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Sviluppo di un sistema di controllo per l'ottimizzazione del comfort termico all'interno di un ufficio

Development of a control system to optimize the thermal comfort inside an office building

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Abstract

Thermal comfort is an important goal for the built environment as it affects occupant satisfaction, health, and productivity.

The present study aims to evaluate in a multidisciplinary way which are the main stimuli to users' thermal comfort inside an air-conditioned office building during the winter season and develop an optimized control system which drives the operations on the AC system in order to maintain a satisfactory thermal environment and match the occupants' demand in terms of thermal comfort.

In this perspective, environmental and biometric parameters were monitored using dedicated sensors connected to a data logger that had the function of storing and transmitting them to the control software. Since thermal sensation is a close measure of what ideal comfort conditions would be, humans feedback on the ambient conditions were also collected by a survey launched at fixed time lapse. In addition, this study investigated the users' behaviors inside an office building during some winter days in a Mediterranean climate. Thus, the driving factors for the human-building interactions were assessed and suitable behavioral models were proposed. The results indicated that the occupants' actions were mainly driven by the operative temperature and the biometric parameters. These data were used for the implementation of an adaptive control algorithm in an automatic system piloting the AC unit. The mechanized system ensured a good quality in terms of thermal comfort and users' satisfaction.

1. Introduction

ASHRAE standard 55 defines [ASHRAE Standard 55-2013, Thermal Environmental Conditions for Human Occupancy, ASHRAE 2013] thermal comfort as the condition of mind that expresses satisfaction with the thermal environment. Improvements in thermal comfort have been associated with enhanced occupant productivity, health and overall satisfaction [1,2].

Humans' comfort sensations are a function of both objective and subjective aspects. The former are related to building properties (e.g. exposure) and environmental conditions, while the latter concern physiological and psychological features, peculiar for each person.

In this perspective, in the present study, environmental parameters were collected by using both outdoor and indoor micro-climate stations, then their influence on the humans' thermal comfort was evaluated using a logistic regression analysis. On the other hand, surveys are used to acquire the subjective aspects as the thermal preference is a closer measure of what ideal conditions would be and it suggests a possible direction of change. Additional human data can significantly improve the accuracy of predicting thermal preferences, therefore biomentric parameters such as heart rate and skin temperature ware recorded using a wristband device.

Since humans' thermal sensation is triggered by all these stimuli, occupants interact with building devices to modify the surrounding and to restore their favorite sensation. Such adaptations have immediate and tangible consequences on the indoor environment and on users' comfort, but their effects on building energy consumptions are not of a secondary relevance.

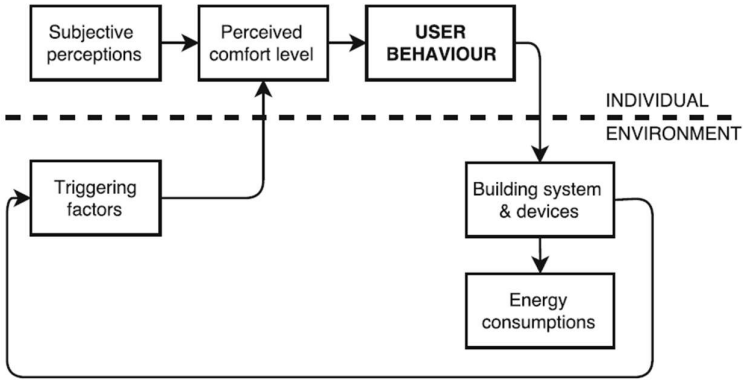

Figure 1. Interaction between the users and the environment

Understanding the behaviors of users in buildings and converting these into mathematical models are essential for accurate simulation results and to improve building design and management, as well as to conserve energy during building operation. Thence, in recent years many researchers direct their

efforts in studying human-building interaction [3].

In the perspective of understanding what makes an environment thermally comfortable to the occupants, researchers have focused on developing empirical models that can represent human perception of thermal comfort in terms of the given conditions or factors (e.g., personal, environmental, etc.).

At first, the predicted mean vote (PMV) [4], which considers occupants as containers that passively undergo the building management. The PMV model treats thermal comfort as a physical-physiological phenomenon and expresses human thermal sensation as an outcome of the heat transfer between a human body and its surrounding environment. It is the most widely accepted model, developed through extensive laboratory experiments by Fanger, which became the basis of the standards ISO 7730 [5] and ASHRAE 55 [6]. In contrast, the adaptive comfort model regards the users as active subjects that modify the surrounding according to their preferences and needs. Currently, there are mainly two adaptive models' standards: the ASHRAE 55 adaptive model by de Dear and Brager [7] and the EN 15251 adaptive model by Nicol and Humphreys [8].

Despite the different attributes of these approaches, these comfort models are limited to evaluating whether or not comfort conditions are matched.

The advance in such perspective concerns the assessment of the behavior the users take to adjust the environment, interacting with building systems and devices. For example, comfort models evaluating a discomfort for cold environment only suggest that the indoor temperature is too low, but do not give any provisions of the interaction between humans and AC system.

To this aim, many researchers directed their efforts in understanding, representing and reproducing people's behaviors in buildings through the development of behavioral models [9]. They are based on experimental data that allow identifying how the environment affects the occupants and the way the users adapt to that with adaptive actions. Indeed, they take action to achieve and maintain their comfort if the environmental conditions in a room are outside their comfort zone [10-12].

These models predict the occurrence probability (P) of an action in relation to one or more predictors ($x_1 \ldots x_n$). Therefore, once environmental and biometrical parameters were collected, the probability of occupants to interact with the AC system installed inside the test chamber is calculated by using a stochastic behavioral model. Users' actions on building devices have a deep influence on the indoor micro-climate and building energy demand. In order to reduce energy waste as well as reach the optimal comfort conditions for the occupants, recently, researchers proposed adaptive control algorithms (ACAs) developed using field surveys [13-15].

The “adaptive” term means that these algorithms are based on the adaptive comfort theory, stating that: “if a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort” [16]. This principle focuses on the human-building interaction, since it asserts that if people perceive the ambient as uncomfortable, they will try to improve their thermal comfort, operating both on building controls (e.g. modify the AC set temperature or using doors, windows, blinds and fans) and on their personal condition (e.g. changing their clothes or taking hot or cold drinks). In the typical office buildings, occupants must passively accept the system operation and personal adjustment are minimal because metabolic rate and clothing level remain fairly constant [17].

Humphreys and Nicol, assessing the validity of the Fanger’s steady-state comfort model [18-19], concluded that a ISO 7730 compliant approach is more likely to bring to erroneous evaluations of thermal discomfort because the model poorly reflects the human thermal adaptation [20-21].

This active-user comfort approach is based on the relationship between the indoor temperature and the comfort temperature which is a function of the outdoor average temperature. Among these ACAs, the Humphreys adaptive algorithm [22] was selected for the present research since it is based on the widely-accepted adaptive comfort theory and its use in real applications requires the recording of few environmental variables.

However, very few researchers focused their efforts on monitoring both environmental and humans bio-signals’ then including them in an customized control loop in order to optimize the indoor thermal comfort among the occupants inside an office building. Thus, according to the contextual lack, the main goal of the present study was to develop an automatic AC – operating system driven by a tailored adaptive control algorithm that, combining both environmental and biometrical parameters, could guarantee a healthy and thermally comfortable environment, interpreting the occupants’ thermal sensation and needs.

2. User-Building Interaction

People's reactions to discomfort can lead to opposite consequences in buildings performances. Wise and conscious users' behaviors can aid the building to perform as well as possible, conversely, wasteful actions can cause relevant energy increases.

In fact, when people feel discomfort, they can operate three different types of adaptations: environmental, personal and psychological [23].

The first one is the most tangible and it concretely influences the indoor environment since it concerns the modification of the devices' status (e.g. AC set-point temperature, windows, fans). The general impact of the second type of adaptation is more limited because it strictly regards the single person (e.g. modify the clothing level). Finally, psychological adjustments are the less effective because they are related to the management of emotions, forcing an adaptation to the existing problems (e.g. ignore the problem) [24]. Among these strategies, only environmental modifications have a direct energy impact. However, some of them can quickly restore users' comfort, but can be extremely inefficient in the energy perspective, dramatically affecting the energy consumptions.

In addition, users working in the same environmental conditions can behave very differently as a result of personal preferences, background, and habits, as well as their responsiveness to energy issues. Some researchers have proposed employing typical 'behavioral styles' (e.g. energy saver, average occupant, and energy waster) to simulate different levels of energy consciousness [25-27], while others have utilized the concept of 'user type' (i.e. active, medium, and passive user) to reproduce variability in use of building controls [28-30]. The classification of active, medium and passive users is determined by the frequency with which occupants interact with devices.

The user type categorization can be assessed by responses to questionnaires [31-32], by the number of recorded actions [33-35], in relation to preferred set-point temperatures [36], or according to numerical indicators [37].

In the present study, all the occupants were free to interact with the room thermostat apart from taking personal and physiological adaptation when they felt discomfort conditions.

3. Impact of Occupants' Behaviors on Indoor Environment

People modify the environment by both their adaptive actions and their own presence, having an undeniable impact on the indoor environment [38].

In fact, when people remain in a room, even without interacting with the surrounding, they modify the indoor microclimate. The heat coming from the body and the breathing process affect especially the indoor temperature, humidity and CO_2 trends. In addition, when people actively interact with the building devices (e.g., increasing or decreasing the set-point temperature of AC system, opening and closing windows or switching the lights) their influence is even more considerable [39].

Perturbations due to human activities can be studied using decomposition methods since the environmental variables' trends can be interpreted as temporal series.

The users' impact on the indoor environment can be also linked and analyzed in relation to different building uses. The occupant density (persons/m^2) can be adopted as the parameter to discern the usage typologies [40]. In residential buildings, in fact, the density is usually low, but the people have the highest level of interaction since they can freely adjust the systems and the devices. In offices, the density increases and the possibilities of adaptation decrease. Finally, in spaces with high density (e.g., school classrooms, conference rooms) occupants can take very few actions and they usually have to submit to building management.

4. Trigger Parameters for Occupants' Behaviors

People's behaviors have an undeniable influence both on building performance and on indoor environmental quality. To predict their actions and obtain accurate predictions, it is of primary importance the understanding of their decision-making process. Since comfort conditions are individually defined, people modify the environment according to personal preferences and needs. This means that users' behaviors are not driven by deterministic rules, but their adjustments vary according to both individual and contextual stimuli. Many studies [41-43] have been carried out with the aim to understand the factors that trigger users' actions and to classify them. The different aspects can be sub-divided in two macro-categories: the first concerns concrete and objective characteristics which are linked to measurable aspects, while the second is related to personal and individual features which are peculiar for each person. The former macro-category includes environmental, time-related and contextual factors. The latter concerns physiological, psychological and social features. In addition to these classes, Peng et al. [44] included also the "random" category to consider unpredictable actions which depend on uncertain factors or follow unknown rules.

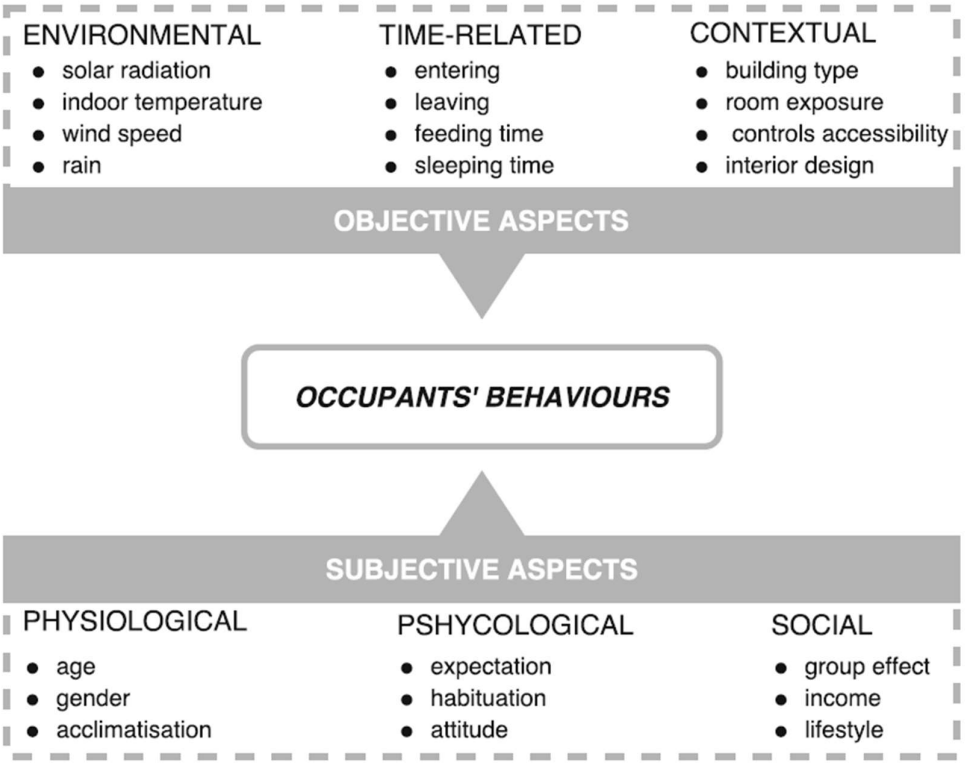

Figure 2. Triggers subdivided between two macro categories and several examples for each aspect.

Among the objective factors, environmental variables are the main triggers for almost all the users'

adaptive actions. Indoor and outdoor temperatures have been recognized as two of the most important stimuli connected to thermal comfort. For this reason, they drive several adaptive actions: window [45-46], air-conditioning [47], thermostat [48] and fan use [49-50]. In general, when both indoor and outdoor temperatures rise, the probability of opening windows [51-52], of switch on the air-conditionings [53] and the fans and to lower the blinds [54] increase as well. Conversely, their reduction leads to higher frequencies in window closing [55] and in turning the heating on [56].

In particular, occupants' adjustments on AC units are performed to increase or decrease the set temperature during the heating or cooling season respectively, affecting not only thermal comfort, but also energy consumptions. Indeed, the set-point temperature management could lead to a sensible reduction in the annual electricity consumptions [57-58]. As expected, when indoor and outdoor temperatures decrease, the probability to raise the set-point temperature of the AC unit increases as well.

Time-related factors have been deeply analyzed in many studies. This category concerns events that are connected to the specific time of the day: for example, the arrival at work or the sleeping time at home. In offices, arrival and departure periods are the most influencing [59]. At arrival, it has been recorded the highest frequency of switching on the AC units, window opening [60], lights up [61] and shading adjustments [62]. Conversely, departures are characterized especially by window closing [63] and turning off lights [64].

Contextual factors have been less studied than environmental and time-related ones, but their importance in users' behaviors has been identified by several studies [65-66].

In particular, a comprehensive review, proposed by O'Brien and Gunay [67] highlights that availability and accessibility of adaptive measures, interior design, mechanical/electrical systems and outdoor views actively contribute to the occupants' decision-making process.

On the other hand, subjective aspects concern features and perceptions connected to the people's personal sphere. Surveys and questionnaires are essential methods to acquire this kind of data. Physiological adaptations concern the strategies the human body use to acclimatize to discomfort [68]. In this perspective, age and gender are the two main aspects that influence people's physical perception. Since the ageing compromises body defences from cold [69], it was noted that older subjects (e.g., age >60) usually prefer a warmer environment in comparison to younger people [70-71]. Researchers which analyzed gender thermal preferences seem to agree in assessing that women prefer warmer temperatures compared to men [72].

Along with physical features, also psychological aspects are extremely important in people's

behaviors. Such type of adaptation is influenced by past experiences and expectations, which can be also conditioned from cultural and cognitive aspects [73]. The psychological component can largely affect thermal comfort, inclinations and energy-related behaviors [74].

Finally, people are also influenced by social forces. Working and living with other subjects, a user can modify its personal habits according to the building or group rules, so it is extremely important encouraging and spreading employees towards positive behaviors [75].

However, a difficulty in recording and quantifying them is still undeniable. These limitations underline the evident necessity for a multidisciplinary approach. In fact, to reach a comprehensive understanding of behavioral adaptations and to transpose them in mathematical models, it would be advantageous the collaboration of different research fields, as engineering, social and psychological sciences. In this direction, some studies [76-77] aimed at applying models and theories from psychology and sociology to conceptualize the human interactions with buildings.

Therefore, the collaboration of reliable measurements and social science is an essential step for the recording of non-objective variables, the realization of suitable questionnaires and so, to improve the entire survey methodology [78].

In order to evaluate the driving factors that affect the users' thermal comfort and include them in the optimized control loop, a logistic regression analysis was applied to experimental data of the present study. The goodness-of-fit (GOF) of the statistical models has been evaluated using the R^2 index. This asseses how well the functions fit the observed data and, as a consequence, evaluates the strength of the relationships. It is a dimensionless estimator and better relationships are indicated by higher values.

5. Occupants' Adaptive Actions

External and internal triggers, in association with peculiar users' comfort requirements, affect the users' perception. As a consequence, they interact with building devices to satisfy their needs. When an occupant stays in a comfortable environment, no action takes place. Only when the environmental conditions exceed the limits of the occupant's comfort zone (i.e., higher or lower than critical levels) and produce detectable stimuli to the human body actions take place. The further the environmental conditions deviate from the limits of the occupants' comfort zone, the greater the stimulus is to the human body, the stronger the occupants' tendency is to make the room more comfortable, and the higher is the likelihood that the occupants take action.

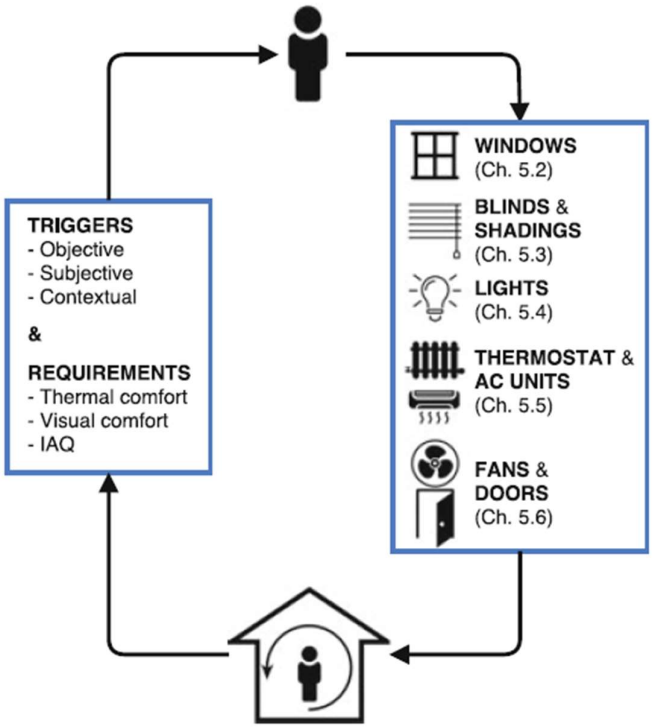

Figure 3. Cycle of interaction between the users and the environment

Indeed, each occupant creates a cycle: based on his/her preferences, education, and other psychological and physiological personal factors, he/she decides whether the environment is comfortable or not and, in the latter case, interacts with building devices (AC, windows) to achieve his/her favorite sensation. Therefore, actions on building controls are governed by an adaptive principle, stating that if a change occurs such as to produce discomfort, people react in ways that tend to restore their comfort (Humphreys and Nicol, 1998). The theory of adaptive comfort first conceived the building users as subjects who actively interact with the environment to modify it and adapt it to their personal needs. As for all decision-making processes, an initial stimulus (such as a discomfort

condition) is the first step; occupants perceive it and traduce this information into a response, interacting with available means. All the human actions on the building devices influence the indoor environmental conditions and the consequent energy consumptions, giving a new starting point for the cycle continuity.

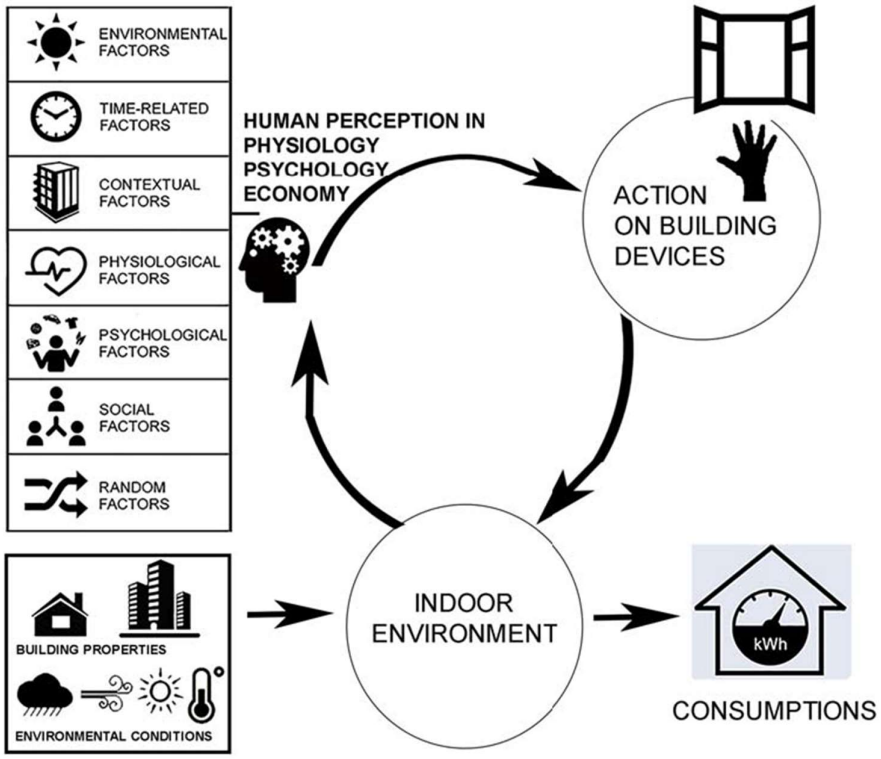

Figure 4. Trigger parameters which affect the building energy consumption

Since the operation of building systems are highly dependent on the presence of occupants, considering the dynamic occupancy information has become crucial to reflect the occupancy dynamism within offices and the random patterns in occupant behavior. Occupancy-related parameters are highly dependent on the season, weather, time of the day, and occupants' habits [79]. Moreover, the collected data must include important occupancy features such as the number of present occupants, period of absence and presence etc [80].

6. Occupancy Data

The acquisition of people's presence in buildings is of primary importance both for the development of behavioral models and for the building management optimization.

In fact, occupants have a great impact on the indoor micro-climate and the energy consumptions of a building, since people presence affects the use of building systems and plug loads and influence heating, ventilation and lighting requirements [81]. Moreover, occupancy is an essential precondition to assess users' interaction with building devices. The first point to deal with concerns technologies for users' presence recording. Many techniques have been adopted to identify people's presence and one of the most used concerns passive infrared sensors (PIR) [82-83]. Such technology is useful for counting people's passages since it recognizes the human motion. However, the number of persons in the space cannot be recorded as well as immobile occupants (e.g., people working at the desk in offices). PIR can be coupled with CO_2 sensors [84] which clearly assess whether a room is occupied [85]. The use of CO_2 sensors alone was discouraged because the CO_2 distribution can be easily biased by ventilation rates [86]. Such limitations can be overcome by using video cameras which clearly detect occupancy and number of occupants. However, this method is quite costly both for the camera installation and the data analysis and, in addition, causes privacy issues [87].

Recently, many applications adopted advanced technology to optimize occupancy detection. Bluetooth technology [88], which is provided by the majority of digital devices, is an accurate and low-cost solution for short-range wireless communication. Similarly, radio-frequency identification (RFID) tags track each person continuously throughout the building [89]. A RFID system usually consists of two components (i.e., the reader and the tag) which operate at a certain frequency. When attached to an object, the tag stores a specific ID allowing a personal identification. Combinations of different tags, readers, and frequencies of communication offer a wide flexibility in customizing RFID systems [90]. RFID tags have been also used coupled with PIR sensors to control lighting in multi-occupant offices [88]. This method provided an accuracy of about 91% and so, the authors suggested adopting it to monitor also building energy, use and security. An improvement has been reached through Wi-Fi based technology. This is a low-cost and simply-implemented technology, which can detect the position and the number of occupants in real-time. Moreover, almost all mobile devices are provided with Wi-Fi, making its application easy also at a large scale. Researcher testing this approach provided a very detailed visualization and analysis of occupancy patterns, also including spatial distributions and temporal variations [91]. In the present experimentation, the occupancy was recorded by questionaries filled by students, considering binary values of 0 and 1 to show the unoccupied and occupied periods, respectively.

7. Behavioral Modelling Approaches

The adaptive comfort models have recognized for the first time the fundamental importance of occupants and the necessity of considering their behavior in the design process. However, they are limited to evaluating whether or not comfort conditions are matched without giving any previsions on actions they will probably take to adjust the environment, interacting with building systems and devices. To that aim, behavioral models have been introduced. Indeed, they are fundamental tools to predict users' behaviors and evaluate buildings' performance both during the design and operation phases.

Early, deterministic approaches are based on fixed and static rules, assuming that one action occurs with certainty, when a predetermined threshold value of one or more environmental triggers is exceeded. The mathematical form is expressed by a "threshold formulas". According to this type of behavioral model, an occupant will definitely take action if the related environmental condition exceeds a certain critical value.

For example, the light-switching model proposed by Hunt [92] defined the lights status according to different times of the day. At the first entrance, the lights were switched on, during the occupied periods were maintained unchanged and switching off behaviors were only connected to departures.

Deterministic approaches start from the assumption that all the users behave in the same way and uniformly react to the stimuli. Even if static rules are the easiest solutions both in terms of development and implementation, numerous studies [93-94] highlighted that people have different preferences, needs and reactions to external triggers. To include such occupants' diversities, behavioral patterns and users' profiles have been proposed in literature. These methods cluster the occupants according to energy-related macro categories. In fact, different background habits, lifestyles and comfort preferences influence behaviors and, consequently, the overall energy use.

Despite the above-mentioned approaches provide more reliable results in comparison to deterministic ones, they still categorize occupants and behaviors according to static classes, providing usually only boundary conditions. For these reasons, stochastic approaches are preferred to reproduce users' random nature. To better reflect users' real actions, stochastic models are usually developed using data acquired during experimental campaigns in order to predict users' behaviors. It should be noted that, at each time-step, the output is not a binary value which clearly defines whether the condition is true or false, but it is a probability, ranged between 0 and 100%. The probability of an occupant's action taking place is expressed as a function of the parameters of the environmental stimulus and the action is randomly performed with a calculated probability. Indeed, in order to assess the occurrence of an event (e.g. modify the AC set temperature), the probabilities should be compared to a series of

numbers randomly generated from a uniform distribution [95]. If the probability is higher than the random number, the output is true (e.g. the set temperature increases or decreases according to the optimal comfort range temperatures), otherwise, it is false. In this perspective of obtaining reliable stochastic results, a certain number of simulations are necessary [96].

The choice of a stochastic approach is followed by the selection of the mathematical form. They are usually based on regression formulas, related to the identification of the users' probability (intended as a group of people) to perform a given action as a consequence of a stimulus, such as the external or internal temperature. The formulas adopted for the relation could be linear, logistic, or Weibull type.

The equation should fit the experimental data as well as possible and, in parallel, it must not present physical impossibilities for the parameter ranges (e.g. probabilities greater than 1). Thence, the objective is determining which mathematical formula is best suited to describing the relationship between the occupant behavior and environmental conditions.

The main advantage of regression formulas is that they reflect a stochastic and gradually changing, rather than a deterministic and suddenly changing, relationship to environmental conditions, which is more realistic and accurate than threshold models [97-99].

Some researchers [100-101] suggested the adoption of linear models to estimate the actions' probability as a function of one or more predictor variables. The linear relationship between the response and the predictors is expressed by the following equation:

$$p_i = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \cdots + \beta_n x_{n,i}$$

where "p_i" is the probability of action occurrence (e.g. light switching), "ß" is the vector of the regression coefficients and "x" is the vector of the predictor variables (e.g. work-plane illuminance). Even if this approach is extremely simple and immediate, it has big limitations. In fact, it poorly predicts the observations at the upper and the lower bounds and the probability can be greater than one [102]. Moreover, in these models, it would be possible for p_i to take values outside the interval [0, 1], thence when the final output is dichotomous (0: no action; 1: action done), the logistic or Weibull ones are preferred.

Generalized linear models have been introduced to overcome these issues.

The most frequently adopted form of the logistic regression models [103-104], are expressed as follows:

$$logit(p_i) = ln\left(\frac{p_i}{1 - p_i}\right) = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \cdots + \beta_n x_{n,i}$$

where “logit” is the linking function for logistic regression. Currently, many researchers [105-107] have evaluated logistic regression models appropriateness for estimating the probability of an adaptive behavior triggered by one or more predictor variables.

Although logistic models are simply observation based on statistical correlations (without incorporating absolute threshold characteristics), the Weibull model encompasses both the threshold and stochastic characteristics of an occupant’s response to an environmental stimulus, by combining the strengths of the above two modelling approaches. In this model, a triggering environmental parameter under which the probability of action is 0 must be set.

The mathematical form of the two parameters Weibull distribution functions is:

$$p = 1 - e^{-\left(\frac{x}{l}\right)^k}$$

where “l” and “k” are the scale and shape parameters. The first represents the linear effect of the environmental stimulus and the second its power effect.

Three parameters distributions have been proposed too. Wang proposed a probabilistic formula with a Weibull distribution that could be used for several adjustment actions: [108]

$$p(x) = \begin{cases} 1 - e^{-\left(\frac{x-u}{l}\right)^k} \frac{\Delta t}{t} & if\ x > u \\ 0 \quad if & x \leq u \end{cases}$$

The third parameter “u” is the threshold for the action occurrence, typical of occupants’ physical response to the trigger “x”. The parameters “u”, “l”, and “k” are three undetermined constant coefficients that quantify the way the occupants react to a certain environmental discomfort and are independent of the environmental stimulus and time. The parameter “u” represents the threshold characteristic of the occupant’s physical response to the environmental stimulus. It is the limit above or below which users’ reaction to discomfort starts and has the same dimension. The quantity “x – u” represents how far the environmental condition “x” exceeds the occupant’s threshold “u”. The coefficient “l” is the scale parameter that represents the linear effect of the environmental stimulus. “l” > 0 has the same dimension as “x” and “(x – u)/l” is a dimensionless measure of the environmental parameter “x”. Finally, “k” is the shape parameter that represents a power exponent for the effect of the environmental stimulus. “k” > 0 and “k” is dimensionless. The temporal frequency is provided by the parameters “Δt” and “t”. The first is a discrete time step in the measurement and/or simulation (set at 10 min) and the second is a known time constant (here fixed at 60 min).

A graphical representation of the three types of the regression formulas is shown in Fig. 5.

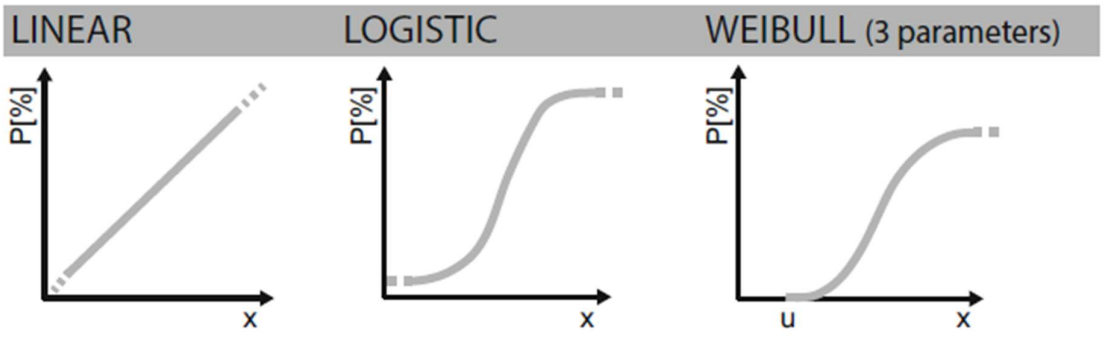

Figure 5. Graphical representation of the linear, logistic and Weibull distribution functions

In literature, the most of behavioral models predicting the AC use was developed using the logistic regression analysis, both with environmental (i.e. outdoor temperature) and individual factors (i.e. users' preferences and background) [109-110].

Following the previous experimentations, even in the present study, a logistic regression analysis was applied to evaluate the interactions between the users and the room thermostat inside the office, thus defining the main stimuli which trigger their actions.

8. Adaptive Control Algorithms (ACAs)

Among the ACAs, the Humphreys adaptive algorithm was selected for the present research.

The algorithm was tailored on the specifics of office buildings and it was only driven by temperature inputs, so it did not consider metabolic and clothing variables as well as CO_2 concentration. In offices, the met and clo parameters are rather constant [111]. In fact, the activity level was the sedentary one (met: 1.0 according to ISO 7730) and the clothing level among the students was very similar along each season [112].

The adaptive comfort temperature (T_{comf}) is that defined by Humphreys and Nicol as the optimal operative temperature and is related to the running mean of the outdoor temperature (T_{rm}). Upper and lower temperature limits for the comfort "dead band" are then defined with reference to this adaptive comfort temperature by summing or subtracting 2 °C.

The algorithm is based on the relation between operative and comfort temperature (indicated with T_{op} and T_{comf} respectively): the operative temperature reflects indoor environmental conditions while the comfort temperature follows outdoor variations. At each time step, the algorithm compares the T_{op} to a dead band around the T_{comf}: if the T_{op} is inside the dead band no action is taken, while raising actions are automatically performed if $T_{op} < T_{comf} - T$, where T is set at 2°C.

The logical structure of the original form of the Humphreys adaptive algorithm is reported in Fig. 6.

Once a discomfort condition was recognized, actuation commands sent specific instruction to the controller including the control setting (e.g. thermostat setpoint, terminal air flow rate), spatial scales (e.g. whole building, single thermal zone), time factors (e.g. duration, schedules), etc.

a) Humphreys' algorithm				
No.	Window algorithm parameter	Symbol	Sample	Derivation or source
1	Outdoor air temperature	T_{out}	1 per hour	Interpolated from climate file (hourly data in file)
2	Daily mean outdoor air temperature	T_{odm}	1 per day	Calculated from 24 hourly data points per day
3	Running mean outdoor temperature (CEN)	T_{rm}	1 per day	$T_{rm}(init) = (1-\alpha)(T_{odm-1} + \alpha\, T_{odm-2} + \alpha^2\, T_{odm-3} \ldots)$ initial value calculated from previous 20 days daily mean, then $T_{rm} = (1-\alpha)T_{odm-1} + \alpha T_{rm-1}$
4	Running mean response to T_{out}	α	Const	Default $\alpha = 0.8$ (0.01–0.99 allowed range)
5	Comfort temperature	T_{comf}	1 per day	If $T_{rm} > 10$, $T_{comf} = 0.33\, T_{rm} + 18.8$ (CEN Standard[1]) If $T_{rm} \leq 10$, $T_{comf} = 0.09\, T_{rm} + 22.6$ (CIBSE Guide A[2])
6	Indoor air temperature	T_{ai}	1 per hour	Available at each timestep (variable)
7	Indoor operative temperature	T_{op}	1 per hour	Available at each timestep (50% mrt, 50% T_{ai})
8	Comfort	Comf	1 per hour	Comf = "yes" if $abs(T_{op} - T_{comf}) \leq 2$ K Comf = "hot" if $(T_{op} - T_{comf}) > 2$ K Comf = "cold" if $(T_{op} - T_{comf}) < -2$ K
9	Logit function	Func	1 per hour	Func = $logit(P_w) = 0.171\, T_{op} + 0.166\, T_{out} - 6.43$
10	Probability function for window open	P_w	1 per hour	$P_w = exp(Func)/(1 + exp(Func))$
11	Random number between 0 and 1	R_n	1 per hour	Generate from Fortran RNG
12	Windows status (0 = closed, 1 = open)	iwin	1 per hour	If Comf = "hot" and window closed (w = 0) then if $P_w > R_n$ then window open (w = 1) If Comf = "cold" and window open (w = 1) then if $R_n > P_w$ then window closed (w = 0)
(b) Modified/integrated inputs of Humphreys algorithm				
8		Comf	1 per minute	Comf = "yes" if $abs(T_{op} - T_{comf}) \leq 1$ K Comf = "hot" if $(T_{op} - T_{comf}) > 1$ K Comf = "cold" if $(T_{op} - T_{comf}) < -1$ K
8_bis		CO_2	1 per minute	Available at each timestep (variable)
8_ter		CO_2 limit	Const	CO_2 limit = 1250 ppm
12	Windows status (0 = closed, 1 = open)	iwin	1 per minute	If $CO_2 > 1250$PPM and window closed (w = 0) then window open (w = 1) If Comf = "hot" and window closed (w = 0) then if $P_w > R_n$ then window open (w = 1) If Comf = "cold" and window open (w = 1) then if $R_n > P_w$ then window closed (w = 0)

Figure 6. Logical structure of the Humphreys adaptive algorithm

9. Case study

In order to evaluate the indoor thermal conditions in a typical office building, this experimentation was performed in a multi-occupied office located in Polytechnique University of Ancona (latitude: 43°35′15” N; longitude: 13°31′01” E; altitude 140 m) and affected by a Mediterranean climate.

Figure 7. External view of the building with the monitored space indicated by the dashed rectangle

This laboratory area has a concrete load-bearing structure with a glazed facade as the external envelope. The indoor partitions consist of plasterboard walls and plasterboard ceiling contains the electrical air conditioning systems. The indoor layout as well as the main features of the tested room in are reported below.

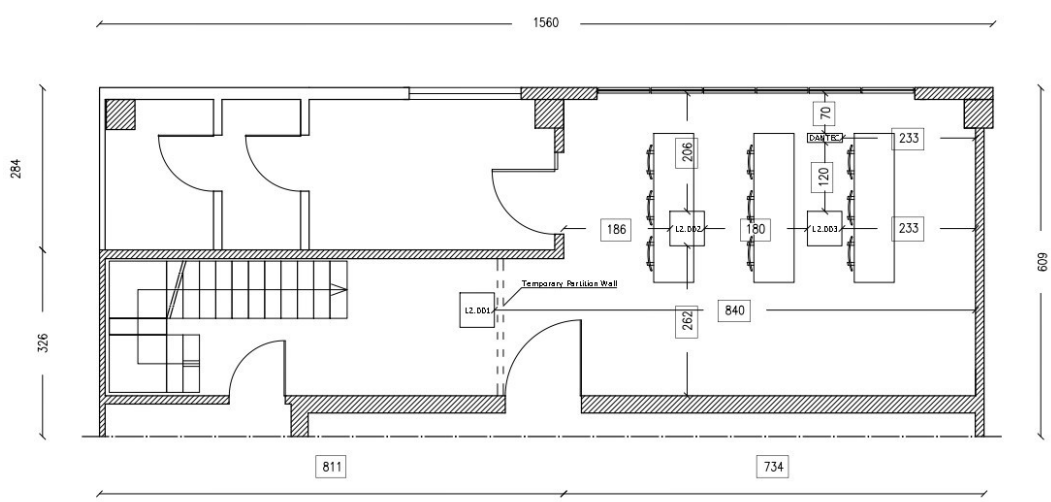

Figure 8. Indoor layout of the monitored office room. Dantec station and AC units are also shown in the plan

Figure 9. Indoor view of the monitored office room

Office features						
Neat floor area (m^2)	Internal Height (m)	Cooling-Heated volume (m^3)	Ratio S/V	Orientation	Glazed surface (m^2)	Opening surface (m^2)
40	2.8	112	0.36	North	18	1.3

Figure 10. Main features of the office

Basic information about participants				
	Age	Number		
		Female	Male	Total
Value	28 ± 5	12	11	23

Figure 11. Basic information about participant

As shown in Fig. 11, the office was occupied by twenty-three people between 23 and 32 years of age (mean:26). Each day's experiment time was from 9:50 a.m. to 5:10 p.m. with slight variations in entrance and exit times depending on daily schedules.

During the experiment, the participants were required to stay in the office room and perform normal activities such as sitting and walking. They were free to manually interact with the room thermostat whenever discomfort conditions were matched.

Data of indoor and outdoor environment parameters and human bio-signals were recorded in a database by a computer.

10. Experimental methods

This study consists of an experimental monitoring campaign that collected data on environmental variables, human bio-signals, users' actions and thermal sensation. The data was used to develop an automatic AC-operating system driven by an adaptive control algorithm that, combining both environmental and biomentrical parameters, could guarantee a thermally comfortable environment inside an office building, matching the users' preferences.

The monitoring campaign was carried out during some days on January 2020. Each situation refers to winter conditions with the heating system on. At first, the tested room was empty then occupied by students with the aim of recording the users' interaction with the AC system and, subsequently, driving the AC system by the automatized control loop.

The work was structured according to the following phases:

1. data collection: recording indoor and outdoor environmental parameters, human bio-signals, users'actions on AC system and their thermal sensation;
2. data analysis: evaluating trigger parameters for the AC use and identifying an ACA in order to reflect the users' thermal preferences;
3. automatic system development: installing a mechanized system to pilot the AC use, driven by the adopted ACA implemented in a PC software.

Therefore, a monitoring system was set up to record environmental and biometrical parameters as well as users' actions on the AC system.

To perform the analysis, only data collected during the occupied period has been considered since the presence of people inside the room is a precondition for the occurrence of any action.

As far as environmental data, the measurements were carried out according to ISO7726:2001:

1. outdoor environmental conditions: outdoor air temperature, solar radiation, wind speed and direction were collected at two minutes intervals by an outdoor micro-climate station located on the roof of the monitored office building;

2. indoor climate conditions: an indoor micro-climate station equipped with a globe thermometer, a humidity probe as well as two hot sphere anemometers to record indoor air temperature and indoor air velocity at the rate of two minutes intervals was used. The predicted mean vote (PMV) and the Percentage of Person Dissatisfied (PPD) were also monitored by the Dantec micro-climate station that acquired the necessary comfort parameters using the above mentioned probes positioned according to the guidelines given in ISO 7726. The PMV and PPD indexes were evaluated in accordance with ISO 7730. The PMV is considered satisfactory in the interval [−0.5, 0.5]. A metabolic rate (M) of 1.0 met was assigned based on the typical activities performed in the office

rooms and the clo values of 1.0 was considered uniform for all the participants in the office.

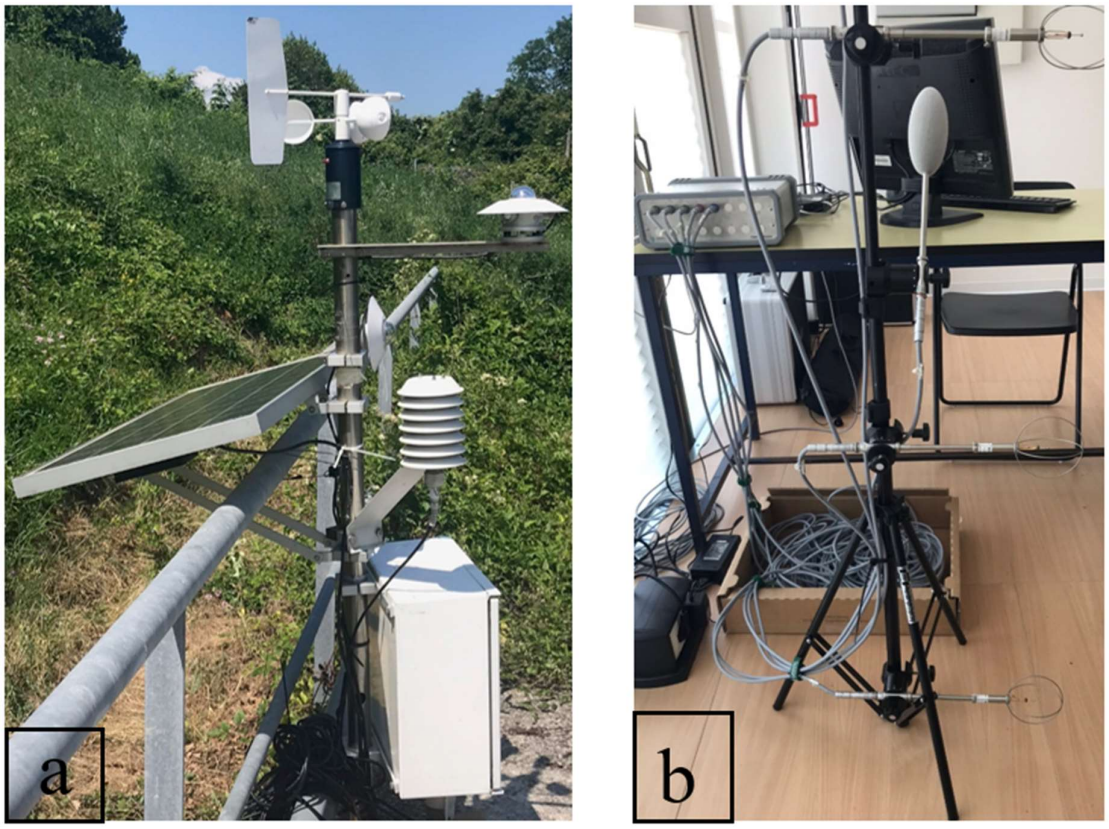

Figure 14. View of the outdoor (a) and indoor (b) micro-climate station

Several studies have also suggested the feasibility of using human bio-signals (e.g., skin temperature, heart rate) to evaluate people's thermal comfort level under laboratory conditions [113-116]. In fact, skin temperature was found to be highly correlated with people's thermal sensation while heart rate is closely related to the metabolic level and work intensity [117-119].

Therefore, in the present study, a wrist-band device provided by Shimmer, equipped with an optical pulse probe and a skin surface temperature probe, was adopted to estimate the occupants' heart rate (HR) and skin temperature, respectively. Thanks to real-time Labview drivers, all the monitor human bio-signal were automatically sent and stored to the software.

Outdoor micro-climate station			
Parameter	Sensor	Accuracy	Range
Outdoor Air Temperature [°C]	Thermohygrometer	0.2°C	-30°C to +70°C
Outdoor Air R.H. [%]	Thermohygrometer	± 1.5 % RH	0 - 100% RH
Horizontal Solar Radiation [W/m^2]	Pyranometer	10.64 µV/Wm^{-2}	0 – 2000 W/m^2
Vertical Solar Radiation [W/m^2]	Pyranometer	10.64 µV/Wm^{-2}	0 – 2000 W/m^2
Wind Speed [m/s]	Cup Anemometer	0 – 75 m/s	3%
Wind Direction [°]	Vane Anemometer	0 – 360°	3°
Indoor micro-climate station			
Parameter	Sensor	Accuracy	Range
Indoor Air Temperature [°C]	Draft Probe	0ºC to +45°C: ± 0.2K -20ºC to +60°C: ± 0.3K +60°C to 80°C: ± 0.5K	-20°C to +80°C
Indoor Air R.H. [%]	Humidity Probe	From 0 to +10°C: +2% RH From 10 to 30°C: +1.5% RH From 30 to 45°C: +2% RH	0 - 100% RH
Indoor Air Velocity [m/s]	Draft Probe	0-1 m/s: ± 2% OR* ± 0.02 m/s 1-5 m/s: ± 5% OR* 5-10 m/s: ±10% OR*	0.05-10 m/s
Indoor Operative Temperature [°C]	Operative Temperature Probe	From 0 to 10°C: ±0.5 K From 10 to 40°C: ±0.2 K From 40 to 45°C: ±0.5 K	0 to 45°C
Wearable devices			
Parameter	Sensor	Accuracy	Range
Skin-surface Temperature [°C]	Shimmer 3 Bridge Amplifier + Unit with skin-surface temperature probe	-	-
Heart Rate [bpm]	Shimmer3 GSR + Unit with optical pulse probe	10KΩ to 4.7MΩ: ± 10% 22KΩ to 680KΩ: ± 3%	10KΩ to 4.7MΩ 22KΩ to 680KΩ

Figure 15. Measurement ranges and specifications of the sensors

Humans feedback on the ambient conditions were also investigated.

In this perceptive, occupants were asked to carry out a survey every 10 minutes that adopted a simple question: “What is your general thermal sensation?” and occupants could choose the answer from a 7-point thermal sensation scale:

- hot (+3)
- warm (+2)
- slightly warm (+1)
- neutral (0)
- slightly cool (-1)
- cool (-2)
- cold (-3)

If the thermal preference was “neutral”, then the occupants were regarded as comfortable.

Otherwise (i.e., "warmer" or "cooler"), they were regarded as uncomfortable. As occupants were more likely to report their uncomfortable state, we assumed that if no reports were received from occupants' vote, they were considered as comfortable in that period or they had reached the comfortable state on their own by performing some adaptive behaviors (e.g., put on a jacket).

In order to evaluate which parameters are the driving factors for AC system operations and include them in the ACA, a logistic regression analysis was applied to experimental data and the resulting R^2 for each correlation.

The implemented Humphreys' adaptive algorithm was used to drive the automatized AC-operating system considering both environmental and biomentric parameters. To adapt the algorithm to the case study, the original form has been applied with modifications which consisted of changing the comfort temperature in relation to the recorded data and the Mediterranean climate, restricting the "dead band" around the comfort temperature from ± 2°C to ± 1°C and setting up limit values of the biometrical parameters in relation to the optimal thermal conditions among occupants (neutral thermal sensation). Whenever the collected users' heart rate and skin temperature were below or above the imposed threshold values, the AC T_{set} changed according to their needs. Sensors monitored both the environmental and biometrical parameters at fixed time laps, sending the collected signals to the data logger, which had the double function of storing data and transmitting them to the control software, developed in a graphic language (LabVIEW 2014 by National Instruments). The normal heating set-point was 22 °C during the winter season, according to the ASHRAE 90.1-2007 recommendations. The adaptive control algorithm, launched at regular time laps, predicted the interaction between the occupants and the AC unit. If a discomfort condition was recognized, the Wi-Fi programmable controller (Coolmaster) received the actuation commands from the server to directly drive the operation of the air conditioning system (e.g. increase or decrease the set-point temperature) as long as the action probability was higher than the random number.

A schematic process of how the automatized control loop performed is shown in Fig. 16.

When the occupants leaved their offices, the AC system was always turned off in order to optimize the energy consumption.

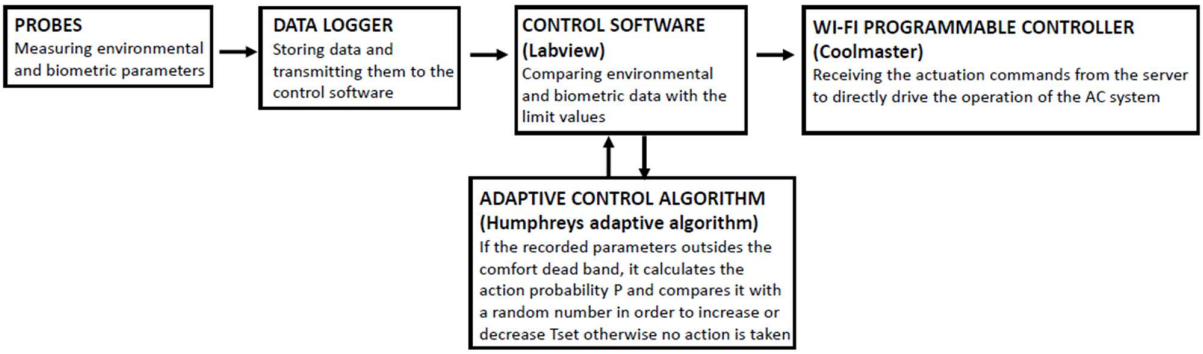

Figure 16. Schematic representation of how the automatic control system performs

11.Results and discussion

11.1 Analysis of the thermal environment and human bio-signal

Some preliminary analyses were carried out in order to evaluate both the outdoor air temperature (Fig. 12) and the indoor air temperature (Fig. 13).

The former varied from 12,5°C to 16°C during the occupancy hours while the latter was monitored at three different heights from the floor level. Results have shown that it ranged from 16°C to 18°C at 10 cm from the floor level, from 18°C to 20,5°C at 60 cm and from 20°C to 25°C at 110 cm. Generally, minimum temperatures were recorded during the early hours of the day before the AC systems turns on. An almost constant temperature profile was kept during the working hours from 10:00 a.m. to 3:30 p.m. where the mean temperature was 17,5°C at 10 cm, 19°C at 60 cm and 21,8°C at 110 cm from the floor level. Higher temperatures were collected during the last working hours from the draft probes placed at 60 cm and 110 cm heights, respectively.

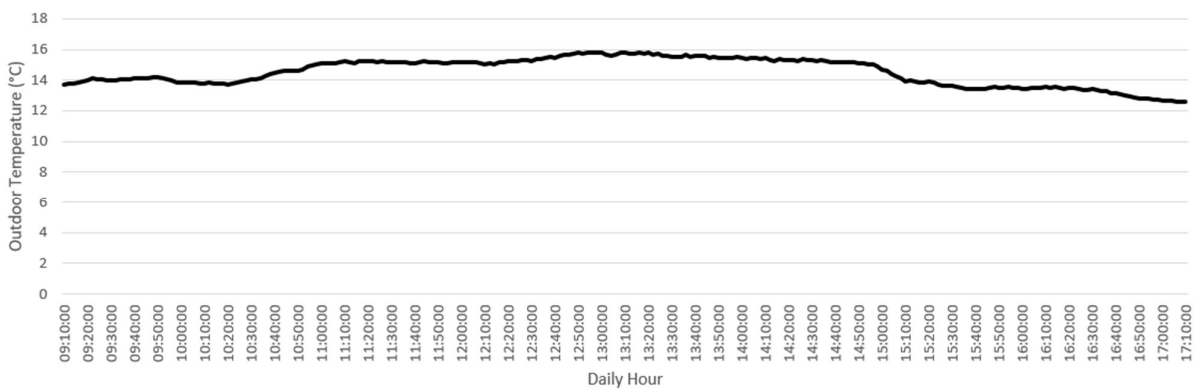

Figure 12. Outdoor Air Temperature profile during the working hours

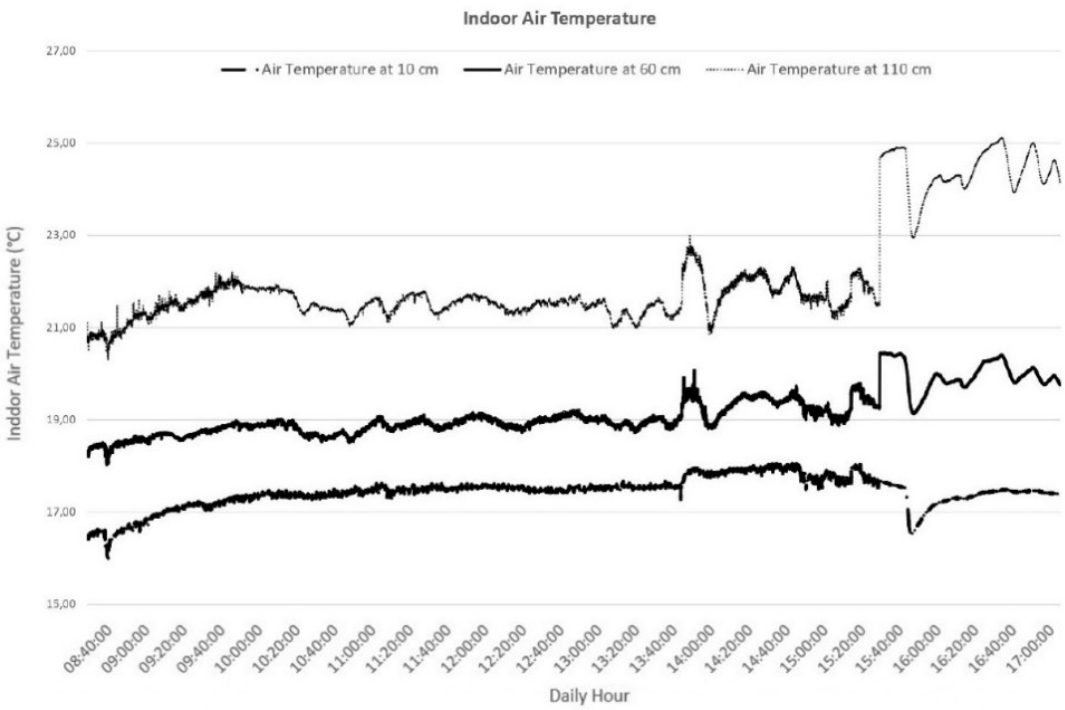

Figure 13. Indoor Air Temperature at three different heights from the floor level during the working hours

Despite of the presence of the large glazed façade, there is an almost uniform thermal environment inside the office, so the equipment location in the middle of the room was adequately representative of the indoor environmental parameters.

Indoor thermal conditions have also been analysed according to the predicted mean vote (PMV) which were also monitored by the Dantec micro-climate station. The PMV is considered satisfactory in the interval [−0.5, 0.5] in accordance with the standard ISO 7730.

For a better understanding of the variation due to occupancy, Fig. 14 reports the PMV values for two typical winter days. The solid and dashed lines refer to an empty and occupied day, respectively. It can be observed from the fluctuations in the occupied trend that occupant adjustment and interactions with the surrounding modify the environment to match their preferred thermal sensation.

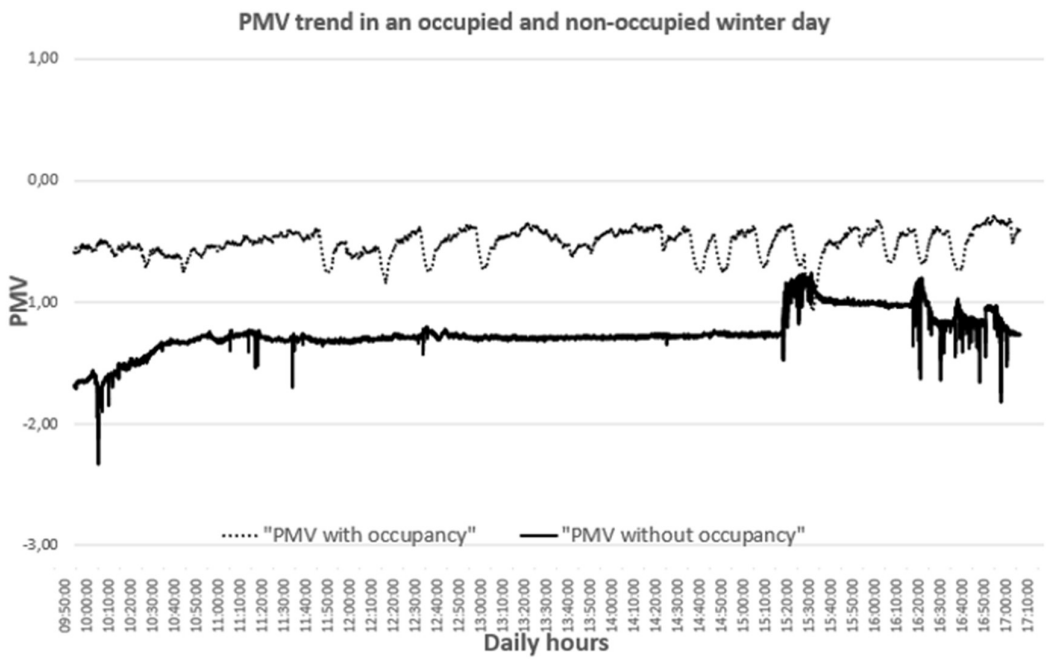

Figure 14. PMV trend in an occupied and non-occupied winter day

Thermal sensation is a close measure of what ideal comfort conditions would be and can be estimated by the wrist skin temperature and heart rate with a high degree of accuracy,

The occupants' biometric data were recorded and the Fig. 15 shows the relationship between the monitored users' wrist skin temperature and the relative thermal sensation.

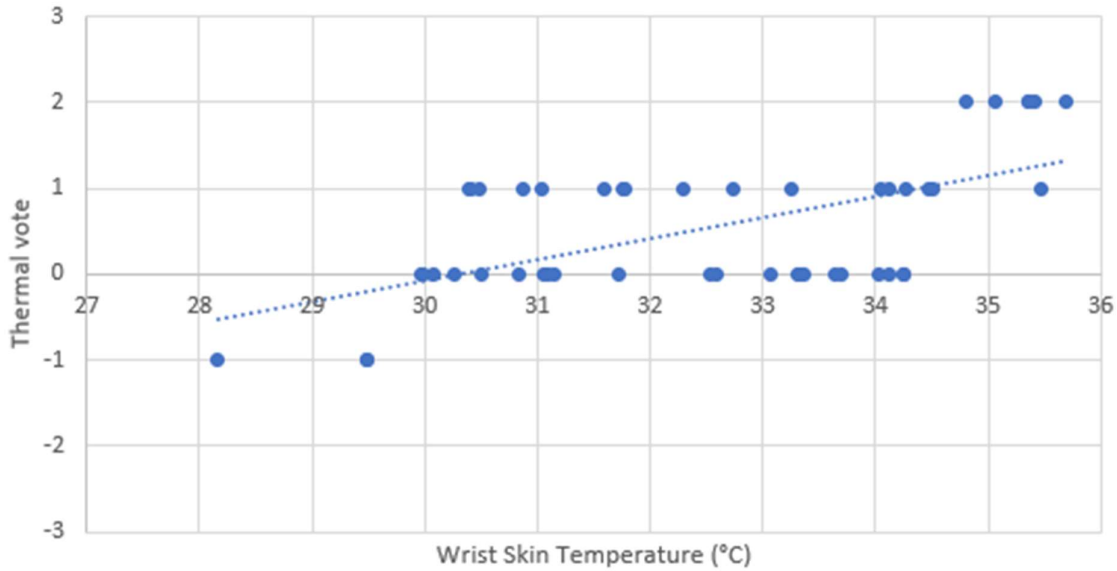

Figure 15. Relationship between the wrist skin temperature and thermal sensation

It was clear that the thermal sensation level increased from -1 (slightly cool) to 2 (warm) with an increase in the wrist skin temperature, reflecting the human thermal sensation.

Therefore, the human thermal sensation correlated positively with the wrist skin temperature. Moreover, the difference in wrist skin temperature indicated that each individual generated a different wrist skin temperature even though they were exposed to the same indoor temperature. Thus, the human subjects may have different thermal sensation votes under the same wrist skin temperature.

Fig. 16 reports the acceptable values of the monitored biometric parameters in relation to the operative temperature inside the office room.

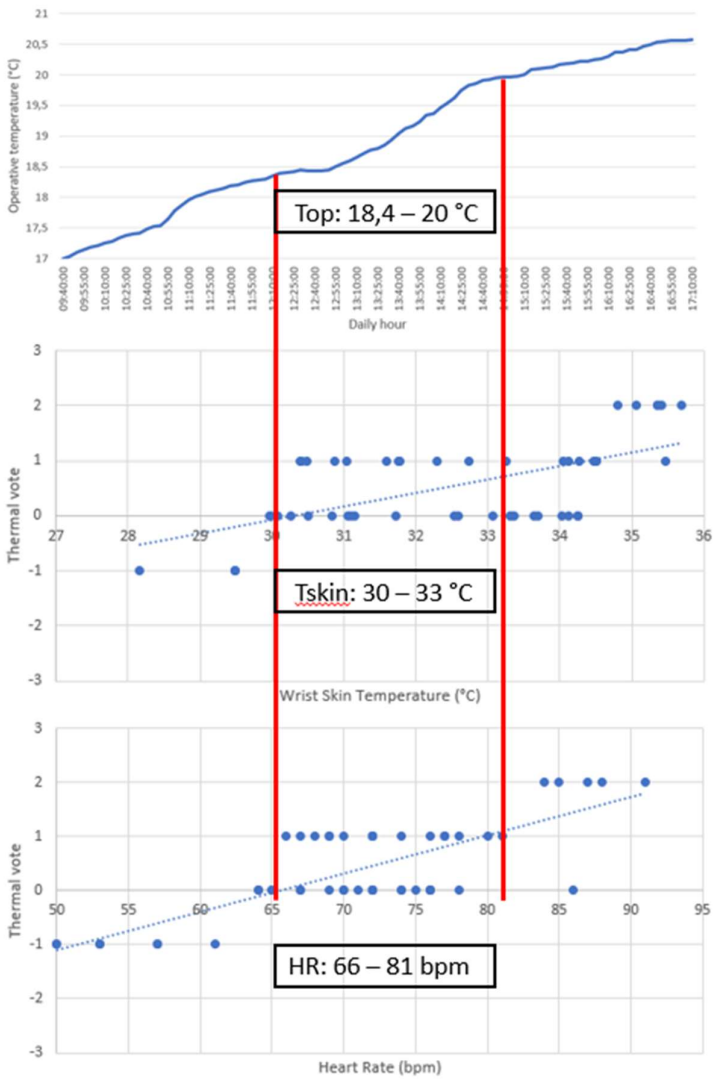

Figure 16. Operative temperature, skin temperature and HR values which matched thermal comfort conditions

It was found that the comfort range of the users' skin temperature was between 30°C and 33°C. These outputs are consistent with the findings of the experimentation carried out by Wei Li et al. [120]. Fig. 17 reports the values of the monitored skin temperature in relation to the type of activity carried out by the occupants.

Clearly, with regard to the sitting still activity, the skin temperature range of 31-34°C matched the neutral thermal sensation among the occupants.

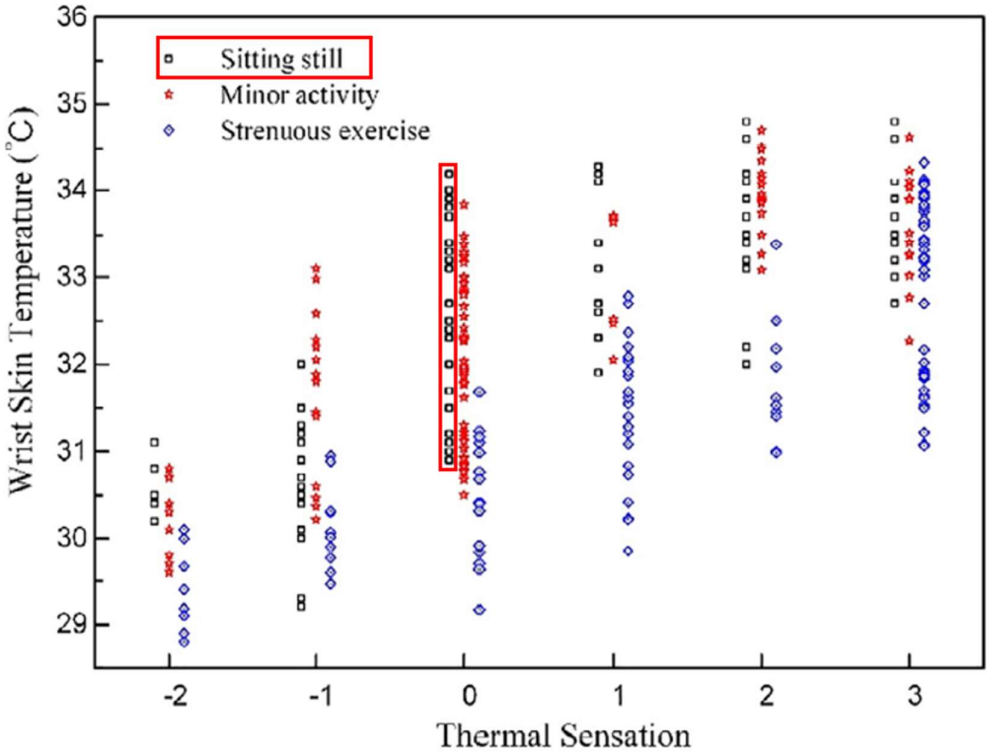

Figure 17. Relationship between the wrist skin temperature and thermal sensation obtained by Wei Li et al.

The same study conducted by Wei Li et al. pointed out the significant relationship between human thermal sensation and human metabolic rate which depends on activity level.

Fig. 18 shows the relationship between the monitored users' heart rate and the relative thermal sensation, during the present work.

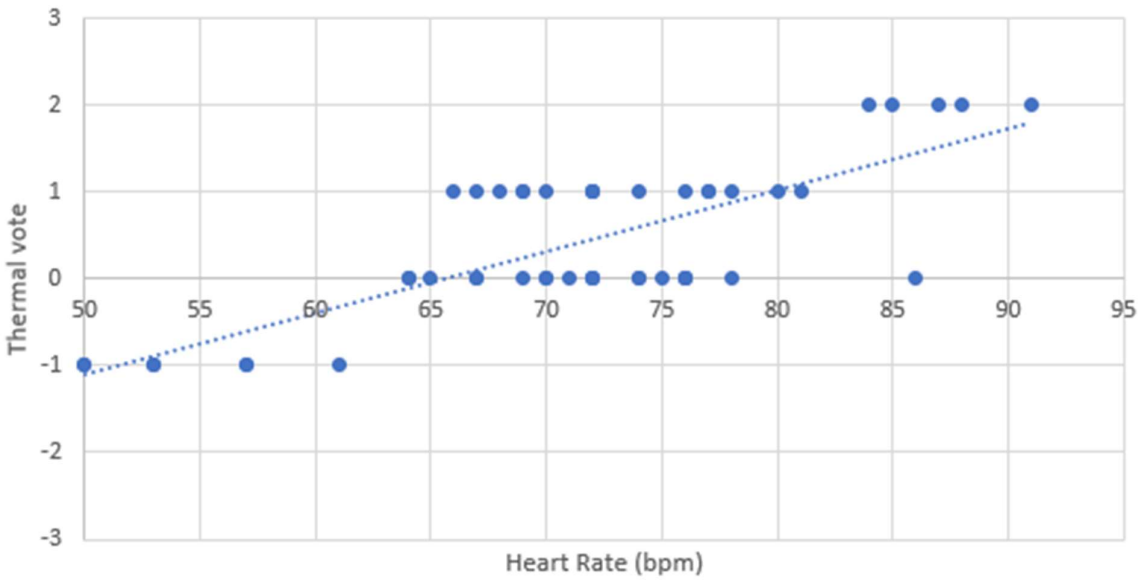

Figure 18. Relationship between the heart rate and thermal sensation

Results indicated that the variation range of the heart rate was 50-91 bpm for the condition of sitting or doing minor activities. As revealed in previous research, the heart rate increased with an increased in thermal sensation levels, thus existed a positive correlation between these two parameters.

It was found that the comfort range of the users' heart rate was between 66 bpm and 81 bpm. Comparing these findings with those of the experimentation carried out by Wei Li et al. it can be seen that their outputs associated with optimal comfort conditions were between 75 bpm and 81 bpm. On the other hand, our finding showed a wider range of heart rate values correlated to acceptable comfort conditions among the occupants (65-80 bpm) perhaps due to the different climate conditions and country.

Fig. 19 reports the values of the monitored heart rate by Wei Li et al. in relation to the type of activity carried out by the occupants. Clearly, with regard to the sitting still activity, the heart rate range of 75-81 bpm matched the neutral thermal sensation among the occupants.

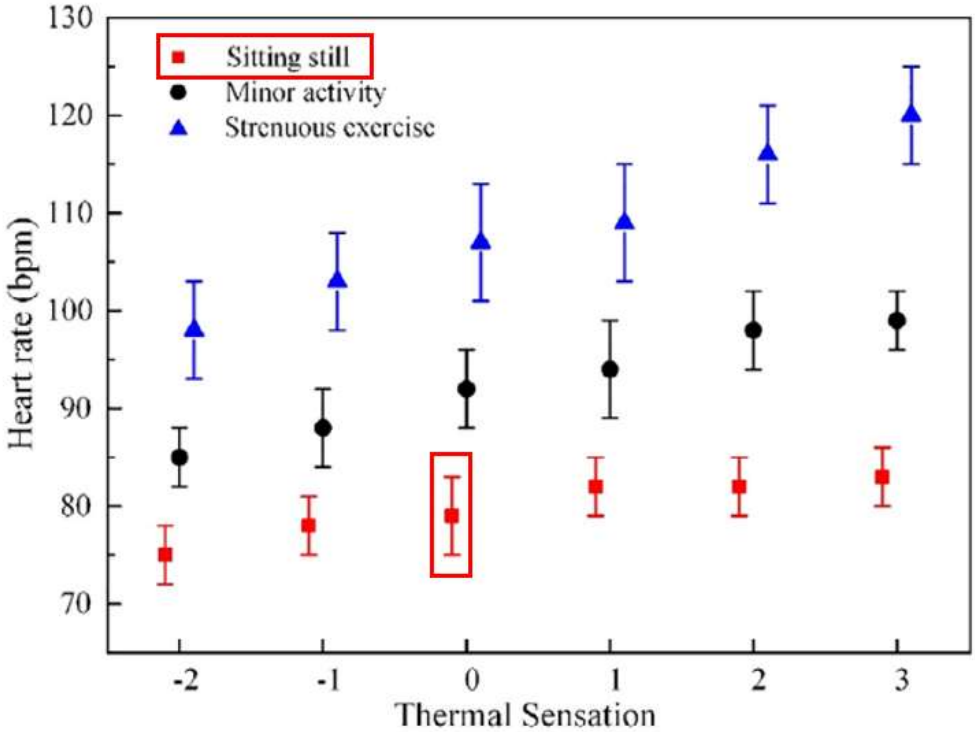

Figure 19. Relationship between the heart rate and thermal sensation obtained by Wei Li et al.

In conclusion, a summary of the environmental and biometric parameters monitored during the survey is reported in Fig. 20.

	Variable	Max	Min	Mean	Median	St. Dev.
Environmental parameters	Outdoor Temperature (°C)	15,79	10,3	13,12	12,965	1,34
	Outdoor Relative Humidity (%)	100	63,6	85,58	85,55	7,7
	Wind Speed (m/s)	3,45	0	0,97	0,97	0,55
	Indoor Temperature_10 cm height (°C)	18,56	15,31	17,65	17,63	0,45
	Indoor Temperature_60 cm height (°C)	20,12	15,92	17,98	17,95	0,51
	Indoor Temperature_110 cm height (°C)	21,27	16,4	18,73	18,6	0,62
	Indoor Relative Humidity (%)	54,61	40,98	50,77	52,43	3,76
	Indoor Operative Temperature (°C)	20,66	16,7	18,66	18,45	0,7
Thermal sensation	PMV index	-0,76	-2,34	-1,25	-1,28	0,16
Biometric data	Mean Skin Temperature (°C)	35,69	28,16	32,47	32,58	1,93
	Heart Rate (bpm)	91	50	71,31	72	9,26

Figure 20. Summary of recorded parameters in relation to occupied period

This gives the variation ranges for each parameter as well as statistical analyses including the mean, median and standard deviation values. These values refer only to periods in which the room was occupied as occupancy is the main precondition for the occurrence of actions.

11.2 Evaluation of the main trigger parameters to take action

In this section, trigger parameters for AC operations are evaluated using a logistic regression analysis which was applied to experimental data. Both environmental and biometrical parameters were investigated as driving factors which leaded occupants to interact with the AC system in order to restore their thermal comfort condition. At first, occupants could freely interact with the AC system through the room thermostat and the frequency of their actions was recorded in order to develop the behavioral models.

As trigger parameters, the indoor operative temperature was initially investigated. Fig. 21 reports the logistic regression model outcomes (black solid line) overlapped on the operative temperature collected data (diamond dots) and the resulting R^2 for this correlation.

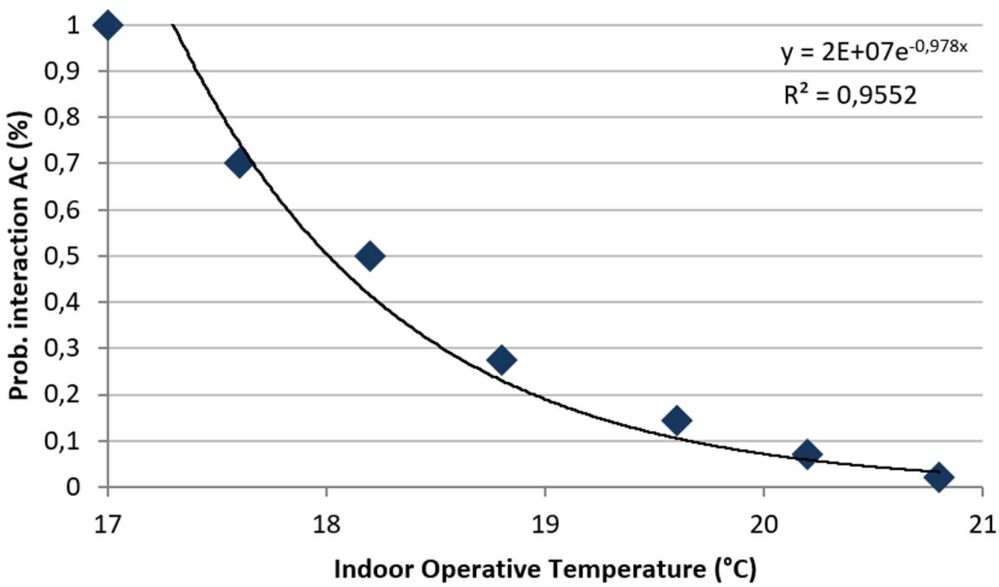

Figure 21. Logistic regression model on the operative temperature with the resulting R^2

Results were consistent with a previous study conducted by Burak Gunay et al. [121] considering that higher values of probability would have been obtained for lower indoor operative temperature values. The overlap between the different outputs is reported in Fig. 22, thus it could be seen that the probability of interacting with the AC system increases with the decrease of the operative temperature inside the monitored office room.

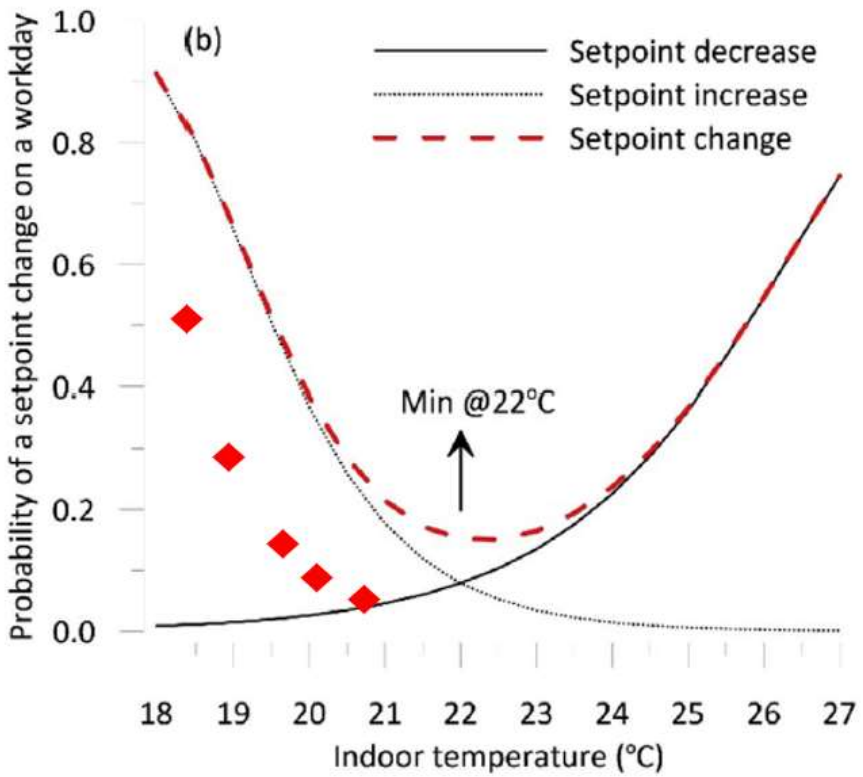

Figure 22. Overlap between the logistic regression model outputs of the study conducted by Burak Gunay et al.

Moreover, further analyses were carried out in order to better understand the users' action on the AC system throughout the day. Thus, Fig. 23 reports the likelihood of observing a setpoint increase/decrease event during the morning and afternoon hours, respectively.

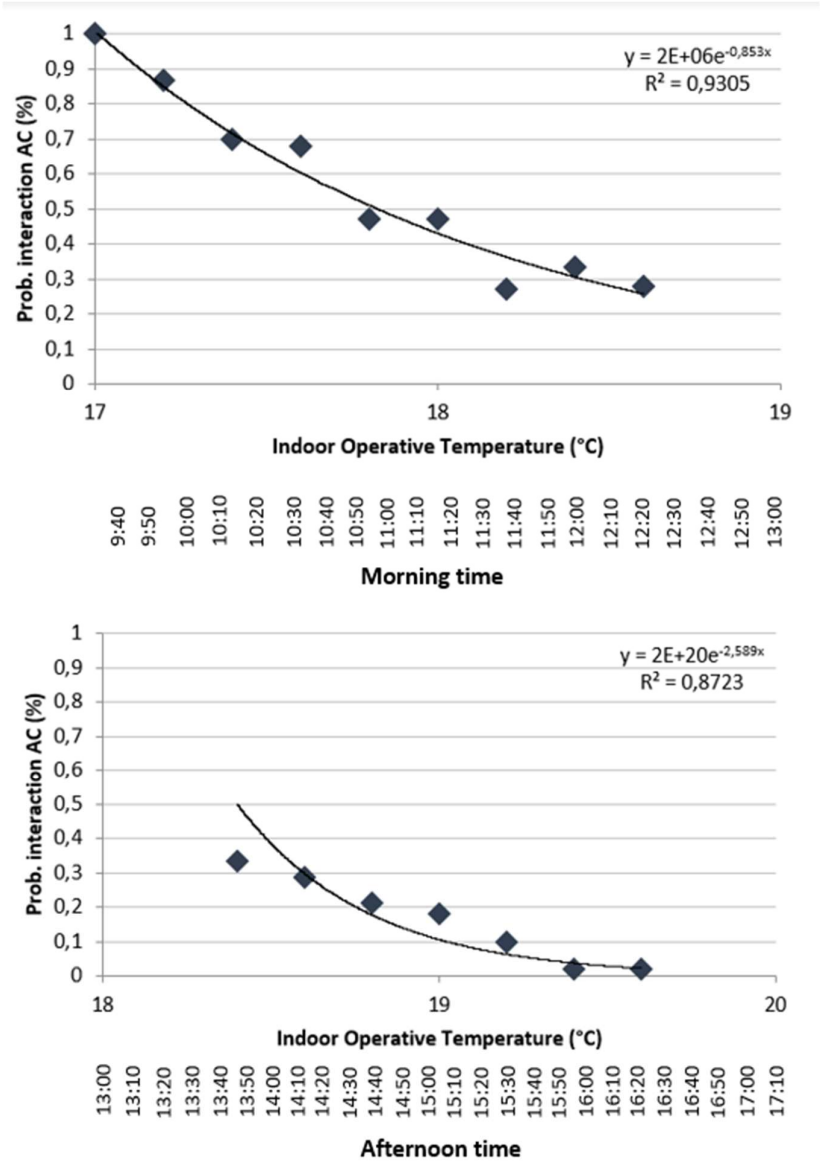

Figure 23. Probability of interacting with the AC system during the morning and afternoon hours with the resulting R^2

As expected, during the early hours of the day especially immediately after the users' arrival in the office, the lower operative temperature values leaded to higher probability outcomes of increasing the setpoint temperature. Whereas, the interaction's probability decreased during the afternoon as the AC system had been running in order to keep the environment more comfortable.

The influence of the outdoor temperature on the users' thermal comfort was also investigated during this experimentation (Fig. 24). The resulting coefficient R^2 which was used to evaluate the goodness-of-fit of the regression model, indicates that exist a fairly week correlation between the outdoor temperature and the thermal comfort perceived by occupants. Therefore, this parameter was not recognized as one of the main stimuli for AC system and human interaction.

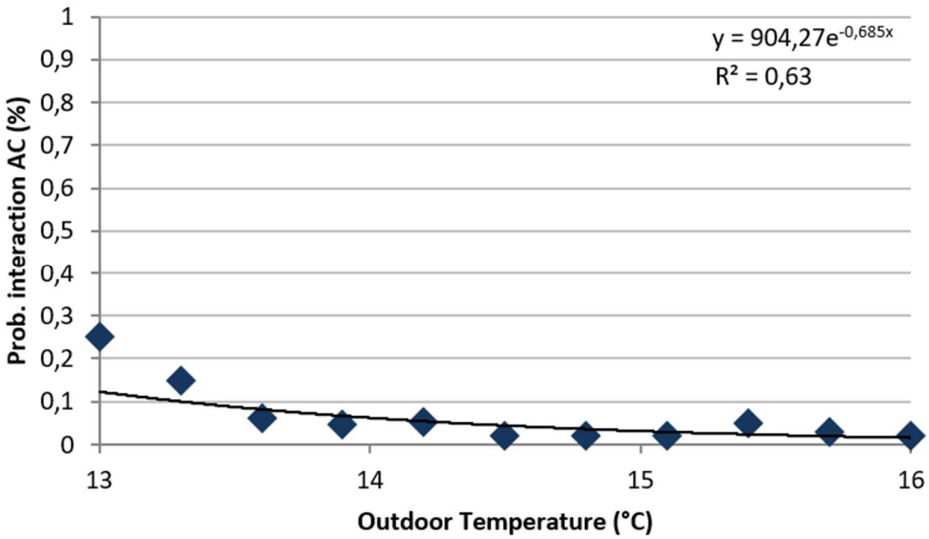

Figure 24. Logistic regression model on the outdoor temperature with the resulting R^2

Secondly, participants' skin temperature and hearth rate were collected by a wrist-band device worn on their left hand where the heating set point temperature was fixed at 22°C.

Logistic regression models applied on the two biometrical parameters as well as the resulting R^2 for each correlation are reported in Fig. 25 and Fig. 26.

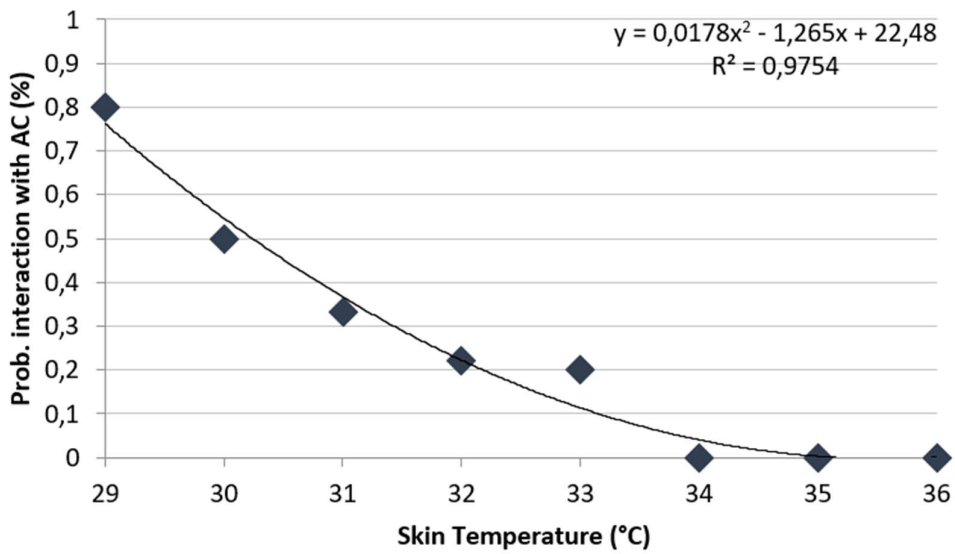

Figure 25. Logistic regression model on the wrist skin temperature with the resulting R^2

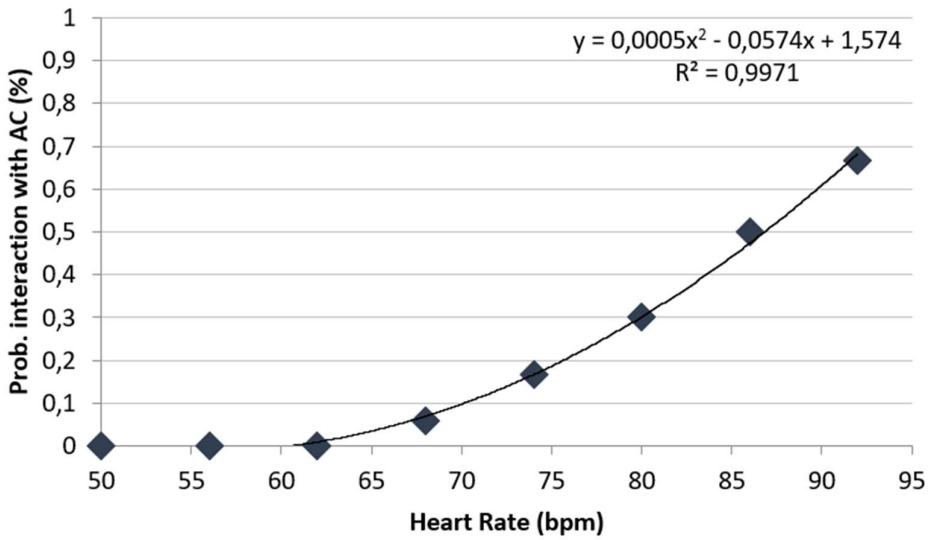

Figure 26. Logistic regression model on the heart rate with the resulting R^2

The resulting coefficients R^2 indicate that exist a very strong correlation between the biometric parameters and the thermal comfort perceived by occupants. Therefore, during this experimentation, human bio-signals were added as inputs in the optimized control loop for the automatic interaction with the AC system to dynamically determine the optimum temperature set-point for the majority vote of the occupants.

11.3 Standard operative mode of the AC system

At first, the AC unit was driven with the standard operative mode. The normal heating set-point was 22 °C during the experimentation, according to the ASHRAE 90.1-2007 recommendations for the winter season.

The occupants could change the temperature set point up to ± 1°C by using the room thermostat. Each thermostat keypress action was programmed to increase or decrease the temperature setpoint by 0,1°C. For example, they would have needed to press the pushbutton five times to change the setpoint by 0,5°C. The thermostat inside the room recorded the operative temperature and compared it with the fixed setpoint. If $T_{op} < T_{set}$, the AC system was turned on in order to bring the indoor temperature close to the setpoint one. The standard AC system driving mode is shown in Fig. 27.

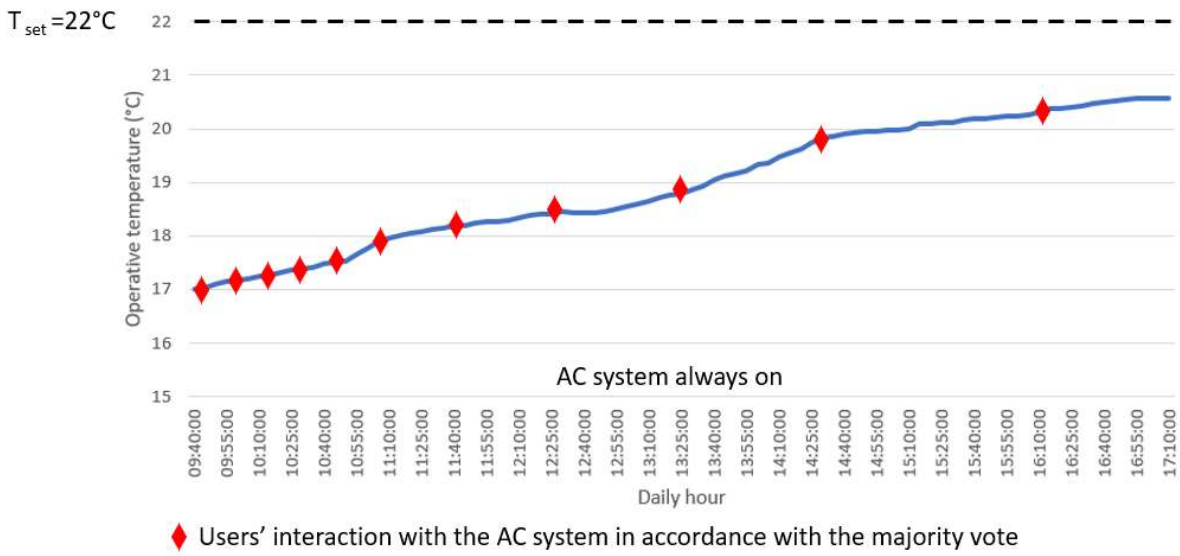

Figure 27. Standard AC system driving mode

11.4 Implementation of the Humphreys' adaptive algorithm

In the present study, the algorithm was tailored on the specifics of the case study by modifying the acquisition rate of the recorded parameters (from 1 hour to every 10 minutes), setting an optimized comfort temperature and integrating new inputs such as heart rate and skin temperature due to their strong correlation with the thermal sensation of the occupants.

In fact, our findings demonstrated that the operative temperature of 19°C with "dead band" around it of ± 1°C was considered more appropriate for the present case study since matched the biometric data associated with acceptable comfort conditions among the occupants in a Mediterranean climate.

Therefore, the first modification of the algorithm's text consisted of restricting the "dead band" around the comfort temperature (where the AC T_{set} remained unchanged) which was fixed at 19°C in relation to the biometric outputs and the acceptable thermal sensations of the monitored occupants. Thus, at each time step, the algorithm compared the T_{op} to a dead band around the T_{comf}: if the T_{op} was inside the dead band no actions were taken, while the AC T_{set} was automatically increase/decrease if (T_{op} - T_{comf}) < -1°C or (T_{op} - T_{comf}) > 1°C, respectively, as well as the probability outputs were higher than the random numbers.

According to the previous research' lack, the main goal of this study was to develop an automatic AC-operating system driven by an adaptive control algorithm that considers even biometric parameters in order to reach a thermally comfortable environment. In this perspective, human bio-signal were recorded and thus correlated to the users' thermal sensation. It was found that acceptable comfort conditions were matched when the operative temperature inside the room was between

18,4°C and 20°C which correspond to HR values of 65-80 bpm and T_{skin} values of 30-33°C. The definition of the users' comfort range was the basis to develop the subsequent part of the implemented Humphreys' adaptive algorithm.

In this case, the operative temperature values associated with the biometric data ware taken into account in order to decide if interacting with the AC system or not.

Since the comfort heart rate and skin temperature values corresponded to the same rage of operative temperatures regarded thermically acceptable, whenever the monitored parameters exceeded the upper or lower limits, actions of increasing or decreasing the AC T_{set} were carried out.

If T_{skin}>33°C and HR>80bpm as well as $P_{AC}>R_n$, the AC T_{set} was automatically decrease, whereas if T_{skin}<30°C and HR<65bpm as well as $P_{AC}>R_n$, the AC T_{set} was automatically increase. On the other hands, if 30°C<T_{skin}<33°C and 65bpm<HR<80bpm (18,4°C<T_{op}<20°C) no actions were taken.

The logical structure of the implemented Humphreys' adaptive algorithm is reported in Fig. 28.

Implemented Humphreys' adaptive algorithm				
No.	AC algorithm parameter	Symbol	Sample	Derivation or source
1	Outdoor air temperature	T_{out}	every 10 min	Interpolated from climate file
2	Daily mean outdoor air temperature	T_{odm}	1 per day	Calculated from 24 hourly data points per day
3	Running mean outdoor temperature (CEN)	T_{rm}	1 per day	$T_{rm}(init)=(1-\alpha)(T_{odm-1} + \alpha T_{odm-2} + \alpha^2 T_{odm-3}\ldots)$ initial value calculated from previous 20 days daily mean, then $Trm=(1-\alpha)T_{odm-1}+\alpha T_{rm-1}$
4	Running mean response to T_{out}	α	Const	Default α=0,8 (0,01-0,99 allowed range)
5	Comfort temperature	T_{comf}	1 per day	If $T_{rm}>10, T_{comf}=0,33T_{rm}+17,8$(CEN Standard) If $Trm\leq 10$, $Tcomf=0,09Trm+22,6$ (CIBE Guide A)
6	Indoor air temperature	T_{ai}	every 10 min	Available at each time step (variable)
7	Indoor operative temperature	T_{op}	every 10 min	Available at each time step (50% mrt, 50%T_{ai})
8	Comfort	Comf	every 10 min	Comf="yes"if $abs(T_{op}-T_{comf})\leq 1°C$ Comf="hot"if $(T_{op}-T_{comf})>1°C$ Comf="cold" if $(T_{op}-T_{comf})<-1°C$
9	Logit function	Func	every 10 min	$Func=logit(P_{AC})=0,171T_{op}+0,166T_{out}-6,43$
10	Probability function for AC interaction	P_{AC}	every 10 min	$P_{AC}= exp(Func)/(1+exp(Func))$
11	Random number between 0 and 1	R_n	every 10 min	Generate from Fortran RNG

12	AC T_{set} status (0=no action, 1=increase/decrease)	i_{AC}	every 10 min	If Comf="hot" and if $P_{AC}>R_n$ then
				T_{set}-1°C (status=1)
				If Comf="cold" and if $P_{AC}>R_n$ then
				T_{set}+1°C (status=1)

13	Hear rate	HR HR limits	every 10 min Const	Available at each time step (variable) $HR_{upper\ limit}$ = 80 bpm $HR_{lower\ limit}$ = 65 bpm
	Comfort	Comf	every 10 min	Comf="yes" if 65 bpm<HR<80 bpm Comf="hot" if HR>80 bmp Comf="cold" if HR<65 bmp

	AC T_{set} status (0=no action, 1=increase/decrease)	i_{AC}	every 10 min	If Comf="hot" and if $P_{AC}>R_n$ then
				T_{set}-1°C (status=1)
				If Comf="cold" and if $P_{AC}>R_n$ then
				T_{set}+1°C (status=1)

14	Skin Temperature	T_{skin} T_{skin} limits	every 10 min Const	Available at each time step (variable) $T_{skin\ upper\ limit}$ = 33 °C $T_{skin\ lower\ limit}$ = 30 °C
	Comfort	Comf	every 10 min	Comf="yes" if 30°C<T_{skin}<33°C Comf="hot" if T_{skin}>33°C Comf="cold" if T_{skin}<30°C

	AC T_{set} status (0=no action, 1=increase/decrease)	i_{AC}	every 10 min	If Comf="hot" and if $P_{AC}>R_n$ then
				T_{set}-1°C (status=1)
				If Comf="cold" and if $P_{AC}>R_n$ then
				T_{set}+1°C (status=1)

Figure 28. Steps in the implementation of the Humphreys' algorithm

11.5 Humphreys' adaptive algorithm operative mode of the AC system

Fig. 29 and Fig.30 show the automatized operation of the AC system driven by the implemented Humphreys' adaptive algorithm which considers the operative temperature and the biometric data, respectively. In the meantime, users' manual actions on the system were performed to adjust the setpoint temperature according to the majority vote to match the preferred thermal sensation (red diamond dots on the graph).

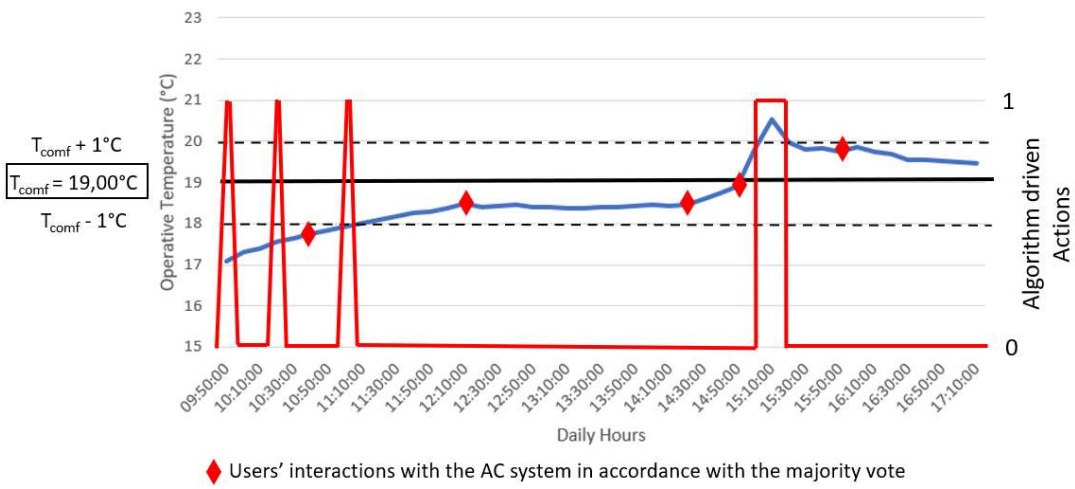

Figure 29. Humphreys' algorithm operative mode trigger by the T_{op}

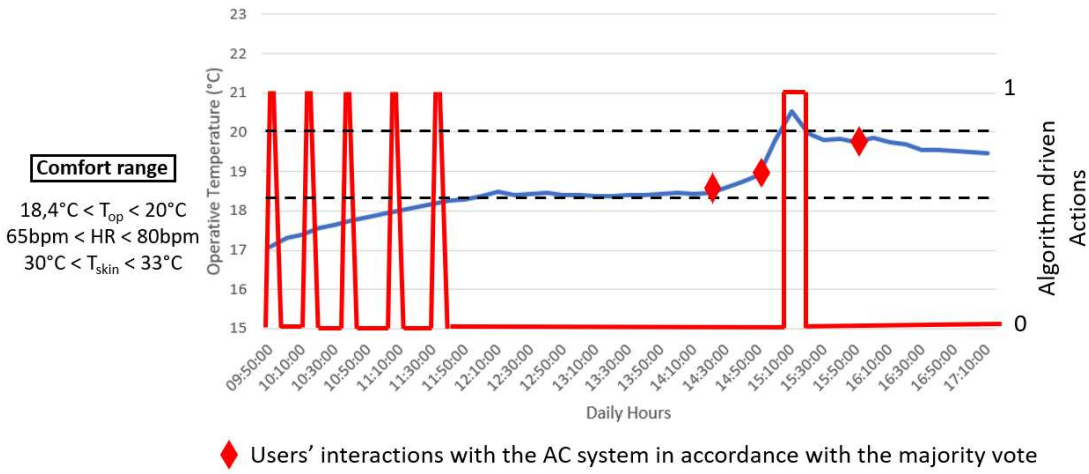

Figure 30. Humphreys' algorithm operative mode trigger by the biometric data

It could be seen that the implemented adaptive control algorithm interpreted properly the occupants needs in terms of thermal sensations, especially with regard to the biometric data inputs where very few manual actions were carried out by users to adjust the setpoint temperature.

12.Conclusions

The main goal of the present study was to develop an automatic AC – operating system driven by a tailored adaptive control algorithm that, combining both environmental and biometrical parameters, could guarantee a healthy and thermally comfortable environment, interpreting the occupants' thermal sensation and needs. To this aim, preliminary analyses were carried out in order to evaluate the thermal environment. The outdoor temperature ranged from 12,5°C to 16°C during occupancy while the mean indoor operative temperature was in the range of 19-21 °C. The PMV values were recorded during the unoccupied and occupied period. In the latter case, the fluctuations of the trend were due to the presence of users which interacted with the surrounding to match their needs. Since thermal sensation is a close measure of what ideal comfort conditions would be, the occupants' biometric data were recorded. It was found that the comfort range of the users' skin temperature was between 30°C and 33°C while the heart rate values between 65 bpm and 80 bpm were linked to acceptable comfort conditions. These data were monitored when the operative temperature inside the room was in the range of 18,4-20°C. Human feedback on the ambient conditions were also investigated by submitting the occupants to a simple question: "What is your favorite thermal sensation?". The possible answers were chosen from a 7-point thermal sensation scale, consistent with the ASHRAE Standard 55. A positive correlation between the human bio-signals and the users' thermal sensation was found. Indeed, both the skin temperature and the heart rate increased with the increasing of the thermal sensation levels. During the experimentation, users were free to perform physical and psychological adaptations to discomfort conditions as well as their manual actions on the room thermostat were recorded. Behavioral models were developed in order to predict the interaction between the occupants and the surrounding. In this perspective, the trigger parameters for AC system operations were evaluated by a logistic regression analysis. Both environmental and biometrical data were investigated as possible driving factors. The indoor operative temperature, the skin temperature as well as the heart rate were found to be the most relevant stimuli to the users interaction with the AC unit due to the high value of the coefficient R^2. Therefore, these three parameters were used as inputs for the development of a tailored adaptive control algorithm which sent actuation commands to the Wi-Fi programmable controller to directly drive the operation of the air conditioning system (e.g. increase or decrease the set-point temperature) if a discomfort condition was recognized. Therefore, the original form of the Humphreys' adaptive algorithm was changed by modifying the acquisition rate of the recorded parameters (from 1 hour to every 10 minutes), setting an optimized comfort temperature and integrating new inputs such as heart rate and skin temperature.

The first modification consisted of restricting the "dead band" around the comfort temperature (from ±2°C to ±1°C) which was fixed at 19°C in relation to the biometric outputs and the acceptable thermal sensations of the monitored occupants. Thus, at each time step, the algorithm compared the T_{op} to the dead band around the T_{comf}: if the T_{op} was inside the dead band no actions were taken, while the AC T_{set} was automatically increase/decrease if (T_{op} - T_{comf}) < -1°C or (T_{op} - T_{comf}) > 1°C, respectively, as well as the probability outputs were higher than the random numbers.

The second modification consisted of integrating human bio-signals to the original form of the adaptive algorithm. Since the Humphreys' algorithm is based on is based on the relation between operative and comfort temperature, the operative temperature range associate with comfortable biometric data was investigated. Thus, it was found that acceptable comfort conditions were matched when the operative temperature inside the room was between 18,4°C and 20°C which correspond to HR values of 65-80 bpm and T_{skin} values of 30-33°C.

Whenever the monitored parameters exceeded the upper or lower limits of the comfort dead band, actions of increasing or decreasing the AC T_{set} were carried out.

If T_{skin}>33°C and HR>80bpm as well as P_{AC}>R_n, the AC T_{set} was automatically decrease, whereas if T_{skin}<30°C and HR<65bpm as well as P_{AC}>R_n, the AC T_{set} was automatically increase. On the other hands, if 30°C<T_{skin}<33°C and 65bpm<HR<80bpm (18,4°C<T_{op}<20°C) no actions were taken. Results demonstrated that the algorithm operative mode was more suitable to assure a thermally comfortable environment, interpreting with adequate accuracy the occupants' needs as very few manual actions were carried out to adjust the setpoint temperature in relation to the majority preferred thermal sensation. The improvement was even more evident with regard to the biometric parameters as inputs.

The findings of this study provided a further step towards understanding the main stimuli which affected the occupants' thermal comfort as well as considering them as inputs for developing a tailored adaptive control algorithm in an automatic system piloting the AC unit which matched the occupants' satisfaction in terms of thermal sensation, health, and productivity. Although many results were consistent with those presented in previous research, the sample size and the monitoring period are rather limited due to the restrictions applied to face the Coronavirus emergency. Thus, a more extensive investigation would be useful to confirm the reported outputs. Future studies will focus on the impact of the automatized control loop on the building energy consumptions.

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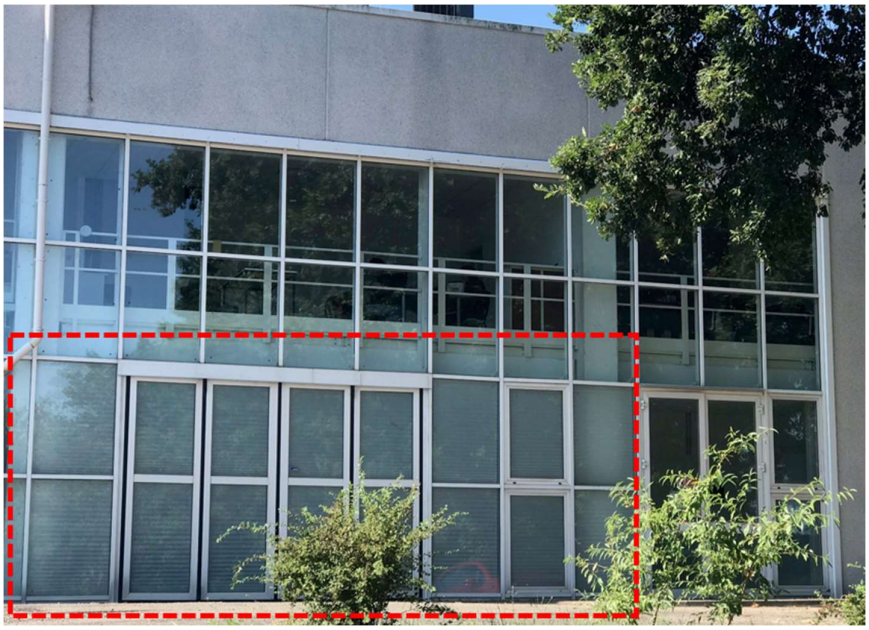
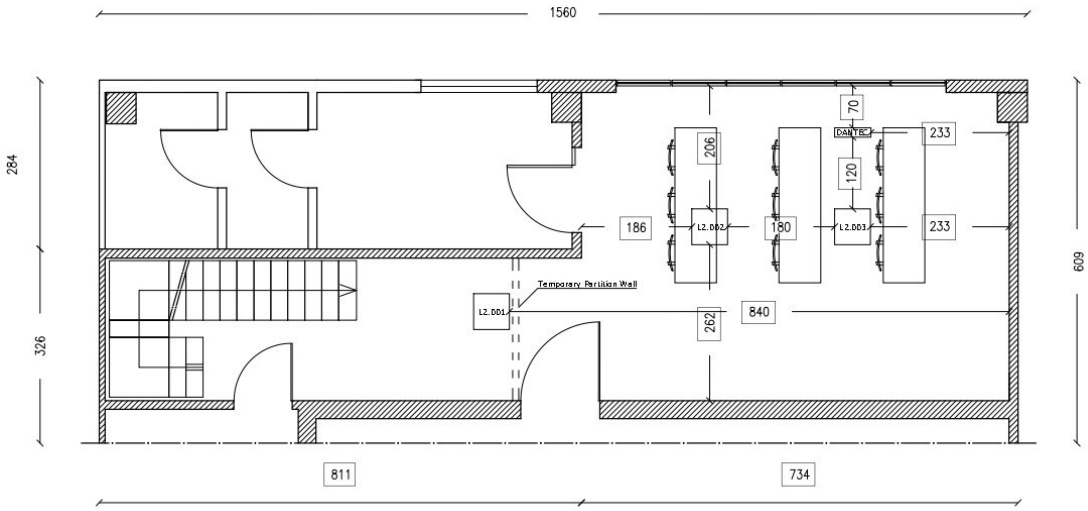
Caso di studio

Con l'obiettivo di valutare le condizioni di comfort termico all'interno di un ufficio, si è scelto di eseguie la presente sperimentazione in un'aula della Facoltà di Ingegneria dell'Università Politecnica delle Marche (latitudine 43°35'15'' N; longitudine 13°31'01'' E; altitudine 140 m s.l.m.) di Ancona soggetta ad un tipico clima mediterraneo.



Vista esterna dell'edificio con indicazione dell'ambiente monitorato

L'edificio è realizzato con una struttura prefabbricata in c.a. a cui è ancorata una facciata continua che costituisce gran parte dell'involucro esterno. Le partizioni interne sono in cartongesso, così come il controssoffitto che ospita l'impianto di climatizzazione.



Pianta relativa alla distribuzione interna degli spazi, con indicazione della posizione della stazione microclimatica

Vista interna dell'ambiente monitorato

Office features						
Neat floor area (m^2)	Internal Height (m)	Cooling-Heated volume (m^3)	Ratio S/V	Orientation	Glazed surface (m^2)	Opening surface (m^2)
40	2.8	112	0.36	North	18	1.3

Principali caratteristiche dell'ambinete

Basic information about participants				
	Age	Number		
		Female	Male	Total
Value	28 ± 5	12	11	23

Informazioni di base sui soggetti coinvolti nella sperimentazione

L'aula è stata occupata da 23 persone di età compresa fra 23 e 32 anni (età media 26). Ogni giorno, il periodo di monitoraggio iniziava alle 9:50 del mattino e terminava alle 17:10 del pomeriggio, con piccole variazioni circa l'ora di ingresso e uscita. Durante la sperimentazione, ai partecipanti è stato chiesto di restare all'interno dell'ambiente ed eseguire normali attività come camminare o rimanere seduti. Essi erano liberi di interagire manualmente con i dispositivi di controllo dell'impianto di climatizzazione. Dati relativi ai parametri ambientali e biometrici sono stati acquisiti e registrati all'interno di un database.

Metodi sperimentali

La presente tesi consiste in una campagna di monitoraggio in cui sono stati acquisiti dati relativi a variabili ambientali, parametri biometrici, azioni e sensazione termica degli occupanti. I dati sono stati poi utilizzati per sviluppare un sistema di controllo automatizzato dell'impianto di climatizzazione guidato da un algoritmo di controllo adattivo che, combinando sia i parametri ambientali che quelli biometrici, potesse garantire un ambiente termicamente confortevole rispecchiando le preferenze termiche degli occupanti.

Lo studio è stato condotto durante alcuni giorni nel mese di Gennaio 2020, quindi si è fatto riferimento a condizioni invernali con l'accensione dell'impianto di riscaldamento.

Inizialmente, la stanza oggetto della sperimentazione è rimasta vuota, poi è stata occupata da studenti con l'intento di registrare le loro interazioni con l'impianto di climatizzazione e, in seguito, controllarlo automaticamente attraverso il sistema automatizzato.

Il presente lavoro si è strutturato secondo le seguenti fasi:

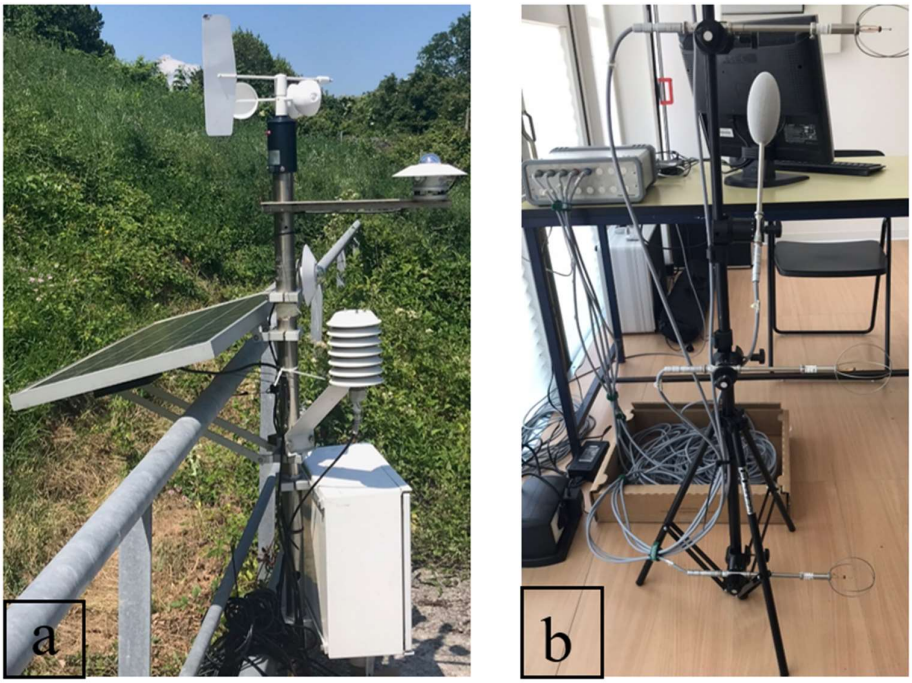
1. raccolta dei dati: acquisizione dei parametri ambientali e biometrici, azioni degli occupanti e loro preferenze termiche;
2. analisi dei dati: valutazione dei parametri scatenanti l'utilizzo dell'impianto e individuazione di un algoritmo di controllo che rispondesse accuratamente alle senzazioni termiche degli occupanti;
3. sviluppo di un sistema automatizzato: installazione di un sitema meccanizzato che ha guidato l'uso dell'impianto di climatizzazione in base all'algoritmo di controllo adattivo.

Di conseguenza, attraverso un sistema di monitoraggio sono atati acquisiti i dati ambientali, biometrici e le azioni degli occupanti. Per svolgere le successive analisi, sono stati considerati soltanto i dati acquisiti in presenza dei soggetti, poichè la loro presenza è la condizione necessaria per definire con quale frequenza sono avvenute le loro azioni.

Le misurazioni dei parametri ambientali sono state eseguite secondo la norma ISO7726:2001:

1. condizioni ambientali esterne: temperatura dell'aria esterna, radiazione solare, velocià e direzione del vento sono stati acquisiti ad intervalli di 2 minuti utilizzando una stazione microclimatica esterna collocata sulla copertura dell'edificio monitorato;
2. condizioni climatiche interne: una stazione microclimatica interna (Dantec), equipaggiata con un globotermometro, un sonda di misurazione dell'umidità e due anemometri, è stata utilizzata per monitorare la temperatura e velocità dell'aria interna ad intervalli di 2 minuti. Il voto medio previsto (PMV) e la percentuale di persone insoddisfatte (PPD) sono stati monitorati attraverso la stessa centralia. Il PMV e il PPD sono stati quindi valutati secondo

la norma ISO 7730: il PMV è considerato soddisfacente se compreso nell'intervallo tra -0,5 e 0,5. Un tasso metabolico (M) di 1,0 met è stato assegnato basandosi sulle tipiche attività eseguite all'interno di un ufficio, mentre i valori di clo pari a 1,0 sono stati assunti uniformi per tutti gli occupanti.



Vista della stazione microclimatica esterna (a) ed interna (b)

Numerosi studi hanno suggerito l'utilizzo dei parametri biometrici (per e.s. temperatura superficiale della pelle e battito cardiaco) per valutare il comfort termico degli occupanti all'interno di un laboratorio di monitoraggio [113-116]. Infatti, la temperatura della pelle risultò altamente correlata alla senzazione termica delle persone, mentre il battito cardiaco al metabolismo e all'intensità di lavoro [117-119].

Pertanto, nel presente studio, si è utilizzato un dispositivo da polso che, attravendo delle particolari sonde, ha permesso di acquisire i dati di temperatura superficiale della pelle e battito cardiaco degli occupanti per poi inviarli automaticamente al software di controllo dell'impianto sviluppato in Labview.

Outdoor micro-climate station			
Parameter	Sensor	Accuracy	Range
Outdoor Air Temperature [°C]	Thermohygrometer	0.2°C	-30°C to +70°C
Outdoor Air R.H. [%]	Thermohygrometer	± 1.5 % RH	0 - 100% RH
Horizontal Solar Radiation [W/m^2]	Pyranometer	10.64 µV/Wm^{-2}	0 – 2000 W/m^2
Vertical Solar Radiation [W/m^2]	Pyranometer	10.64 µV/Wm^{-2}	0 – 2000 W/m^2
Wind Speed [m/s]	Cup Anemometer	0 – 75 m/s	3%
Wind Direction [°]	Vane Anemometer	0 – 360°	3°
Indoor micro-climate station			
Parameter	Sensor	Accuracy	Range
Indoor Air Temperature [°C]	Draft Probe	0ºC to +45°C: ± 0.2K -20ºC to +60°C: ± 0.3K +60°C to 80°C: ± 0.5K	-20°C to +80°C
Indoor Air R.H. [%]	Humidity Probe	From 0 to +10°C: +2% RH From 10 to 30°C: +1.5% RH From 30 to 45°C: +2% RH	0 - 100% RH
Indoor Air Velocity [m/s]	Draft Probe	0-1 m/s: ± 2% OR* ± 0.02 m/s 1-5 m/s: ± 5% OR* 5-10 m/s: ±10% OR*	0.05-10 m/s
Indoor Operative Temperature [°C]	Operative Temperature Probe	From 0 to 10°C: ±0.5 K From 10 to 40°C: ±0.2 K From 40 to 45°C: ±0.5 K	0 to 45°C
Wearable devices			
Parameter	Sensor	Accuracy	Range
Skin-surface Temperature [°C]	Shimmer 3 Bridge Amplifier + Unit with skin-surface temperature probe	-	-
Heart Rate [bpm]	Shimmer3 GSR + Unit with optical pulse probe	10KΩ to 4.7MΩ: ± 10% 22KΩ to 680KΩ: ± 3%	10KΩ to 4.7MΩ 22KΩ to 680KΩ

Specifiche ed intervalli di misurazione dei sensori di acquisizione

Per lo sviluppo del sistema di controllo è stata presa in considerazione anche la sensazione termica degli occupanti. Pertanto, durante la sperimentazione, ai soggetti è stato chiesto di rispondere ogni 10 minuti ad un sondaggio che ha posto loro la seguente domanda: "Qual è la tua generale sensazione termica?". Le risposte ammesse facevano parte della scala di sensazione termica in accordo con la norma ASHRAE 55 e costituita dai seguenti sette punti:

- caldo (+3)
- mite (+2)
- leggermente mite (+1)
- neutra (0)
- leggermente fresco (-1)
- fresco (-2)
- freddo (-3)

Se la senzazione termica era neutra, le persone erano ritenute soddisfatte delle presenti condizioni ambientali all'interno dell'ufficio; in caso contrario, erano riscontrate situazioni di discomfort.

Con l'intento di valutare i principali stimoli per l'interazione degli occupanti con l'impianto di climatizzazione e includerli all'interno dello sviluppo dell'algoritmo di controllo adattivo, la regresione logistica è stata applicata ai dati sperimetali, analizzando poi i coefficienti R^2 di ogni relazione per valutare l'adeguatezza dei modelli.

L'algoritmo di Humphreys implementato è stato quindi utilizzato per guidare le operazioni sull'impianto di climatizzazione invernale, considerando sia i parametri ambientali che biometrici.

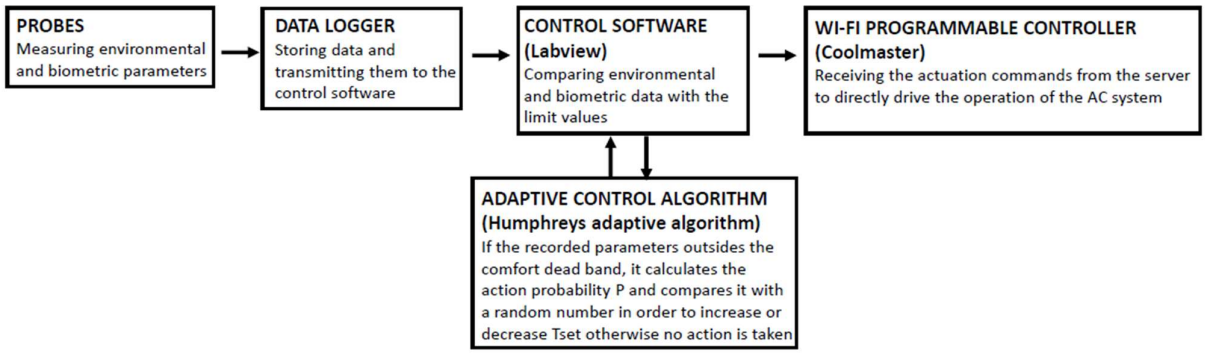
La forma originale è stata modificata cambiando la temperatura di comfort in relazione alle esigenze del presente caso di studio (la dead band si è ristretta da ±2°C a ±1°C), e considerando come nuovi inputs anche i dati biometrici degli occupanti.

Qualora tali valori fossero risultati eccendenti il limite inferiore o superiore della fascia di comfort individuata dal monitoraggio degli occupanti, l'algoritmo di controllo avrebbe modificato la temperatura di setpoint per andare incontro alle esigenze dei soggetti.

I sensori e i dispositivi di acquisizione hanno monitorato i parametri ambientali e biometrici ad intervalli di tempo prefissati, per poi inviarli ad un data logger che ha avuto la doppia funzione di immagazzinare i dati e trasmetterli al software di controllo (Labview 2014 by National Instruments).

La temperatura di setpoint invernale è stata fissata a 22°C in accordo con la norma ASHRAE 90.1-2007. L'algoritmo di controllo, lanciato con determinati intervalli di tempo, ha previsto l'interazione degli occcupanti con l'impianto di climatizzazione. Se fosse stata individuata una condizione di discomfort, il dispositivo di controllo Wi-Fi (Coolmaster) avrebbe ricevuto i comandi di azionamento dal server per dirigere le operazioni di incremento o diminuzione della temperatura di setpoint (la probabilità di azione doveva risultare superiore al numero random).

La schematizzazione del processo del sistema di controllo è rappresentata in figura.

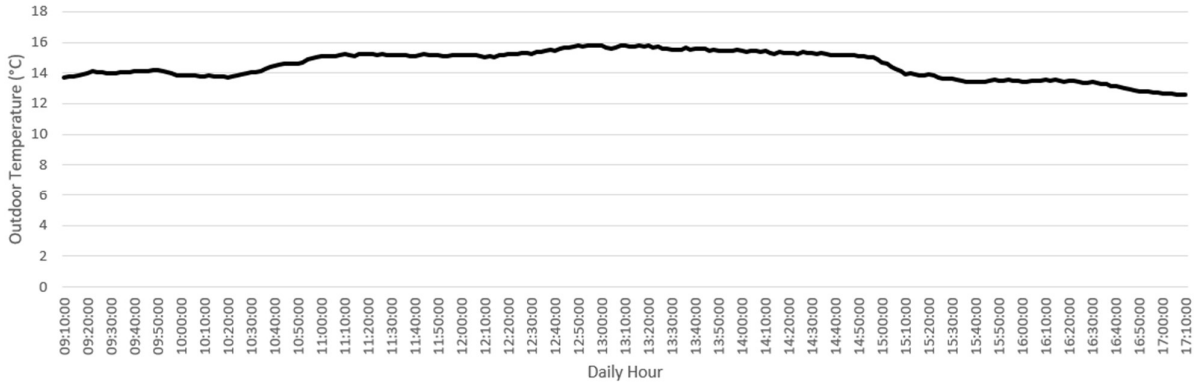


Rappresentazione schematica del funzionamento del sistema di controllo

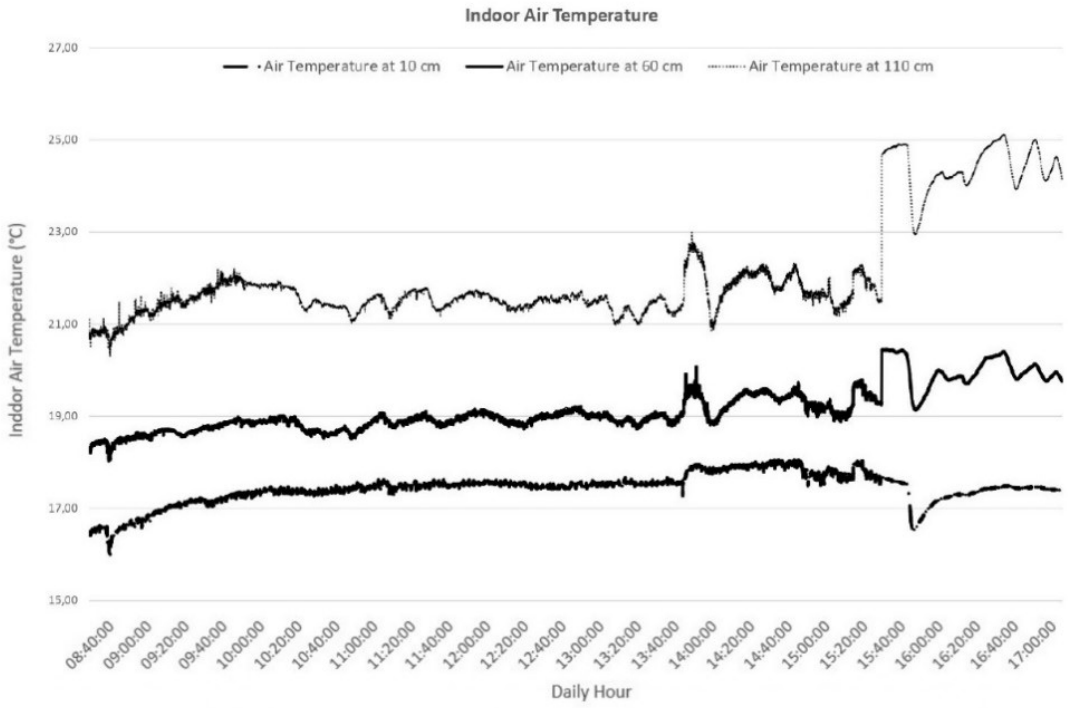
Risultati e discussione

Analisi dell'ambiente termico e dei parametri biometrici

Analisi preliminary sono state svolte per valutare l'andamento sia la temperatura dell'aria esterna sia della temperatura dell'aria interna, come mostrato nelle seguenti figure.



Profilo della temperatura esterna durante le ore lavorative

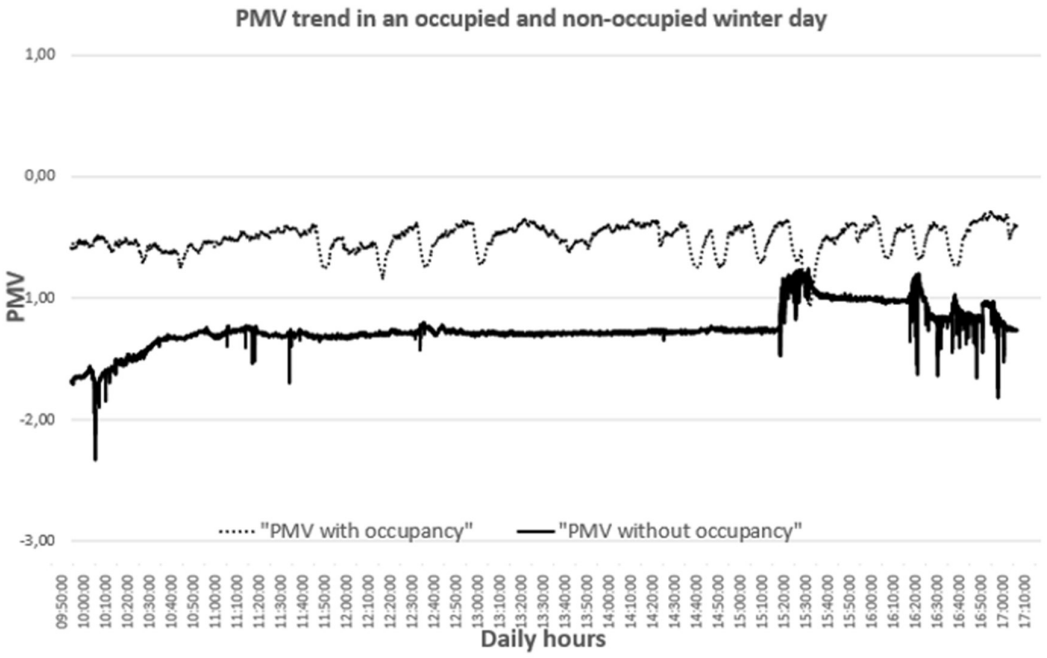


Profilo delle temperature interne acquisite a tre diverse altezze da terra durante le ore lavorative

La temperatura dell'aria esterna variava da 12,5°C a 16°C durante le ore di lavoro.

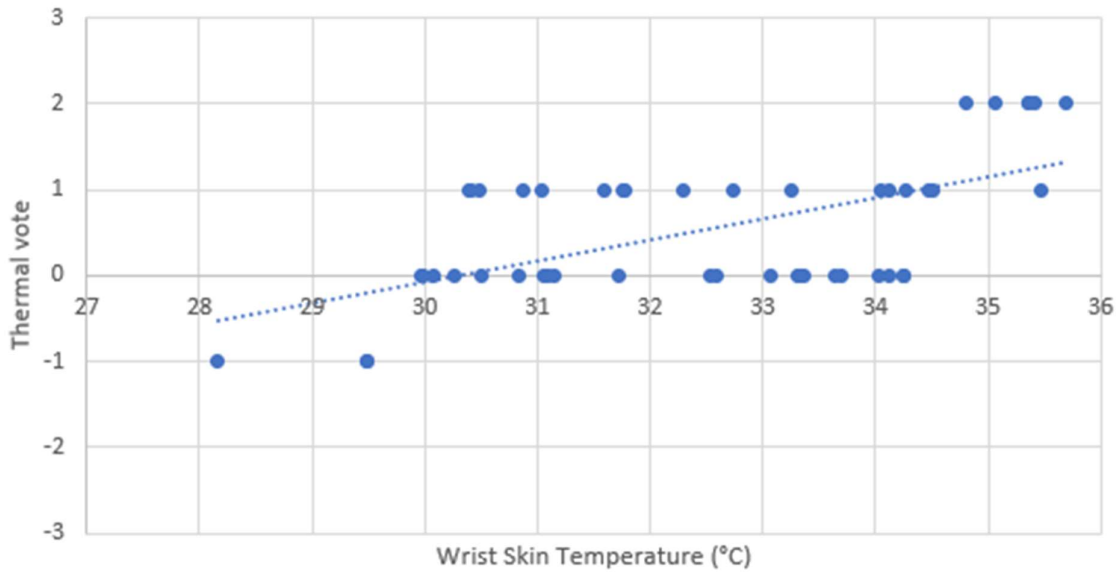
La temperatura dell'aria interna acquisita a 10 cm di altezza dal pavimento risultava tra 16°C-18°C,

a 60 cm risultava tra 18°C a 20,5°C, mentre a 110 cm risultava tra 20°C e 25°C. Le temperature minime sono state monitorate durante le prime ore dell'occupazione subito dopo l'accensione dell'impianto di climatizzazione, mentre un profilo quasi costante si è registato dale 10:00 alle 15:30. Nonostante la presenza della grande facciata vetrata, si è riscontrato un ambiente termico abbastanza uniforme che ha portato al collocamento della centralina climatica Dantec nel centro della stanza.
Le condizioni termiche interne sono state ulteriormente valutate rispetto al PMV misurato. In accordo con la norma ISO 7730, valori soddisfacenti sono compresi nell'intervallo [-0,5,0,5].
La figura seguente riporta i valori di PMV misutati dalla stazione climatica interna, in presenza ed in assenza di occupanti.



Andamento del PMV in assenza e in presenza di occupanti durante una tipica giornata invernale

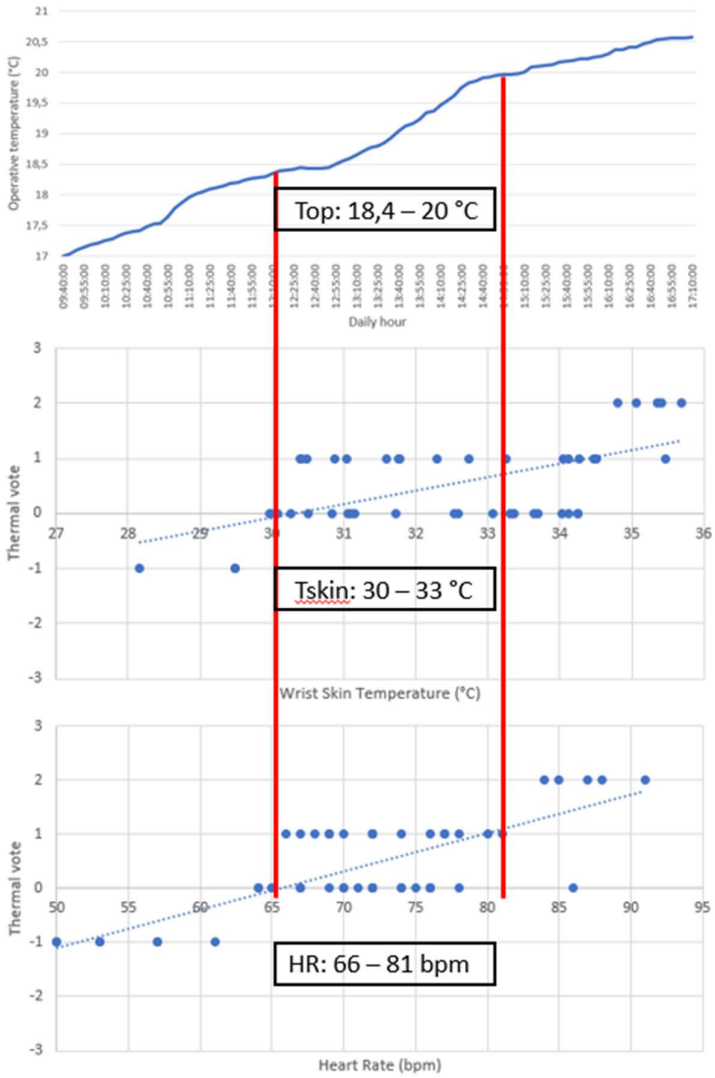
Si nota che le fluttazioni nell'andamento del voto medio previsto sono dovute all'interazione dei soggetti con i dispositivi di controllo ambientale.
La sensazione termica è una grandezza importante che fornisce indicazioni circa le ideali condizioni di comfort delle persone e può essere stimata con un alto livello di precisione attraverso la temperatura delle pelle e il battito cadiaco degli occupanti. La figura seguente riporta la relazione fra i valori acquisiti della temperatura superficiale delle pelle e la relativa senzazione termica degli occupanti.



Relazione fra la temperatura superficiale della pelle e la sensazione termica degli occupanti

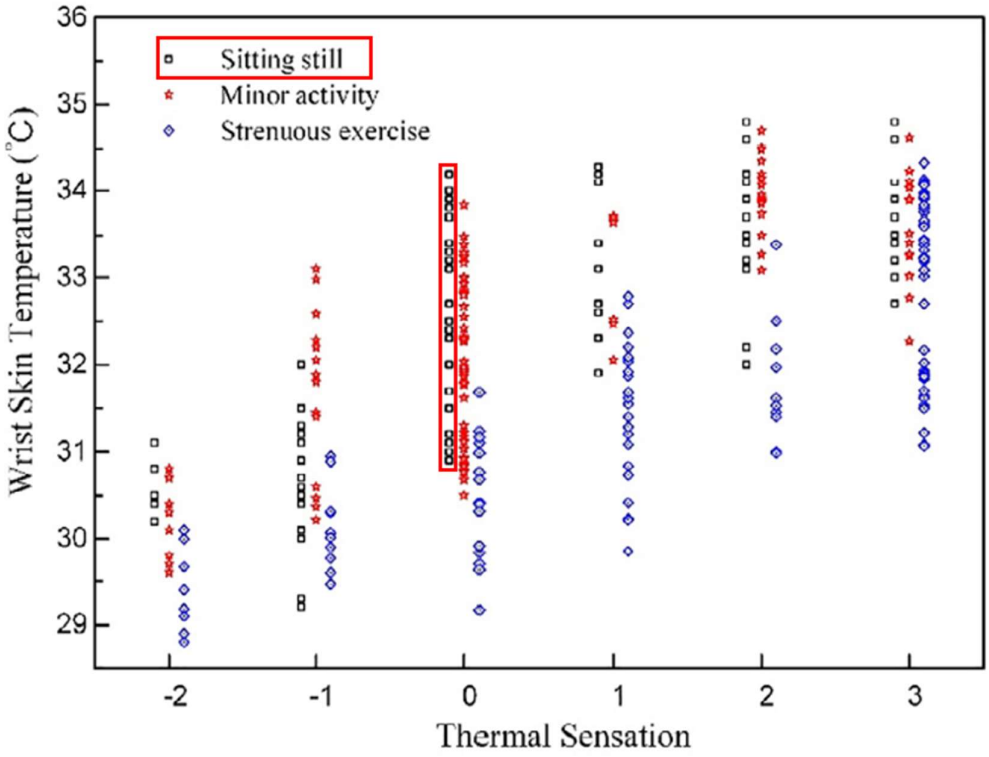
Chiaramente, il livello di sensazione termica è cresciuto da -1 (leggermente freddo) a 2 (mite) in base all'incremento della temperatura superficiale della pelle. Quindi si nota una relazione lineare tra la sensazione termica delle persone e la temperatura superficiale della pelle.

Tuttavia, i soggetti possono avere diverse sensazioni termiche pur avendo gli stessi valori di temperatura superficiale della pelle. La figura seguente riporta il range di valori accettabili dei parametri biometrici in relazione alla temperatura operativa all'interno dell'ambiente.



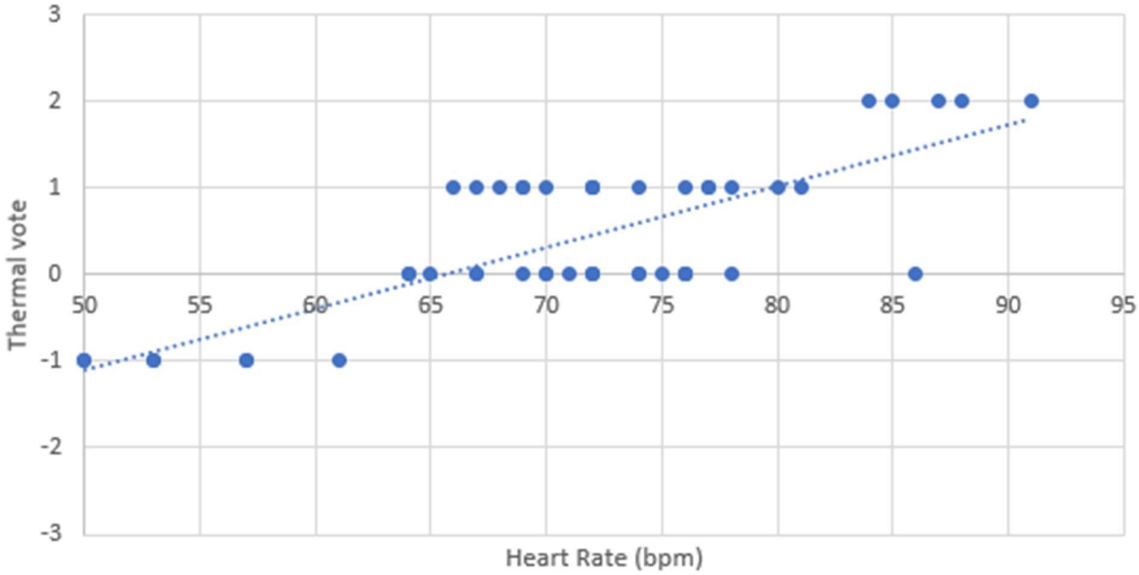
Parametri biometrici che rispecchiano le condizioni di comfort termico in relazione all'andamento della Top

E' stato visto che il range di comfort della temperatura superficiale della pelle degli occupanti era tra 30°C e 33°C. I risultati sono coerenti con quelli ottenuti da Wei Li et al. [120] per una attività sedentaria e mostrati nella figura successiva.



Relazione fra la temperatura superficiale della pelle e la sensazione termica ottenuta da Wei Li et al.

Lo stesso studio ha posto l'attenzione sulla significativa relazione esistente fra tasso metabolico e sensazione termica. La figura seguente mostra i valori del battito cardiaco monitorati nel presente lavoro e correlati con la sensazione termica degli occupanti.

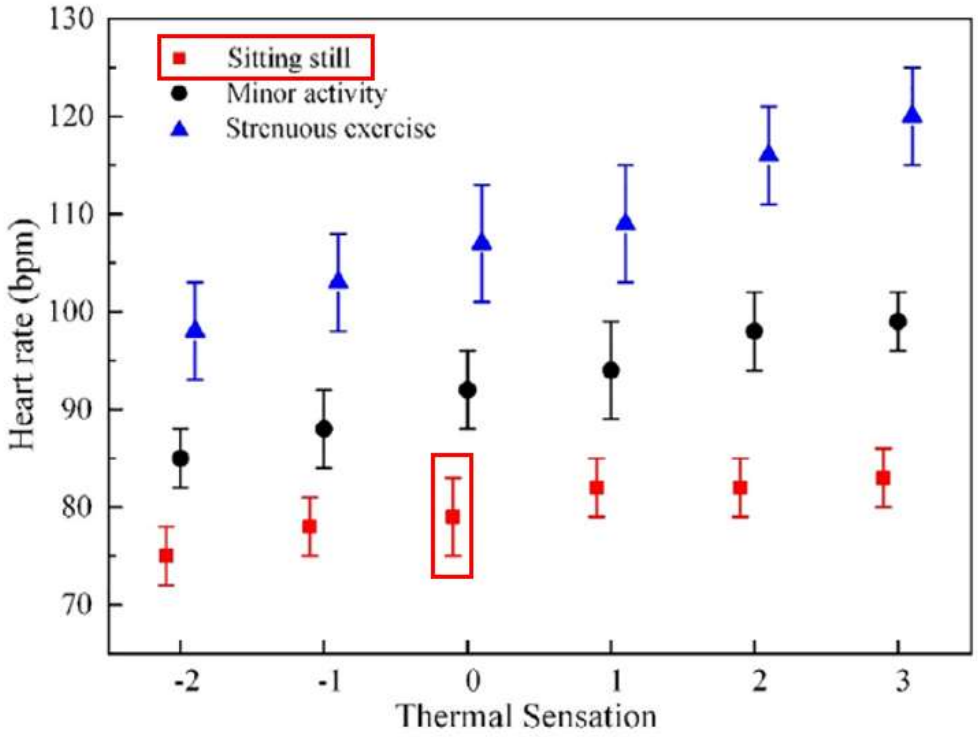


Relazione fra il battito cardiaco e la sensazione termica degli occupanti

I risultati indicano che il battito cardiaco oscillava tra 50 e 91 bpm per occupanti seduti o che hanno eseguito lievi atività motorie.

Come previsto da studi precedenti, il battito cardiaco è cresciuto con l'incremento della sensazione termica degli occupanti, perciò esiste una relazione lineare fra i due parametri.

Il range di comfort termico dei soggetti si è raggiunto per valori di battito cardiaco compresi tra 66 e 81 bpm. Confrontando i risultati con quelli ottenuti da Wei Li et al. si nota che, in questo caso, il range di valori corrispondenti alla sensazione termica neutra risulta più stretto (75-81 bpm), probabilmente a causa delle differenti condizioni climatiche e diverso paese in cui si è condotta la ricerca. La figura seguente riporta i risultati di Wei Li et al. del battito cardiaco in relazione al tipo di attività svolta.



Relazione tra battito cardiaco e sensazione termica ottenuta da Wei Li et al.

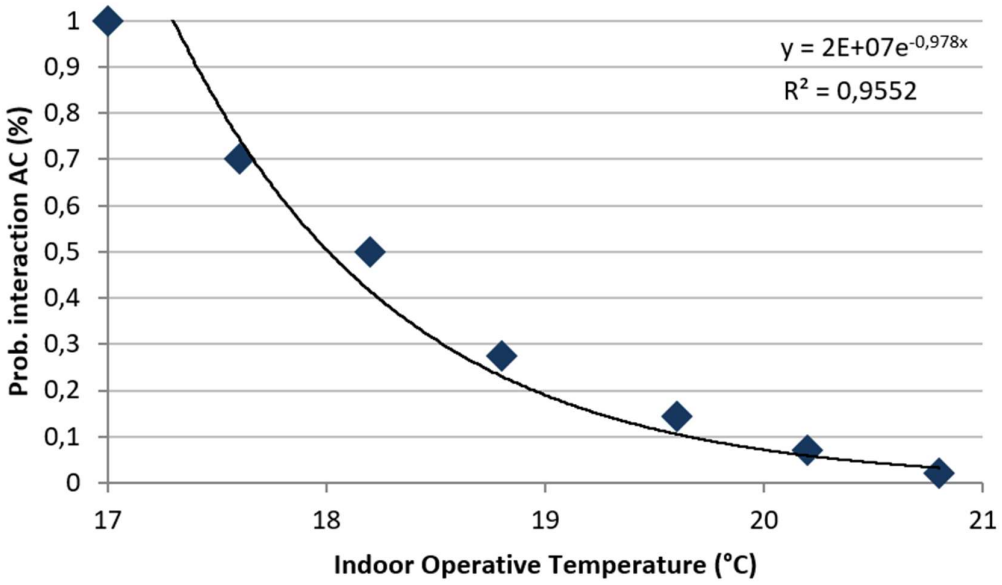
Concludendo, un riassunto dei parametri ambientali e biometrici monitorati in presenza di occupanti (incluse analisi statistiche) è riportato nella figura seguente.

	Variable	Max	Min	Mean	Median	St. Dev.
Environmental parameters	Outdoor Temperature (°C)	15,79	10,3	13,12	12,965	1,34
	Outdoor Relative Humidity (%)	100	63,6	85,58	85,55	7,7
	Wind Speed (m/s)	3,45	0	0,97	0,97	0,55
	Indoor Temperature_10 cm height (°C)	18,56	15,31	17,65	17,63	0,45
	Indoor Temperature_60 cm height (°C)	20,12	15,92	17,98	17,95	0,51
	Indoor Temperature_110 cm height (°C)	21,27	16,4	18,73	18,6	0,62
	Indoor Relative Humidity (%)	54,61	40,98	50,77	52,43	3,76
	Indoor Operative Temperature (°C)	20,66	16,7	18,66	18,45	0,7
Thermal sensation	PMV index	-0,76	-2,34	-1,25	-1,28	0,16
Biometric data	Mean Skin Temperature (°C)	35,69	28,16	32,47	32,58	1,93
	Heart Rate (bpm)	91	50	71,31	72	9,26

Riassunto dei parametri monitoranti durante il periodo di occupazione

Valutazione dei principali stimoli all'interazione fra soggetti e impianto di climatizzazione

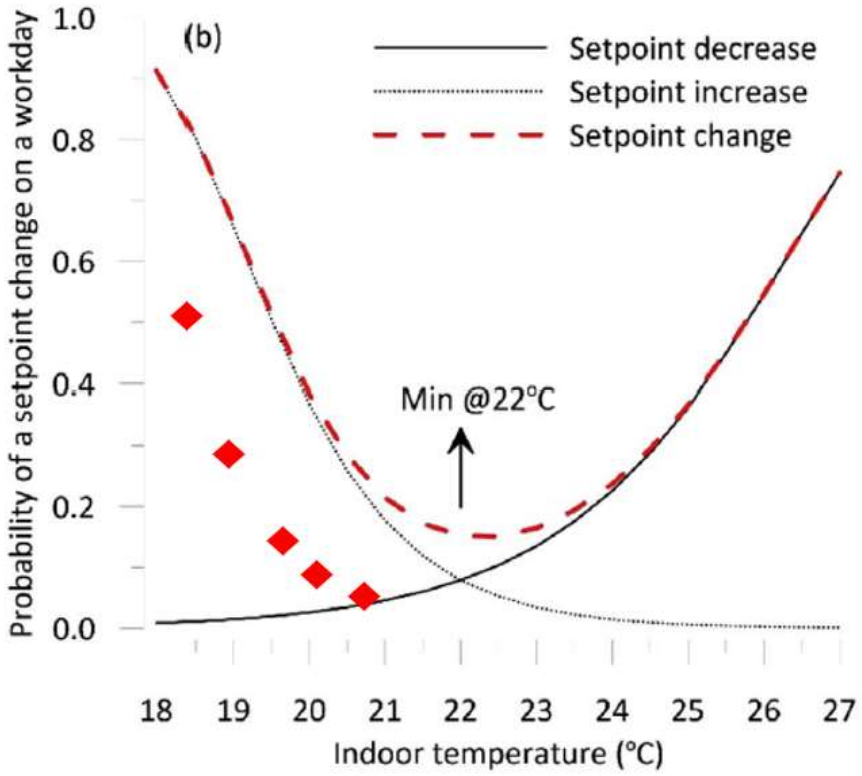
I principali stimoli sono stati individuati attraverso la regressione logistica applicata ai dati sperimentali. Sia i parametri ambientali che biometrici sono stati investigati. Inizialmente, gli occupanti sono stati lasciati liberi di interagire con l'impianto di climatizzazione attraverso l'uso di un termostato e la frequenza delle loro azioni è stata acquisita per sviluppare i modelli comportamentali. La figura seguente riporta i risultati della regressione logistica (linea nera continua) sovrapposti con i dati di temperatura operativa acquisiti durante il monitoraggio (punti romboidali) e il risultante valore di R^2.



Regressione logistica applicata alla temperatura operativa e il risultante valore di R^2

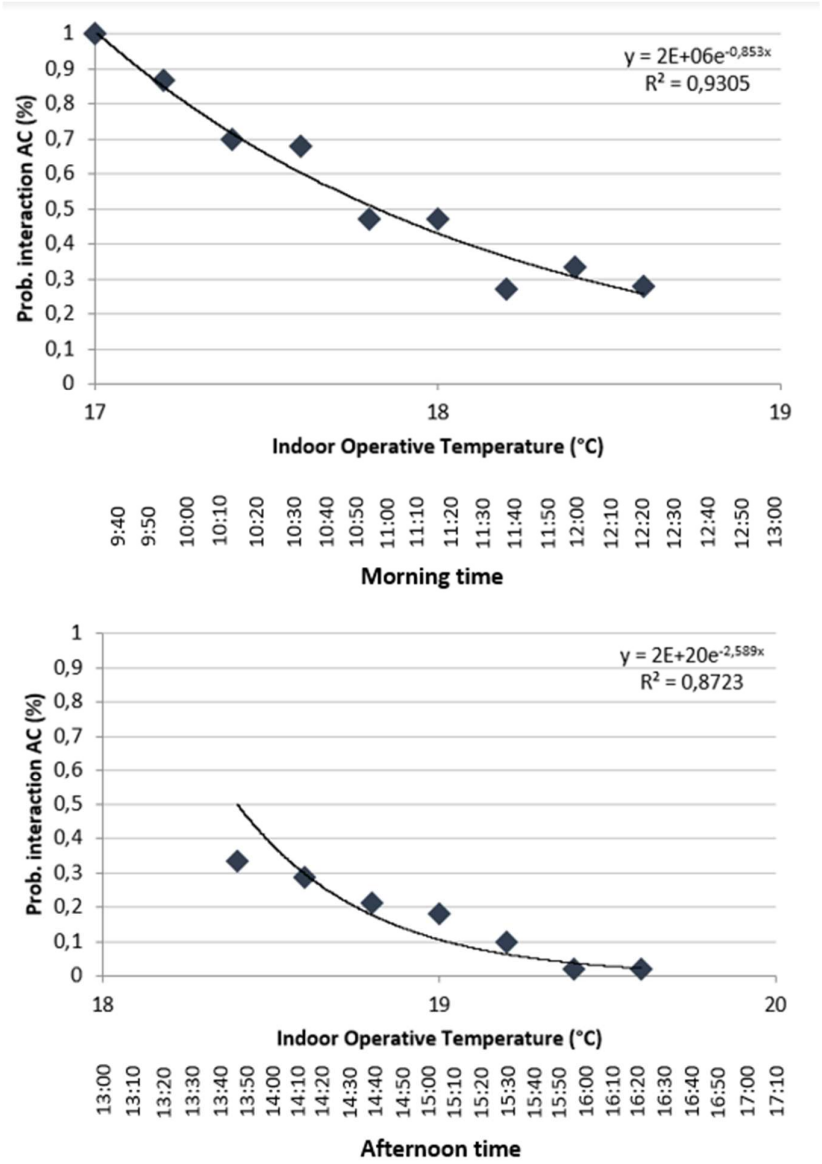
I risultati risultano consistenti a quelli ottenuti da un precedente studio condotto da Burak Gunay et al. [121] considerando che i ricercatori avrebbero ottenuto valori di probabilità più alti considerando delle temperature operative più basse. La figura seguente riporta la sovrapposizione fra i risultati della

presente ricerca (punti romboidali) e quelli ottenuti da Burak Gunay et al.



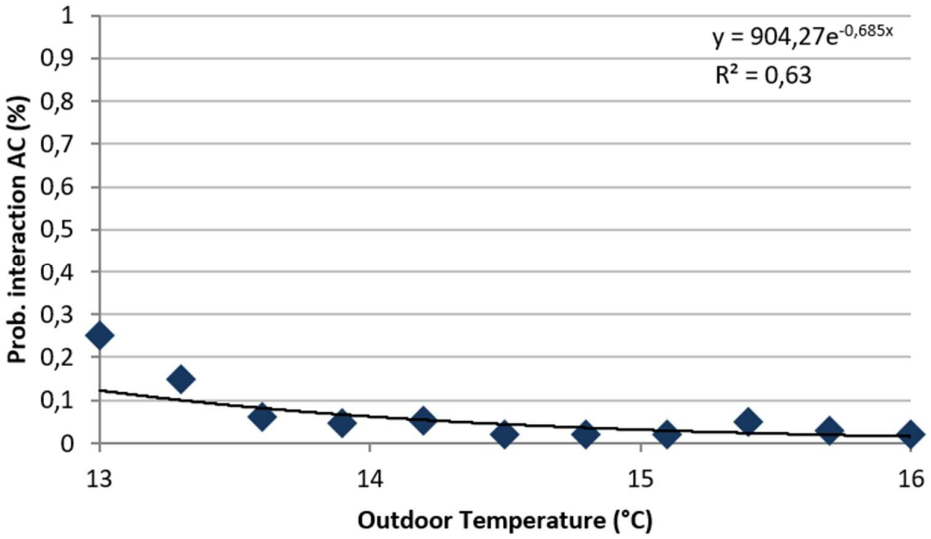
Sovrapposizione fra i risultati del presente studio e quelli ottenuti da Burak Gunay et al.

Inoltre, la probabilità di interazione con l'impianto di climatizzazione è maggiore durante la prima metà della giornata, poichè al mattino l'ambiente risultava termicamente meno condortevole dato che la temperatura operativa era più bassa. Il confronto fra i valori di probabilià durante mattina e pomeriggio è riportato nella figura seguente.



Probabilità di interazione con l'impianto, rispettivamente durante la mattina e il pomeriggio con i relativi valori di R^2

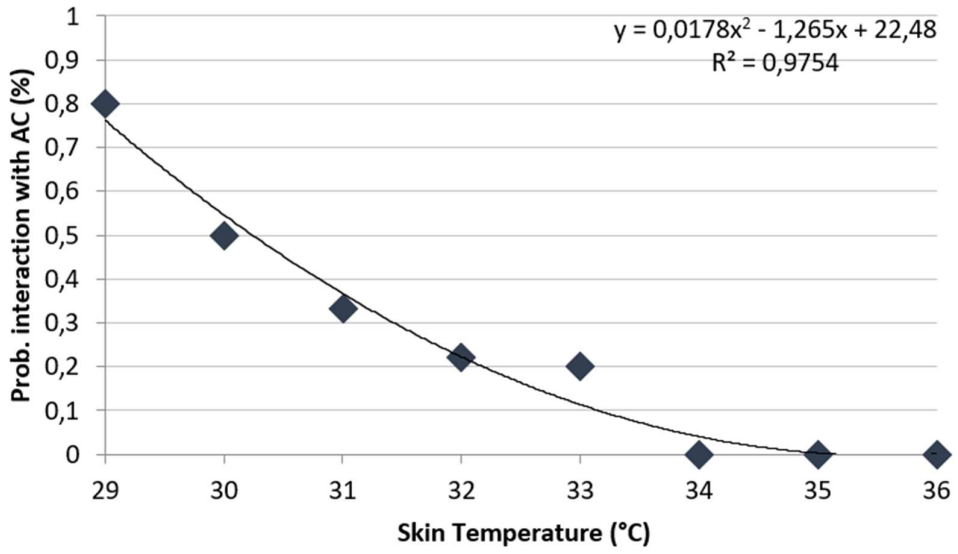
L'influenza della temperatura esterna sul comfort termico degli occupanti è stata ulteriormente investigata durante la sperimentazione e il risultato della regressione logistica è riportato di seguito.



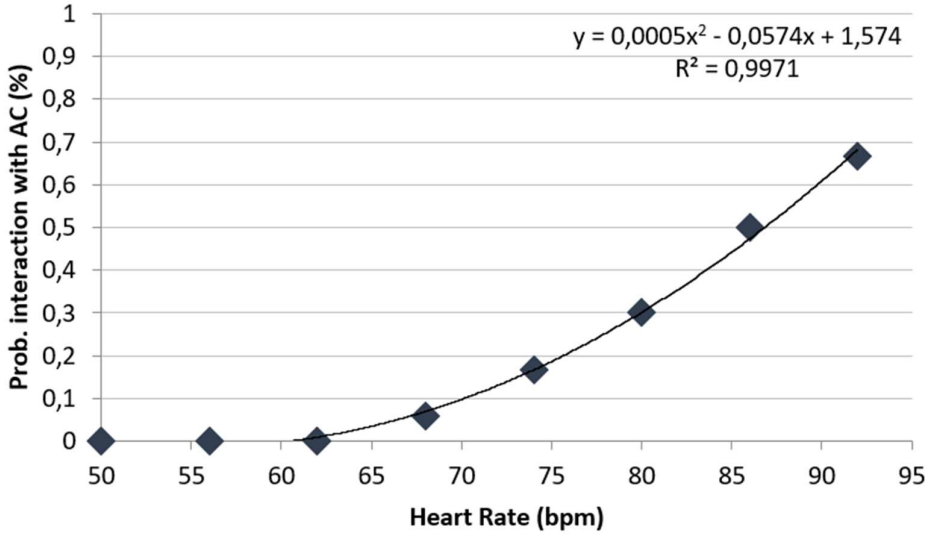
Regressione logistica applicata alla temperatura esterna e il risultante valore di R^2

Il risultante coefficiente R^2 dimostra che esiste una debole relazione fra la temperatura dell'aria esterna e il comfort termico degli occupanti. Pertanto, questo parametro ambientale non è stato considerato all'interno dello sviluppo del sistema di controllo dell'impianto di climatizzazione.

Successivamente, la temperatura superficiale della pelle e il battito cardiaco degli occupanti sono stati misurati attraverso un dispositivo applicato al polso destro, impostando la temperatura di setpoint dell'impianto a 22°C. La regressione logistica, applicata ad entrambi i parametri biometrici e i rispettivi coefficienti R^2 sono riportati in seguito.



Regressione logistica applicata alla temperatura della pelle e il risultante valore di R^2

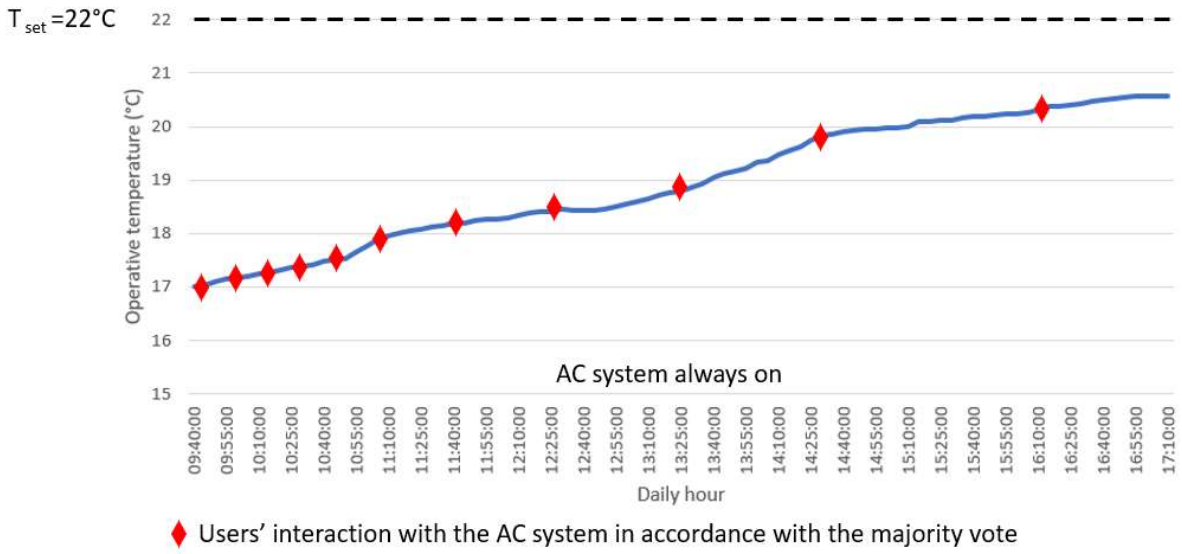


Regressione logistica applicata al battito cardiaco e il risultante valore di R^2

Dai risultati dei coefficienti R^2 si nota l'esistenza di una forte correlazione fra i parametri biometrici e il comfort termico percepito dagli occupanti. Di conseguenza, la temperatura superficiale della pelle e il battito cardiaco sono stati aggiunti agli inputs nello sviluppo dell'algoritmo di comfort adattivo per dirigere le azioni di gestione della temperatura di setpoint dell'impianto di climatizzazione.

Funzionamento standard dell'impianto di climatizzazione

La temperatura di setpoint di climatizzazione invernale è stata fissata a 22°C in base alla norma ASHRAE 90.1-2007. Gli occupanti erano liberi di interagire con il termostato per incrementare la temperatura fino a ± 1°C attraverso steps di ± 0,1°C. Il normale funzionamento dell'impianto prevedeva che, qualora il termostato avesse rilevato una temperatura interna inferiore a quella di setpoint, allora avrebbe acceso automaticamnete l'unità di climatizzazione con l'obiettivo di raggiungere il valore fissato di temperatura.



Funzionamento standard dell'impianto di climatizzazione con indicazione delle azioni manuali svolte dagli occupanti

Implementazione dell'algoritmo di Humphreys

Nel presente studio di ricerca, l'algoritmo di controllo è stato adattato alle esigenze del caso di studio, modificando la frequenza di acquisizione dei dati (da ogni ora a ogni 10 minuti), settando una diversa temperatura di comfort e integrando i parametri biometrici come nuovi inputs, vista la loro forte correlazione con la sensazione termica degli occupanti.

Infatti, i nostri risultati hanno dimostrato che la temperatura operativa di 19°C unita ad una dead band di ±1°C, meglio corrisponde alle condizioni di comfort termico dei soggetti monitorati in un clima mediterraneo. Quindi, ad istanti di tempo prefissati, l'algoritmo confrontava la temperatura operativa interna all'ambiente con la dead band intorno alla temperatura di comfort fissata a 19°C: se T_{op} risultava all'interno della fascia suddetta allora non veniva eseguita nessuna azione, viceversa la temperatura di setpoint era automaticamente aumentata o diminuita se $(T_{op}-T_{comf}) < -1°C$ o se $(T_{op}-T_{comf}) > 1°C$, rispettivamente e se la probabilità risultava maggiore del numero random.

In relazione alle mancanze di precedenti studi di ricerca, il principale obiettivo di questo lavoro era lo sviluppo di un sistema di controllo automatizzato che includesse anche i parametri biometrici degli occupanti, integrandoli come nuovi inputs nell'algoritmo di comfort adattivo.

Poichè sia la temperatura superficiale della pelle che il battito cardiaco associate al comfort termico degli occupanti sono stati acquisiti all'interno della stessa fascia di temperatura (18,4°C-20°C), ogni qualvolta tali valori eccedevano i limiti della dead band definita in seguito, le azioni sull'impianto erano automaticamente eseguite. Se T_{skin}>33°C e HR>80bpm e P_{AC}>R_n allora la temperatura di setpoint veniva instantaneamente diminuita; al contrario se T_{skin}< 30°C e HR<65bpm e P_{AC}>R_n allora la temperatura di setpoint veniva instantaneamente incrementata. Qualora, 30°C<Tskin<33°C e 65bpm<HR<80bpm, quindi la temperatura operativa era compresa fra 18,4°C e 20°C, allora nessuna azione veniva eseguita.

La struttura logica dell'algoritmo di Humphreys implementato è mostrata di seguito.

Implemented Humphreys' adaptive algorithm				
No.	AC algorithm parameter	Symbol	Sample	Derivation or source
1	Outdoor air temperature	T_{out}	every 10 min	Interpolated from climate file
2	Daily mean outdoor air temperature	T_{odm}	1 per day	Calculated from 24 hourly data points per day
3	Running mean outdoor temperature (CEN)	T_{rm}	1 per day	$T_{rm}(init)=(1-\alpha)(T_{odm-1} + \alpha T_{odm-2} + \alpha^2 T_{odm-3}\ldots)$ initial value calculated from previous 20 days daily mean, then $Trm=(1-\alpha)T_{odm-1}+\alpha T_{rm-1}$
4	Running mean response to T_{out}	α	Const	Default α=0,8 (0,01-0,99 allowed range)
5	Comfort temperature	T_{comf}	1 per day	If $T_{rm}>10, T_{comf}=0,33T_{rm}+17,8$(CEN Standard) If $Trm\leq 10$, $Tcomf=0,09Trm+22,6$ (CIBE Guide A)
6	Indoor air temperature	T_{ai}	every 10 min	Available at each time step (variable)
7	Indoor operative temperature	T_{op}	every 10 min	Available at each time step (50% mrt, 50%T_{ai})
8	Comfort	Comf	every 10 min	Comf="yes"if $abs(T_{op}-T_{comf})\leq 1°C$ Comf="hot"if $(T_{op}-T_{comf})>1°C$ Comf="cold" if $(T_{op}-T_{comf})<-1°C$
9	Logit function	Func	every 10 min	$Func=logit(P_{AC})=0,171T_{op}+0,166T_{out}-6,43$
10	Probability function for AC interaction	P_{AC}	every 10 min	$P_{AC}= exp(Func)/(1+exp(Func))$
11	Random number between 0 and 1	R_n	every 10 min	Generate from Fortran RNG

12	AC T_{set} status (0=no action, 1=increase/decrease)	i_{AC}	every 10 min	If Comf="hot" and if $P_{AC}>R_n$ then
				T_{set}-1°C (status=1)
				If Comf="cold" and if $P_{AC}>R_n$ then
				T_{set}+1°C (status=1)

13	Hear rate	HR HR limits	every 10 min Const	Available at each time step (variable) $HR_{upper\ limit}$ = 80 bpm $HR_{lower\ limit}$ = 65 bpm
	Comfort	Comf	every 10 min	Comf="yes" if 65 bpm<HR<80 bpm Comf="hot" if HR>80 bmp Comf="cold" if HR<65 bmp

	AC T_{set} status (0=no action, 1=increase/decrease)	i_{AC}	every 10 min	If Comf="hot" and if $P_{AC}>R_n$ then
				T_{set}-1°C (status=1)
				If Comf="cold" and if $P_{AC}>R_n$ then
				T_{set}+1°C (status=1)

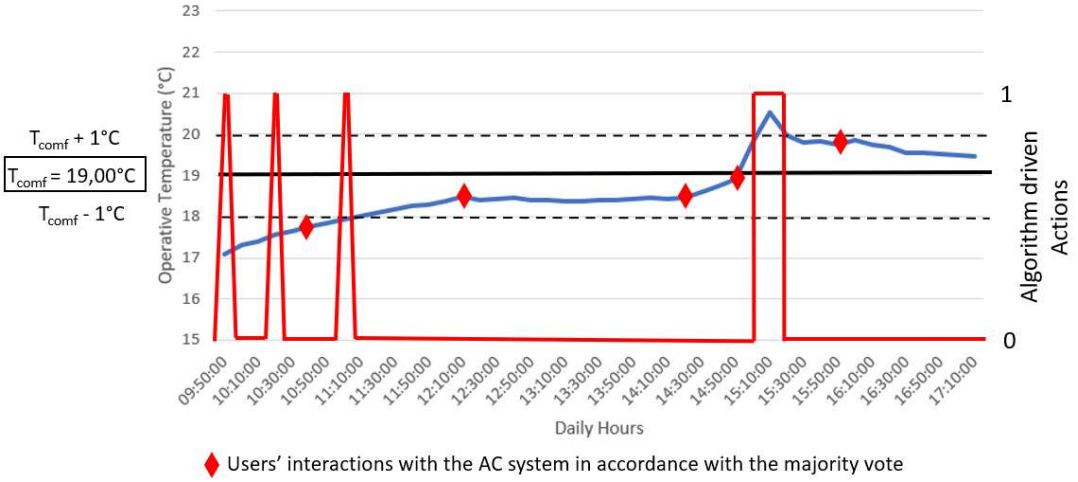
14	Skin Temperature	T_{skin} T_{skin} limits	every 10 min Const	Available at each time step (variable) $T_{skin\ upper\ limit}$ = 33 °C $T_{skin\ lower\ limit}$ = 30 °C
	Comfort	Comf	every 10 min	Comf="yes" if 30°C<T_{skin}<33°C Comf="hot" if T_{skin}>33°C Comf="cold" if T_{skin}<30°C

	AC T_{set} status (0=no action, 1=increase/decrease)	i_{AC}	every 10 min	If Comf="hot" and if $P_{AC}>R_n$ then
				T_{set}-1°C (status=1)
				If Comf="cold" and if $P_{AC}>R_n$ then
				T_{set}+1°C (status=1)

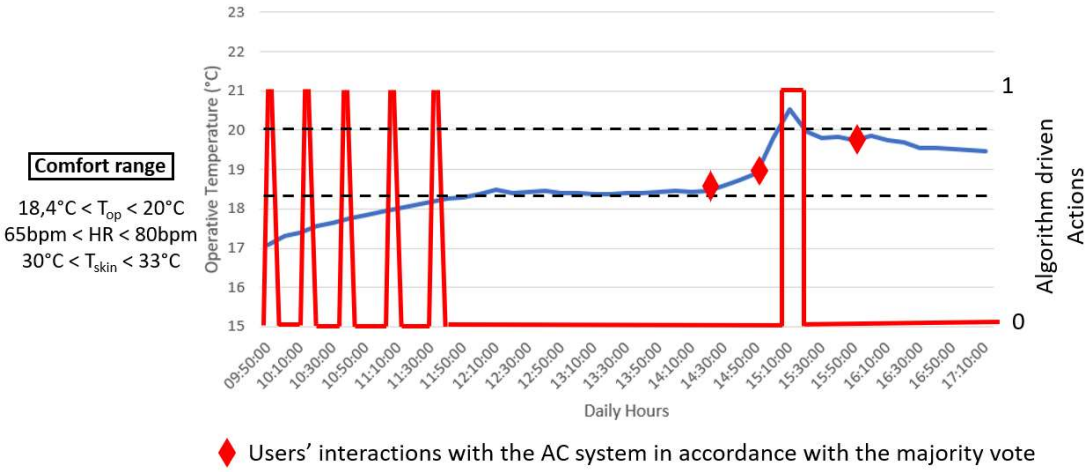
Steps nell'implementazione dell'algoritmo di Humphreys

Funzionamento dell'impianto di climatizzazione in relazione all'algoritmo di Humphreys

Le figure seguenti riportano l'azionamento dell'impianto di climatizzazione in funzione dei comandi che il dispositivo di controllo (Coolmaster) ha ricevuto dall'algoritmo, considerando sia la temperatura operativa che i dati biometrici come inputs. Nel frattempo, le azioni manuali degli occupanti sul termostato sono state registrate ed individuate sul grafico da punti ronboidali.



Operazioni condotte dall'algoritmo considerando la T_{op} come input



Operazioni condotte all'algoritmo considerando i parametri biometrici come input.

Dai risultati ottenuti si nota che l'algoritmo di controllo adattivo ha ben interpretato le sensazioni termiche degli occupanti, soprattutto quando sono stati considerati i parametri biometrici, poichè si sono registrate pochissime azioni manuali da parte dei soggetti in presenza di possibili situazioni di discomfort.

Conclusioni

Il principale obiettivo dello studio di ricerca era quello di sviluppare un sistema di azionamento automatico dell'impianto di riscaldamento, guidato da un algoritmo di controllo adattivo che considerasse sia i parametri ambientali che biometrici degli occupanti.

A tal fine, analisi preliminari sono state svolte per valutare le condizioni termiche dell'ambiente. Si è visto che la temperatura esterna oscillava da 12,5°c a 16°C durante le ore di occupazione, mentre valori medi della temperatura dell'aria interna erano compresi fra 19-21°C. Il voto medio previsto (PMV) è stato acquisito sia durante il periodo di occupazione sia durante quello in cui la stanza è rimasta vuota. Nel primo caso, le fluttuazioni del trend sono dovute alla presenza dei soggetti che hanno interagito con i dispositivi di controllo ambientale per raggiungere le condizioni termiche desiderate. I parametri biometrici degli occupanti sono stati monitorati attraverso dispositivi applicati al polso destro degli stessi. I risultati hanno mostrato che il comfort termico dei soggetti è associato a valori della temperatura superficiale della pelle compresi tra 30-33°C e di battito cardiaco tra 65-80bpm. Tali dati sono stati acquiti quando la temperatura operativa interna era nel range di 18,4-20°C. La valutazione degli occupanti circa le condizioni termiche dell'ambiente è stata eseguita tramite un sondaggio, presentato ogni 10 minuti, in cui veniva posta la seguente domanda:"Qual è la tua generale sensazione termica?". Le risposte permesse erano scelte dalla scala di sensazione termica definite in accordo con la norma ASHRAE 55. E' stata trovata una correlazione lineare fra i parametri biometrici degli occupanti e la loro sensazione termica. Durante la sperimentazione, gli utenti erano liberi di interagire con l'impianto di climatizzazione invernale, acquisendo la frequenza delle loro azioni per poi procedure allo sviluppo dei modelli di comportamento predittivi. Attraverso gli stessi, si sono valutati i principali stimoli che hanno influenzato il comfort termico degli occupanti, utilizzando una regressione logistica. Sia i parametri ambientali che biometrici sono stati considerati e si è visto che la temperatura operativa, la temperatura superficiale della pelle e il battito cardiaco hanno influenzato maggiormente le interazioni fra gli occupanti e l'impianto. Conseguentemente, questi tre parametri sono stati utilizzati come inputs per lo sviluppo di un algoritmo di controllo che ha inviato comandi di azionamento al controller Wi-Fi (Coolmaster) con lo scopo di guidare le operazioni sull'impianto di climatizzazione. La forma originale dell'algoritmo di Humphreys è stata cambiata modificando la frequenza di acquisizione dei dati (da ogni ora a ogni 10 minuti), settando una temperatura di comfort ottimizzata sulla base delle esigenze del caso di studio e integrando i parametri biometrici come nuovi inputs. I risultati hanno dimostrato che l'algoritmo ha interpretato correttamente la volontà degli occupanti dato che solo in poche situazioni gli utenti hanno ricorso ad azioni manuali per modificare la temperatura di setpoint qualora la maggioranza avesse percepito un

ambiente non sufficientemente comfortevole.

Questo studio rappresenta quindi un ulteriore passo avanti per la comprensione dei principali stimoli che influenzano il comfort termico degli occupanti e considerarli come inputs all'interno di un sistema di controllo finalizzato a pilotare l'impianto di climatizzazione, assicurando la soddifazione dei soggetti in termini di sensazione temica, salute e produttività.

Nonostante i risultatati siano conformi a quelli ottenuti da precedenti studi di ricerca, il numero dei dati e il periodo di monitoraggio sono risultati piuttosto limitati in quanto interrotti a causa delle restrizioni introtte per fronteggiare l'emergenza da Coronavirus. Quindi, una ricerca più esaustiva sarebbe utile per confermare i risultati presenti in letteratura. Studi futuri saranno inoltre focalizzati sull'impatto del sistema di controllo automatizzato sui consumi energetici dell'edificio.