from office and classroom buildings with naturally-ventilated, mixed-mode, and air-conditioned buildings. Each model is described in further detail bellow.

Models 1-3: Thermal Acceptability Regressions

Models 1-3 are thermal acceptability regressions that use the ASHRAE Thermal Comfort Global Database II. These models predict the probability that an occupant evaluates a given ASHRAE sensation as "Acceptable" or "Unacceptable" (TSA) for 3445 usable occupant TSA responses from HVAC buildings (Model 1), 9228 usable occupant TSA responses from MM buildings (Model 2), and 3366 usable occupant TSA responses from NV buildings (Model 3). Each of these thermal acceptability models includes the season of an occupant's response (SEAS) as one of the predictors besides the anthropometric and environmental variables.

Models 4-6: Thermal Sensation Regressions

Models 4-6 predict the probability that an occupant would report feeling a certain ASHRAE Sensation given the season (SEAS), their anthropometric variables, besides environmental variables. Each of these Models 4-6 is distinguished by the building type of its underlying data (HVAC, N=3445 usable ASH responses; MM, N=9228 usable ASH responses; and NV, N=3366 usable ASH responses).

Models 7-9: Thermal Preference Regressions

Models 7-9 are thermal preference regressions. Each of these models predict the probability that an occupant wants a certain type of change (PREF) in a given ASHRAE sensation (ASH), again separately for 3445 usable PREF responses from HVAC buildings

(Model 7), 9228 usable PREF responses from MM buildings (Model 8), and 3366 usable PREF responses from NV buildings (Model 9). Also, these models include the season (SEAS) as one of the predictors besides the anthropometric and environmental variables.

5 MODEL DEVELOPMENT & VALIDATION

This chapter portrays the analysis and discussion of field data that respond to the general and specific objectives proposed by the research. A priori, for a better understanding and contextualization of the results, it was opted to analyze the data from different perspectives (personal, environmental) for the construction and discussion of the models, it was possible to develop a consolidated understanding. The thermal and personal parameters were evaluated by performing a descriptive analysis. The entire procedure in section 2.1 (cf. Chapter 2) was necessary to investigate indicators involved in the models. In the following, it is the outcome and discussion of the field data, the descriptive analysis as well as the statistical modeling.

5.1 CHARACTERIZATION AND PRESENTATION OF DATA

The results of this thesis were analyzed mainly based on data extracted from ASHRAE Thermal Comfort Global Database II, which involves, after the quality-assurance process, approximately 81,846 rows of pairs subjective comfort votes and objective instrumental measurements of thermal environmental parameters[9], collected from field studies conducted between 1995 and 2016 and others from the RP-884 database [35]. As previously noted, some variables are very limited in some seasons or building types, also in case of lack of data. Additionally, for our study purpose, we are interested in the data of anthropometric (or demographic) parameters, thermal sensation, and preference as

[9] https://datadryad.org/stash/dataset/doi:10.6078/D1F671

well as indoor climatic variables; this led us to consider only the classrooms, and offices building, which leaves a total of 16,153 occupant responses from the "Thermal Comfort" database. Therefore, our sub-dataset covers two seasons (52.11% in winter and 47.89% in summer), coming from office and classroom buildings.

5.1.1 Environmental Variables

Several environmental parameters contribute to the analysis of thermal comfort in indoor environments, directly influencing its determination. During the field studies, variables related to the thermal environment in the occupied zones were measured (e.g., air temperature, relative humidity, globe temperature, air velocity). Table (5-1) summarizes the measured environmental variables, highlighting the minimum and maximum values of the air temperature measured during the studies (13.4ºC and 39.8ºC, respectively).

Table 5-1. Variability of measured environmental conditions collected throughout the field studies.

Parameter	Minimum	Maximum	Mean	St. Dev.*
Air Temperature (ºC)	13.40	39.80	25.82	4.25
Relative Humidity (%)	14.50	88.80	54.19	15.40
Air Velocity (m/s)	0.00	2.38	0.20	0.25
Standard Effective Temperature (ºC)	10.93	38.94	27.97	2.99

*Standard Deviation

Besides, the values of the air temperature and relative humidity of the air in both seasons ((a) Winter, and (b) Summer) were distributed according to the frequency and range of measured values (cf. Figures (5-1) & (5-2)).

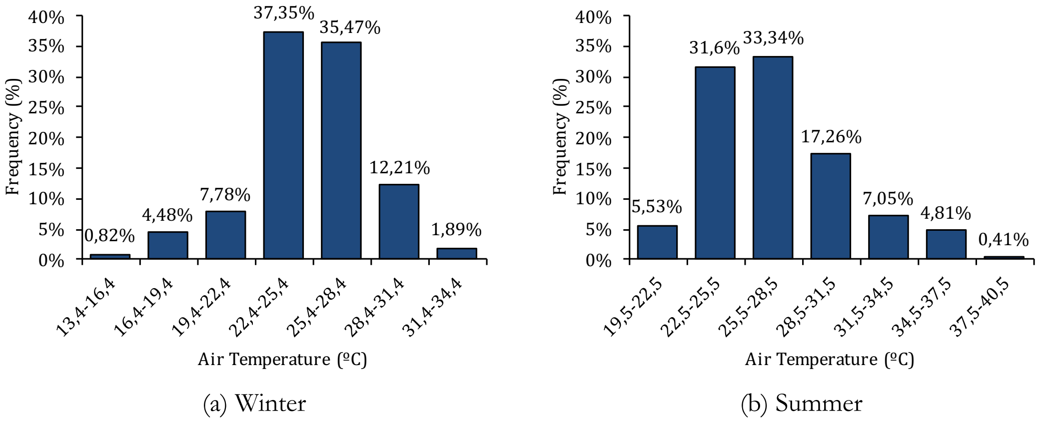
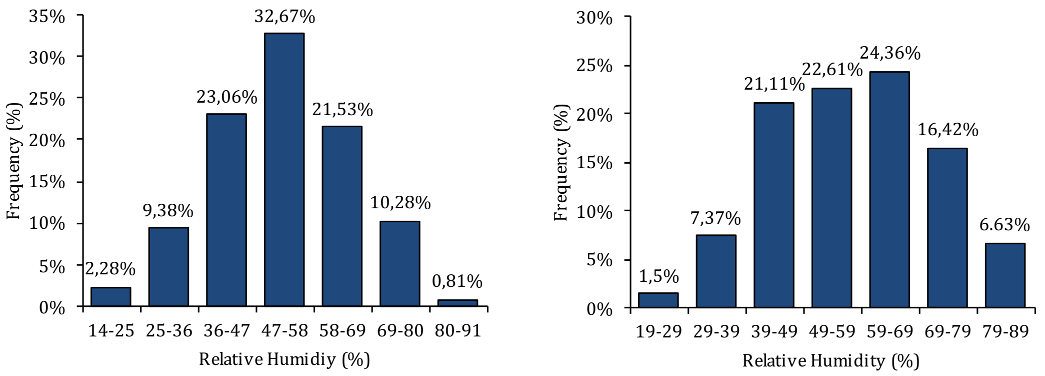


Figure 5-1. Variation in the Air Temperature and frequency of the values observed in (a) Winter (n=8,418), and (b) Summer (n=7,735).

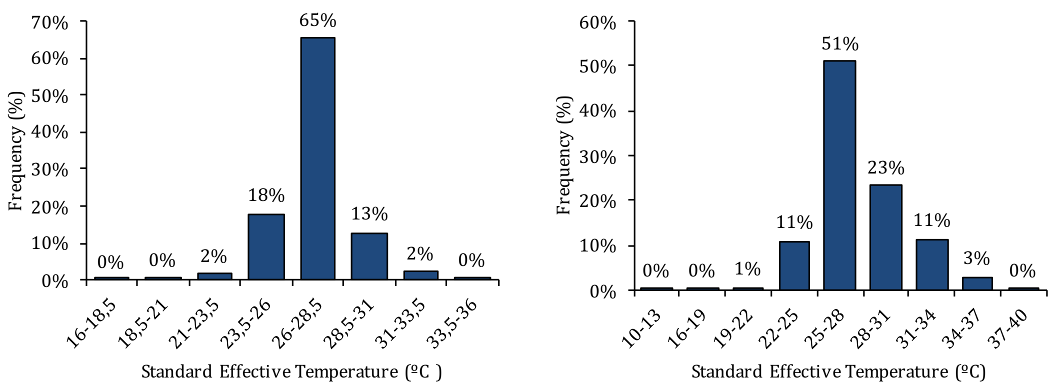
It is observed that the air temperature oscillated predominantly between 18-20,5ºC and 28ºC in winter (cf. Figure 5-1 (a)) and between 19-22ºC and 34ºC (cf. Figure 5-1 (b)), while the relative air humidity oscillates between 14% and ~59% in winter with higher concentration between 41% and 50% (cf. Figure 5-2 (a)), while in summer, a higher concentration of values was between ~41% and ~80% with lower values were between ~21% and ~31% (cf. Figure 5-2 (b)).



(a) Winter (b) Summer

Figure 5-2. Variation in the Relative Humidity and frequency of the values observed in (a) Winter (n=8,418), and (b) Summer (n=7,735).

The observation of high values of relative air humidity directed the research to the use of the Standard Effective Temperature Star (SET*), derived from the two-node model of Gagge et al. [269], where the exchanges of radiant and latent heat between the middle, the skin and the body's core take place minute by minute. Examining Figure (5-3), it was observed that the standard effective temperature (SET*) index presented a larger temperature range when compared to the internal air temperature range observed in Figure (5-1). Such differences are considered by SET*, as a complete index, which in addition to weighing the metabolism and clothing, includes humidity and air velocity as input parameters.



(a) Winter (b) Summer

Figure 5-3. Histograms of the Standard Effective Temperature values (SET*) observed in the building throughout (a) Winter (n=8,418), and (b) Summer (n=7,735).

5.1.2 Occupants' Characteristics

Table (5-2) presents the description of the physical characteristics, clothing, and metabolism of the occupants. Among the 16,153 votes considered valid for this study, 5,526 are female (34.2%) and 10,627 are male (65.8%). The minimum age of the occupant registered was 17 and the maximum 75 years; the height of the participants varied between 1.2 and 2.03 m, the weight between 33 and 130 kg, while the BMI ranged between 11.39 and 52.5 kg/m^2, besides the clothing level which varied between 0.09 and 2.24 clo.

Table 5-2. Statistical description of the individual characteristics of the occupants involved in the field studies.

Parameter	Minimum	Maximum	Mean	St. Dev.*
Age (years)	17	75	36.32	9.53
Height (m)	1.20	2.03	1.67	0.09
Weight (kg)	33	130	66.54	12.88
Body Mass Index** (kg/m^2)	11.39	52.50	23.70	3.99
Clothing Insulation (clo)	0.09	2.24	0.71	0.25
Metabolism (Met)	0.70	2.10	1.10	0.16

*Standard Deviation
** Calculated for the purpose of this study

The highest frequency of clothing level values occurred between 0.54 and 0.69 clo (cf. Figure (5-4)), for both male and female occupants. However, it is interesting to observe that the male clothing level has a greater distribution of values in the horizontal interval when compared to the distribution of the female clothing level, concentrated in a larger interval (i.e., between 0.54 and 0.84 clo). Crossing the clothing data with the seasons, a clear relationship of dependence between both variables can be observed, which allows us to affirm that the amount of clothing that occupants wear is directly related to the seasons (cf. Figure (5-5)).

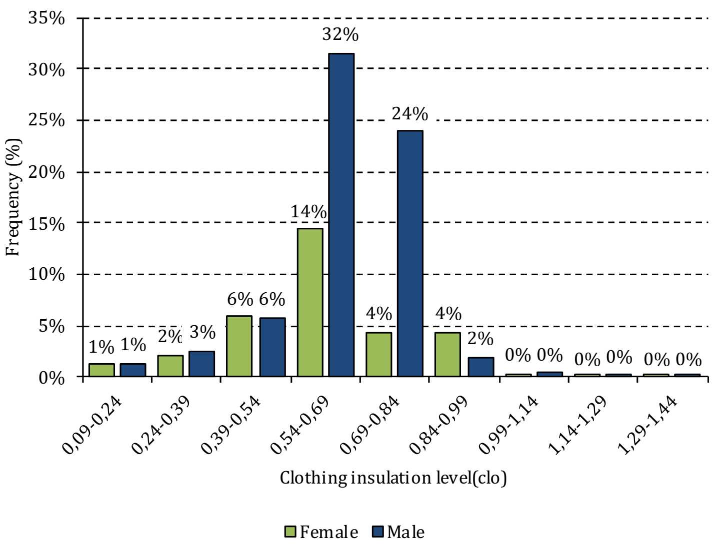


Figure 5-4. Distribution of clothing insulation between male and female occupants.

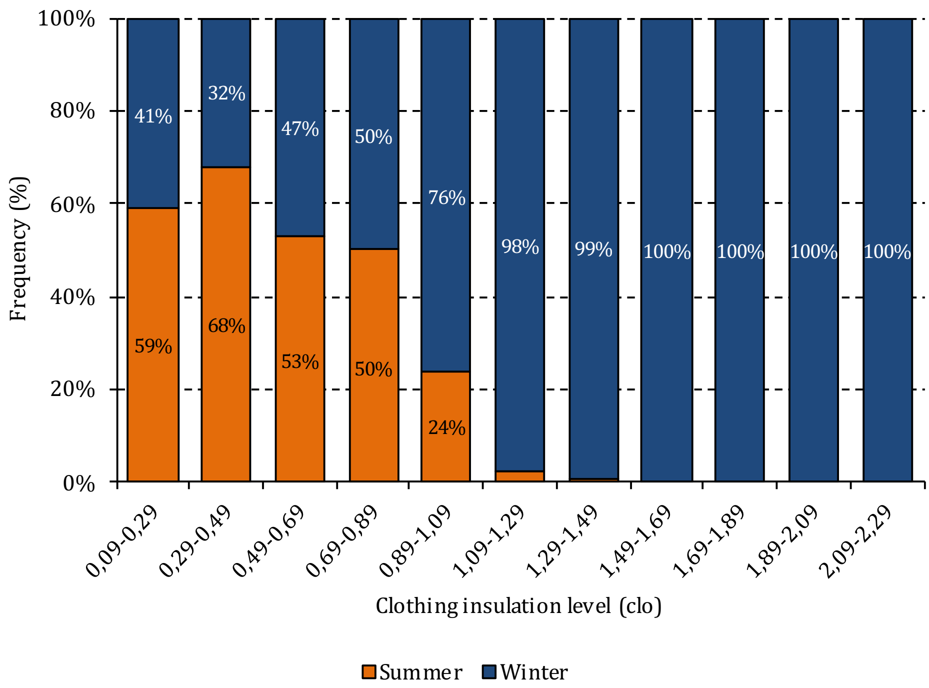


Figure 5-5. Relationship between the users' clothing and the considered seasons.

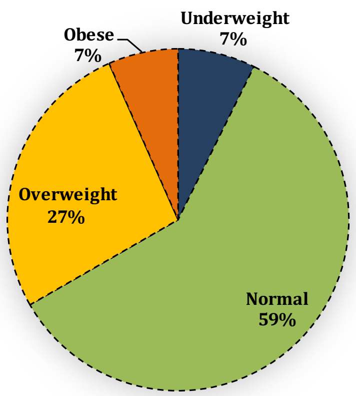


Figure 5-6. Classification of occupants according to the weight classes.

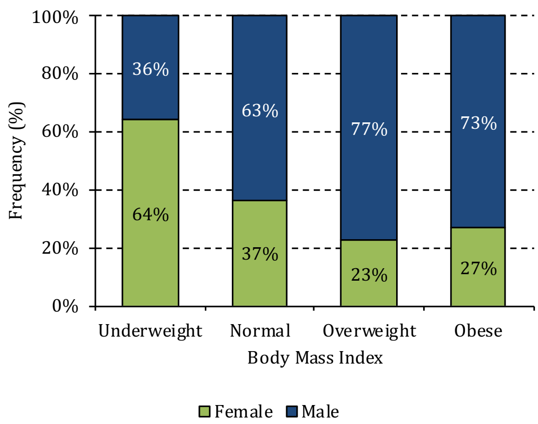


Figure 5-7. Distribution of the different weight classes according to the occupants' gender.

Figure (5-6) presents the comparison of the different weight classes of buildings occupants according to the body mass index (BMI). The frequency of obese occupants is quite low (~5%) when compared to the frequency of normal and overweight occupants, which are predominant in this case. Occupants who, according to the BMI, are classified as underweight, represent almost 6% of the buildings' population. Although there are no significant differences between the frequency of underweight occupants according to the BMI when considering the gender of the occupants, some distinctions can be emphasized, such as the share of the rest of classes, the majority of male occupants are overweight, or classified as normal (Figure (5-7)).

5.1.3 Thermal Comfort Indices: Thermal Sensation, Preference, and Acceptability

Initially, thermal sensation votes of occupants were analyzed. Figure (5-8) shows the frequency of thermal sensation comfort votes as a function of the Standard Effective Temperature (SET*). In ranges of SET* with high population concentration (i.e., from 22ºC to 36ºC), it is observed that almost 80% on average of the occupants were comfortable when the votes oscillate within ±1 of the seventh scale of sensations. Otherwise, less than 25% stated uncomfortable from both cold and heat.

When analyzing the thermal acceptability votes, little difference can be seen; when comparing the percentages of thermal acceptability with thermal sensations votes to express the same degree of comfort (cf. Figures (5-8) & (5-9)). According to Figure (5-9), thermal acceptability can reach more than 69%, on average, in SET* values between 22ºC and 36ºC.

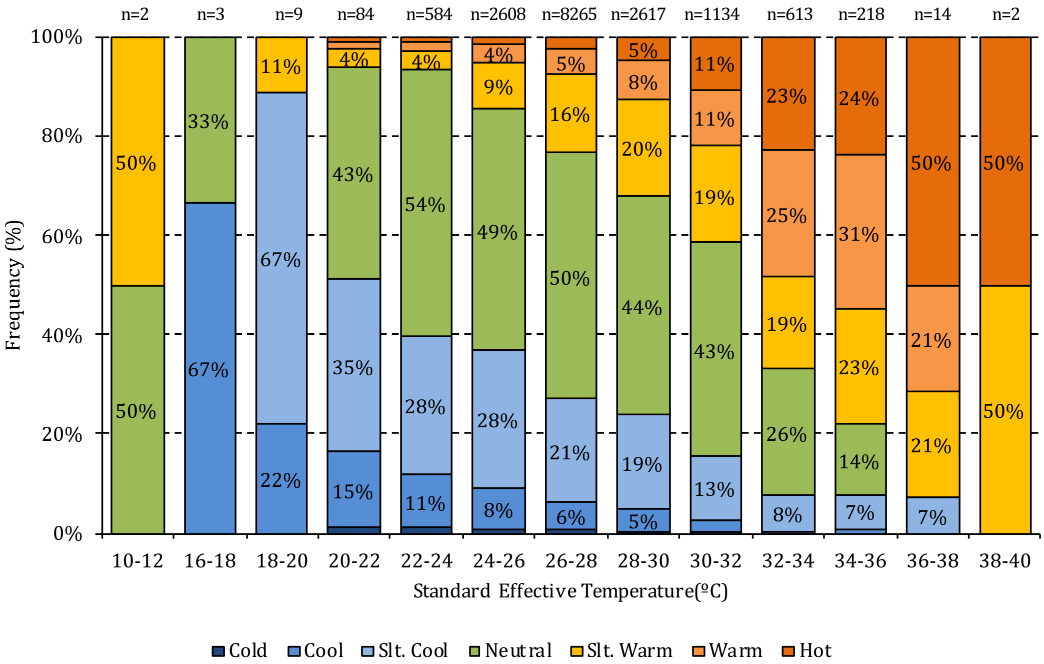


Figure 5-8. Thermal sensation according to the standard effective temperature (SET*).

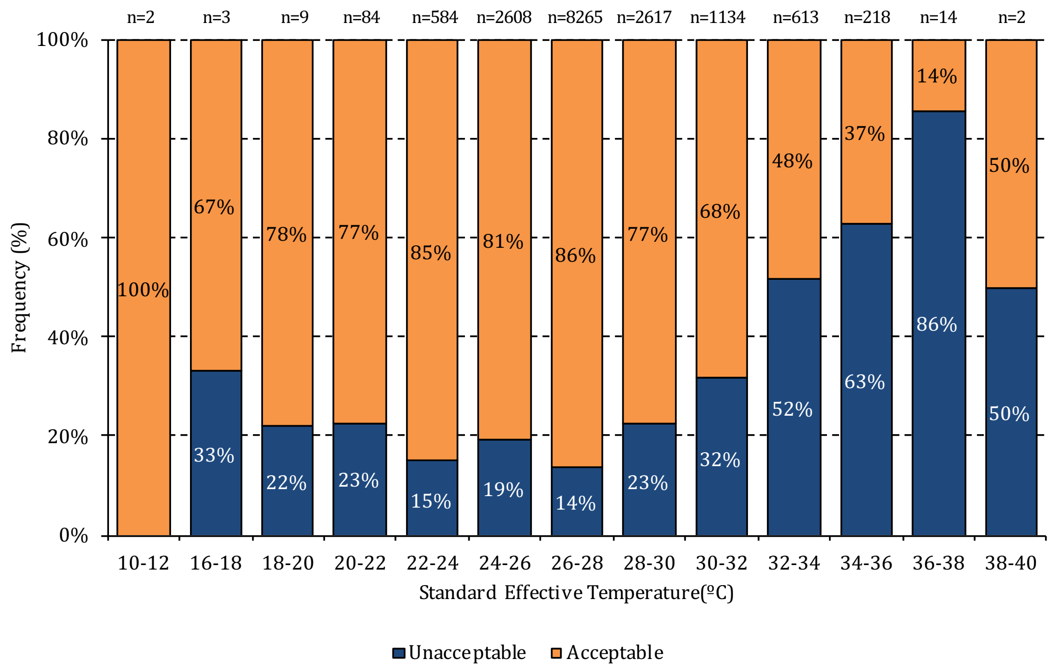


Figure 5-9. Thermal acceptability of the occupants according to the Standard Effective Temperature (SET*).

Complementary to Figures (5-8) and (5-9), Figure (5-10) presents the relationship between thermal sensation votes and those of thermal acceptability. It is observed that above than 80% of the population in the grouping referring to "Slightly cool", "Neutral", and "Slightly warm" were actually comfortable (i.e., "Acceptable" thermal conditions). These results reaffirm the following thermal sensation analyses, which adopted the interval between ±1 as "comfortable", while the "Unacceptable" thermal conditions were registered in a considerable percentage (~ 47% on average) in the ±2 and ±3 bars.

Among the thermal preference votes, such differences are significant. Figure (5-11) shows the frequency of occupants' votes obtained from the question: "At this time, would you prefer to be?". In the graph, the color blue represents the votes of occupants who would prefer the environment to be "cooler", orange represents the preference for a "warmer" environment, and the color green represents total satisfaction with the thermal environment, since "no change" is necessary. From the same figure, it is possible to conclude that there is a considerably greater tendency to desire for a warmer environment in air-conditioned buildings when compared to the preference of the occupants in buildings with mixed-mode systems, who desire in a significantly higher percentage a cooler environment – even the SET* groupings are the same. It is necessary to consider that some differences may be related to the external conditions of the buildings. However, in some intervals where the SET* is higher (i.e., 34ºC and beyond), there is still a preference for higher temperatures in mixed environments.

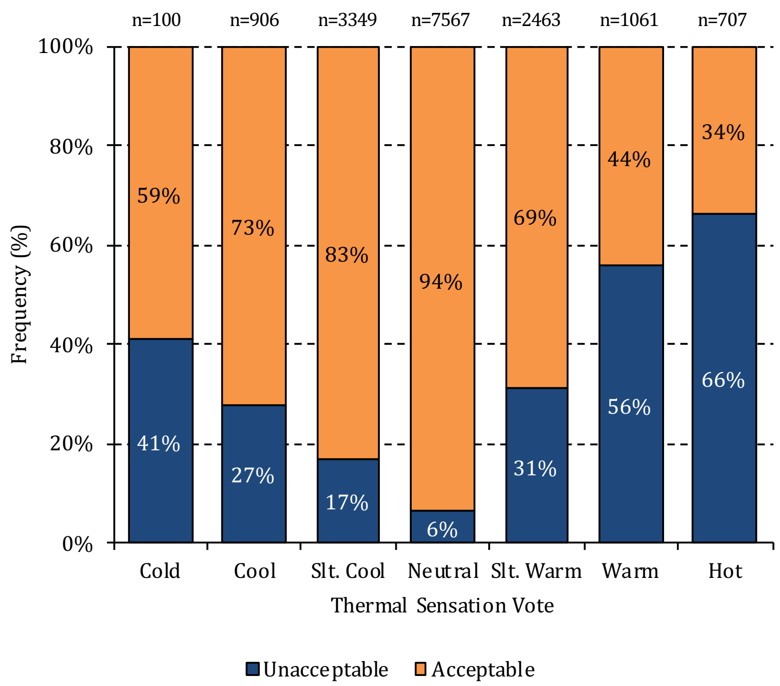


Figure 5-10. Thermal Acceptability (TSA) versus Thermal Sensation Votes (TSV).

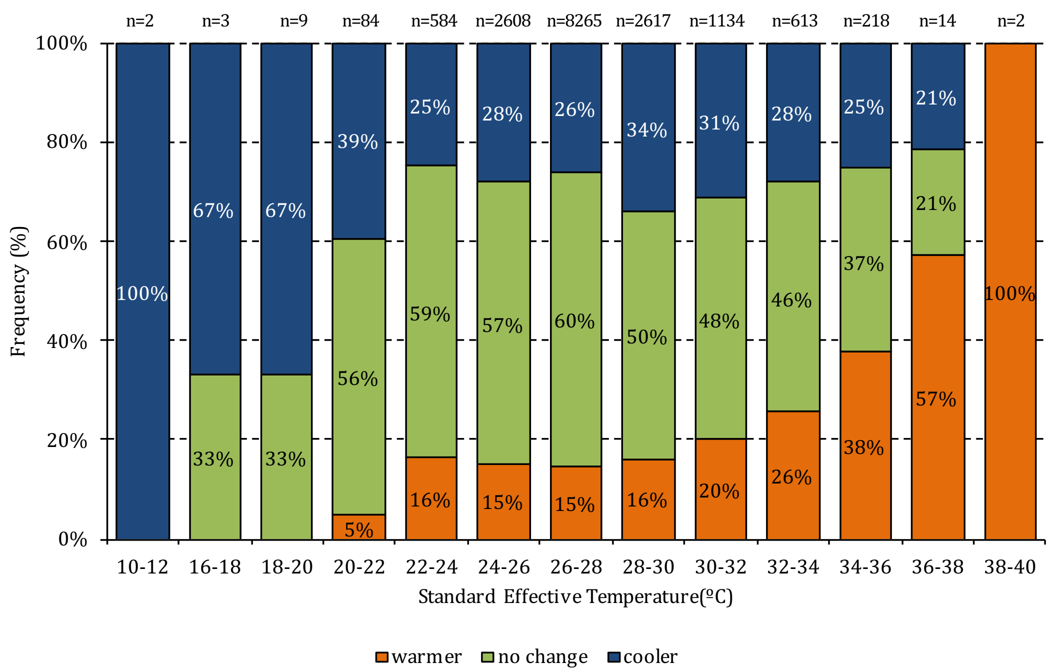


Figure 5-11. Frequency of thermal preference votes according to the Standard Effective Temperature (SET*).

5.2 ANTHROPOMETRIC INDICATORS ASSOCIATED WITH THERMAL COMFORT

For the analyses investigating the influence of anthropometric characteristics associated with thermal comfort, a database with a significantly larger sample volume was used when compared to the one used in one of our previous works [29]. Such procedure was adopted with the objective of expanding the size of the data sample, and to further diversity the anthropometric characteristics of the occupants, hence enabling more complete analyses. The building type or the environmental air-conditioning system in operation were ignored in this part of the results since they have little relevance concerning the main focus of the analyses.

Accordingly, the data used in the development of this block of analysis totaled 16,153 votes extracted from the ASHRAE Thermal Comfort Global Database II (as previously explained in Section 5-1-2). In the original database, there is a significant unbalance in terms of gender, which may have a negative impact on data analysis related to the anthropometric parameters. In this regard, Figure (5-12) shows the frequency of available votes according to the observed effective standard temperature (SET*). It is worth noting that the largest volume of data is concentrated between 24°C and 34°C, hence the sample is considered valid between 22°C and 36°C.

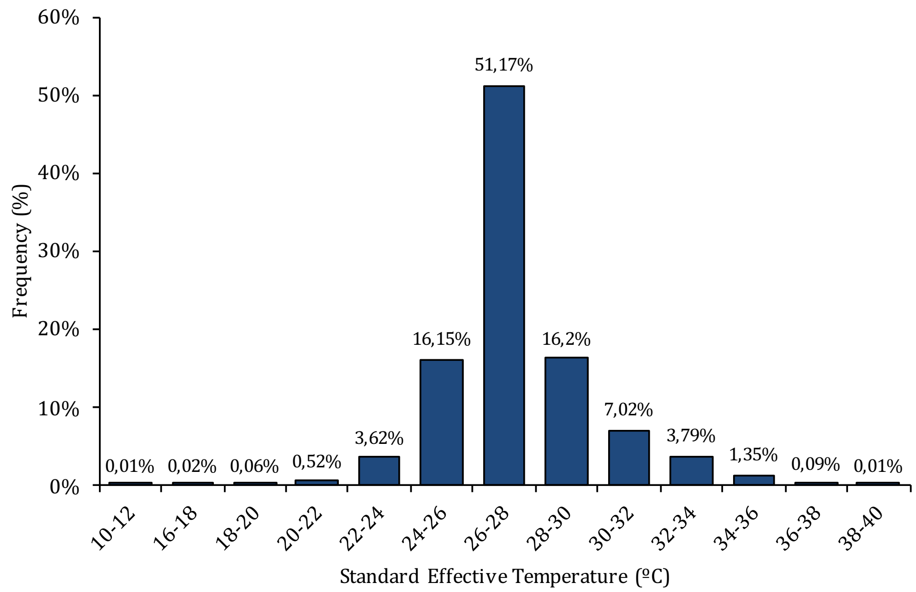


Figure 5-12. Frequency of the standard effective temperature values observed from the dataset (n=16,153).

Table (5-3) presents the statistical description of the individual characteristics of the considered data sample. Although some minimum and maximum values of the anthropometric characterization of occupants remain identical to those observed in Table (5-2) of Section (5-1-2). It can be seen that the means and standard deviations of individual factors in some cases present alteration, such as age, clothing, and body mass index. It is important to emphasize that the metabolic activity of both data samples is similar (between 0.7 clo and 2.1 clo).

Table 5-3. Statistical description of the individual occupant characteristics involved in the valid extracted data sample.

Parameter	Minimum	Maximum	Mean	St. Dev.*
Age (years)	17	75	36.27	9.51
Height (m)	1.20	2.03	1.67	0.09
Weight (kg)	33	130	66.55	12.89
Body Mass Index** (kg/m^2)	12.47	44.64	23.74	3.99
Clothing Insulation (clo)	0.09	2.10	0.71	0.16
Metabolism (Met)	0.70	2.10	1.09	0.16

*Standard Deviation
** Calculated for the purpose of this study

The distribution of the frequency of votes according to gender and age of the occupants, grouped at three-years intervals (Youth (<30], Adults (30 – 50], and Seniors (50+)), can be seen in Figure (5-13). Among the analyzed votes, 34.2% were female occupants and 65.8% male. Most of the analyzed data is located between 22 and 55 years of age. According to Figure (5-14), the Body Mass Index (BMI) of the participants is directly related to the age group, since the frequency of normal weight occupants is higher in youth and adults' groups (i.e., ranges (<30] and (30 – 50] years); besides, in group above than 50 years, the frequency obese people is significant compared to groups bellow 30 years.

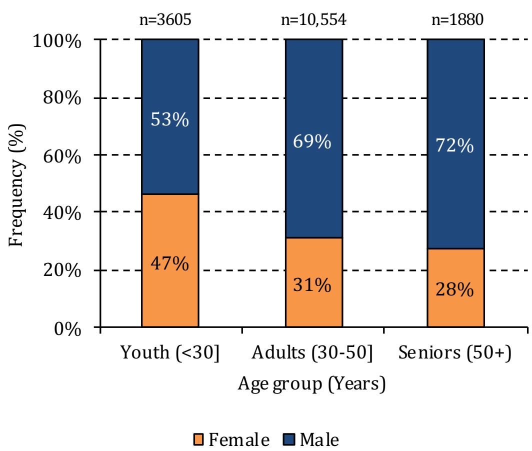


Figure 5-13. Characterization of participants according to gender and age group.

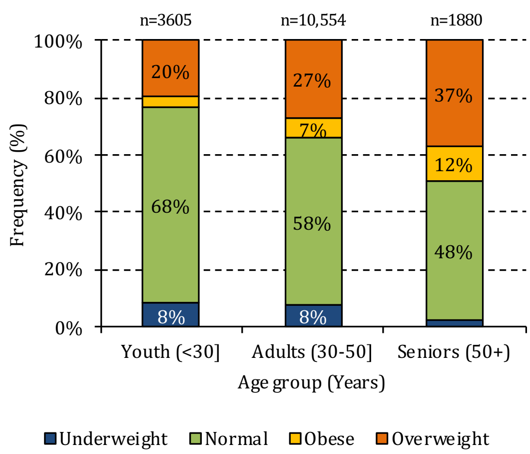


Figure 5-14. Characterization of participants according to the weight class and considered age group.

5.2.1 Gender

The first personal characteristic analyzed in this part of the results is gender. The total number of votes (~16,153) was divided between the male and female group; therefore, thermal sensation and preference votes were investigated based on SET* groupings. The votes of thermal acceptability of both groups were discarded as these data do not present significant differences when compared to the thermal sensation data of the comfort interval (±1), as discussed previously.

5.2.1.1 Thermal Sensation

The differences between the thermal sensation votes of the male and female groups are presented in Figures (5-15) and (5-16). From the analysis of the frequency of votes between both groups, it is possible to observe a considerable proportion of thermal discomfort votes in the male group, which reaches around 20% on average in the SET* data group range between 32ºC and 36ºC, and ~29% on average in the female group while considering the same SET* ranges. Still considering the male group, the discomfort caused by the cold is not significant and reached almost 12% in a cold situation. In the female voting group, a lower frequency of votes was observed on the scale of discomfort from cold, which is close to the frequency of discomfort from cold in some intervals (~15% on average) (cf. Figure 5-16).

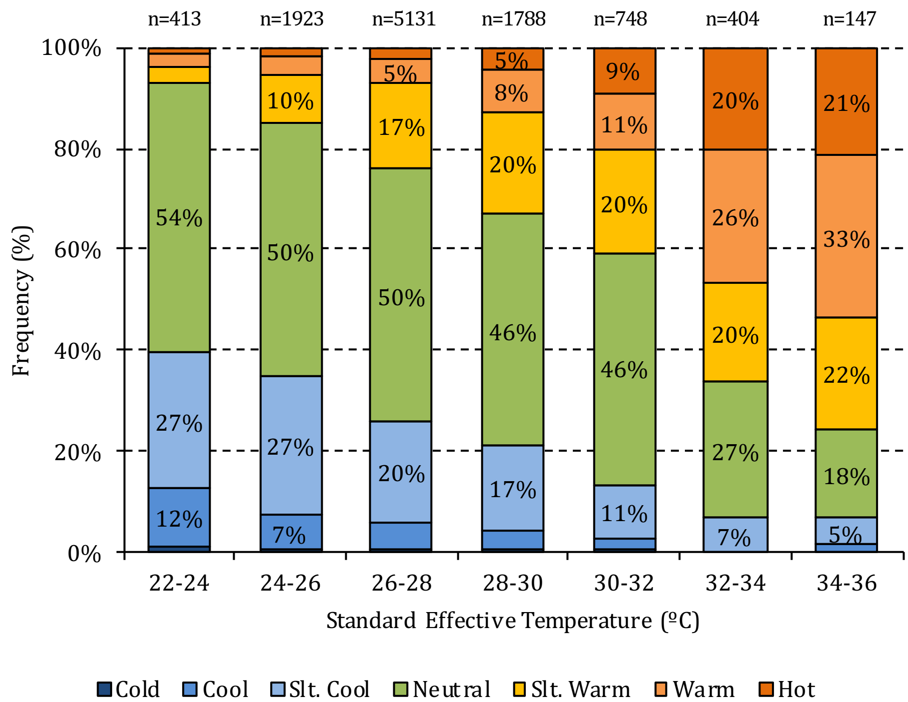


Figure 5-15. Frequency of votes on the thermal sensation scale according to SET* in the "male" occupants' group.

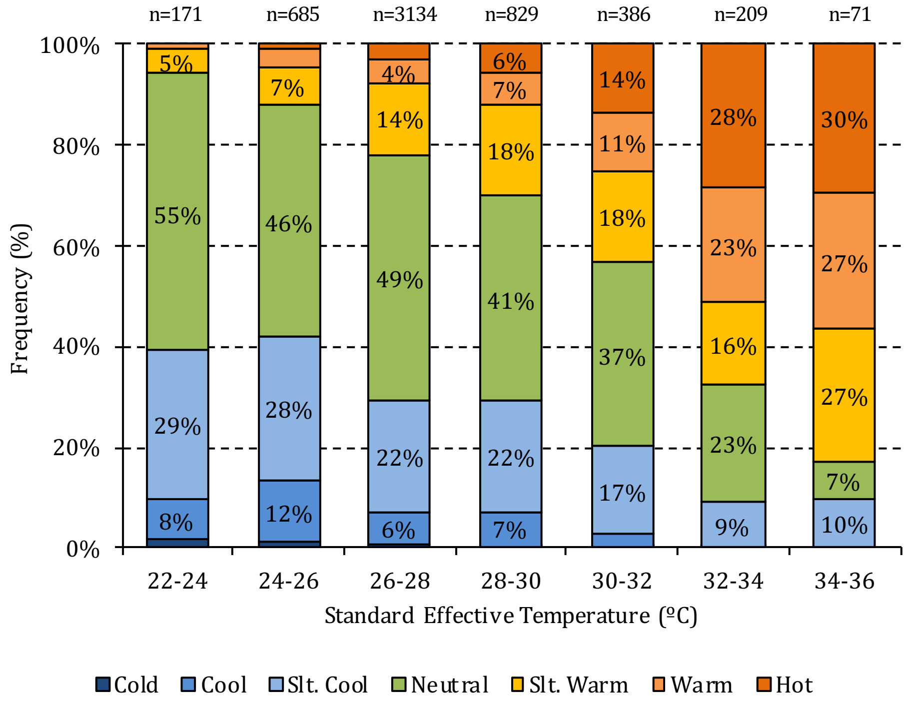


Figure 5-16. Frequency of votes on the thermal sensation scale according to SET* in the "female" occupants' group.

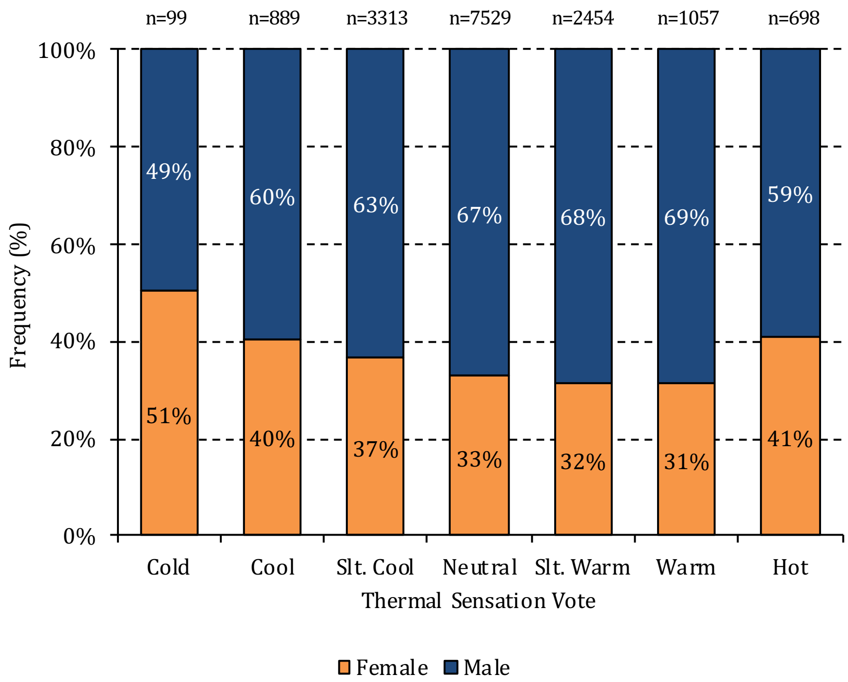


Figure 5-17. Frequency of thermal sensation votes between "males" and "females".

Although these differences in the ranges of discomfort from cold between males and females are minimal, Figure (5-17) shows that the vast majority of votes collected in Cold (-3) come from the female group, while Cool (-2) comes from the male group. Male votes appear at a higher frequency on the scale of heat discomfort (Warm (+2)). Otherwise, both groups are almost similar for the Hot (+3) scale.

5.2.1.2 Thermal Preference

The analysis of thermal preference votes pointed out even more significant differences between the two groups investigated. Among the male occupant votes (cf. Figure (5-18)), it can be observed that in none of the SET* situations more than 60% of preference was reached so that the current condition of the environment would not be changed. The main cause of discomfort in this group of occupants is, for the most part, heat; the proportion of votes for a cooler environment reached around 28% on average and the maximum was 36% when the effective standard temperature ranged between 28ºC and 30ºC. Also, in this group, the preference for a cooler environment could reach 21% in higher temperatures (i.e., between 34ºC and 36ºC); otherwise, it is always greater than 20% of the votes, since the initial value is considered (SET* of 22°C).

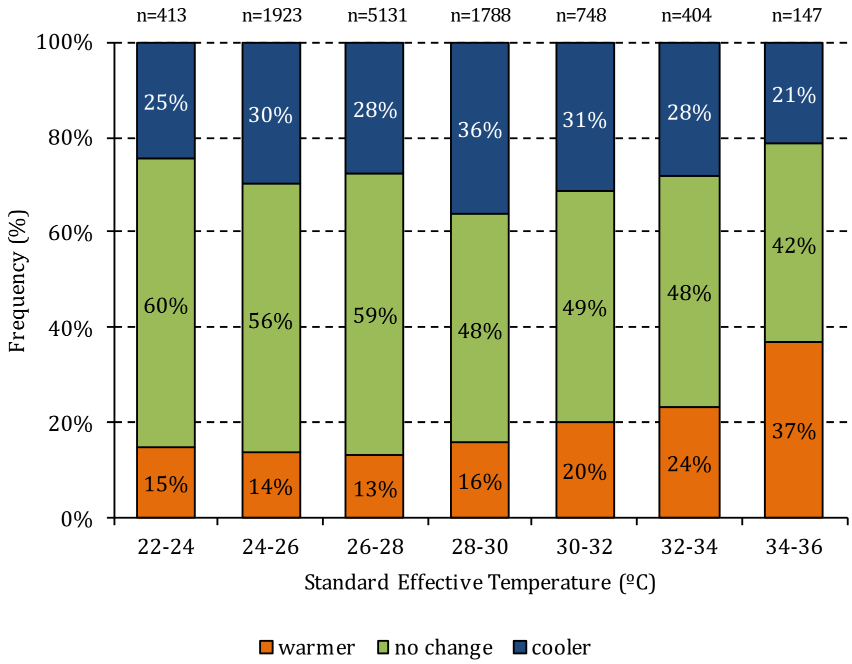


Figure 5-18. Thermal preference according to the SET* value scale in the "male" group.

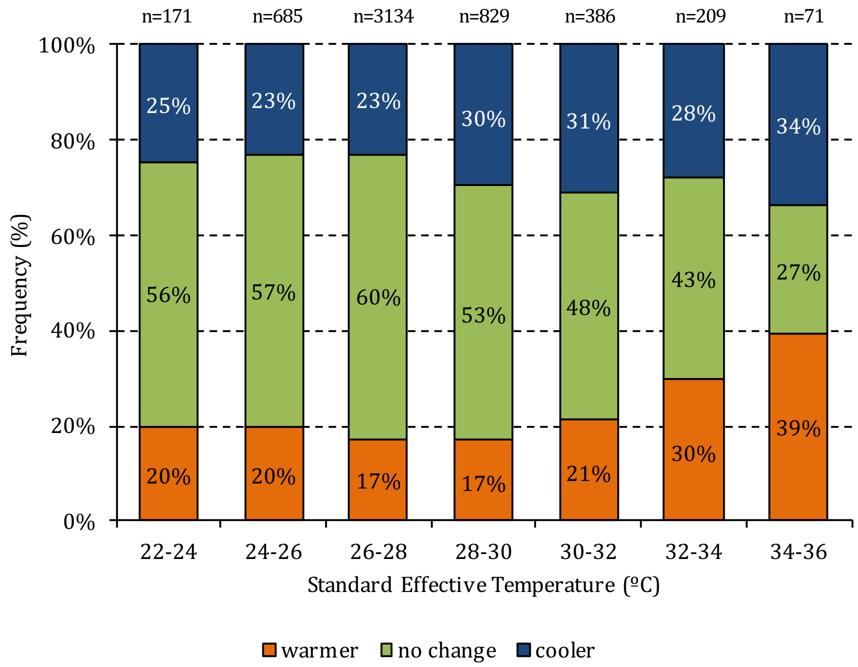


Figure 5-19. Thermal preference according to the SET* value scale in the female group.

In the female group (Figure (5-19)), thermal preference occurs in a higher percentage on the blue scale, represented by the "hottest" vote. The behavior of this group presents dispersions that can be linked to the sensitivity of women to external climate conditions, noting that low SET* values can be associated with the use of air-conditioning. If the data of high values grouping of SET* were occasionally analyzed, artificial conditioning was found to be in operation in 100% of cases, preferably in a "warmer" environment.

5.2.2 Age

5.2.2.1 Thermal Sensation

The second block of analysis of this item considered the influence of age on the perception of thermal comfort according to different age groups. As previously noted in Section (5-2), for purpose of data analysis and presentation, the votes were grouped considering three predetermined age groups: (1) Youth group: occupants under 30 years of age; (2) Adults groups: occupants between 30 and 50 years of age; and (3) Seniors group: occupants over 50 years of age. Analyzing thermal sensation votes together, little difference can be observed between the groups. However, it is possible to note that the frequency of heat discomfort votes is slightly higher in Figure (5-21), relative to the votes of the age Adults' group (while considering the population bars intensity). In all situations, it is observed that thermal comfort votes (light green bar, ±1) represent the majority in all groups, occurring in a higher percentage at temperatures between 22°C and 32°C (Figures (5-20), (5-21) and (5-22)).

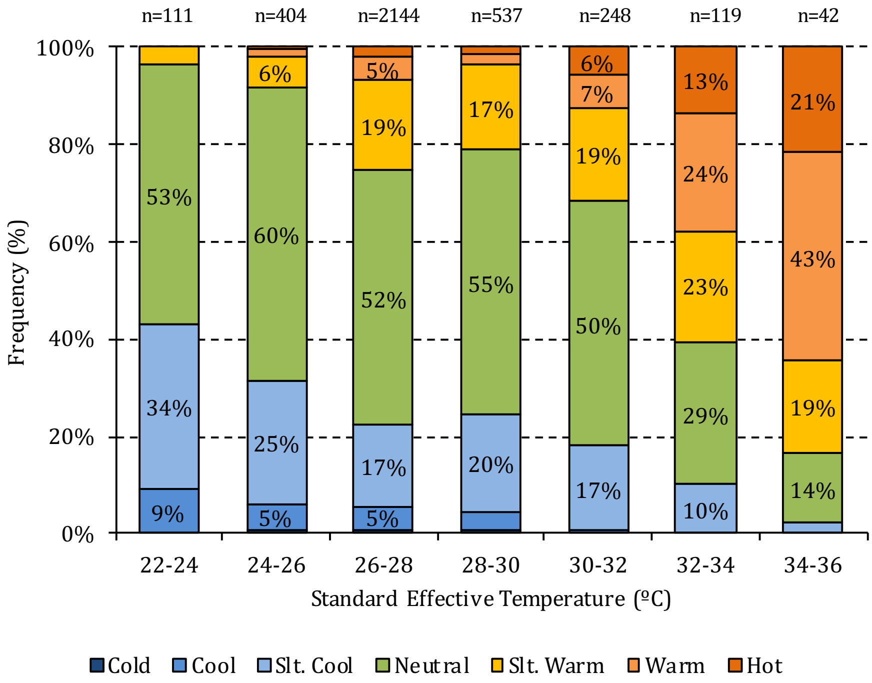


Figure 5-20. Thermal sensation of occupants of age group of Youth (Age < 30 years) according to the internal SET*.

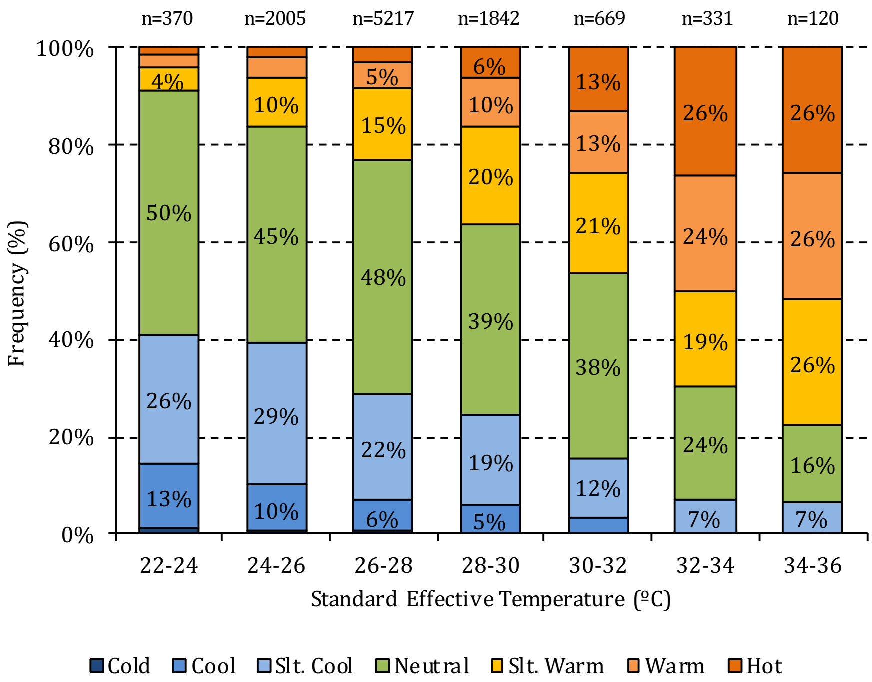


Figure 5-21. Thermal sensation of occupants of age group of Adults (30 ≤ Age <50 years) according to the internal SET*.

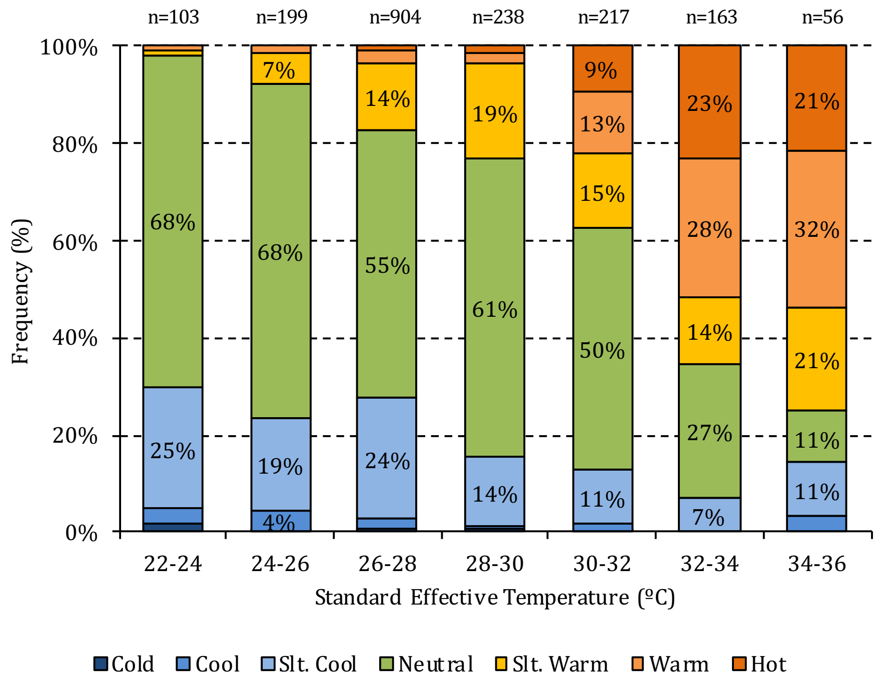


Figure 5-22. Thermal sensation of occupants of age group of Seniors (Age ≥ 50 years) according to the internal SET*.

5.2.2.2 Thermal Preference

The thermal preference analyses of these groups presented similar behavior to that observed in the thermal sensation votes, with significant differences only among the occupants of the age group of Youth compared to Adults and Seniors. According to Figures (5-23), (5-24) and (5-25), the age group of Youth has a predominance of votes on the "warmer" scale, Adults' group has a predominance on "cooler" scale, while Seniors' groups have a balanced distribution between the number of votes for a "warmer" and "cooler" on average, regarding the distribution of the population according to the SET* ranges.

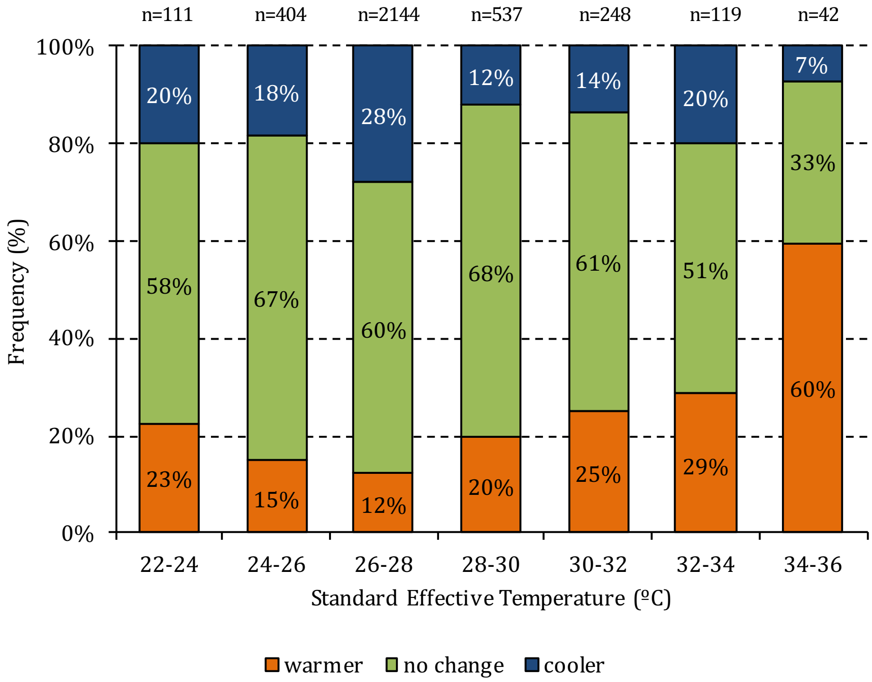


Figure 5-23. Thermal preference votes according to SET* values in age Youth's group.

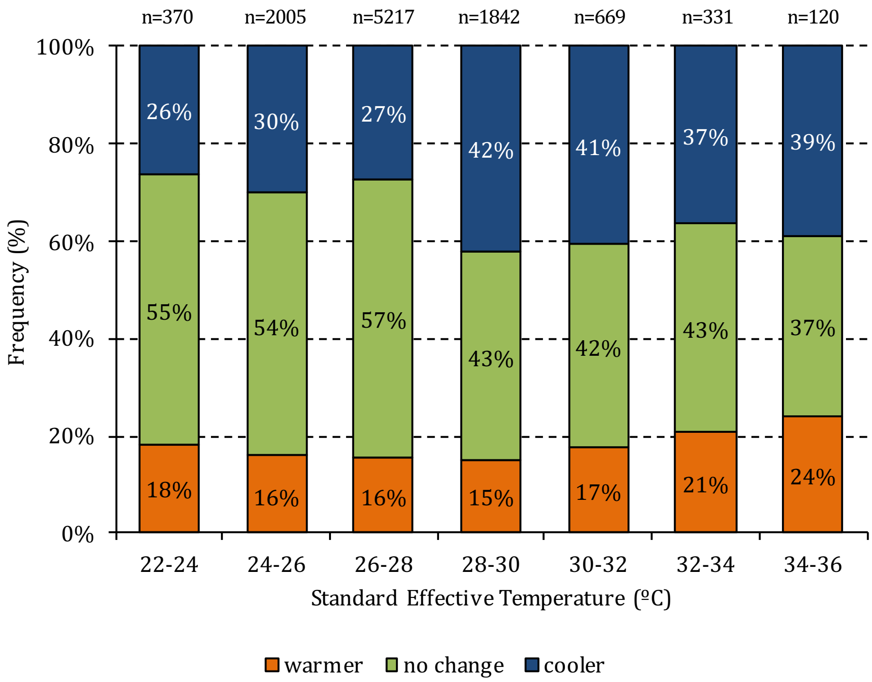


Figure 5-24. Thermal preference votes according to SET* values in age Adults' group.

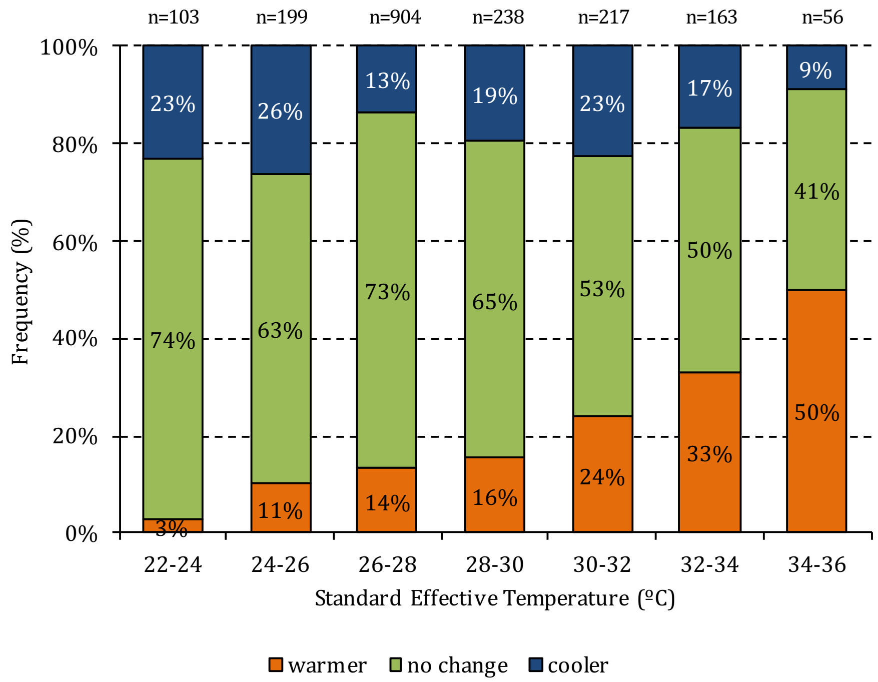


Figure 5-25. Thermal preference votes according to SET* values in age Seniors' group.

5.2.3 Weight

Among the personal characteristics analyzed in this study, the difference related to the weight of the occupants was considered and grouped according to the Body Mass Index (BMI), recognized by the WHO[10] as the main reference for the classification of different weight ranges. Thus, the four main weight classes of this index were used, including the ones related to the "underweight" and "obese" data sample (cf. Figure (5-6) in Section (5-1-2)), which although too small in comparison to the others, was used only for visual analysis and comparisons in general.

5.2.3.1 Thermal Sensation

Figures (5-26), (5-27), (5-28), and (5-29) show the effects of different weight classes on thermal sensation votes, analyzed based on SET* values that resulted in sufficient sample size for comparisons (in this case, between 22°C and 36°C). No significant difference was observed in the second and third figures (disregarding the visual analysis of the "underweight" and "obese" groups), although the frequency of heat discomfort votes shows a slight increase as the occupants' body mass index moves towards overweight. In

[10] World Health Organization: http://www.who.int/gho/ncd/risk_factors/bmi_text/en/

the "obese" group of occupants, it is only noticed that the frequency of votes of discomfort by cold is higher than others (between 22ºC and 24ºC).

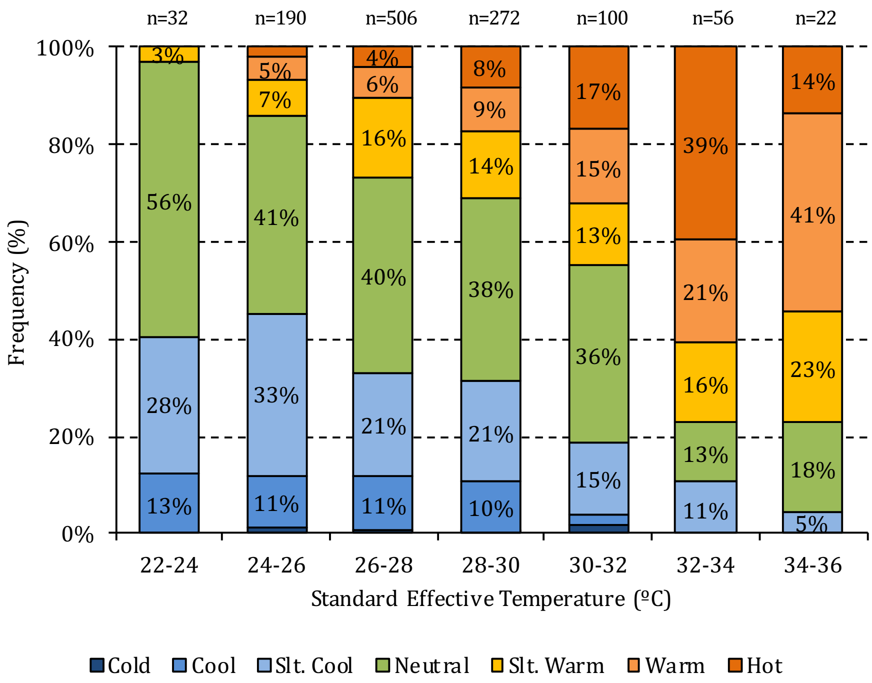


Figure 5-26. Thermal sensation votes of the occupants classified as "Underweight".

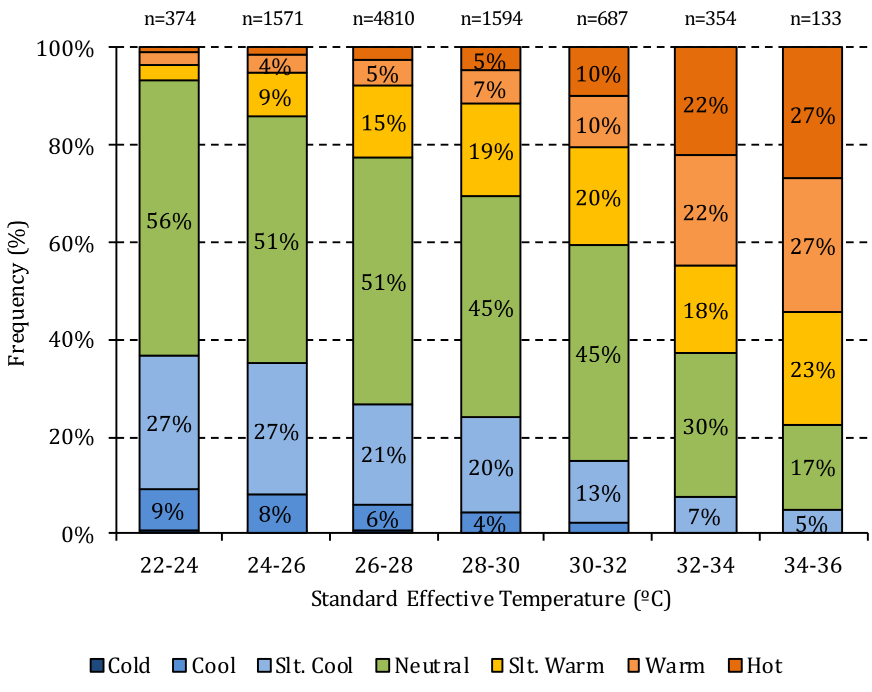


Figure 5-27. Thermal Sensation Votes of the occupants classified with the "Normal" weight.

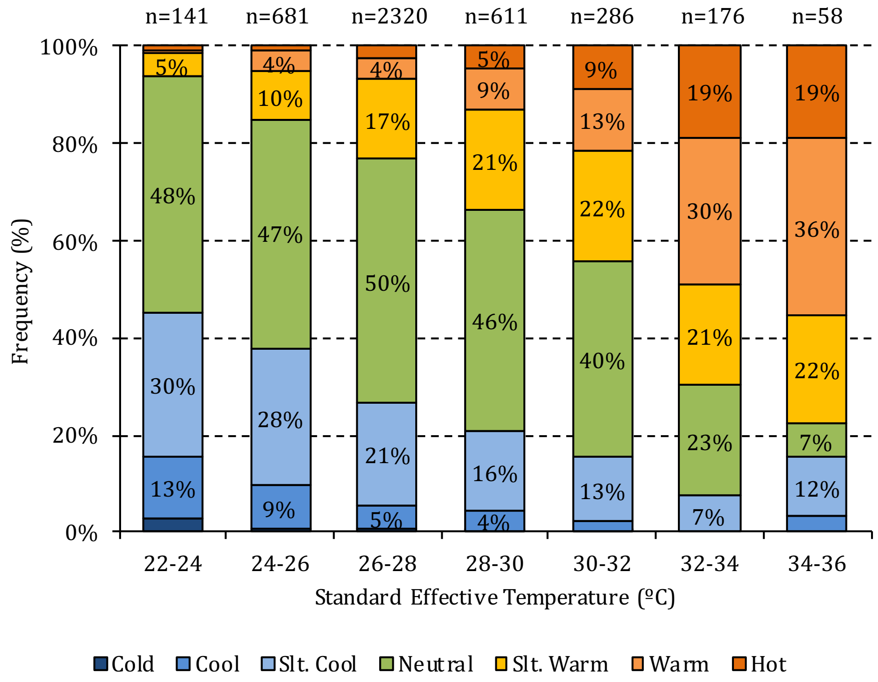


Figure 5-28. Thermal Sensation Votes of the occupants in the "Overweight" classification.

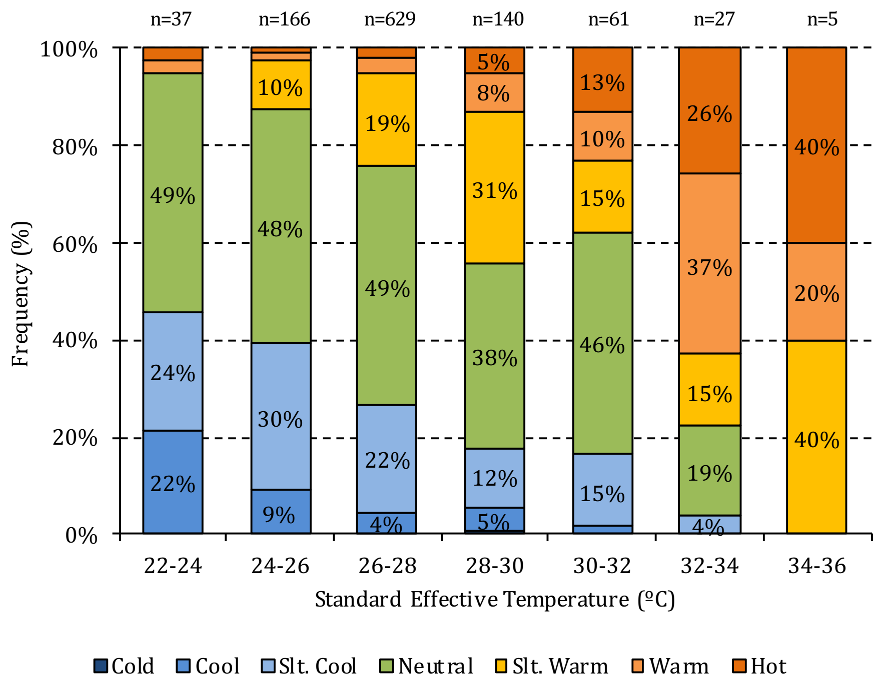


Figure 5-29. Thermal Sensation Votes of the occupants classified as "Obese".

5.2.3.2 Thermal Preference

Although the analyses of thermal sensation votes did not show any difference according to the four BMI classifications, when thermal preference votes were measured, the differences between groups are quite significant. Starting with the group of occupants with normal weight (cf. Figure (5-31)), which proved to be the one with the highest proportionality between the "hottest" and "coolest" votes. From Figure (5-32), it can be seen that the frequency of votes of a "cooler" environment begins to increase and becoming higher in the group of occupants classified as obese (Figure (5-33)). It is also noted that the highest number of votes who prefer "not to change" the current condition of the environment in the normal-weight occupant group occurs in the 26ºC to 28ºC range. This same condition remains in the "overweight" group of occupants. It should also be noted that although the data sample is small in the "underweight" and "obese" groups, the predominant preferences are for a "cooler" in both "underweight" and "obese" groups (cf. Figures (5-30) and (5-33)).

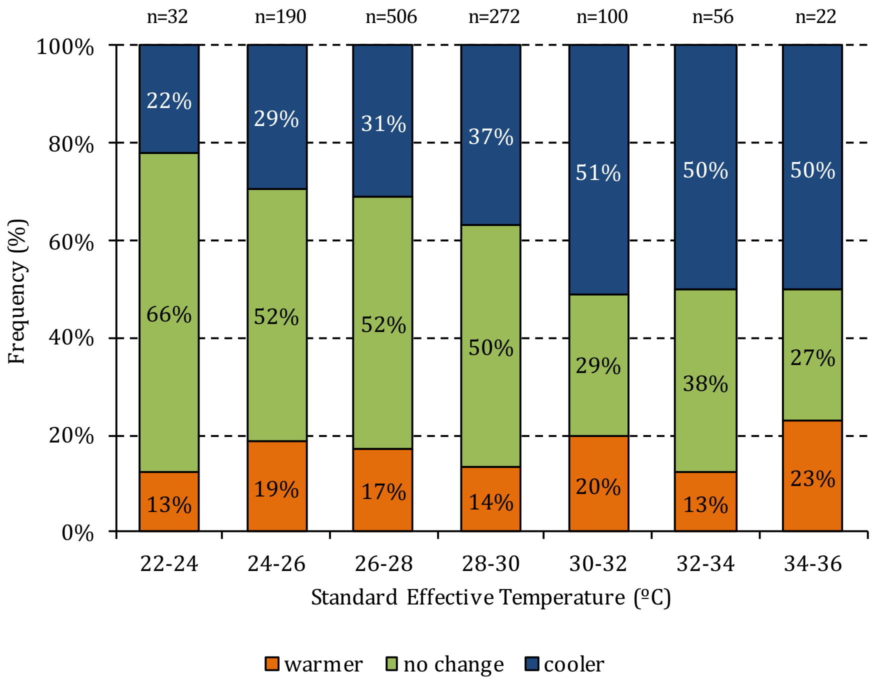


Figure 5-30. Thermal preference according to SET* of the "Underweight" occupants.

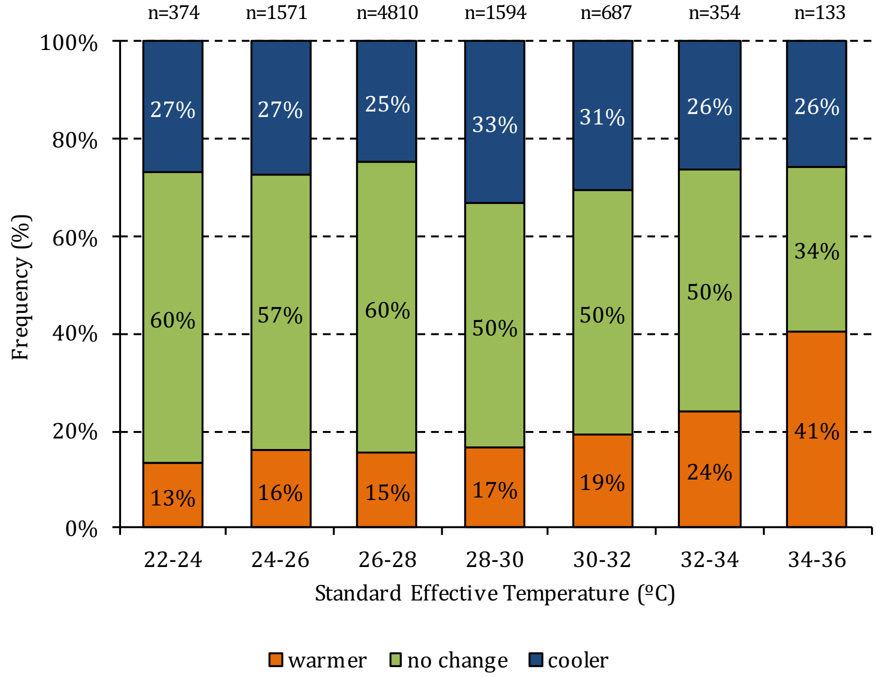


Figure 5-31. Thermal preference according to SET* of the occupants with "Normal" weight.

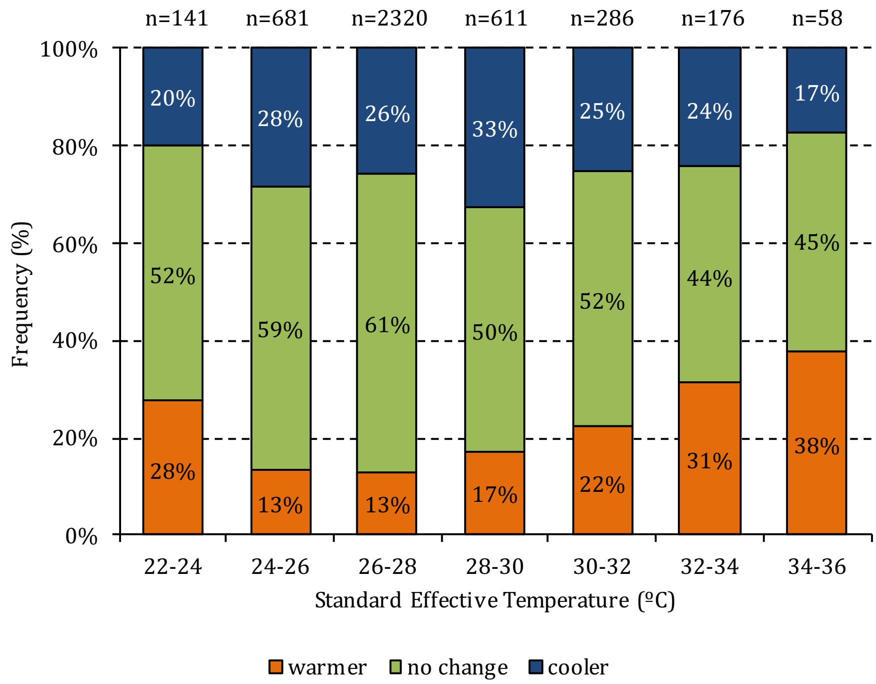


Figure 5-32. Thermal preference according to SET* of the "Overweight" occupants.

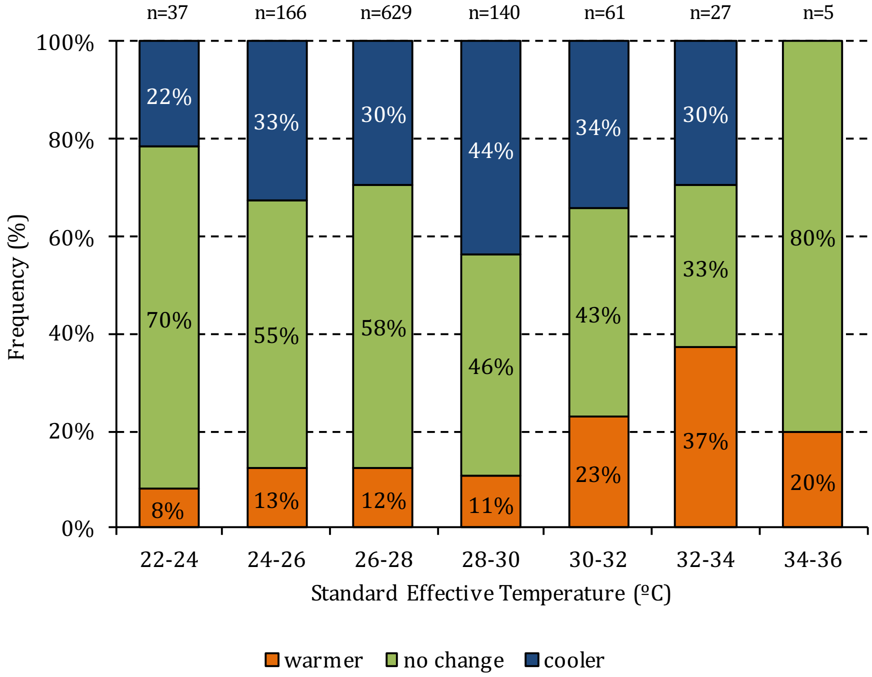


Figure 5-33. Thermal preference according to SET* of the "Obese" occupants.

5.3 RESULTS: LOGIT MODEL ESTIMATION

5.3.1 Features' Selection

In multiple regression models, it is necessary to determine a subset of independent variables, which best explains the response variable, i.e., among all the available explanatory variables, we must find a subset of important variables for the model. Building a model that includes only a subset of explanatory variables involves two conflicting goals:

1. Obtaining as much information through a model with as many independent variables as possible;
2. Decreasing the estimation variance and the cost of collection by using a model with as few variables as possible.

Thus, striking a balance between these two trade-offs is of interest. To do this, we use a technique, called *variable selection*. The input data of this process is constituted by the initial set of variables that form the representation space and the set of learning data of the studied problem. The variable selection process can be described as follows:

- From the initial set of variables, the selection process determines a subset of variables that it considers most relevant;
- The subset is then subjected to an evaluation procedure. This procedure allows the performance and relevance of the subset to be evaluated;

- Depending on the result of the evaluation procedure, a stopping criterion determines whether the subset of variables can be subjected to the learning phase. If this is the case, the selection process is stopped, otherwise, another subset of variables is generated.

The main concerns and implications of variable selection are diverse:

- The selection of variables will first allow us to determine which variables are considered relevant;
- The selection of variables allows us to remove the noise generated by certain variables;
- Redundant variables are also removed.
- The size of the representation space is thus reduced. The cost of calculating the learning phase is also reduced.

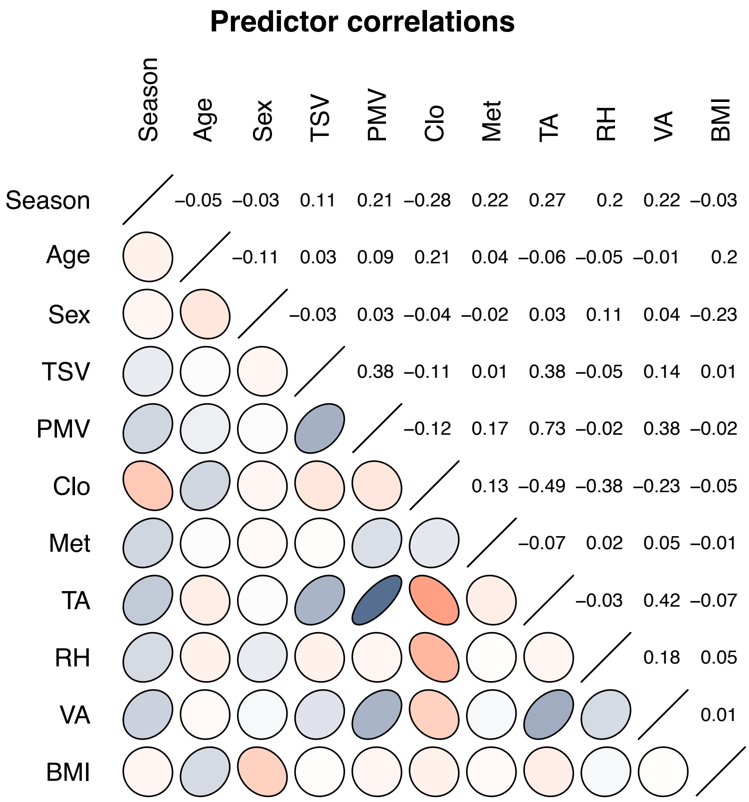


Figure 5-34. Correlation matrix for the selected variables, each cell presents the Person's coefficient.

In this context, we performed a correlation analysis to eliminate the highly correlated variables from further analysis. Figure (5-34) depicts the correlation matrix for the continuous independent variables selected. It is observed that the clothing insulation is highly inversely correlated with the air temperature (compared to other variables), and the same for the air temperature, which is considerably correlated with the air velocity. Therefore, we continue our analysis with the following independent variables: Season, Age, Gender, ASHRAE sensation votes (TSV), PMV, Clo, Met, TA, RH, VA, and BMI.

5.3.2 Models 1-3: Thermal Acceptability

The first models developed in this study are binary logistic regression model that use the anthropometric parameters to predict the probability that an individual finds his/her actual thermal sensation "Acceptable" (TSA = 1) or "Unacceptable" (TSA = 0), using the data from ASHRAE Thermal Comfort Global Database II field studies.

After the feature selection process, Table (5-4) provides details about the parameter estimates for the Acceptability models. As previously noted, the parameters of this model are estimated from environmental and personal/anthropometric variables and are estimated separately according to the building cooling strategy. This table gives more information about the variable's significance and their contributions to the model. It is observed that most of the variables are statistically significant in all models, for example, in HVAC buildings, Season, Sex, Met, TA, and RH are the most significant while the ASH sensation votes effect is a bit smaller compared to the rest of variables (p-values<0.05); in MM buildings, more variables were included such as Age, Clo, and VA; while in NV Buildings, the personal/anthropometric parameters, such as BMI, Met, Clo, Sex have significant contributions in the model.

Given that our model's final objective is to classify new instances into one of the two categories, whether the occupant will have an "Acceptable" sensation in a given environment or not based on a set of environmental and personal/anthropometric variables. We want the model to give high scores to positive instances (1: Acceptable sensation) and low scores (0: Unacceptable sensation) otherwise. Ideally, in a double density plot, the distribution of scores to be separated, and the scores of the negative instances to be on the left and the scores of the positive instances to be on the right. However, in our case, both distributions are slightly skewed to the right. Not only is the predicted probability for the negative outcomes low, but the probability for the positive outcomes is also lower than it should be.

The reason for this is because all the datasets only consist of 13.3% of negative instances (Unacceptable sensation) for HVAC buildings, 22.8% in MM buildings while in NV buildings, the percentage of 16.5% of negative instances are about 16.5%. Thus, our predicted scores sort of getting pulled towards a lower number because of the majority of the data being positive instances.

Our *skewed* double density plot, however, can tell us that the *Accuracy* will not be a suitable measurement for this model. Since the prediction of a logistic regression model is a probability, in order to use it as a classifier, we'll have to choose a cutoff (threshold) value. Where scores above this value will be classified as positive, those below as negative. For this, we will use another measurement (instead of Accuracy) allowing to decide which cutoff value to choose, i.e., the ROC curve.

One of the interesting aspects of logistic regression, in general, is how the change in one factor or explanatory variable can affect the dependent variable. This role is played by looking at the *Odds Ratio* (cf. Table (5-4)).

Table 5-4. Regression summary and the related Odds Ratio of including variables in the Acceptability Models 1, 2 and 3.

Parameter	**Model 1 (HVAC buildings)**		**Model 2 (MM buildings)**		**Model 3 (NV buildings)**	
	Estimate	*Odds ratio*	*Estimate*	*Odds ratio*	*Estimate*	*Odds ratio*
β_0 (Intercept)	-1.51****	NA	-1.89****	NA	-0.017****	NA
β_1 (SEAS (Summer))	4.70 (0.41) ****	56.97	4.43 (0.28) ****	83.11	4.37 (0.51) ****	31.23
β_2 (Age)	0.001 (0.005)	NA	0.015(0.003) ****	1.016	-0.005 (0.004)	NA
β_3 (Sex (Female))	4.31 (0.4) ****	41.37	5.11 (0.28) ****	148.36	5.80 (0.50) ****	102.65
β_4 (ASH-Votes)	-0.092 (0.04) *	0.86	-0.25 (0.02) ****	0.76	-0.42 (0.04) ****	0.65
β_5 (Clo)	-0.40 (0.27)	NA	-2.07 (0.13) ****	0.18	-2.94 (0.18) ****	0.076
β_6 (Met)	-0.90 (0.21) ****	0.52	0.041 (0.18)	NA	-0.71 (0.24) **	0.63
β_7 (TA)	-0.37 (0.01) ****	0.73	-0.28(0.009) ****	0.78	-0.22 (0.01) ****	0.83
β_8 (RH)	0.037 (0.004) ****	1.024	-0.004 (0.002) *	1.00	0.006 (0.003) *	1.01
β_9 (VA)	0.043 (0.3)	NA	1.24 (0.13) ****	2.87	-0.10 (0.2)	NA
β_{10} (BMI)	-0.02 (0.01)	NA	0.001 (0.006)	NA	-0.02 (0.01) *	1.00
	N = 3445 Subjects		N = 9228 Subjects		N = 3366 Subjects	

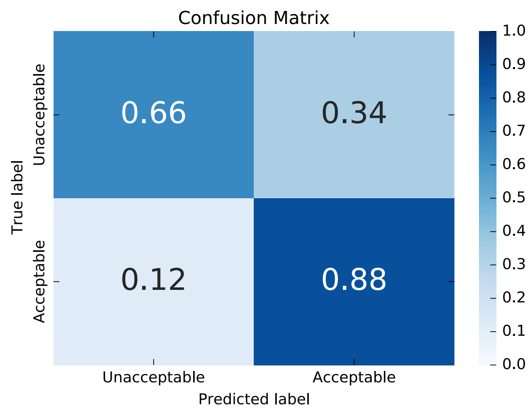
**** p-value<0.0001
*** p-value < 0.001
** p-value < 0.01
* p-value < 0.1
Std. deviation is shown in parenthesis; 95% Confidence Intervals

For HVAC buildings, most of β coefficients are clearly distinct from zero ($p<0.0001$) (cf. Table (5-4)). Estimates for β_1 (attached to summer season) are positive indicating the expectation that the HVAC environment, with the change from summer to winter, has an increased chance of moving from "Unacceptable" sensation to "Acceptable" in the order of 56.97 times, in terms of Odds Ratio. Similarly, estimates for β_3 (attached to Sex attribute) are positive and reflecting that the expectation for an occupant could find "Acceptable" sensation is in the order of 4.31 times when the change is from female to male. Estimates for the β_8 coefficient (attached to the RH predictor) is positive, reflecting the expectation that by increasing one percentage in RH, it will be perceived as more acceptable by 1.042 in HVAC buildings, whereas, for β_7 coefficient (attached to TA) which is negative, the expectations are by increasing TA by one degree has the chance to decrease the "Acceptable" sensation by 0.73 times. For β_6 coefficient (attached to Met variable), is negative and shows that by increasing by one unit in Met, the TSA has the chance to decrease by 0.52 times. Finally, estimates for β_4 (attached to ASHRAE sensation votes) estimates are all substantially smaller (p-value<0.05), which indicates that the calculation of TSA (Acceptability votes) are less sensitive (even though the relationship is still clearly present, and operates in the opposite directions. In terms of Odds Ration, the probability that an occupant will find a given sensation "Acceptable" decreases by 0.86 times.

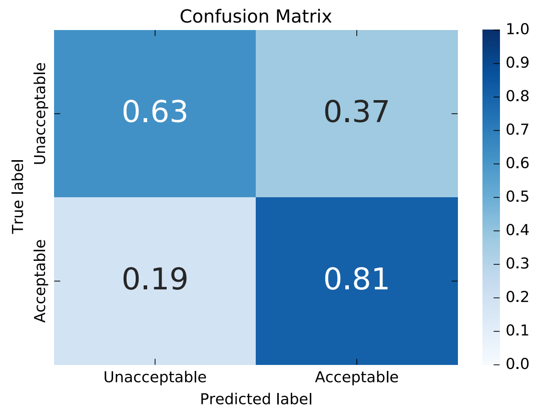
For MM buildings, it is clearly apparent that almost all the variables contribute significantly to the model, except RH (p-value<0.05). It is noticed that estimates for β_1 and β_3 coefficients (attached to Season and Sex attributes) are positive, which means that the change from summer to winter has an increased chance that an occupant will find "Acceptable" sensation increases in the order of 83.11 times for the season and by order of 148.36 times when Sex has to change from female to male. Estimates for β_2 (attached to Age variable) are positive, reflecting that the expectations that an occupant find "Acceptable" sensation in such environments will increase by increasing Age by one unit (a year) by 1.016 times. While the estimates for β_{10} (attached to VA variable) are positive as well, and indicating that the expectations for occupants with increased VA by one unit, has the effect to increase the occupant sensation from "Unacceptable" condition to "Acceptable" in the order of 2.87 times. While in NV buildings, β_1, β_3, β_4, β_5, and β_7 coefficients are also clearly distinct from zero (p<0.0001), however, the estimates for β_6, β_8, and β_{10} (attached to Met, TA, and BMI resp.) are only distinct from zero at the p-value<0.01 for Met and p-value<0.05 for RH and BMI thresholds indicating a reduced influence of metabolic rate acceptability sensation for warm sensations. The estimates for β_8 (attached to RH variable) are positive indicating that the probability that an occupant will find an "Acceptable" sensation increases by 1.01 times when RH increases by one unit. However, for β_{10} coefficient (attached to BMI attribute), the estimates are negative which means that the chance that people with high weight to find "Acceptable" sensation decreases by 1.00 times.

On the other hand, with the adjusted models, it was used to evaluate the model accuracy on a test-set (which represents 30% of the dataset in our case). It was verified that, through the confusion matrices (cf. Figure (5-35)), that Model 1 was accurate by

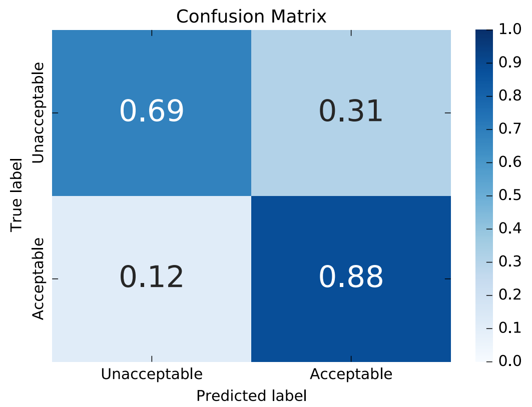
77%, Model 2 by 72%, while the accuracy of Model 3 was about 79%. Also, these confusion matrices show how the model behaves in predicting data.



(a) Model-1



(b) Model-2



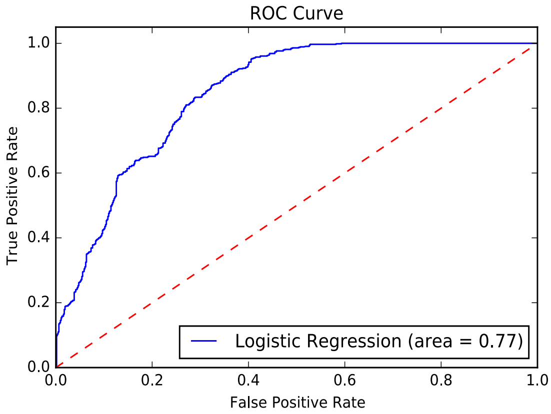
(c) Model-3

Figure 5-35. Confusion matrices for Model 1 ((a) HVAC buildings), Model 2 ((b) MM buildings) and Model 3 ((c) NV buildings).

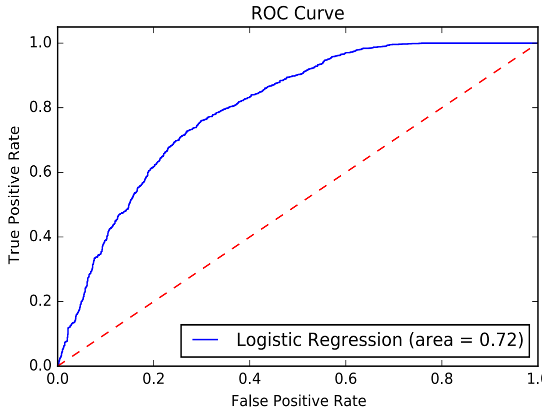
Table 5-5. Relative values of performance metrics for Models 1-3.

		Performance Metrics		
		Precision	Recall	F1-Score
Model 1	Acceptable	0.72	0.66	0.79
(HVAC buildings)	Unacceptable	0.84	0.88	0.74
Model 2	Acceptable	0.69	0.81	0.74
(MM buildings)	Unacceptable	0.77	0.63	0.69
Model 3	Acceptable	0.74	0.88	0.81
(NV buildings)	Unacceptable	0.86	0.69	0.77

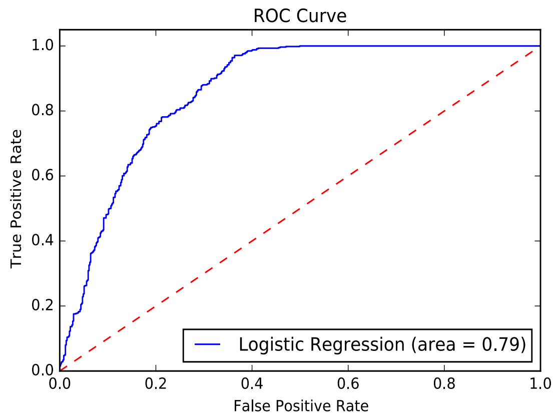
Besides the confusion matrix, the ROC curve could be a proper way to interpret the prediction accuracy. The ROC curves for the three models are plotted in Figure (5-36). As shown in Figure (5-36), the area under the curve (AUC) means the possibility of ranking positive instances higher than negative instances. The higher AUC is, the better model is fitted. AUC is the highest for Model-3 (HVAC buildings), and that is the lowest for Model-2 (NV buildings). The logistic regression model is a sensitive classifier to detect whether people have "acceptable" sensations or not.



(a) Model-1.



(b) Model-2.



(c) Model-3.

Figure 5-36. ROC curves for Acceptability models for (a) HVAC buildings; (b) Mixed-Mode buildings; (c) Naturally-Ventilated buildings.

5.3.3 Models 4-6: Thermal Sensation

Models 4-6 are ordinal logistic regressions that use the environmental and personal/ anthropometric variables to predict the probability of observing certain individual ASHRAE sensation votes ("Uncomfortably Cold", TSV=-1; "Comfortable", TSV=0; "Uncomfortably Hot", TSV=1), using the data from ASHRAE Thermal Comfort Global Database II of field studies.

The choice of such a model involves a compromise between the complexity of the model, which in this case is observed by the number of variables involved, and by the observed errors (in this case, the deviance). The method used for the model's selection is the *Stepwise-backward*. Thus, the analysis starts with the total of the regressors and after fitting the model, the AIC (Akaike Information Criterion) index is observed. One variable is then removed, the one with the highest p-value, and the model is adjusted again. If the AIC observed in the second situation is lower than the AIC observed in the previous step, the variable that was excluded should remain excluded. Otherwise, the variable is added back to the model and the process is terminated. The process continues until there are no more variables to be excluded or when the AIC no longer improves.

Table (5-6) provides details about the parameters estimates for models 4-6 and their related Odds ratio. The table reveals that most of β coefficients for Models 4-6 are positive and distinct from zero, with a p-value<0.0001. However, β_2 and β_8 estimates for Models 5 and 6 are substantially smaller, indicating that distributions of Age and VA are less sensitive compared to the other included variables (though the relationship is still clearly present and operates in the same directions for Model 4 and the opposite direction for Model 6).

Table 5-6. Regression summary and the related Odds Ratio of including variables in the Acceptability Models 4, 5 and 6.

Parameter	Model 4 (HVAC buildings)		Model 5 (MM buildings)		Model 6 (NV buildings)	
	Estimate	*Odds ratio*	*Estimate*	*Odds ratio*	*Estimate*	*Odds ratio*
Intercept_1	9.63 (0.95) ****	NA	8.25 (0.47) ****	NA	3.84 (0.80)	NA
Intercept_2	14.07 (0.99) ****	NA	11.41 (0.48) ****	NA	7.85 (0.81)	NA
β_1 (SEAS (Summer))	-0.24 (0.1) *	0.78	0.04 (0.06)	NA	0.86 (0.11) ****	2.31
β_2 (Age)	0.014 (0.005) **	1.014	0.007 (0.003) *	1.007	0.014 (0.004) **	1.01
β_3 (Sex (Female))	-0.49 (0.1) ****	0.61	-0.05 (0.06)	NA	0.076 (0.09)	NA
β_4 (Clo)	0.14 (0.33)	NA	0.85 (0.13) ****	2.30	0.34 (0.21)	NA
β_5 (Met)	0.93 (0.27) ***	2.52	0.87 (0.19) ****	2.41	-0.086 (0.27)	NA
β_6 (TA)	0.39 (0.03) ****	1.47	0.24 (0.01) ****	1.26	0.26 (0.02) ****	1.27
β_7 (RH)	0.003 (0.005)	NA	0.016 (0.002) ****	1.02	-0.022 (0.003) ****	0.96
β_8 (VA)	-1.03 (0.35) **	0.36	-0.15 (0.12)	NA	-0.70 (0.22) **	0.54
β_9 (BMI)	0.0012 (0.013)	NA	0.022 (0.006) **	1.02	-0.054 (0.012) ****	0.95
	N = 3445 Subjects		N = 9228 Subjects		N = 3366 Subjects	

**** p-value<0.0001
*** p-value < 0.001
** p-value < 0.01
* p-value < 0.1
Std. deviation is shown in parenthesis; 95% Confidence Interval

It is worth noting that more personal/anthropometric variables (such as BMI and Clo) are considered in Model 5. However, estimates for β_9 (attached to BMI attribute) are more significant in the case of NV buildings compared to MM buildings, similarly for environmental variables (TA, RH, and VA), which can be explained that in NV buildings, thermal sensation depends more on these variables than the personal variables (Met or Clo).

From Table (5-6), Models 4-7 can be formulated as:

a) **Model 4 (HVAC Buildings):**

$$\hat{\pi}_2 = \frac{e^{-(9.63-0.24*SEAS+0.014*Age-0.49*Sex+0.93*Met+0.39*TA-1.03*VA)}}{1+e^{-(9.63-0.24*SEAS+0.014*Age-0.49*Sex+0.93*Met+0.39*TA-1.03*VA)}} \tag{5-1}$$

$$\hat{\pi}_3 = \frac{e^{-(14.07-0.24*SEAS+0.014*Age-0.49*Sex+0.93*Met+0.39*TA-1.03*VA)}}{1+e^{-(14.07-0.24*SEAS+0.014*Age-0.49*Sex+0.93*Met+0.39*TA-1.03*VA)}} \tag{5-2}$$

b) **Model 5 (MM Buildings):**

$$\hat{\pi}_2 = \frac{e^{-(8.25+0.007*Age+0.85*Clo+0.87*Met+0.24*TA+0.016*RH+0.022*BMI)}}{1+e^{-(8.25+0.007*Age+0.85*Clo+0.87*Met+0.24*TA+0.016*RH+0.022*BMI)}} \tag{5-3}$$

$$\hat{\pi}_3 = \frac{e^{-(11.41+0.007*Age+0.85*Clo+0.87*Met+0.24*TA+0.016*RH+0.022*BMI)}}{1+e^{-(11.41+0.007*Age+0.85*Clo+0.87*Met+0.24*TA+0.016*RH+0.022*BMI)}} \tag{5-4}$$

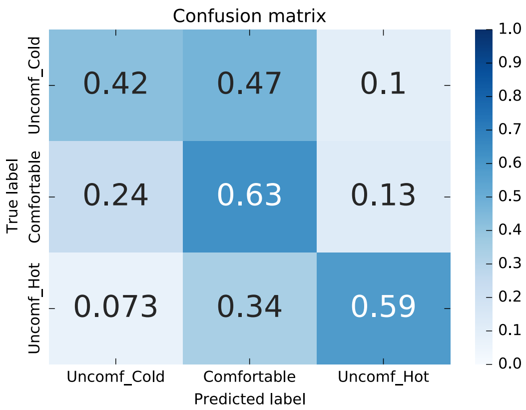
c) **Model 6 (NV Buildings):**

$$\hat{\pi}_2 = \frac{e^{-(3.84+0.86*SEAS+0.014*Age+0.26*TA-0.022*RH-0.70*VA-0.054*BMI)}}{1+e^{-(3.84+0.86*SEAS+0.014*Age+0.26*TA-0.022*RH-0.70*VA-0.054*BMI)}} \tag{5-5}$$

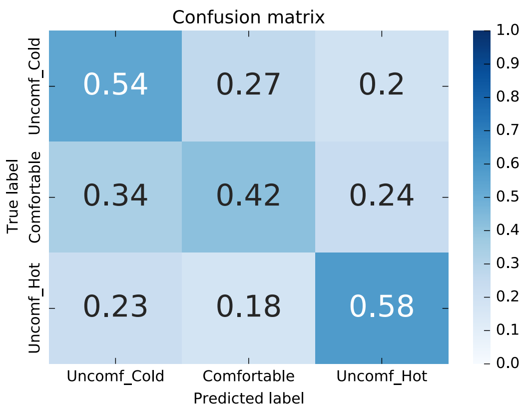
$$\hat{\pi}_3 = \frac{e^{-(7.85+0.86*SEAS+0.014*Age+0.26*TA-0.022*RH-0.70*VA-0.054*BMI)}}{1+e^{-(7.85+0.86*SEAS+0.014*Age+0.26*TA-0.022*RH-0.70*VA-0.054*BMI)}} \tag{5-6}$$

For each model, the intercept *Uncomfortably-Cold |Comfortable* corresponds to $\hat{\pi}_2$, which can be interpreted as the log of odds of believing that the thermal sensation is *Comfortable* versus believing that the sensation is *Uncomfortably-Cold* or *Uncomfortably-Hot*. Similarly, the intercept *Comfortable |Uncomfortably-Hot* corresponds to $\hat{\pi}_3$, and it can be interpreted as the log of odds of believing that the thermal sensation is *Uncomfortably-Cold* or *Comfortable* versus believing that the sensation is *Uncomfortably-Hot*.

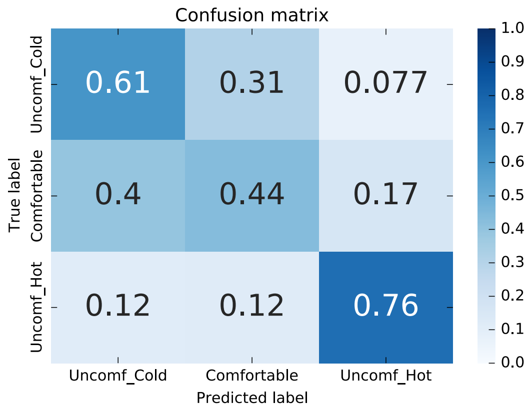
Similarly, with each model's adjustment, it was verified through confusion matrices (cf. Figure (5-37)) that the accuracy of Model 4 is about 58%, for Model 5 is 60%, while the Model 6 was accurate by 52%. The confusion matrix of Model 6 depicts that the model is slightly biased towards the 'Uncomfortably Hot' sensation since it is right in 76% of total test cases. This fact may come from the sample test used, which tends to this value. In category 'Comfortable', the model scores about 44% of the points, while in the category 'Uncomfortably Cold', the model scores about 61%.



(a) Model-4



(b) Model-5



(c) Model-6

Figure 5-37. Confusion matrices for Model-4 ((a) HVAC buildings), Model-5 ((b) MM buildings) and Model-6 ((c) NV buildings).

Table 5-7. Relative values of performance metrics for Models 4-6.

		Performance Metrics		
		Precision	Recall	F1-score
Model 5 (HVAC buildings)	Uncomfortably Cold	0.36	0.42	0.39
	Comfortable	0.78	0.63	0.69
	Uncomfortably Hot	0.19	0.59	0.29
Model 6 (MM buildings)	Uncomfortably Cold	0.40	0.54	0.46
	Comfortable	0.71	0.42	0.53
	Uncomfortably Hot	0.27	0.58	0.37
Model 7 (NV buildings)	Uncomfortably Cold	0.54	0.61	0.57
	Comfortable	0.50	0.44	0.47
	Uncomfortably Hot	0.76	0.76	0.76

The overall suitability test of each model shows up p-value < 0.001. this implies that there are models for each building type with the present data relating the categorized TSV and the considered predictors. However, the computed values of Pseudo – R^2 (0.40 for HVAC buildings; 0.35 for MM buildings, and 0.38 for NV buildings) show that the adjustment is still poor. Hence the factors that may contribute to this low adherence of the models to the data are the sample size, in addition to existing latent explanatory variables, or maybe risk factors that influence the TSV value that was not included in this data set. Despite all this, the proposed model provides some insight into the matter in question, showing that environmental comfort factors associated with personal and anthropometric factors interfere in human thermal sensation in closed environments.

5.3.4 Models 7-9: Thermal Preference

Models 7, 8, and 9 are ordinal logistic regressions that use the anthropometric and environmental variables, as well as the individual ASHRAE sensation vote (ASH-Votes) to predict the probability that an occupant wants a certain type of change in their current thermal sensation ("Cooler", PREF = 1; "No Change", PREF = 2; "Warmer", PREF = 3), using the data from the ASHRAE Thermal Comfort Global Database II of field studies. All models (7, 8, and 9) cover the preference outcome in HVAC, MM as well as NV buildings.

Table (5-8) covers details about the parameter estimates for the thermal preference regressions. For HVAC and MM buildings, most of β coefficients are distinct from zero with a p-value<0.0001 (compared to NV buildings). Estimates for β_4 are negative in all cases, reflecting that the expectation that as ASH votes move warmer, i.e., when ASH moves toward the extreme of +3, the probability that an occupant will want to feel "Warmer" (PREF = 3) will decrease, and vice versa for the case when the ASH votes move in the colder direction. Also, it is observed that almost all variables (environmental and personal) are included significantly in all buildings' types, unless for BMI, whose coefficient estimates are smaller in MM and NV buildings.

Table 5-8. Regression summary and the related Odds Ratio of including variables in the Preference Models 7, 8 and 9.

Parameter	Model 7 (HVAC buildings)		Model 8 (MM buildings)		Model 9 (NV buildings)	
	Estimate	*Odds ratio*	*Estimate*	*Odds ratio*	*Estimate*	*Odds ratio*
Intercept_1	-3.84 (0.91) ****	NA	1.08 (0.2) ****	NA	0.34 (0.78)	NA
Intercept_2	-0.39 (0.91)	NA	3.65 (0.2) ****	NA	3.31 (0.78) ****	NA
β_1 (SEAS (Summer))	-0.53 (0.09) ****	0.56	0.13 (0.05) *	NA	-0.23 (0.09) *	0.80
β_2 (Age)	-0.015 (0.005) **	0.98	0.026 (0.003) ****	1.02	0.011 (0.004) **	1.01
β_3 (Sex (Female))	0.22 (0.09) *	1.20	0.39 (0.05) ****	1.52	-0.002 (0.08)	NA
β_4 (ASH-Votes)	-0.69 (0.06) ****	0.50	-0.63 (0.02) ****	0.54	-0.084 (0.04) *	NA
β_5 (Clo)	0.29 (0.31)	NA	-0.83 (0.13) ****	0.47	0.74 (0.2) ***	1.81
β_6 (Met)	1.14 (0.25) ****	3.20	1.33 (0.18) ****	3.33	0.89 (0.25) ***	2.43
β_7 (TA)	-0.12 (0.02) ****	0.88	0.012 (0.01)	NA	0.025 (0.01)	NA
β_8 (RH)	-0.003 (0.005)	NA	-0.003 (0.002)	NA	-0.01 (0.003) **	1.00
β_9 (VA)	1.04 (0.32) **	2.68	0.57 (0.13) ****	1.69	0.012 (0.2)	NA
β_{10} (BMI)	0.007 (0.01)	NA	-0.012 (0.006) **	NA	-0.025 (0.01) **	1.00
**** p-value<0.0001	N = 3445 Subjects		N = 9228 Subjects		N = 3366 Subjects	

*** p-value < 0.001
** p-value < 0.01
* p-value < 0.1
Std. Deviation is shown in parenthesis; 95% Confidence Interval

In this case, through Table (5-8), the Models 7-9 can be formulated as:

a) Model 7 (HVAC Buildings):

$$\hat{\pi}_2 = \frac{e^{-(-3.84-0.53*SEAS-0.015*Age-0.69*ASH+1.14*Met-0.12*TA+1.04*VA)}}{1+e^{-(-3.84-0.53*SEAS-0.015*Age-0.69*ASH+1.14*Met-0.12*TA+1.04*VA)}} \tag{5-7}$$

$$\hat{\pi}_3 = \frac{e^{-(-0.39-0.53*SEAS-0.015*Age-0.69*ASH+1.14*Met-0.12*TA+1.04*VA)}}{1+e^{-(-0.39-0.53*SEAS-0.015*Age-0.69*ASH+1.14*Met-0.12*TA+1.04*VA)}} \tag{5-8}$$

b) Model 8 (MM Buildings):

$$\hat{\pi}_2 = \frac{e^{-(1.08+0.026*Age+0.39*Sex-0.63*ASH-0.83*Clo+1.33*Met+0.57*VA-0.012*BMI)}}{1+e^{-(1.08+0.026*Age+0.39*Sex-0.63*ASH-0.83*Clo+1.33*Met+0.57*VA-0.012*BMI)}} \tag{5-9}$$

$$\hat{\pi}_3 = \frac{e^{-(3.65+0.026*Age+0.39*Sex-0.63*ASH-0.83*Clo+1.33*Met+0.57*VA-0.012*BMI)}}{1+e^{-(3.65+0.026*Age+0.39*Sex-0.63*ASH-0.83*Clo+1.33*Met+0.57*VA-0.012*BMI)}} \tag{5-10}$$

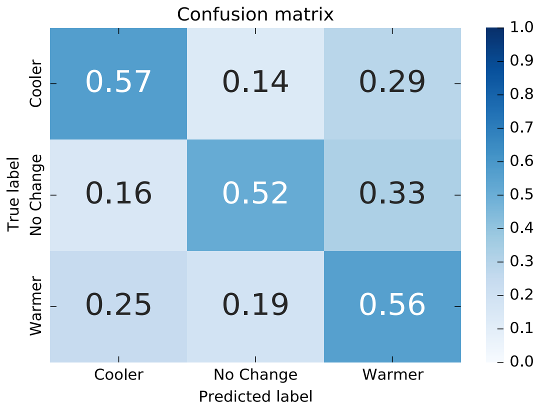
c) Model 9 (NV Buildings):

$$\hat{\pi}_2 = \frac{e^{-(0.34+0.011*Age+0.74*Clo+0.89*Met-0.01*RH-0.025*BMI)}}{1+e^{-(0.34+0.011*Age+0.74*Clo+0.89*Met-0.01*RH-0.025*BMI)}} \tag{5-11}$$

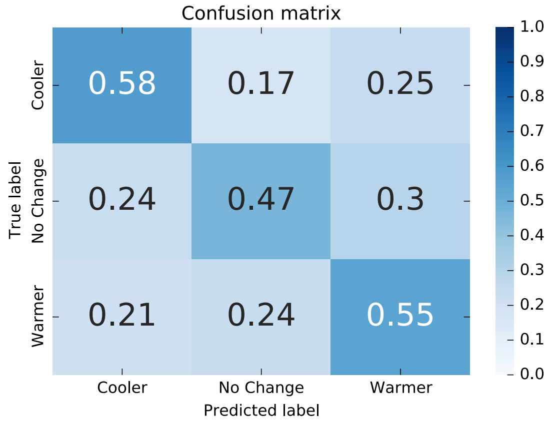
$$\hat{\pi}_3 = \frac{e^{-(3.31+0.011*Age+0.74*Clo+0.89*Met-0.01*RH-0.025*BMI)}}{1+e^{-(3.31+0.011*Age+0.74*Clo+0.89*Met-0.01*RH-0.025*BMI)}} \tag{5-12}$$

For each model, the intercept *Cooler |No Change* corresponds to $\hat{\pi}_2$, which can be interpreted as the log of odds of believing that the thermal sensation is *Comfortable* versus believing that the sensation is *Uncomfortably-Cold* or *Uncomfortably-Hot*. Similarly, the intercept *No Change |Warmer* corresponds to $\hat{\pi}_3$, and it can be interpreted as the log of odds of believing that the thermal sensation is *Cooler* or *No Change* versus believing that the sensation is *Warmer*.

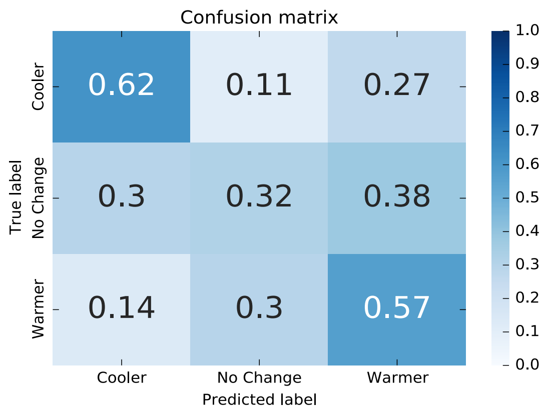
Similarly, with each model's adjustment, it was verified through the confusion matrices (cf. Figure (5-38)) that Model 7 is accurate by 55%, the accuracy of Model 8 is 53%, while for Model 9 is about 50%. It is worth noting that the confusion matrix of Model 9 shows that the model is biased towards 'Cooler' and 'Warmer' preferences, which may be explained that the test-set tends towards these values. Otherwise, in the category 'No Change', the model scores only 32% of the points.



(a) Model-7



(b) Model-8



(c) Model-9

Figure 5-38. Confusion matrices for (a) Model-7 (HVAC buildings), (b) Model-8 (MM buildings) and (c) Model-9 (NV buildings).

Table 5-9. Relative values of performance metrics for Models 7-9.

		Performance Metrics		
		Precision	Recall	F1-Score
Model 7 (HVAC buildings)	Cooler	0.59	0.57	0.58
	No Change	0.61	0.52	0.56
	Warmer	0.47	0.56	0.51
Model 8 (MM buildings)	Cooler	0.56	0.58	0.57
	No Change	0.53	0.47	0.50
	Warmer	0.50	0.55	0.52
Model 9 (NV buildings)	Cooler	0.58	0.62	0.60
	No Change	0.44	0.32	0.37
	Warmer	0.46	0.57	0.51

5.4 DISCUSSIONS

This section presented the analysis of the influence of personal characteristics on the general thermal perception of occupants verified from different standard effective temperature ranges (SET*). Among the items investigated are gender (male and female), age (under 30 (Youth-group), between 30 and 50 years old (Adults-group), and over 50 years old (Seniors-group)), and weight, according to the classification of body mass index (underweight, normal weight, overweight, and obese).

Among the characteristics analyzed, gender and physical condition were those that presented the greatest changes in thermal comfort perception. Focusing only on thermal sensation votes, it was observed that men show greater intolerance to heat, and women complain more of discomfort from cold. Among the different weight classes, overweight and obese occupants have the highest levels of heat-related complaints, although the thermal sensation analysis does not show this fact. In this sense, thermal preference seems to be a much more accurate indicator for such a phenomenon, clearly pointing out the differences between groups. Therefore, focusing only on thermal preference, two important reflections are outlined:

1. Among the three age groups observed, it was found that occupants over 30 years old are those who prefer higher temperatures compared to younger occupants. Such preference may occur due to changes in basal metabolism and the sedentary lifestyle of older people. In this work, it was observed that the share of occupants who preferred not to change the current thermal condition in age group 1 was highest in the 28°C to 30°C range, while in age group 2 was between 26°C and 28°C, while in group 3 this condition occurred below 24°C (SET*).
2. Between the genders, ages, and physical conditions considered, the difference in preferred temperature values reached in some cases 3.0°C ± 0.5°C. Such results could be even more expressive if some of these analyzed characteristics were combined and compared to each other.

5.5 CONCLUSION

In this chapter, we have used the Logistic regression parameter estimation approach to develop the probability of thermal acceptability, sensation, and preference for office and classroom building occupants. With these models, we have extended Fanger's PMV-PPD representation of thermal satisfaction/dissatisfaction to the field and derived new direct projections of thermal comfort indicators (sensation, acceptability, and preference) in terms of anthropometric variables such as BMI and Age. This enables a better understanding of personalized thermal comfort and how it figures into a more effective and sustainable building design.

6 CONCLUSION

This thesis evaluated the thermal comfort conditions of occupants in air-conditioned, mixed-mode, and naturally-ventilated buildings. The data analyzed were based on the answers to 16,153 votes regarding thermal sensation, preference, as well as acceptability, extracted from the ASHRAE Thermal Comfort Global Database II field studies, which covered two seasons (winter and summer) of the year. The results found form a kind of framework for future work, archiving important information that can be studied and incorporated in future versions of standards and evaluation methods for these types of buildings. The following pages conclude the thesis with a summary of its key outcomes, as well as a list of suggestions for future development of the work.

6.1 SUMMARY OF KEY OUTCOMES

1. **Covering the role of the personal interaction of occupants using AI-based tools to achieve energy-efficiency and comfort optimization in buildings.** The performed systematic review presented a comprehensive review discussing Artificial Intelligence (AI) techniques for Building Energy Management Systems (BEMS) that enable energy efficiency while considering thermal comfort. Besides, in order to evaluate the outputs of AI-based methods in energy savings and thermal comfort enhancement, assessments of the implementations of these techniques conducted in the published works have been reviewed and compiled according to the eligibility criteria. The research method used in the peer-reviewed publications was primarily empirical case-study, with data sources and data on thermal comfort and energy usage were collected predominantly through the

execution of real-world studies (questionnaires or interviews with the occupants and data measurements) or by using current and publicly accessible datasets.

The findings of the study showed that multiple types of AI-based techniques were used in different parts of building control systems. In particular, artificial neural networks (ANNs) have been used to overcome problems related to recognition and identification, and their function focused on learning algorithms that allow them to retain and classify data. In building management, ANNs were implemented to describe thermal comfort and estimate the Predicted Mean Vote (PMV) index. Fuzzy Logic (FL) is one of the recent tendencies which was developed to model human decision-making. Research works using FL have been documented since the late 1990s to treat thermal comfort as a subjective or fuzzy parameter. They were built to monitor conditions where the highest level of satisfaction and optimum energy-efficiency were achieved, most of the FL-based studies used the PMV comfort index. This line of management approaches focused on experience and judgment, aim at achieving simple, scalable. and effective regulation, without resorting to a system model. Their efficiency is generally compared to traditional controls, and their advantage resides primarily attributed to the fact that additional awareness of system behavior (expressed in natural language – fuzzy or incorporated learning techniques – ANNs) or a degree of optimality (i.e., Genetic Algorithms) is assumed.

The review shows that the implementation of AI and ML technology in the building industry is still an ongoing research endeavor. This is partly attributed to the fact that this type of algorithms typically needs a massive quantity of high-quality real-world data, yet buildings or, more specifically, the energy sector has so far had little data. Adjustments and technical advancements are contributing to a rise in the quantity and sophistication of data (Smart Meter Installation, Internet of Things (IoT), Cloud Storage, and so forth) allowing to build much more effective data-driven research. The work concludes by describing the research challenges facing the research community namely the need for more data for AI-based modeling in buildings, IoT based smart and connected buildings to facilitate efficient management and data collection for further studies. Smart buildings will also present security, privacy, and data sensitivity issues as well as big-data streaming. Context-awareness mechanisms that improve the intelligence of buildings in adapting to human behavior to adjust dynamically comfort and improve energy in a more fine-grain manner is also of high importance to the community. Another line of research includes also humans in the loop, comfort modeling for dynamic temperature set-point adjustments. This type of research will need mixed-methods types of research where AI and ML techniques will open up opportunities for more energy savings while keeping the building comfortable. In particular, adjusting dynamic set-points in commercial buildings will depend on how comfort modeling is connected to human activity in the building. Tracking human activity brings the notion of context-awareness as another line of research that will provide value to efficient building management with satisfactory comfort levels to its occupants. As these models are exchanging data about the building and its occupants, security and privacy become important issues to investigate in smart buildings. Indeed, smart buildings bring about many interesting research challenges that are still an active line of research with many opportunities with the application of AI and ML.

2. **Individual-level model of occupant thermal comfort and a model validation method.** The developed models allow simultaneous consideration of office and classroom buildings occupants and comfort/productivity. When focusing mainly on the building types, regardless of the season, it can be stated that in naturally ventilated and mixed-mode buildings, thermal comfort indicators depend more on anthropometric (or personal) parameters (such as Age, Sex, BMI) than air-conditioned buildings. In this type of buildings, the occupants activate the air-conditioning even they might feel comfortable. However, it was also found indicative of the influence of the operation of the air conditioning and the way they dress, which interferes with the use of the air conditioning. Analyzing the thermal perception of occupants under the different forms of buildings types, it is further concluded that there is a strong tendency to thermal discomfort by excessive cold during the operation of air-conditioners, and to thermal discomfort by heat when natural ventilation is used. Concerning the suitability of the current methods of thermal comfort for indoor environments evaluation indicated by ASHRAE 55, it is concluded that the method derived from the PMV-PPD model is the one that presents unsatisfactory results when compared to the actual sensation and thermal comfort votes from the investigated buildings. However, it is important to emphasize that this problem is not directly related to the model, but to the way, standards restrict its application. According to O. Fanger,

dissatisfaction related to the thermal environment (and consequently thermal acceptability) is defined by the -2 and -3, and +2 and +3 votes of the seventh scale of thermal sensation. Thus, limiting thermal comfort or acceptability to an interval of ±0.5, as in the case of ASHRAE 55/2013, or at worst to ±0.7 as ISO 7730/2005 (which still suggests as ideal the brief interval between ±0.2), in addition to contradicting the theoretical foundation of the model, ends up erroneously characterizing thermal comfort votes in thermal discomfort (the percentage of people who reported thermal discomfort was less than 10% in all intervals of PMV calculated and analyzed: ±0.5, ±1.0 and ±1.5).

As final considerations, the evaluation of thermal comfort is made in different ways, when considering the various parts of the world and its climatic and cultural characteristics. Given the wide variety of models, approaches, and existing applications for thermal comfort assessment, it is important to understand that the use of such models should be carefully thought-out and limited to the conditions for which they are intended. The ability to adapt and control environmental conditions has provided space for occupants to experience more thermally comfortable environments, which can provide a significantly higher level of overall satisfaction, as well as a better thermal and energy performance of the building.

During thermal comfort experiments, it is important to emphasize that the occupants can, in most cases, react in different ways under the same environmental conditions. Thus, it is correct to assume that anthropometric or psychosocial factors, besides the parameters already considered by the current models, directly influence the thermal perception and the quality of the internal environment supplied to the occupants. Anthropometric parameters such as age, weight, and height actively contribute to thermal perception, and when combined, may produce unproven effects. According to the studies discussed in this report, there is little evidence of the influence of such characteristics on the operation of air conditioners; but in general, it is known that female occupants are sensitive to lower temperatures, while the older people may prefer higher temperatures than those preferred by younger people. Obese people are more sensitive to heat, which can make these users prefer cooler environments. Although prominent in a few studies, such results require further investigation.

6.2 LIMITATIONS OF THE WORK

The main limitations of this research are restricted to those arising from field experiments where the main study variables are related to the responses and behavior of real occupants performing their work routine. However, it is important to point out that there are still limitations related to the aspects:

1. **Waist measurement.** As our thesis aims to estimate the relationship between the anthropometric parameters (mainly the waist, BMI including height and weight) and the thermal comfort of the occupants. However, the database used does not include the waist measurements, so our developed models may not cover the body dimensions aspect of the users. In this regard, including such parameters in our model is required.

2. **Body mass and height.** In this study, we considered the body mass index (relationship between body mass and height) as a parameter for the classification of people overweight, people with normal weight, and people underweight. This index does not measure body fat and may not adequately reflect the ratio between muscle and fat, which may lead to erroneous classifications.

6.3 FUTURE WORK ITEMS

During the development of this work, some ramifications concerning the topic were observed that could be explored, seeking a greater understanding and expansion of information:

1. New filed surveys on commercial buildings and human behaviour for people performing different activities in the four seasons of the year; such conditions would provide new analysis and effective conclusions regarding the effect of outdoor conditions and users' behaviors on their thermal comfort.

2. Elaboration and validation of new methods for analysis focused on differences and variability of anthropometric characteristics, seeking more conclusive results of the combined effect of such characteristics on the thermal perception of occupants;

3. Analysis of unusual factors and their influence on thermal perception, such as stress, mood, physical condition, smoking habits, and daily workload. Few researches focused on aspects of this type in thermal comfort studies. However,

it is known that these often influence the final analyses and can generate erroneous results.

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