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A review of thermal comfort models and indicators for indoor environments

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ABSTRACT

This paper reviews the most used thermal comfort models and indicators with their variants, discussing their usage in control problems referring to energy management in indoor applications. The first part addresses the recent literature referring to the thermal comfort concepts, models of human thermal comfort, thermal comfort models and indicators, thermal comfort standards, control systems, optimisation methods, and practical assessments. Then, the ambient and personal parameters used to represent thermal comfort and thermal sensation are recalled. The following part reviews the definitions and usage of a number of thermal comfort indices, mainly related to the Predicted Mean Vote (*PMV*), the Actual Mean Vote (*AMV*), and the Predicted Percentage Dissatisfied (*PPD*), with their modifications and variants, indicating a number of applications to different situations in indoor environments. The last part reviews the thermal comfort models used to define control strategies in indoor applications, discussing the characteristics and parameters of models based on artificial neural networks, autoregressive variants, fuzzy control, and hybrid models combining different approaches. The characteristics of these models and their usage to predict the indoor air temperature and the *PMV* index are discussed with reference to the identification of the several inputs used in relevant literature contributions.

1. Introduction

Maintaining thermal comfort for humans is one of the key aspects related to the general concept of comfort encountered in human life and activities. Thermal comfort is taken into account, together with visual comfort, acoustic comfort, protection against electromagnetic radiation and air quality, to ensure appropriate quality and sustainability of the living environment [1,2].

Thermal comfort has a wide connotation, also including physiological and psychological aspects, in addition to the ambient characteristics [3,4]. The implications of thermal comfort in the human activities are increasingly considered in various energy management contexts, together with energy efficiency, environmental impact and economics.

Buildings are a key component of the living environment, in which thermal comfort has to be guaranteed during time. In the indoor environment, the thermal comfort highly depends on the operation of controlled technologies such as heating, ventilation and air conditioning (HVAC). Building automation and control are exploited to improve energy efficiency and comfort management [5]. Specific definitions concerning building automation are given in relevant standards [6].

This paper reviews the main concepts referring to thermal comfort in indoor applications, discussing the relevant indicators. After recalling the basic aspects, the review is mainly based on recent contributions appeared in the literature. A synthetic overview of the contents addressed by recent reviews in a detailed way is shown in Table 1. The main contents addressed include:

- *Basic concepts*: Djongyang et al. [7] review the *physiological basis* of comfort, considering the human body thermoregulatory system. Cheng et al. [8] review the characterisation of human physiological and psychological responses. Karjalainen [9] reviews thermal comfort and gender aspects with respect to deviations from an optimal temperature. Baird and Field [10] present a survey of the users' perception of thermal comfort in commercial and institutional buildings, with data taken from eleven countries. Mishra and Ramgopal [11] discuss human thermal comfort in different climatic zones, pointing out adaptive opportunities emerging in various human groups concerning clothing, window opening, and availability of technologies for space conditioning. Veselý and Zeiler [12] present a dedicated review on the impact of *personalised conditions* (ventilation and cooling, heating and conditioning systems) used in HVAC systems on the thermal comfort, recalling that better comfort may be obtained in a non-uniform thermal environment with respect to a uniform one, also allowing better energy efficiency. Halawa et al. [13] review and discuss the impact of the thermal radiation field on comfort, consumption and control.
- *Models of human thermal comfort*: Djongyang et al. [7] recall the formulation of the mathematical modelling of the heat transfer

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Table 1
Categorisation of recent literature review references concerning thermal comfort.

review paper reference	*basic concepts*	*models of human thermal comfort*	*thermal comfort models for buildings*	*thermal comfort indicators*	*thermal comfort Standards*	*control systems*	*optimisation methods*	*practical assessments*
Fu et al. [14]		o						
Katić et al. [15]		o						
Wang and Srinivasan [29]						o		
Zomorodian et al. [37]								o
Martínez-Molina et al. [38]								o
Croitoru et al. [18]			o		o			o
Rupp et al. [33]								o
Attia and Carlucci [25]								
Veselý and Zeiler [12]		o						
Halawa et al. [13]		o						
Holopainen et al. [21]				o				
Alfano et al. [2]					o			o
Yang et al. [24]					o			o
Shaikh et al. [26]						o	o	
Perera et al. [27]						o		
Afram and Janabi-Sharifi [28]						o		
Nguyen and Le [31]							o	
Kwong et al. [36]								o
Baird and Field [10]	o							
Mishra and Ramgopal [11]	o							
Taleghani et al. [23]					o			
Evins [32]							o	
Cheng et al. [8]	o	o						
Karjalainen [9]	o							
Halawa and van Hoof [17]			o		o			
Carlucci and Pagliano [20]				o				
Khodakarami et al. [35]								o
Djongyang et al. [7]	o	o	o	o				o
Van Hoof et al. [16]			o		o			
García [19]				o				
Roaf et al. [22]					o			
Dounis and Caraiscos [30]						o		
Peeters et al. [34]								o

between the human body and the environment, with the main effects due to conduction, convection, radiation, moisture, clothes and metabolism. Cheng et al. [8] evaluate the thermal environment for an indoor application by coupling two human thermal comfort models with a Computational Fluid Dynamics (CFD) numerical simulator able to represent in considerable details complex patterns of airflow and air temperature distribution. Fu et al. [14] review different human thermo-regulation models, highlighting the aspects referring to the active system (the human body) and the passive system (the heat exchange between the human body and the environment), including remarks referring to biology. Katić et al. [15] present a detailed review of the thermophysiological models applied to the human body, summarising the main attributes and constraints of the various models.

- *Thermal comfort models for buildings*: The thermal comfort has been classically characterised by considering ambient and human body parameters, resorting to extended heat transfer models. Van Hoof et al. [16] review thermal comfort models for indoor applications in the period from the second half of the 1990s to 2010. Djongyang et al. [7] review the contributions dealing with the adaptive model approach, referring to the behavioural, psychological and psysiological adaptation of the humans in an indoor environment. Halawa and van Hoof [17] dedicate their entire contribution to review and discuss the adaptive model approach. Croitoru et al. [18] address in more detail the human thermo-physiological models and the adaptive psychological models, again promoting the coupling of the thermoregulatory model of the human body with a CFD numerical approach as the most effective tool to assess the thermal comfort in an indoor environment.
- *Thermal comfort indicators* (definitions and details are recalled in Section 4): Djongyang et al. [7] recall two classical indicators – the Predicted Mean Vote (*PMV*) and the Predicted Percentage of Dissatisfied (*PPD*). García [19] reviews the general thermal comfort indicators (*PMV* and *PPD*) and the local thermal comfort indicators such as the percentage of local dissatisfaction (*PD*). Carlucci and Pagliano [20] provide an extended review of 15 indices for long-term thermal comfort evaluation, taken from a list of over 75 stress and discomfort indices historically proposed. Holopainen et al. [21] compare different approaches to assess thermal comfort in terms of the *PPD* calculated with *PMV*, its adaptive version *aPMV*, and an indicator of overall thermal sensation.
- *Thermal comfort Standards*: Many reviews contain dedicated references to the Standards, more often related to dedicated points addressed. Roaf et al. [22] present the evolution of the XX century Standards for thermal comfort and discuss their contents, highlighting the need for introducing more control in the light of possible increase of the energy cost. Van Hoof et al. [16] address the aspects

of local discomfort, transient conditions, adaptive models, and long-term evaluation included in the Standards. Specific discussions on the way the adaptive thermal comfort approach is included in the Standards are included in Halawa and van Hoof [17], and Taleghani et al. [23]. Overall and local discomfort indices are related to the corresponding Standards in [2]. Yang et al. [24] discuss the implications of the adaptive thermal comfort models on the Standards. Attia and Carlucci [25] present further considerations on the application of different standards for zero energy residential buildings in hot climates.

- *Control systems*: Control system applications in buildings consider different types of controllers. A general classification used in Shaikh et al. [26] considers conventional, model-based and intelligent controllers. Conventional controllers (on/off, proportional-integral and proportional-integral derivative) act on equipment affecting thermal comfort (such as HVAC, air-handling systems, rooftop units, fan coils, heat pumps, and variable air volume boxes). A second type of controllers consists of predictive, adaptive and optimal model-based controllers including thermal comfort aspects in the modelling [27]. The intelligent controllers reviewed in Shaikh et al. [26] are based on learning methods (artificial intelligence, fuzzy, neural, neuro-fuzzy), model-based predictive control methods, and agent-based control methods. Afram and Janabi-Sharifi [28] review data driven, physics-based and grey box methods for modelling HVAC systems. Prediction methods based on artificial intelligence are reviewed in Wang and Srinivasan [29], by addressing their concepts, applications, advantages and drawbacks. The review in Dounis and Caraiscos [30] addresses in a detailed way computational intelligent methods such as fuzzy logic-based approaches, neural networks, and hybrid methods, creating a separate section for agent-based intelligent control systems and multi-agent solutions.
- *Optimisation methods:* Thermal comfort is one of the components of building design optimisation. Nguyen and Le [31] consider the phases of pre-processing (including the choice of the relevant variables, the settings of objective functions and constraints, the choice of the optimisation algorithm and its coupling with the building simulation program), optimisation (through suitable algorithms), and post-processing (interpretation of the results, and sensitivity analysis). The points reviewed start from the definition of the problems (static or dynamic) and of the number of objectives (for single- or multi-objective problems), and take into account the presence of constraints and the possible formulation of optimisation under uncertainty. The review of Evins [32] is focused on the optimisation methods, indicating that thermal comfort is the second objective mainly considered (together with energy) in multi-objective approaches. Shaikh et al. [26] also address computational optimisation methods and simulation tools.
- *Practical assessments*: Alfano et al. [2] present an assessment of the thermal environment in building applications, discussing the main aspects of design and assessment of the thermal comfort taking into account the role of humidity and of the temperatures measured in the long term. Yang et al. [24] discuss the implications of thermal comfort on energy consumption in buildings. Croitoru et al. [18] review the main methods used to assess the quality of a thermal environment, taking into account the response of the humans, the use of sensors and the application of CFD simulations. Rupp et al. [33] review a number of experiments carried out in controlled environments (climate chambers), semi-controlled environments (simulating indoor spaces), and several real-case studies in buildings with different applications (kindergardens, schools, universities, offices, residential buildings, and others). Other papers focus on specific applications, referring to residential buildings in Peeters et al. [34], sleeping environments in Djongyang et al. [7], hospitals in Khodakarami et al. [35], educational buildings in Kwong et al. [36] and Zomorodian et al. [37], tropical buildings in Kwong et al. [36], and historic buildings in Martínez-Molina et al. [38].

In indoor applications, the main variable used to ensure thermal comfort is the internal air temperature. Relative humidity is also commonly considered [39]. The control schemes proposed to improve thermal comfort are based on a number of other variables, used as inputs to the control system. Prediction of relevant outputs is an effective way to develop suitable control strategies for thermal comfort assessment and improvement. A typical predicted output is the indoor air temperature, which can be associated to control actions in the building automation system. However, in the presence of many variables affecting thermal comfort, the opinion of the occupants is extremely important to understand the overall effect of the interaction of these variables [1]. Thereby, the control strategies may depend on the prediction of a thermal comfort indicator such as *PMV* [40].

In the context underlined above, the specific contributions of this paper are:

- To review the main thermal comfort indices used in uniform and non-uniform thermal ambients. For this purpose, the personal and ambient parameters appearing in these indices are first recalled. Then, the emphasis is set on the *PMV* and *PPD* indices, with their variants and modifications presented in the literature.
- To review the thermal comfort models used to predict the indoor air temperature and the *PMV* index for the definition of control strategies in indoor environments. The main models presented in many literature contributions are identified. The input variables used in these models are then highlighted. Finally, the characteristics and suitability of the models to represent the non-linear interactions among the variables are discussed.

The next sections of this paper are organised as follows. Section 2 recalls the main approaches used to define thermal sensation and comfort. Section 3 presents the main parameters used in the study of thermal comfort for indoor spaces, addressing in particular the definitions of the relevant temperatures. Section 4 illustrates and discusses the thermal comfort indices used in different thermal environments and conditions. Section 5 deals with the thermal comfort models used to define control strategies for indoor applications. The last section contains the conclusions.

2. General concepts of thermal comfort and approaches

The term *thermal comfort* is used to suggest information about the thermal state of a human within a given thermal environment. On the practical point of view, thermal comfort is described by means of three main approaches, called physiological, psychological, and rational [41]:

1. The *physiological* approach represents the thermal perception of a human due to the nervous sensors from thermal receptors inside the skin to hypothalamus. In the human body, there are cold sensors and warm sensors. The humans have the capacity to keep approximately constant body temperature (the normal temperature of the body is 37 ºC +/−1 ºC), which does not depend on the ambient temperature; the thermoregulatory centre in the hypothalamus keeps the body temperature in the normal range. The human feels thermally neutral when the signals transmitted by cold and warm sensors have equal magnitudes, otherwise the human feels warm or cold [42]. In particular:
   a. The *cold sensors* are placed on the skin and when the body temperature decreases under 34 ºC, they send appropriate signals. The cooling process includes sweating (leading to evaporation) and increasing the blood flow over the skin.
   b. The *warm sensors* are found in hypothalamus and when the body temperature is over 37ºC, they send appropriate signals. The warming process is given by shivering to increase the muscle activity and by decreasing blood flow over the skin.
   c. When the body is superheated, a cold sensation is very pleasant,

but when the body is already cold this sensation could be unpleasant. Much more, the skin temperature is not the same in different parts of the body [43]. The sensation in any part of the skin depends on ambient temperature, time, place, and clothing. Thermal comfort is achieved when the heat developed by metabolism equals the heat lost from the body [42]. The major physiological factors influencing heat balance are the skin temperature and sweat rate for a given metabolism [44]. The physiological approach deals with *acclimatisation*, namely, the response to continuous exposure to one or more inputs from the thermal environment, which modifies the settings of the physiological thermoregulation system in a time scale of days or weeks. Longer-term versions of the physiological approach address the *genetic adaptation* occurring at timescales longer than an individual's lifetime [45].

2. According to the *psychological* approach, thermal comfort is "*that condition of mind which expresses satisfaction with the thermal environment*". This general definition has been provided in the two standards mostly used for indoor thermal environment assessment, BS EN ISO 7730-1995 [46] and ASHRAE 55-2004 [47], with successive editions upgraded during the years. Yet, in various references these standards have been considered to be unsuitable to take into account the comfort level in real situations [48–50]. Another definition given in the ASHRAE Standard 55-2004 [47] is "*that condition of mind which expresses satisfaction with the thermal environment and is assessed by subjective evaluation*". However, these general definitions have to be quantified for the purpose of carrying out technical analyses in different types of applications. In the UK, the Health and Safety Executive (HSE) [51] specifies that an environment is considered with "reasonable comfort" when about 80% of its occupants feel thermally comfortable. The thermal comfort is evaluated by determining whether the occupants are satisfied or not with their thermal environment. Local discomfort or dissatisfaction is considered when the body is too warm or cold, or when a certain part of the body is too cold or warm [52]. The psychological adaptation depends on the experiences and habits of the individuals, as well as their expectations on what may be offered by the indoor environment [53,54].
3. In the *rational approach*, thermal sensation depends on the heat balance of the human body. To obtain thermal comfort, the heat flowing from and to the human body have to be balanced, and the skin temperature, as well as the sweat rate, have to fall inside specific ranges depending on the metabolic activity [55,56]. Liu et al. [4] present an assessment method of these approaches to highlight their significance to improve control strategies for specialists for obtaining thermal comfort and energy efficiency. Their research indicates that the physiological approach is the main factor necessary to achieve an acceptable thermal environment. The behavioural and psychological approaches are considered as having similar weights. Hensen [52] explains the difference between thermal comfort and thermal sensation. Thermal comfort is considered an emotional experience described in terms of "pleasant" and "unpleasant", while thermal sensation is considered a rational experience described in terms of "cold" and "warm". Both thermal comfort and thermal sensation depend on the ambient and personal parameters [57], which are presented below.

3. Parameters related to thermal comfort

3.1. Types of parameters

3.1.1. Personal and ambient parameters

Thermal comfort of occupants inside buildings depends on the heat balance of the body. The heat balance of the body is affected by two main groups of factors [58]:

1. *Personal parameters* representing characteristics of the occupants, defined as follows:

- *Clothing insulation (or level of clothing)* I_{cl}, that is, the amount of thermal insulation the person is wearing, in *clo* units (1 clo = 155 m^2 °C·W).
- *Metabolic heat rate*, or *activity level* $\dot{M}$ (internal heat production of the body) is the net heat output from the human body in a given period of time, or the rate of trasformation of chemical energy into heat and mechanical work by aerobic and anaerobic activities within the body, in *met* units (1 met = 58.2 W m^{-2}). Its value is always positive because the body always produces heat; the surface of the body could be from 45 W m^{-2} for a person who rests to 500 W m^{-2} for a person who runs.

2. *Ambient parameters* such as *temperatures*, *air velocity*, and *relative humidity*. The rationale for using these parameters is that the human thermoregulatory system is adequate to create heat balance within the ambient factors. The temperature parameters and some related indices are specified in Section 3.2, taking into account the many temperature definitions to be considered in the analysis of thermal comfort. The definitions of air velocity and relative humidity are recalled here:

- The *air velocity* v_{ar} [m s^{-1}] is the rate of air movement to a given distance over time. The air velocity can produce discomfort when is higher than 40 feet/min (that is, 0.2032 m/s) or when cold temperatures are combined with any air movement [59].
- The *relative humidity RH* is the ratio between the measured (actual) water vapour pressure in the air and the maximum quantity of water vapour pressure contained by the air at a known temperature [60]. It is typically expressed in per cent:

$$RH = 100 p_w \bullet p_{sat}^{-1} \tag{1}$$

where p_w is the actual or measured water vapour pressure in an air mass [Pa], and p_{sat} is the saturated vapour pressure of pure water in [Pa].

The actual water vapour pressure in an air mass [59,61] is given by:

$$p_w = H_{wv} \bullet (101325 + p) \bullet (0.62198 + 0.37802 \bullet H_{wv})^{-1} \tag{2}$$

where H_{wv} is the concentration of water vapour.

The saturated vapour pressure of pure water [59] is expressed in function of the temperature T as:

$$\begin{aligned} p_{sat} = {} & 1000 \exp(-5800 \bullet T^{-1} - 5.516 - 0.04864 \bullet T \\ & + 4.176 \bullet 10^{-5} \bullet T^2 - 1.445 \bullet 10^{-8} \bullet T^3 + 6.546 \bullet \ln T) \end{aligned} \tag{3}$$

The relative humidity suggested by different organisation ranges concerning thermal comfort for human is between 30–60%. The relative humidity higher than 70% provokes thermal discomfort for humans [62,63].

For indoor spaces, *RH* depends on the air temperature and the water vapour content of the air, being maintained in a range little enough to be comfortable, but large enough to avoid problems associated with very dry air. *RH* has a low value when the temperature is high and the water evaporation is fast.

In many studies, the *RH* effect is considered to affect thermal comfort [47,64,65], perception of indoor air quality [66], health of the occupants [67] and energy consumption [68]. The *RH* effect has a big influence on the heat balance for the human body at high metabolic rates, in hot environments (high operative temperatures) and under transient conditions [69].

3.1.2. Other parameters

In addition to the parameters indicated above, there are additional entries affecting thermal comfort and heat dissipation from the body, such as *food and drink, acclimatisation* (in the case of buildings with great outdoor-indoor temperature gradient, acclimatisation is more problematic), *body shape, subcutaneous fat, age and gender,* and *state of health* [70]. For the purpose of thermal comfort analysis, the factors indicated are transformed into quantitative parameters, associated with recommended values, or linked through appropriate equations.

3.2. Temperature definitions and indices

3.2.1. Dry bulb (air) temperature

The *dry bulb (air)* temperature T_{db} is the temperature of the indoor air surrounding the body. The range temperature recommended by different organisations is between 18 °C to 23 °C and the temperature difference in the occupied zones cannot exceed 1 °C [59]. The temperature range necessary for optimising the indoor thermal comfort is recommended to be from 19 °C to 28 °C being applicable for the sedentary or near sedentary physical activity levels that are general office activities. This recommendation considers that people must be suitably dressed depending on the external seasonal demands [71].

3.2.2. Mean radiant temperature

The *mean radiant* temperature T_{MR} is the temperature of a black body that changes the same amount of thermal radiation with a human and the surroundings of the human [72,73]. The expression of the mean radiant temperature from Fanger [74] considers only the thermal radiation transmitted by the walls. In the simplest form, T_{MR} is expressed as the weighted average of the temperatures taken at different surfaces in steady-state conditions:

$$T_{MR} = \left(\sum_{i=1}^{n} T_i \bullet S_i\right) \bullet \left(\sum_{i=1}^{n} S_i\right)^{-1} \tag{4}$$

where T_{MR} is the mean radiant temperature, T_i is the temperature of surface *i* (computed or measured), and S_i is the area of surface *i*.

3.2.3. Standard effective temperature

The *standard* effective temperature (SET^*) is a temperature index of thermal sensation and thermal discomfort for uniform thermal environments [75,76].

The temperature range of thermal sensation on the SET^* scale indicated in [77] includes SET^* values <17 (cool, moderate hazard), 17 ÷ 30 (comfortable, no danger) 30 ÷ 34 (warm, caution), 34 ÷ 37 (hot, extreme caution), and >37 (very hot, danger).

3.2.4. New effective temperature

The *new* effective temperature ET^* combines the influence of air temperature, humidity, radiant conditions, and air movement creating an equal thermal sensation. ET^* is the dry bulb temperature of a thermal environment at 50% *RH* and a precise uniform radiation [78]. ET^* is a temperature index that determines the connection between the body's thermoregulatory capacity (warm and cold perception) and various temperatures and humidity of the ambient. The most recommended comfort conditions are $ET^* = 24°C$, $T_{db} = T_{MR}$, $RH = 40\%$ (the range is from 20% to 60%), $v_{ar} < 0.2 m\bullet s^{-1}$ [78]. When the wet and dry bulb temperatures are equal, the air is totally saturated with moisture.

The expression of ET^* developed by Missenard [79] represents the effective temperature of the body at various meteorological parameters (T_{db}, RH, and v_{ar} at 1.2 m above the ground) to obtain the heat transfer between the body and the environment [77]:

$$\begin{aligned} ET^* &= 37 - (37 - T_{db}) \bullet [0.68 - 0.0014 \bullet RH + (1.76 + 1.4 \bullet v_{ar}^{0.75})^{-1}]^{-1} \\ &\quad + -0.29 \bullet T_{db} \bullet (1 - 0.01 \bullet RH) \end{aligned} \tag{5}$$

The temperature range of thermal sensation on the ET^* scale indicated in [77] includes ET^* values <1 (very cold), 1 ÷ 9 (cold), 9 ÷ 17 (cool, moderate hazard), 17 ÷ 21 (comfortable, no danger), 21 ÷ 23 (warm, caution), 23 ÷ 27 (hot, extreme caution), and >27 (very hot, danger).

3.2.5. Physiological effective temperature

The *physiological effective* temperature *PET* [80,81] used for both hot and cold climates, offers the real effect of the climate perception on individuals. *PET* represents the equivalent temperature, in the indoor conditions, at which the heat balance of the human body is kept with the same core and skin temperatures as the corresponding temperatures in the outdoor conditions to be evaluated [77].

The temperature range of thermal sensation on the *PET* scale indicated in [77] includes *PET* values <4 (very cold), 4 ÷ 8 (cold), 8 ÷ 18 (cool, moderate hazard), 18 ÷ 23 (comfortable, no danger), 23 ÷ 35 (warm, caution), 35 ÷ 41 (hot, extreme caution), and >41 (very hot, danger).

3.2.6. Operative temperature

The *operative* temperature T_{op} is obtained from air temperature, mean radiant temperature and air speed. It is defined [82] as the uniform temperature of an imaginary black enclosure in which an occupant would exchange the same amount of heat by radiation and convection as in the actual non-uniform environment. The expression of the operative temperature is:

$$T_{op} = (T_{MR} \bullet h_r + T_{db} \bullet h_c) \bullet (h_r + h_c)^{-1} \tag{6}$$

where T_{MR} is mean radiant temperature in [°C], h_r is the radiative heat transfer coefficient in [W m^{-2} °C^{-1}], and h_c is the convective heat transfer coefficient in [W m^{-2} °C^{-1}].

The mean radiant temperature affects the operative temperature [83]. The operative temperature for moderate thermal environments and for $T_{MR} - T_{db} < 4°C$ is considered to be [84]:

$$T_{op} = (T_{MR} + T_{db})/2 \tag{7}$$

Ranges of the operative temperature for the occupants involved in light, primarily sedentary activity (1.2 mets) at 50% relative humidity and mean air velocity of 0.15 m s^{-1} are shown in Table 2, indicating the T_{op} values accepted by 80% and 90% of the occupants in buildings with central HVAC systems. It is recommended to avoid the inferior limits for some cases as children, disabled persons and the elders [85].

Two simplified expressions of T_{op} are presented in [2]:

- The first expression of T_{op} is given by the weighted average of air temperature and mean radiant temperature:

$$T_{op} = \alpha \bullet T_{db} + (1 - \alpha) \bullet T_{MR} \tag{8}$$

where α is a coefficient that depends on the relative air velocity.

This equation is also included in the Standard ANSI/ASHRAE

Table 2
Operative temperature for occupants in buildings with central HVAC systems [85].

period	*type of clothing insulation*	*clothing insulation*	*optimum temperature* T_{opt} [°C]	*operative temperature* T_{op} [°C]	
		I_{cl} [clo]		*80% accepted*	*90% accepted*
Winter	heavy slacks, long sleeve shirt, sweater and office chair	1.05	22.5 °C	20.5 –24.5 °C	21.3 –23.7 °C
Summer	light slacks, short sleeve shirt and office chair	0.65	23.5 °C	21.5 –25.5 °C	22.3 –24.7 °C

55-2013 [86], but with the restriction that the metabolic range must be in the range from 1.0 to 1.3 met, and without solar radiation. This equation also indicates an important specification at a high air velocity (when the heat transfer coefficient by convection is higher, the value of air temperature is bigger than the mean radiant temperature).

- The second expression of T_{op} is the simple average between air temperature and mean radiant temperature:

$$T_{op} = (T_{db} + T_{MR})/2 \tag{9}$$

with v_{ar}<0.2 m/s, and the absolute value of the difference between the radiant temperature and the air temperature is less than 4 ºC.

3.2.7. Globe thermometer temperature

The *globe thermometer temperature* T_g is an approximate measure of the operative temperature that takes into account the influence of air temperature, velocity of air movement, and solar radiation. It is the temperature measured by the globe thermometer.

3.2.8. Wet bulb temperature

The *wet bulb temperature* T_{wb} is the temperature recorded by a thermometer that has its bulb covered by clothes and is wet with distilled water.

3.2.9. Wet bulb globe temperature

The *wet bulb globe temperature WBGT* is an apparent temperature that estimates the effect of temperature, humidity, wind speed, and sunlight on humans. According to [87], in outdoor conditions *WBGT* depends on the wet bulb temperature T_{wb}, the globe thermometer temperature T_g, and the dry bulb air temperatureT_{db}:

$$WBGT = 0.7 \bullet T_{wb} + 0.2 \bullet T_g + 0.1 \bullet T_{db} \tag{10}$$

while in indoor conditions *WBGT* depends on T_{wb} and T_g:

$$WBGT = 0.7 \bullet T_{wb} + 0.3 \bullet T_g \tag{11}$$

Blazejczyk et al. [77] present a study based on a simplified equation of *WBGT* written as:

$$WBGT = 0.567 \bullet T_{db} + 0.393 \bullet p_a + 3.94 \tag{12}$$

where p_a is the air vapour pressure, expressed by considering the dew point temperature T_d in °C, as:

$$p_a = 6.11 \bullet e^{[5417.753 \bullet (273.16)^{-1} \bullet (273.16 + T_d)^{-1}]} \tag{13}$$

The temperature range of thermal sensation on the *WBGT* scale indicated in [76] includes *WBGT* values <18 (comfortable, no danger), 18 ÷ 24 (warm, caution), 24 ÷ 28 (hot, extreme caution), 28 ÷ 30 (very hot, danger), and >30 (sweltering, extreme danger).

3.2.10. Indoor neutral temperature

The concept of neutral temperature is based on the concept of thermal neutrality, namely, a state without net heat exchange between the environment and the body, considered as the ideal thermal state [88]. The neutral temperature is defined as the temperature corresponding to mean thermal sensation equal to zero. On these bases, the indoor neutral temperature is the temperature of the indoor space that gives a response equal to zero in the ASHRAE thermal sensation scale.

4. Comfort indices for uniform and non-uniform thermal ambients

Thermal comfort depends on steady-state conditions and transient conditions (changing in time), occurring in uniform and non-uniform thermal environments.

In the case of uniform thermal environment in steady-state conditions, the indices that predict thermal sensation and comfort by means of the ambient and personal parameters are the *SET* and *PET* introduced in Section 3.2, and the *PMV* index [64,89] described in this section with its applications and variants.

Let us consider a group of persons that give their votes on the thermal sensation they feel in a given environment. The votes are represented with a variable called Thermal Sensation Vote (*TSV*). The *TSV* entries are expressed on the typical ASHRAE 7-point scale [90]. The *PMV* represents the mean vote determined from the average of the *TSV* values [91]. Another voting scale called Comfort Sensation Vote (*CSV*), introduced in Japan [92], has four values expressing comfortable (0), slightly uncomfortable (−1), uncomfortable (−1) and very uncomfortable (−3) sensations.

In the case of non-uniform thermal environment, the simultaneous presence of airflows and heaters in the living zone may lead to different temperatures in different parts of the body, exacerbating the discomfort conditions.

4.1. Predicted Mean Vote (PMV)

4.1.1. PMV calculation

The *PMV* index is computed by using the Fanger comfort equation for human body heat exchange [55,64,93]. The *PMV* index treats the body like a whole being, useful to predict responses in the steady-state air-conditioned environment, and cannot predict transient responses [15].

The *PMV* index is computed by including four physical parameters (air temperature, air velocity, humidity, mean radiant temperature) and two personal parameters (metabolic rate and clothing insulation). The expression of the *PMV* index is presented in the Standard [94], depending on the following quantities:

$$PMV = f(\dot{M},\ \dot{W},\ f_{cl},\ p_a,\ T_{db},\ T_{cl},\ h_c) \tag{14}$$

where $\dot{W}$ is the rate of mechanical work (or effective mechanical power) in [W m^{-2}], T_{cl} is the mean temperature of clothing [°C], andf_{cl} is ratio of clothed surface area to the nude surface area. The explicit formulation of the *PMV* index is:

$$\begin{aligned} PMV = {} & [0.303 \bullet\ e^{(-0.036 \bullet \dot{M})} + 0.028] \\ & \bullet \{(\dot{M} - \dot{W}) - 3.05 \bullet\ 10^{-3} \bullet [5733 - 6.99 \bullet (\dot{M} - \dot{W}) - p_a] \\ & \bullet 0.42[(\dot{M} - \dot{W}) - 58.15] - 1.7 \bullet\ 10^{-5} \bullet \dot{M} \bullet (5867 - p_a) - 0.0014 \bullet \dot{M} \\ & \bullet (34 - T_{db}) - 3.96 \bullet\ 10^{-8} \bullet f_{cl} \bullet [(T_{cl} + 273)^4 - (T_{MR} + 273)^4] \\ & - f_{cl} \bullet h_c \bullet (T_{cl} - T_{db})\} \end{aligned} \tag{15}$$

Among the terms appearing in the *PMV* equation:

- The clothing surface temperature T_{cl} can be obtained by solving in an iterative way the implicit equation:

$$\begin{aligned} & T_{cl} - 35.7 + 0.28 \bullet (\dot{M} - \dot{W}) + I_{cl} \\ & \bullet \{3.96 \bullet\ 10^{8} \bullet f_{cl} \bullet [(T_{cl} + 273)^4 - (T_{MR} + 273)^4] \\ & + f_{cl} \bullet h_c \bullet (T_{cl} - T_{db})\} = 0 \end{aligned} \tag{16}$$

- The convective heat transfer coefficient can be solved by iterations and is given by:

$$h_c = \begin{Bmatrix} 2.38 \bullet |T_{cl} - T_{db}| \text{ for } 2.38 \bullet\ |T_{cl} - T_{db}|^{0.25} > 12.1 \bullet\ \sqrt{v_{ar}} \\ 12.1 \bullet\ \sqrt{v_{ar}} \text{ for } 2.38 \bullet\ |T_{cl} - T_{db}|^{0.25} > 12.1 \bullet\ \sqrt{v_{ar}} \end{Bmatrix} \tag{17}$$

- The ratio of clothed surface area f_{cl} is expressed by:

$$f_{cl} = \begin{Bmatrix} 1.00 + 1.290 \bullet I_{cl} \ \text{ for } \ I_{cl} \le 0.078 \quad \mathrm{m^2 \bullet K \bullet W^{-1}} \\ 1.05 + 0.645 \bullet I_{cl} \ \text{ for } \ I_{cl} \le 0.078 \quad \mathrm{m^2 \bullet K \bullet W^{-1}} \end{Bmatrix} \tag{18}$$

The *PMV* index written under empirical form is presented in the ASHRAE Handbook [95]:

$$PMV = \alpha_p \bullet T_{db} + \beta_p \bullet p_a + \delta_p \tag{19}$$

where α_p, β_p and δ_p are the coefficients for indoor environments, taking into account the exposure time and sex.

The experimental study of Yang and Su [96] deals with the effects of the radiant temperature on the thermal comfort expressed by *PMV*. Lin and Deng [97] present the equation of the *PMV* index described by Fanger to address the disequilibrium between the actual heat flow from a human body and the heat flow required to obtain optimum comfort for a given activity and environment:

$$PMV = [0.303 \bullet e^{-0.036 \bullet M} + 0.028] \bullet L = \gamma \bullet L \tag{20}$$

where γ is the sensitivity coefficient, and L is the thermal load on the body, defined in the actual environment as the difference between the internal heat production and the heat loss, by considering a person that reaches the comfort values of evaporative heat loss and skin temperature by sweating at the actual activity level.

Another empirical model of the *PMV* is exposed in [19] and [98], presenting a study about indoor parameters on thermal comfort and indoor air quality. Furthermore, for indoor environments, some examples of coefficients referring to the general Eq. (19), indicated in [90,99] and [100], are presented in Table 3.

A *PMV* expression for sleeping environments is presented in [7] and [97] under the following form:

$$PMV = 0.0998 \bullet (40 - R_t^{-1} \bullet a) - 0.0998 \bullet b \tag{21}$$

in which the coefficients a and b are:

$$a = (162.62 + h_c \bullet (34.6 - T_{db}) - 4.7 \bullet T_{MR}) \bullet (4.7 + h_c)^{-1} \tag{22}$$

$$b = 0.056 \bullet (34 - T_{db}) - 0.692 \bullet (5.87 - p_a) \tag{23}$$

where R_t is the total resistance of a bedding system including the air layer around a covered body [m^2 °C W^{-1}].

Han et al. [101] use a regression model and simplify the conventional *PMV* equation taking into account just the main variables. Therefore, the independent variables are the air temperature T_a, the mean radiant temperature T_{MR}, and the relative humidity RH, while the air velocity due to the indoor environment is neglected:

$$PMV_{regression} = f(T_{db}, T_{MR}, RH) \tag{24}$$

The significant variables are sorted by using standardised regression coefficients:

$$PMV_s = f(T_{db}, T_{MR}) \tag{25}$$

The result of this analysis is 7.0% more thermal comfort and 5.6% more energy reduction for the simplified *PMV* control that the model achieved by room temperature control with room thermostats.

4.1.2. Comments on the PMV applications

The *PMV* index adopted by ASHRAE predicts the mean response of a large group of people by using the linguistic expressions *hot*, *warm*, *slightly warm*, *neutral*, *slightly cool*, *cool* and *cold*, corresponding to a 7-points thermal scale from cold (−3) to hot (+3) [102]. In a comfortable environment, people will express a value close to 0 for the *PMV*. In general, the thermal comfort range is considered between −0.5 and +0.5. The tolerance of ± 0.5 units around zero is used by the ISO 7730 standard [89], the Renewable Energy Road Map [103], and the EN 15251 standard [30,104,105]. If the *PMV* value is closer to zero, the thermal comfort sensation of the occupants is better [106].

The rationale of the ± 0.5 units tolerance is also addressed by Humphreys [107], who affirms that the people in cold climates might prefer a sensation slightly warmer than neutral, while the people in hot climates might prefer a sensation slightly cooler than neutral.

Fountain et al. [108] shows that when the people are in the same environment, the particular differences are usually higher than 1.0 scale unit. They introduce two hypotheses: the first hypothesis specifies that the optimum temperature corresponds to a *neutral* thermal sensation and the second one specifies the term *acceptability*, linked to specific thermal sensations on the ASHRAE 7-point scale [109].

According to the Standard ISO 7730 [94], *PMV* could be applied to the range +2 to −2, considering the rate of metabolic heat production $\dot{M}$ from 46 to 232 $W \bullet m^{-2}$, the clothing insulation I_{cl} from 0 to 0.310 $K \bullet m^2 \bullet W^{-1}$, the air temperature from 10 to 30 °C, the mean radiant temperature from 10 to 40 °C, the relative air velocity from 0 to 1 $m \bullet s^{-1}$, and the water vapour partial pressure from 0 to 2700 Pa. Fanger takes into account the votes of the dissatisfied persons considering the thermal environment as cold, cool, warm, or hot, or out of the *PMV* range of −2 to +2. The data obtained demonstrate that the discomfort progressively rises, appearing under conditions warmer and cooler than neutral [109]. Webb and Parsons [110] specify that at the *PMV* of −1.5 and 0, the range of responses for physically disabled people is higher than for healthy people.

The *PMV* index applies to healthy adults and cannot be used for children or persons who are elderly or disabled [109]. The *PMV* is also recommended in indoor spaces, often offices, for applications in air-conditioned environment (HVAC systems) in order to create the artificial climates for these spaces, as well as for different activities and clothing habits [47,89]. The *PMV* is not recommended for predicting the overall thermal comfort of the occupants in non-air-conditioned buildings, like naturally ventilated spaces, due to the relatively high difference between the *PMV* and thermal comfort analyses [111]. Further references [45,112] justify that *PMV* can be better predicted in air-conditioned environments. In the case of naturally ventilated buildings, the researches show that there is a difference between the *PMV* and the thermal sensation declared by the occupants (e.g., the *PMV* could underestimate or overestimate the thermal sensation of the occupants [113,114]). The thermal sensation for indoor spaces is differently perceived from that of outdoor spaces, thereby the models for the indoor thermal comfort are not applicable to outdoor spaces [56]. The study presented in Gilani et al. [115] addresses the percentage deviation in the prediction level of the *PMV* index for naturally ventilated and HVAC buildings. The results show that for naturally ventilated buildings the *PMV* equation underestimates the thermal sensation by 13% in the summer season, and overestimates it by 35% in the winter season. Conversely, for HVAC buildings there is an overestimation of 31% for the summer season and 33% for the winter season.

The *PMV* is appropriate for steady-state conditions. It can also be used during small oscillations of one of more variables, by considering the time-weighted averages of the variables during the previous hourly period [94]. The *PMV* model is considered a static model that predicts any air temperature between 10 and 35 °C as neutral, depending on the other five variables of the model. Therefore, it establishes a definite range as acceptable around the neutral temperature, depending on the permitted percent dissatisfied [116]. The *PMV* is used to compute the thermal load of the human body and to describe the degree of warm and cold sensations. This indicator is computed for conditions when the human body is in thermal equilibrium [117]. The *PMV* index is obtained when personal variables (clothing insulation and metabolic

Table 3
Values of the coefficients α_p, β_p, and δ_p for indoor environments.

α_p	β_p	δ_p	*reference*
0.202	0.553	−5.151	Orosa and Oliveira [150]
0.243	0.278	−6.802	ASHRAE
0.252	0.240	−6.859	
0.245	0.248	−6.475	

rate or activity level) are estimated due to the tables, and the environmental variables (air temperature, air velocity, mean radiant temperature and relative humidity) are measured [64,118].

4.2. Modified PMV indices

4.2.1. Adaptive Predicted Mean Vote (aPMV)

The term Adaptive Predicted Mean Vote (*aPMV*) describes the thermal comfort in a warm environment and predicts "the same *optimum operative temperature* as the analytic *PMV* approach, but uses mean outdoor effective temperature as the only input instead of the usual four inputs (clothing insulation, metabolic rate, relative humidity, and air velocity) required by the analytic *PMV* method" [85]. The aim of *aPMV* is to consider the psychological and heat balance approaches together [21]. Since the *PMV* is not adequate for a hot and humid climate, the *aPMV* is considered more generally useful to establish thermal comfort for the occupants and for conserving energy as well [119]. In [120] the *aPMV* index is called actual thermal sensation.

The *optimum operative temperature* represents the operative temperature that satisfies the largest possible number of people at a given clothing and activity level [85]. In their research, de Dear and Brager [85] propose an adaptive model under the form of a regression equation that links the neutral indoor temperature to the average monthly outdoor temperature, in such a way that this temperature is the only variable used.

The temperatures during the summer (reduced temperature) and winter (higher temperature) are set to achieve thermal comfort according to the *PMV* model. For the same environment, according to the *aPMV* model, the occupants feel comfortable during the summer and the winter, taking into account the energy saving of the building [121]. Singh et al. [122] denote *aPMV* as Corrected Predicted Mean Vote (*cPMV*) and suggest the values necessary for behavioural, physiological and psychological adaptation to obtain the adaptive coefficients for the four seasons of the year at three different climates. The values of these coefficients are negative in the winter, pre-summer and pre-winter months, and positive in the summer months.

Yao et al. [123] show a relationship between *aPMV* and *PMV* from Fanger's laboratory study for naturally ventilated buildings:

$$aPMV = (PMV^{-1} + \beta)^{-1} \quad (26)$$

The term β is called "adaptive coefficient" for the *aPMV* model in naturally ventilated buildings, and represents the ratio between the psychological and behavioural impact coefficient P_τ and the physical stimulus τ (i.e., the difference between the indoor resultant air temperature T_{Ma} and the thermal neutral temperature T_{n}) [124]:

$$\beta = P_\tau/\tau = P_\tau \bullet (T_{\mathrm{Ma}} - T_{\mathrm{n}})^{-1} \quad (27)$$

The adaptive coefficient β is useful to correct the overestimation and underestimation of the *PMV* indicator [21]. Therefore, in the case of naturally ventilated buildings, several studies determined the adaptive coefficients.

Yao et al. [123] obtain the value $\beta = -0.125$ for cold conditions and $\beta = 0.293$ for warm conditions, within a range slightly larger than the β range from 0.029 to 0.167 obtained in [120]. This difference is caused by the relative humidity, which has a high effect on the thermal sensation in free-running buildings (i.e., buildings that do not consume energy for heating or cooling in the period of observation) [125]. The value $\beta = 0.444$ is indicated in [126] for the summer in Indian warm and humid climatic zones. Shen and Yu [127] analyse the thermal comfort adaptive model in non air-conditioned houses during the summer and winter for a specific zone in China. Considering psychological and behavioural adaptation effects of humans, the values obtained are $\beta = -0.196$ in cool conditions and $\beta = -0.334$ in warm conditions. The data analysis shows that *aPMV* behaves better with *TSV* than the original *PMV*. Xu et al. [121] introduce an *aPMV* model, and show the results of the relationship between *aPMV* and *PMV* for Beijing. To optimise β, a genetic algorithm is used, obtaining for Beijing climate the values $\beta = -0.136$ for winter conditions, and $\beta = 0.285$ for summer conditions. Conceição et al. [128] present the adaptive model developed for a kindergarden by means of experimental measurements. According to the numerical simulation *aPMV* and *PMV* are determined. Therefore, in summer conditions the *aPMV* decreases with 50% than the *PMV*, and in winter conditions the *aPMV* decreases with 30% than the *PMV*. Li et al. [124,129] present the empirical values of β for various regions in China, with values of $\beta < 0$ obtained for $PMV < 0$, and $\beta > 0$ obtained for $PMV \geq 0$.

In the thermal environment of a cotton textile workshop, Yang et al. [130] show the values $\beta = 0.2189$(for workers) considering that *aPMV* gives a cooler vote than the *PMV*, and $\beta = -0.1187$ (for students) considering that *aPMV* gives a warmer vote than the *PMV*. The range of *aPMV* is from 0.94 to 2.02 for workers and from 1.10 to 2.78 for students. Wu et al. [131] analyse thermal discomfort and adaptive responses in residential buildings for China, using the raw field data from the database of the standard GB/T50785-2012. The adaptive coefficient prescribed by the standard is $\beta = -0.49$ for cold winter, and $\beta = 0.21$ for hot summer.

The results obtained by Yao et al. [123] are that for cool conditions and winter period ($PMV < 0$ and T_{Ma}-$T_{\mathrm{n}} < 0$, corresponding to β<0 and $aPMV > PMV$) the indoor thermal temperature is less than the comfort temperature (i.e., the *aPMV* is giving cooler feeling than the *PMV*). Much more, for warm conditions and summer period ($PMV > 0$ and T_{Ma}-T_{n} >0, corresponding to β>0 and $aPMV < PMV$) the indoor thermal temperature is higher than the comfort temperature (i.e., the *aPMV* is giving warmer feeling than the *PMV*). When $\beta = 0$, then $aPMV = PMV$, and the indoor temperature is equal to the comfort temperature. The ranges of *aPMV* for indoor thermal environments in free-running buildings are $-0.5 \leq aPMV \leq 0.5$ for category I (90% satisfactory), $-1 \leq aPMV < -0.5$ or $0.5 < aPMV \leq 1$ for category II (75% satisfactory), and $0.5 < aPMV \leq 1$ for category III (unacceptable) [124].

Finally, in the case of air-conditioned buildings, Kim et al. [132] analyse the *aPMV* model, showing good prediction performance only when the original *PMV* value ranges from −1.5 to +1.5. The values of β are −1.40 in cool conditions and −5.74 in warm conditions.

4.2.2. Extended Predicted Mean Vote (ePMV)

The *ePMV* model introduced by Fanger and Tofum [116] highlights expectations of people based on local climate and popularity of mechanical conditioning. The *PMV* model works well inside the air-conditioned buildings, while the *ePMV* model is only suitable for warm and humid climates in non-air conditioned building where the indoor air temperature rises significantly [49,85].

The *ePMV* model includes a correction factor called *expectancy factor* e_p, which is multiplied by *PMV* to obtain the corrected value of *PMV* representing the mean *TSV* of the persons:

$$ePMV = e_p \bullet PMV \quad (28)$$

The *ePMV* model considers a superior limit of +2 °C when the term e_p is reduced, otherwise, no inferior limit is considered [116]. The expectancy factor is then helpful to compensate some for discrepancies arising between the observed and predicted sensation votes [133]. The expectancy factor considers the greater acceptability to warm conditions of humans who live in regions with long summer and in non-air conditioned buildings [134].

Even a one-decimal modification of the e_p factor can change the final result of *PMV* in a tangible way. If e_p is interpreted in a wrong way, an overestimation/underestimation of the *PMV* value variation can occur [134].

The expectancy factor depends on the annual duration of the warm weather for non-air conditioned buildings [116]. The duration of the warm period describes the expectation range (considered as high, moderate and low), and the quantity of air-conditioned buildings within a zone describes the reduced or greater value within this range [134]. Therefore, the expectation ranges for non-air conditioned buildings in warm climates are as follows:

- the range of e_p is 0.5 ÷ 0.7 for naturally ventilated buildings located in regions with a few air-conditioned buildings (all seasons) and the expectation is low; in particular, if the warm weather is almost all year, $e_p = 0.5$ for just few or none air-conditioned buildings, otherwise, $e_p = 0.7$ in the warm period in all seasons, and air-conditioned buildings are common;
- the range of e_p is 0.7 ÷ 0.9 for naturally ventilated buildings located in regions with some air-conditioned buildings (summer period) and the expectation is moderate; in particular, for the warm weather during the summer, the range of e_p is from 0.7to0.8 for just few or none air-conditioned buildings, and is from 0.8to0.9 for air-conditioned buildings;
- the range of e_p is 0.9 ÷ 1 for naturally ventilated buildings located in regions where air-conditioned buildings are common (warm periods) and the expectation is high.

The results of the *ePMV* model assessments for naturally ventilated buildings in different territories are reported in various contributions. Fanger and Tofum [116] and Alfano et al. [135] perform a comparison of observed *TSV* with predictions using *ePMV* for warm climates. The expectancy factors obtained for different zones are $e_p = 0.6$ for offices and houses (Thailand and India), 0.7 for schools (Singapore and Greece), 0.82 for schools and houses (China) [136,137], and 0.9 (Australia). The expectancy factors of the *ePMV* model in [120] are in the range from 0.770 to 0.974, consistent with the moderate expectation suggested in [116].

For India, on a typical summer day the *PMV* values reported in [138] are from 2 to more than 3, corresponding to "*warm*" and "*hot*" thermal sensation of the occupants, respectively. The value $e_p = 0.7$ is used to obtain better correlation of *ePMV*. From another study for India [139], the values of *TSV* obtained are numerically lower than the measured *PMV* values. By applying an expectancy factor of 0.6, the *ePMV* becomes well correlated with the actual*TSV*.

For the Mediterranean climate in winter and in summer seasons, Alfano et al. [135] show that the value $e_p = 0.9$ is in good agreement with the range of 0.9 ÷ 1 indicated in [116].

For the Netherlands, considered as a moderate outdoor climate [140], the analysis reported in [141] deals with adaptive thermal comfort during the hot summer period. The expectation considered high during summer periods occurs for a short period. The expectancy factor estimated at 0.9 (considered as minimum) determines a *PMV* of 0.93. For Denmark, Petersen et al. [142] investigate the applicability of *PMV* and *ePMV* models to predict thermal comfort for private homes during the summer period. This analysis is considered by them a pilot study regarding gathering and analysing the data to examine if these models are adequate or can be corrected to predict thermal comfort in homes. The analysis consists of *TSVs* and measurements collected over a period of three summer months. The graph concerning the expectancy factor versus clothing insulation shows a rise of e_p with the reduction of clothing insulation, suggesting that the occupants have a great expectation to the thermal indoor conditions when they have reduced clothing insulation. The comparison between *PMV* and *TSV* shows that the *TSV* values are greater than *PMV* values, demonstrating that the *PMV* model undervaluated the subjective thermal sensation as performed in [50].

4.2.3. New Predicted Mean Vote (nPMV)

The New Predicted Mean Vote (*nPMV*) is recommended by Humphreys and Nicol [50] for air-conditioned buildings. This method is based on adaptive comfort theory, equilibrating the difference between the *PMV* predictions and thermal sensation of occupants in buildings [132]. The equation of *nPMV* is written in [50] under the following form:

$$nPMV = \gamma \cdot [PMV - f_{\text{PMV\_ASHRAE}}] \tag{29}$$

with the coefficient $\gamma = 0.8$.

The predictive regression expression of the function $f_{\text{PMV-ASHRAE}}$ evaluates the relationship between the *PMV* model and the actual thermal sensation [50]:

$$f_{\text{PMV\_ASHRAE}} = -4.03 + 0.0949 \cdot T_{\text{op}} + 0.00584 \cdot RH\% + 1.201 \cdot \dot{M} \cdot I_{\text{cl}} + 0.000838 \cdot T_{\text{out}}^2 \tag{30}$$

and T_{out} is the outdoor mean air temperature.

Kim et al. [132] obtained the *nPMV* model proposed in [50] using the statistical investigation of the field measurement data in their research. The predictive model for *PMV_vote* is suggested by using multiple regression analysis. The expression of the *nPMV* is:

$$nPMV = \gamma \cdot [PMV - f_{\text{PMV\_vote}}] \tag{31}$$

in which γ is determined using statistical indicators by means of statistical tests.

The predictive regression expression of the function $f_{\text{PMV\_vote}}$ is given by:

$$f_{\text{PMV\_vote}} = -4.369 + 0.005 \cdot T_{\text{op}} + 4044.633 \cdot RH\% + 1.518 \cdot \dot{M} \cdot I_{\text{cl}} + 0.000271 \cdot T_{\text{out}}^2 \tag{32}$$

The results obtained in this study demonstrate that *nPMV* can raise the accuracy and performance of the original *PMV* having a relevant contribution in decreasing the cooling energy for air-conditioned buildings. Wong and Khoo [143] assess the thermal conditions in naturally ventilated classrooms. The *nPMV* model obtained is not appropriate to forecast thermal sensations at reduced temperatures (27–28 ºC) and at higher temperatures (31–32 ºC). In these cases, a gap of 0.2–0.3 units appears between the actual thermal sensation and the one predicted with the *nPMV* model.

4.3. Actual Mean Vote (AMV)

Actual Mean Vote (*AMV*) is defined as the occupants' thermal sensation in a given comfort space being ranged on the 7-point scale of the ASHRAE Standard 55 from "very cold" to "very hot" [144]. *AMV* characterises the thermal comfort in the tropical zones in function of occupant's behaviour and psychology. *AMV* has to be used in place of the *PMV* model, which is not proper for this climate. The *PMV* index could be considered a prediction of thermal comfort perceived by the occupants of a building while the *AMV* index is the thermal comfort perceived by occupants during their votes [145].

Oseland [112] observes some discrepancies between the *PMV* and *AMV* values computed for offices and homes as compared to climate chamber investigations, and assignes the discrepancies to contextual and adaptation effects. These discrepancies are due to the particular differences (e.g., age, gender, and body structure) [9,109,146]. Furthermore, the results of the *PMV* index are consistent with the real votes only in environments (e.g., HVAC) with uniform and stable conditions [147].

Azizpouret al. [148] analyse the *PMV* and *TSV* for a University hospital in Malaysia. From the data obtained in their study for all thermal zones, the *TSV* values are less than the *PMV* values in the ASHRAE 7-point scale, being in good agreement with the adaptive model that specifies that persons in hot-humid region are well adapted to warm weather and tolerating much better this state than persons in other climates. The linear regression between the operative temperature T_{op} and both *PMV* and *TSV* reveals that the neutral temperature for occupants in hot-humid zone is greater than what expected by standards.

Simons et al. [149] compare *PMV* within the office with *AMV* given by occupants. The results show a discrepancy between *PMV* and average *AMV* (*PMV* recorded 1.5 for naturally ventilated buildings between slightly warm and warm, and *AMV* of 0.5).

Yao et al. [123] introduce a theoretical adaptive model of thermal comfort based on the black-box theory to describe warm environment, and explain for the case of free-running buildings why the *PMV* is higher than the Actual Mean Vote (*AMV*).

Hermawan et al. [145] investigate the differences between *AMV* and *PMV* models in Indonesia, for wooden walls classical houses in the coast and mountain regions useful to provide the adaptive thermal comfort. The results show a difference between *PMV* and *AMV* of 0.73 for the coast region and 0.81 for mountains region. The *AMV* value for the coast region is −0.28, while for the mountain region is −1.12, this difference being explained by the fact that occupants in the coast buildings feel more comfortable than others in the mountain buildings.

Kajtár et al. [150] investigate two ways of thermal comfort under steady-state conditions in the winter period for an office-building complex in Hungary. One *PMV* is determined by measurements and another is the thermal sensation of occupants using a five-stage thermal comfort scale (cool, slightly cool, neutral, slightly warm, and warm). Additionally, the relationship between *PMV* and *AMV* valid in the range of thermal neutrality $-1.7 \le PMV \le 0.5$, necessary to characterise the thermal environment is determined as:

$$AMV = PMV + 0.275 \tag{33}$$

It is observed that there is a low the difference between *AMV* and *PMV*, and the results demonstrate the applicability of the *PMV* model.

The *AMV* definition is also used to obtain a general expression of the adaptive coefficient β defined in Section 2.5.1 for *aPMV* calculations, based on the least square method applied to a number n of datasets [151]:

$$\beta = n^{-1}\left(\sum_{i=1}^{n} aPMV_i^{-1} - \sum_{i=1}^{n} PMV_i^{-1}\right) = n^{-1}\left(\sum_{i=1}^{n} AMV_i^{-1} - \sum_{i=1}^{n} PMV_i^{-1}\right) \tag{34}$$

where *aPMV* considers various conditions of thermal environment due to the occupants' responses [120], *PMV* is obtained from Fanger's equation, and *AMV* is the actual mean vote of building occupants [132]. The coefficient β is important, in order to be multiplied by *PMV* for obtaining the result close to *AMV* [152]. For example, in [131], using the residential buildings data from the database of the standard GB/T50785-2012 for China, the choice of an appropriate coefficient β makes the *aPMV* value close to the *AMV*.

Al-Rashidi et al. [153] specify that applying the expectancy factor in naturally ventilated classroom in Kuwait an improvement of *PMV* model is obtained, but a big difference with the *AMV* (Actual Mean Vote) occurs. Baruah et al. [152] analyse the thermal comfort at the end of the winter period and beginning of summer in naturally ventilated classrooms. The graph representing the *PMV* method versus *AMV* or *aPMV* (indicated as *cPMV*) shows that the *aPMV* values (from −1.32 to 1.45) come closer to *AMV* values (from −2 to +2), while the *PMV* values are ranged from −1 to 3.

4.4. Predicted Percentage Dissatisfied (PPD)

The *PPD* model computes the percentage of persons that are dissatisfied with a certain thermal comfort. The *PPD* index *depends on the PMV index* (i.e., the number of people voting −3, −2, +2 or +3 within the *PMV* scale) and this dependence is given by the following equation presented by Fanger [55]:

$$PPD = 100 - 95 \bullet \exp(-a_P \bullet PMV^4 - b_P \bullet PMV^2) \tag{35}$$

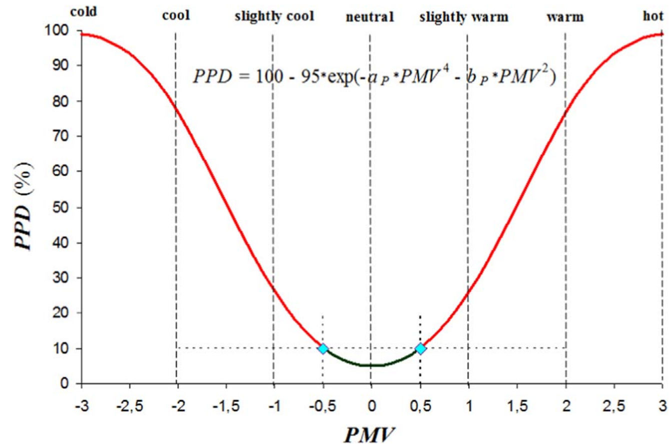

Fig. 1. Dependence of *PPD* on *PMV*.

where $a_P = 0.03353$ and $b_P = 0.2179$.

The *PPD* indicator gives the number of thermally dissatisfied people within a big group. The rest of the group would vote −1, 0 or +1 on the *PMV* scale. The minimum *PPD* is 5%. The recommended acceptable *PMV* range for thermal comfort from the ASHRAE Standard 55–2010 is $-0.5 < PMV < +0.5$, corresponding with $PPD < 10\%$ for an indoor space, as shown in Fig. 1.

Table 4 shows the distribution of individual thermal sensation votes for different values of mean vote, based on experiments on 1300 subjects [94].

The dependence of *PPD* in function of the *PMV* described by Fanger, according to the references [154–156] and [157], is presented below. Mayer [154] obtains a *PPD* value of 16% corresponding to a *PMV* value of 0.5:

$$PPD = 100 - 83.4 \cdot \exp\left[c_1 \cdot (PMV - 0.4)^4 + d_1 \cdot (PMV - 0.4)^2\right] \tag{36}$$

where $c_1 = 0.01$ and $d_1 = 0.5479$.

Yoon et al. [155] report a *PPD* value of 18%, corresponding to a *PMV* value of −0.8:

$$PPD = c_2 \cdot PMV^2 + d_2 \cdot PMV + e \tag{37}$$

where $c_2 = 11.37$, $d_2 = 18.34$, and $e = 24.42$.

Araujo and Araujo [156] show a *PPD* value of 47.5%, corresponding to a *PMV* value of −0.0:

$$PPD = 100 - 52.5 \cdot \exp\left[-c_1 \cdot PMV^4 - d_1 \cdot PMV^2\right] \tag{38}$$

where $c_1 = 0.01$ and $d_1 = 0.5479$.

De Paula Xavier and Roberto [157] present the expression of the *thermal sensation index*:

$$TS = 0.219 \bullet T_0 + 0.012 \bullet RH - 0.547 \bullet v_a - 5.83 \tag{39}$$

This equation is similar to the *PMV* indicator obtained for a case study in a Brasilian school and corresponds to a *PPD* indicator. For a neutral thermal sensation, the *PPD* value is 25.4%:

Table 4
Predicted of sensation votes for given *PMV* values.

PMV	PPD	persons predicted to vote (%)		
		0	−1, 0 or +1	−2, −1, 0, +1 or +2
+2	75	5	25	70
+1	25	30	75	95
+0.5	10	55	90	98
0	5	60	95	100
−0.5	10	55	90	98
−1	25	30	75	95
−2	75	5	25	70

$$PPD = c_3 \cdot S^2 - d_3 \cdot S + e_1 \quad (40)$$

where c_3 = 18.94, d_3 = 0.24, and e_1 = 25.41.

Furthermore, van Hoof [109] presents the chart showing the curves of the *PPD* indicator in function of the *PMV* indicator for different relationships.

The extension of the studies, with experiments on a number of participants declaring their *thermal sensation* on the scale from −3 (cold) to 3 (hot), where 0 represents the neutral thermal sensation (comfortable), provides the basis for the development of specific indicators such as the *PMV*. From the studies in the European offices and from the dataset [85], Humphreys and Nicol [158] indicate that the preferred thermal sensation on the ASHRAE scale depends on both the prevailing outdoor temperature and the present indoor temperature. Much more, the desired thermal sensation rises for increasingly high room temperatures. People chooses (on average) warmer sensations than neutral in the cold outdoors and warm indoors and colder sensations than neutral in the warm outdoors and cool indors. Some improved theoretical analyses of human heat exchange with the environment are addressed in the Standards ISO-7730 [159] and ASHRAE-55 [160], due to the experimental data obtained in climate chambers [161].

For a *PMV* between −0.85 and +0.85, the *PPD* is 20 and the assumption of a stricter *PPD* of 10% corresponds to a *PMV* between −0.5 and +0.5. As a result, there can be three kinds of comfort zones, depending on the admissible ranges *PPD* and *PMV*, as shown in Table 5 [19]. The values of *PPD* and *PMV* corresponding to the thermal sensation are shown in Table 6.

While the *PPD* is kept approximately under 10%, some provisional violations of *PPD* are accepted. Baldi et al. [105] propose to limit the temporary violation of *PPD*, by imposing the constraint *PPD* < 15% at every time step in each building. This constraint is suggested for the buildings' dissatisfied occupants who would alter the operation of the HVAC (e.g., by opening windows or by manually changing the set points). The result of their simulations about the *PPD* violation is that the violation of 15% in instantaneous *PPD* never occurs. It is found that the thermal comfort is always below the recommended threshold of 10% (minimising the *PPD* equation, the best thermal comfort is obtained).

Olanipekun [162] investigates the applicability of *ePMV-ePPD* model in non air- conditioned hostel building at a University in Nigeria. The environment is considered to be comfortable when the range of *ePMV* is [−1, +1]. The selected expectancy factor is equal to 0.5 in order to evaluate *ePMV-ePPD* model considering that the weather of the region is warm all year and there are few air-conditioned buildings. Most of the *ePMV* values computed belong to the range recommended by the Standards ASHRAE 55 and ISO 7730. The *ePPD* values obtained present only a little overestimation of the percentage of dissatisfied under neutrality conditions.

4.4.1. Transient Predicted Percentage Dissatisfied (TPPD)

The Transient Predicted Percentage Dissatisfied (*TPPD*) is a new overall thermal comfort index for transient conditions. It is based on the replacement of Steady-State Energy Balance model by Two-Node Energy Balance model in transient conditions. In Wölki et al. [163] it is indicated that the operative temperature is less than the normal comfort range, but the corresponding thermal comfort indices (*PPD* = 80%, *TPPD* = 5%) are on a comfortable level.

Table 5
The *PPD* index in function of the *PMV* index [19].

Classes of thermal comfort	*PPD*	*PMV* range
A	< 6	−0.2 < *PMV* < 0.2
B	< 10	−0.5 < *PMV* < 0.5
C	< 15	−0.7 < *PMV* < 0.7

Table 6
PPD and *PMV* indicators corresponding to thermal sensation.

PMV sensation scale						
cold	cool	slightly cool	neutral	slightly warm	warm	hot
−3	−2	−1	0	1	2	3
PPD (%)						
100	75	25	5	25	75	100

4.4.2. Lowest Possible Percentage Dissatisfied (LPPD)

The *LPPD* index is applicable for thermal non-uniform environments and describes the lowest possible percentage of dissatisfied persons in a room with an HVAC installation in operation. *LPPD* is more useful for big rooms than for rooms of small dimensions, and its value is less than 10% in the occupied areas for an acceptable ambient [42]. If the value of *LPPD* index is higher than 10%, two improvements are recommended (e.g., the thermal insulation of building, or the air distribution system, or both) [43].

4.4.3. Human Thermal Model (HTM)

In the HTM method [164], the *PPD* index is calculated in the same way as in the *PPD* Eq. (35), by replacing *PMV* with the overall thermal sensation. Holopainen et al. [21] compare the results of different methods useful for computing thermal comfort (the Fanger's *PMV* method, the *aPMV* method, and the HTM method). The adequate variations of the indoor temperatures are established due to the three categories of thermal environment (A, B, C) described in the Standard ISO-7730-2005. The results showed that the HTM and *aPMV* methods are more flexible at the indoor conditions than the Fanger's *PMV* method.

5. Thermal comfort models to define control strategies

5.1. Types of thermal comfort models

Thermal comfort models are used in the definition of control strategies for indoor applications. The usage of artificial intelligence control methods taking into account Artificial Neural Networks (ANNs), fuzzy control or hybrid control has produced more pleasant environments in buildings [165]. In the review of the modelling methods for HVAC systems, Afram and Janabi-Sharifi [28] classify the control strategies and indicate that soft control methods like ANN and fuzzy control, as well as the hybrid control method (ANN-fuzzy), are useful to obtain appropriate models for addressing thermal comfort. Similar considerations are presented in [27], with the identification of the role of thermal comfort in advanced HVAC control carried out with intelligent control techniques.

The characteristics and parameters of ANN, autoregressive, hybrid autoregressive-ANN, fuzzy control, and hybrid ANN-fuzzy models for predicting the indoor air temperature and the *PMV* index are summarised and discussed below.

5.1.1. Artificial Neural Networks

ANNs are known as useful tools to predict the evolution of system variables and to approximate non-linear functions [166]. A simple ANN structure is divided into three layers (input layer, hidden layer and output layer). The neurons of the input layer receive the input variables of the network and connect them to the nodes of the hidden layer. The neurons in the hidden layer are connected to the output layer. The output layer processes these data in order to obtain the output variable (e.g., the indoor air temperature). An example referring to the prediction of the indoor air temperature as the output variable [167] is shown in Fig. 2. Each connection between nodes is associated to a weight. The weights are adjusted during the execution of the ANN

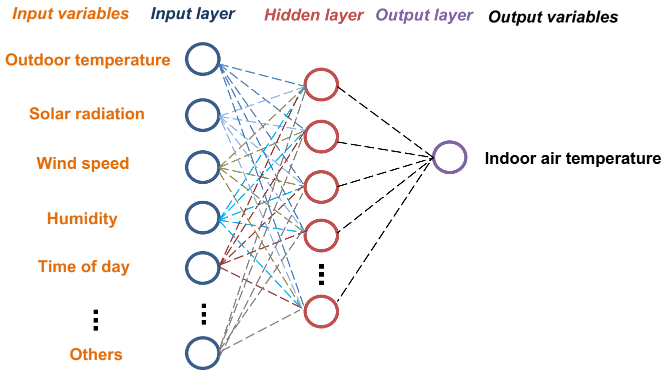

Fig. 2. Structure of an ANN to predict the indoor air temperature.

with the aim to provide the optimal values of the output from a supervised learning approach. The weights are assigned in the ANN *training* phase, in which known inputs and outputs are provided, in such a way that the ANN adapts the weights to fit the outputs given from predefined cases. The trained ANN is then used to provide the outputs by introducing the real-life input parameters.

The error back-propagation (BP) is an efficient learning algorithm that improves the performance of the ANN by reducing the total error through the change of the weights in the direction of the gradient [168,169]. The Levenberg–Marquardt (LM) algorithm is frequently used to minimise the sum of square errors.

Complex ANN structures are divided in more hidden layers, with variable numbers or neurons in each hidden layer [170,171].

The basic advantage of ANN is the good quality of the predictions, while a drawback is the large number of variables sometimes used in order to take into proper account the various aspects affecting the output.

5.1.2. Autoregressive and hybrid autoregressive-ANN models

Given a time series of data, autoregressive models are used to predict future values of the time series on the basis of the past values [172]. In the simplest AutoRegressive (AR) model, the output y_t at the present time t is a linear combination of the previous N_y values of the output y_{t-i}, … y_{t-Ny}, and of the error ε_t at the present time t. The relation $y_t = \sum_{i=1}^{N_y} a_i y_{t-i} + \varepsilon_t$ is written by using the polynomial $A(q) = 1 - \sum_{i=1}^{N_y} a_i q^{-i}$, where q^{-i} is the shift operator that takes the term to which it is multiplied and shifts it back of i positions, namely, $q^{-i} y_t = y_{t-i}$. The AR model is then written as $A(q) y_t = \varepsilon_t$.

The AutoRegressive eXogenous (ARX) model adds the previous N_x values of the input to the AR model, resulting in the relation $y_t = \sum_{i=1}^{N_y} a_i y_{t-i} + \sum_{k=1}^{N_x} b_k x_{t-k} + \varepsilon_t$. By using the shift operator $B(q) = \sum_{k=1}^{N_x} b_k q^{-k}$, the ARX model is written as $A(q) y_t = B(q) x_t + \varepsilon_t$. The relation providing the output y_t from the ARX model is represented in Fig. 3.

A further aspect is to add the Moving Average (MA) option to the above models, including in the model the N_ε previous values of the error ε. With the same rationale used above, let us introduce the shift operator $C(q) = 1 + \sum_{j=1}^{N_\varepsilon} c_j q^{-j}$. The AutoRegressive–Moving-Average model with eXogenous inputs (ARMAX) model, in which the moving average term of the errors is added to ARX, is then expressed as $A(q) y_t = B(q) x_t + C(q) \varepsilon_t$. The relation providing the output y_t from the ARMAX model is represented in Fig. 4.

In synthesis, the ARX and ARMAX models are black-box *linear* parametric models very efficient to model the output variable with reduced prediction errors [173]. In general, *non-linearity* may be exploited to obtain a better approximation of the model to the real system, constructing a dynamic network in which the output depends on inputs, previous inputs and previous outputs, in order to learn from time-varying patterns. The most used dynamic network for thermal comfort applications is the Neural Network Auto-Regressive model with eXogenous inputs (NNARX), whose structure is depicted in Fig. 5. In the NNARX, the input values and the outputs at previous time steps are used as inputs to the neural network, in which the LM algorithm is typically used to minimise the prediction error. Following the same rationale, the Neural Network Auto-Regressive Moving Average with eXogeneous input mode (NNARMAX) adds the errors at the previous time steps as inputs to the neural network (Fig. 6).

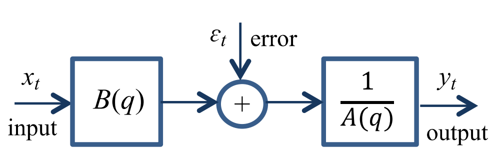

Fig. 3. ARX model.

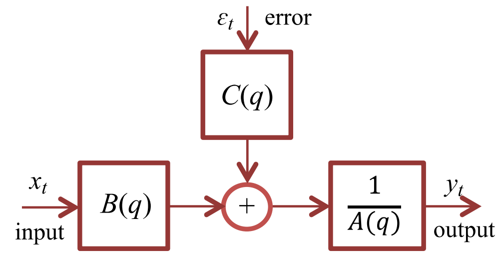

Fig. 4. ARMAX model.

5.1.3. Fuzzy control

Fuzzy logic is suitable for non-linear systems that are complex to be modelled from the mathematical point of view [174]. The propositions used in the fuzzy logic approach are generally expressed by values ranging from 0 (completely false) to 1 (completely true) [175]. The fuzzy variables are represented through their membership function, having a given shape such as triangular, trapezoidal, Gaussian, or bell. Fig. 7 shows an example of definition of the triangular-shaped fuzzy variable *PMV* [176].

A fuzzy model represents a non-linear mapping between the input and output variables. There are three elements that form a fuzzy logic: a rule base, a database and a reasoning mechanism. The rule base has a number of fuzzy linguistic *if–then* rules to obtain relationships among inputs and outputs (the rules are written as: *if* variable is set, *then* action), the database gives the membership functions useful for the fuzzy rules. The reasoning mechanism activates the inference procedure, which depends on an established condition and on the rules to obtain the output variables [92]. Fuzzy logic is composed of three elements (Fig. 8) [177]: fuzzification (where according to the membership functions the input variables are converted into input fuzzy variables), approximation rules (corresponding to specific conditions) and defuzzification (where the fuzzy outputs are converted into discrete values). If the number of membership functions and rules increase, the fuzzy model becomes more difficult to be solved [27].

5.1.4. Hybrid ANN-fuzzy control

The most used hybrid approach to obtain predictions of comfort-related variables is the Adaptive Network-based Fuzzy Inference System (ANFIS) [178]. ANFIS uses in combination ANN with a fuzzy logic model based on the Takagi–Sugeno fuzzy inference system [179]. The ANFIS model can model and assess non-linear functions, as well as predicting chaotic time-dependent behaviour [180]. The advantages of

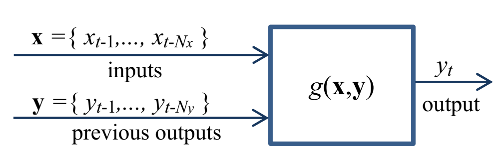

Fig. 5. NNARX model.

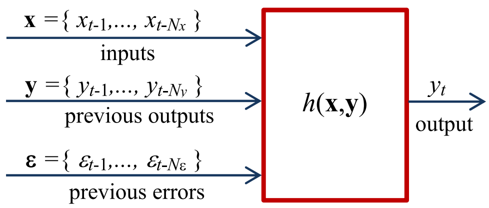

Fig. 6. NNARMAX model.

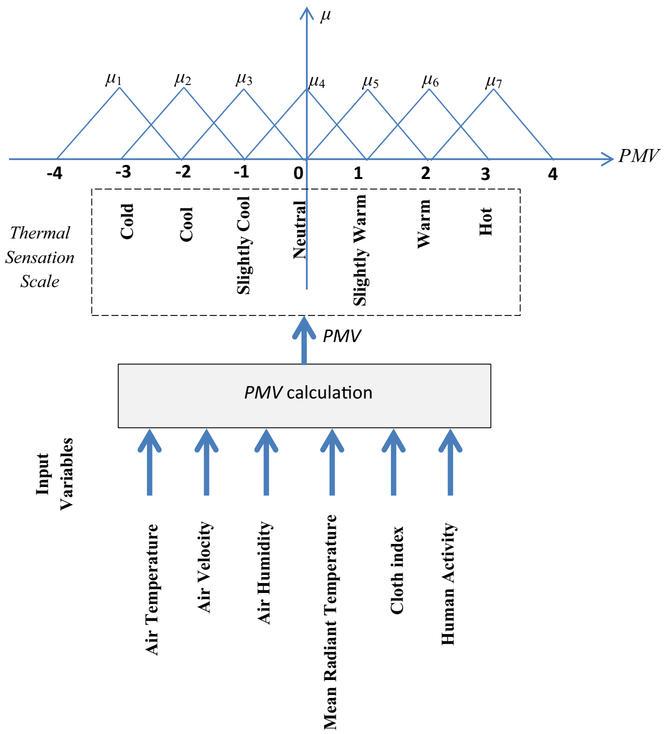

Fig. 7. Example of definition of the fuzzy variable *PMV* depending on a set of input variables.

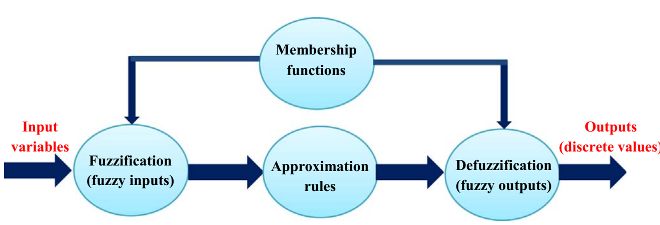

Fig. 8. Components of the fuzzy logic control.

this neuro-fuzzy approach are that the combination of the two models offers solutions to problems that are not solved by a single controller. The drawback is the difficulty to tune up the controller parameters [27].

The structure of ANFIS contains five layers (Fig. 9). Given the input variables x_1, ..., x_N, in *Layer 1* (called fuzzification layer), each variable is fuzzified by calculating its membership value that indicates to what degree the input belongs to a fuzzy set (e.g., by using Gaussian membership function with the corresponding *antecedent* parameters). In *Layer 2* (called rule layer), a number of user-defined rules are established; each rule $r = R_1$,..., R_R takes the membership function values of the relevant input data and calculates an output value w_i (with i = 1,... R) called *firing strength*. The number of inputs taken from the calculation depends on the rule definition, so that it is not necessary to use all the inputs for all the rules. In *Layer 3* (called normalisation layer), the firing strengths are normalised with respect to the sum of the values of the firing strengths of each rule, obtaining the values $\overline{w}_1$, ..., $\overline{w}_R$. In *Layer 4* (called defuzzification layer), each normalised firing strength is defuzzified, by multiplying it by a linear combination of the inputs depending on given *consequent* parameters (i.e., the coefficients c_{r0}, c_{r1}, ..., c_{rN} of the linear combinations $f_r = c_{r0} + c_{r1}\, x_1 + ... + c_{rN}\, x_N$, for r = 1,... R). *Layer 5* provides the final output value y as the sum of the outputs $\overline{w}_r f_r$ from *Layer 4* over r = 1,... R.

In the ANFIS structure, *Layer 3* and *Layer 5* perform fixed operations. Once the rules have been defined, *Layer* 2 is fixed as well. Conversely, *Layer 1* and *Layer 4* are *adaptive*, i.e., the antecedent parameters used for the definition of the number and type of membership functions (in *Layer 1*) and the consequent parameters (in *Layer 4*) may be changed during an iterative learning process. In particular, a forward-backward learning algorithm is typically used. In the forward step, the antecedent parameters (*Layer 1*) are kept constant, and the consequent parameters are calculated from a least-square estimator (or a heuristic method). In the backward step, the consequent parameters are kept constant, and the antecedent parameters are adjusted by using an error back-propagation procedure.

5.2. Models for indoor air temperature prediction

Thermal comfort is typically considered by the building occupants to be more important than visual comfort, acoustic comfort and air quality [181]. Temperature control is a key aspect to ensure individual thermal comfort in an indoor environment. Deviations from the ideal reference temperature [31], or the square of these deviations [182] may be associated with a thermal discomfort price, on the basis of a price coefficient expressed in mu/°C or mu/(°C)^2, where mu stands for "monetary units". The price coefficient expresses the willingness of the occupants to avoid comfort degradation. These definitions of discomfort price do not take into account the duration of the deviations. The Expected Thermal Discomfort (*ETD*) metric introduced in [183] calculates the deviation of the indoor air temperature with respect to the reference point, integrated over time, also highlighting the differences between positive or negative deviations.

To assess the indoor air temperature inside a building, two types of models are used: physical or white-box models based on the energy and mass balance integral–differential equations, and data-driven or black-box models based on ANN and developed after sufficient data are available from the field [184,185].

Table 7 contains a synthesis of the models and input parameters used for indoor air temperature prediction in a number of literature contributions. Over 40 parameters have been found in various contributions. The parameters most frequently used are the outdoor air temperature, the solar radiation, the indoor air temperature itself, and the indoor and outdoor relative humidity. Some details on the approaches followed in the relevant references are indicated in the following subsections.

5.2.1. Artificial Neural Networks

The ANN model can efficiently solve the non-linear problem of predicting the indoor air temperature as the output variable, by using the outdoor data (air temperature, air humidity, solar radiation, wind speed, etc.) as input variables, with their correlation [186,187]. Kalogirou [169] presents a review about ANNs in energy applications in buildings. He also discusses about indoor air temperature prediction, highlighting that the ANN is a useful alternative method in predicting various parameters.

The ANN models with good reliability and accuracy in the prediction of the indoor air temperature are the Multilayer Perceptron (MLP) with error Back-Propagation (BP), and the Radial Basis Functions (RBF). The references using these modelling techniques are indicated in Table 8, highlighting some characteristics such as the specific model, the number of hidden neurons, and the input variables used.

In order to provide an overview of the literature references using ANN, the references are divided into three categories on the basis of the method used:

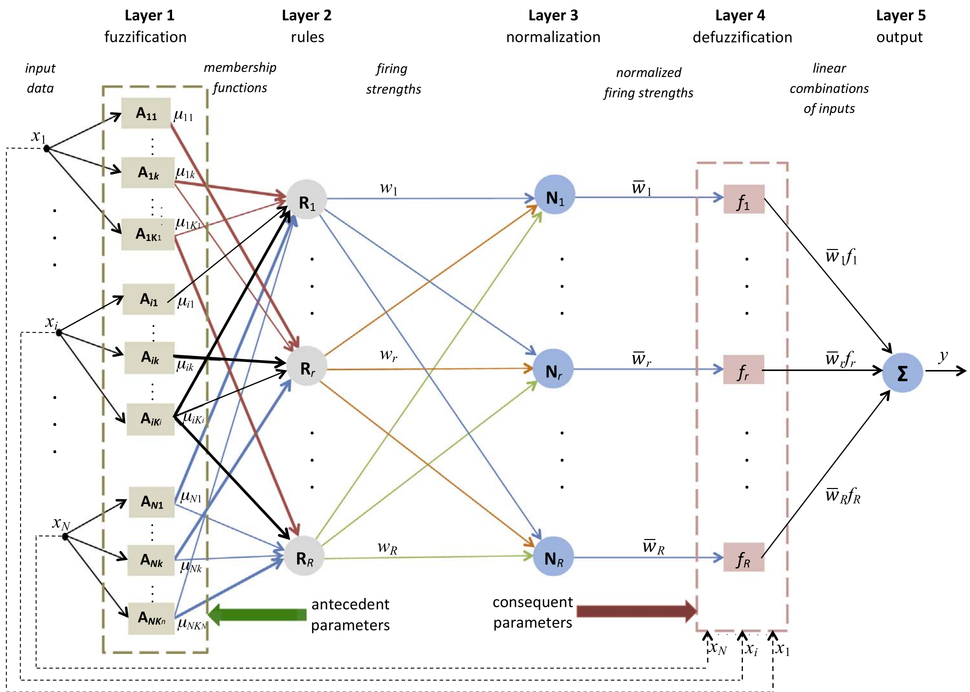

Fig. 9. The structure of ANFIS.

5.2.1.1. Non-specified ANN method. In various results, the generic term ANN is indicated when the method is not specified. In particular, Pollard and Stoecklein [167] perform a comparison between a non-linear ANN model and linear ARX models for a residential building application. The results show that the non-linear ANN model better predicts the upper and lower indoor air temperatures due to the dynamical nature of the ANN. Kalogirou [168] presents a simulated program by means of ANN to describe the thermal behaviour of a building. The matching of the predicted and actual data is very good for the winter case, and just a little variation is observed for the summer case. The conclusion is that the ANN model offers an accurate thermal control being faster than the dynamic simulation programs. Moon et al. [188] propose an ANN model used in control logic to predict the indoor air temperature change. The model uses predictive controls of the heating system and openings at different weather conditions. The model demonstrates good accuracy and successful adaptability for different weather conditions and envelope orientations. Kim et al. [189] test various control logics by combining rule-based control and ANN-based control. The impact of the control logic on the indoor thermal environment is analysed under different winter conditions. The results show that ANN-based control is useful for the stable thermal environment, and system operation and rule-based control is useful to raise the energy efficiency of the building. Moon and Jung [190] use an ANN with multiple hidden layers to determine the optimal initial moment to start the command to reduce the temperature in residential buildings, in order to avoid unnecessary consumption in the periods of no-occupation of the building, by maintaining satisfactory thermal comfort during the occupation period.

5.2.1.2. ANN with BP. The ANN using BP is adopted in many applications, referring to different types of buildings. Some examples and results are summarised below.

Some references address *residential* buildings. Moon et al. [191] investigate some control strategies for residential buildings by introducing ANN using BP in home climatic control. The results show that ANN-based predictive control methods can accurately predict indoor air temperature and humidity, being a favourable non-linear method than standard thermostat control in controlling home climatic control appliances. Moon and Kim [192] develop a residential thermal control strategy to control overall thermal conditions. The ANN-based predictive control logic shows that the system predicts with high-precision indoor environment parameters in order to create more comfortable thermal conditions. Moon [193] investigates predictive control logics with ANN and adaptive control methods to control indoor air temperature and humidity for residential buildings. The temperature and humidity control with ANNs is well limited within the comfort range, and the comfort periods of temperature and humidity control with ANNs increase by 3.7% in both winter and summer. Further studies in which the ANN-based residential thermal control logic demonstrates good accuracy in controlling the indoor air temperature conditions are presented in [192–197]. The results show a stabilisation of the indoor air temperature in the defined thermal comfort ranges (23–26 °C in summer and 20–23 °C in winter) with reduction of the possibility of falling outside the comfort range.

Other references analyse an ANN using BP for modelling the thermal behaviour of a low-energy *solar building*. The indoor air temperature prediction presented in [198] shows that the ANN could decrease the heating energy consumption, while maintaining the indoor air temperature within the desirable range. The study in [199] aims at determining when to switch off the heating system controller to save the energy consumption. The total number of input neurons is 196, and is reduced to 10 inputs by applying a Singular Value Decomposition technique. The simulated results show that the ANN model presents a good accuracy in predicting the indoor air temperature depending on a reduced number of input variables.

With reference to *general aspects* in buildings, Buratti et al. [200] adopt an ANN with BP for improving the performance of energy building and thermal comfort. Many parameters that depend on the thermal behaviour of buildings' envelopes are taken into account. The results show that the simulated temperature from ANN is less than the monitored temperature, explaining this difference with the presence of solar radiation and large transparent surfaces that affect the experimental data. Zamora-Martinez et al. [201] investigate the predictive control logic by developing the ANN method to predict the indoor air temperature, useful for decreasing energy consumption in the case of

Table 7
Models and input data to predict the indoor air temperature with ANN.

Article	Models	Number of hidden neurons	Total number of input neurons	Input data: Environment floor level	Orientation of the buildings	Opening condition of inner surface (envelope)	Outdoor Relative Humidity	Opening condition of outer surface (envelope)	Indoor Air Quality	Wind Velocity (and direction)	Solar Radiation	Chilled water valve opening level	Outdoor air damper opening level	Chilled water temperature	Outdoor Air Temperature	Prediction error (measurements vs. model outputs)
[167]	ANN$^{(\circ)}$	8	15								4				6	
[188]	ANN$^{(\circ)}$,LM	15	7			1		1			1				1	
[189]	ANN$^{(\circ)}$, LM	10	6			1		1							1	
[190]	ANN$^{(\circ)}$, LM	3x4 ***	5												3**	
[187]	BP, LM	10	4				1			1					1	
[191]	BP	17	8				2*								2*	
[192]	BP	17	8				2*								2*	
[193]	BP, LM	17	8				2*								2*	
[197]	BP, LM	4x10 ***	6			1		1							1	
[198]	BP	12+6	12								3$^{\circ\circ}$				4$^{\circ\circ}$	
[199]	BP, LM	7	(196) 10								(48)				(48)	
[200]	BP	35,75	21	1	1						3				1	
[201]	BP	8–24	1–5						1		1					
[204]	BP	10, 30, 50, 70	6				1			1					1	

Article	Models	Input data: Cavity temperature	Radiator electrical power	Activity in the building	Indoor Relative Humidity	Indoor Air Temperature	Hot water temperature	Sky cloudiness	Auxiliary Heating Power	Supply air relative humidity	Supply air temperature from the air handling unit	Supply air flow rate from the air handling unit	Heating control signal (valve position)	Time of the day	Hour
[167]	ANN$^{(\circ)}$					1								2	
[188]	ANN$^{(\circ)}$,LM	1				2*									
[189]	ANN$^{(\circ)}$, LM	1				2*									
[190]	ANN$^{(\circ)}$, LM						2*								
[187]	BP, LM													1	
[191]	BP				2*	2*									
[192]	BP				2*	2*									
[193]	BP, LM				2*	2*									
[197]	BP, LM	1				2*									
[198]	BP					1$^{\circ\circ}$									
[199]	BP, LM					(48)							(48)		
[200]	BP					1								1	1
[201]	BP				1	1									
[204]	BP				1	1									

Article	Models	Input data: Time of the year	Time of the month	Rain	HVAC reference temperature	Surface of investigated environment	Ratio between surfaces	Mean transparent surface	Thermal transmittance	Periodic thermal transmittance	Thickness	Phase shiftand attenuation factors	Surface mass	Heating system status	Room carbon dioxide concentration

(continued on next page)

Table 7 *(continued)*

Article	Models	Number of hidden neurons	Total number of input neurons	Input data: Environment floor level	Orientation of the buildings	Opening condition of inner surface (envelope)	Outdoor Relative Humidity	Opening condition of outer surface (envelope)	Indoor Air Quality	Wind Velocity (and direction)	Solar Radiation	Chilled water valve opening level	Outdoor air damper opening level	Chilled water temperature	Outdoor Air Temperature	Prediction error (measurements vs. model outputs)
[167]	ANN$^{(\circ)}$	2														
[188]	ANN$^{(\circ)}$,LM															
[189]	ANN$^{(\circ)}$, LM															
[190]	ANN$^{(\circ)}$, LM															
[187]	BP, LM															
[191]	BP															
[192]	BP															
[193]	BP, LM															
[197]	BP, LM															
[198]	BP													$4^{\circ\circ}$		
[199]	BP, LM															
[200]	BP		1			1	1	1	3	1	1	2	1			
[201]	BP			1												
[204]	BP	1														

Article	Models	Number of hidden neurons	Total number of input neurons	Input data: Environment floor level	Orientation of the buildings	Opening condition of inner surface (envelope)	Outdoor Relative Humidity	Opening condition of outer surface (envelope)	Indoor Air Quality	Wind Velocity (and direction)	Solar Radiation	Chilled water valve opening level	Outdoor air damper opening level	Chilled water temperature	Outdoor Air Temperature	Prediction error (measurements vs. model outputs)
[210]	RBF	–	4								1				1	
[211]	RBF, LM	2–20	(20) 8								2				2	
[212]	RBF	6–8	4								1				1	
[215]	RBF	3–10	13–20				0–1				4–6				2–5	
[216]	ARX	10	10								3				2	
[218]	ARX	20	21				5				5				5	
[219]	ARX	12	10				1							1	1	
[220]	ARX/ ARMAX/ OE	4/ 6/ 8	13/ 16/ 16				1/ 2/ 2							1/ 1/ 2	2/ 2/ 2	0/ 1/ 0
[221]	ARX/ ARMAX	10	3–9												4^{*}	
[223]	ARX, LM	4,6	14				5								4	
[224]	ARX/ ARMAX	24	21				4				4				4	
[203]	MLP (n time intervals)	10	4 n				n			n	n				n	
[205]	MLP, LM	30	7												1	
[206]	MLP, LM	10	36,48				12								12	
[207]	MLP,LM	10–16	11				1				1	1	1	2	2	
Article	Models	Input data														

(continued on next page)

Table 7 *(continued)*

Article	Models	Number of hidden neurons	Total number of input neurons	Input data												
				Environment floor level	Orientation of the buildings	Opening condition of inner surface (envelope)	Outdoor Relative Humidity	Opening condition of outer surface (envelope)	Indoor Air Quality	Wind Velocity (and direction)	Solar Radiation	Chilled water valve opening level	Outdoor air damper opening level	Chilled water temperature	Outdoor Air Temperature	Prediction error (measurements vs. model outputs)
		Cavity temperature	Radiator electrical power	Activity in the building	Indoor Relative Humidity	Indoor Air Temperature	Hot water temperature	Sky cloudiness	Auxiliary Heating Power	Supply air relative humidity	Supply air temperature from the air handling unit	Supply air flow rate from the air handling unit	Heating control signal (valve position)	Time of the day	Hour	
[210]	RBF				1	1										
[211]	RBF, LM				2	2										
[212]	RBF				1	1										
[215]	RBF					7–9										
[216]	ARX					3			2							
[218]	ARX					1		5								
[219]	ARX				1	1	1			1	1	1				
[220]	ARX/ ARMAX/ OE				1/ 2/ 2	2/ 2/ 2					2/ 2/ 2	2/ 2/ 2		2/ 2/ 2		
[221]	ARX/ ARMAX		2*			2*								1		
[223]	ARX, LM				2	3										
[224]	ARX/ ARMAX					4		1								
[203]	MLP (n time intervals)															
[205]	MLP, LM					6										
[206]	MLP, LM			12	12											
[207]	MLP,LM			3												
Article	Models	Input data														
		Time of the year	Time of the month	Rain	HVAC reference temperature	Surface of investigated environment	Ratio between surfaces	Mean transparent surface	Thermal transmittance	Periodic thermal transmittance	Thickness	Phase shiftand attenuation factors	Surface mass	Heating system status	Room carbon dioxide concentration	
[210]	RBF															
[211]	RBF, LM															
[212]	RBF															
[215]	RBF															
[216]	ARX															
[218]	ARX															
[219]	ARX														1	
[220]	ARX/ ARMAX/ OE															
[221]	ARX/ ARMAX															
[223]	ARX, LM															
[224]	ARX/ ARMAX															
[203]	MLP (n time															

(continued on next page)

Table 7 (*continued*)

Article	Models	Number of hidden neurons	Total number of input neurons	Input data												
				Environment floor level	Orientation of the buildings	Opening condition of inner surface (envelope)	Outdoor Relative Humidity	Opening condition of outer surface (envelope)	Indoor Air Quality	Wind Velocity (and direction)	Solar Radiation	Chilled water valve opening level	Outdoor air damper opening level	Chilled water temperature	Outdoor Air Temperature	Prediction error (measurements vs. model outputs)
	intervals)															
[205]	MLP, LM															
[206]	MLP, LM															
[207]	MLP,LM															

(°) The generic term ANN is indicated when the specific method is not specified; * 2 values (absolute value and change of the variable in a predefined period); ** 3 values (absolute value, change of the variable, and difference with respect to the set point); °° 3 values (predicted value, predicted difference, last difference, last and previous values); *** number of hidden layers x number of neurons in each layer.

HVAC system. The experimental results obtained by using 11 sets of input data show great improvement by correlating the indoor air temperature with different weather signals. Lu et al. [202] use a combined numerical–ANN model for the simulation of unheated and uncooled indoor temperature and humidity for buildings. The numerical model is used to predict the indoor air temperature, and then passes the output to an ANN. The numerical results show that the indoor air temperatures simulated by the combined model are more accurate than the predictions obtained by the numerical model used alone. Pandey et al. [203] deal with an experimental test structure, with measurements of outdoor variables like outdoor temperature, solar radiation intensity, and wind velocity. The ANN uses 12 training algorithms, and the input data are taken for *n* time intervals. The results demonstrate that the ANN model gives successful prediction rates for all cases (95.2–97.9% for the roof pond system, 95.1–97.8% for the reflective roof system, and 95.2–98% for the insulated roof).

Ozbalta et al. [204] consider the case of an *educational* building, and propose a number of ANN models trained and tested by means of datasets that contain the outdoor conditions, day of year and indoor thermal comfort parameters. Six ANN models are compared with multiple regressions to predict the daily indoor air temperature and relative humidity. This prediction is useful for assessing the thermal comfort and energy consumption. The results illustrate that the ANN models are more accurate than multiple regression models.

Two references propose ANN models for modern building in a *humid region*, obtaining accurate predictions of the indoor air temperature. Kémajou et al. [205] develop an ANN-based non-linear autoregressive model, using as inputs the external air temperature and the last six hourly data of the indoor air temperature. Mba et al. [206] apply three ANN models to generate predictions for 24 h and one month in advance, also for the relative humidity.

Multi-zone buildings are addressed in [207] by using ANN-based thermal dynamics modelling. A forward selection method is used for model selection of the input variables that affect the indoor air temperature, and for enhancing the model accuracy and efficiency. Five models are tested, with different sets of input variables. The results show that the multi-zone model has a better accuracy in predicting the range temperature compared with the single-zone models, and the multi-zone model is more reliable to obtain energy savings.

Finally, Ashtiani et al. [187] propose, test and compare two models based on ANN and regression method to assess the correlation between indoor air temperatures and outdoor conditions in an *urban heat island*. The results show that the ANN model demonstrates a better performance compared with the time series model, as well as closer predictions near to the maximum indoor air temperatures.

5.2.1.3. ANN with the RBF model. The RBF model is indicated to have faster convergence rate than BP [208], and to have a good approximation property for arbitrary non-linear functions [209]. Ferreira et al. [210] use a RBF model to predict the indoor air temperature in the case of a greenhouse depending on the indoor relative humidity and the external parameters like outside air temperature and solar radiation. Some references [211–213] address improvements in the RBF model structure offering solutions with different degree of complexity. In particular, in [211] 18 models are used, and the number of inputs is reduced from 20 to 8 by using a Multi-Objective Genetic Algorithm (MOGA). Teixeira et al. [214] use a non-linear RBF method and compare it with a hybrid RBFLIC method (RBF with Linear Input Connections) for punctual temperature modelling in a homogeneous medium. The improvement in the ANN structure performance (about 28%) is obtained by using the MOGA parametrisation. Ruano et al. [215] use multi-objective algorithms to design the RBF with 5 models, also constructing an adaptive model in which all method parameters are changed. From the results, the static RBF model provides better results than physical models. The adaptive

Table 8
Models and input data to predict the indoor air temperature with fuzzy and hybrid neuro-fuzzy models.

Article (first author and reference)	ANN Model	Fuzzy logic Model / Type of membership functions	Number of hidden neurons	Total number of input neurons	Number of membership functions	Total number of inputs to the fuzzy/ ANFIS	Input data: Error	Floor temperature	Outdoor Relative Humidity	Wind Velocity (and direction)	Solar Radiation	Outdoor Air Temperature	Indoor Relative Humidity	Indoor Air Temperature	Sky cloudiness	Temperature of the terrain
Škrjanc [225]	–	Takagi-Sugeno / triangular	–	–	3	5					2	1			1	1
Meana-Llorián [226]	–	Fuzzy Inference System / triangular	–	–	7	3						1	1	1		
Atia [179]	BP	ANFIS Sugeno / triangular	15	6	7	2	1	1	1	1	1	1				
Alasha'ary [180]	BP	ANFIS Sugeno / gaussian	–	4	5	4				2	1	1				
Marvuglia [166] (winter scenario)	NNARX	Fuzzy Logic Controller (FLC) / triangular	30	25	5	2				7		4	9	5		
Marvuglia [166] (summer scenario)	NNARX	Fuzzy Logic Controller (FLC) / triangular	10	27	5	2				9		5	8	5		
Collotta [227] (winter scenario)	NNARX	Fuzzy Logic Controller (FLC) / gaussian	30	23	7	2				7		6	5	5		
Collotta [227] (summer scenario)	NNARX	Fuzzy Logic Controller (FLC) / gaussian	10	19	7	2				6		3	6	4		

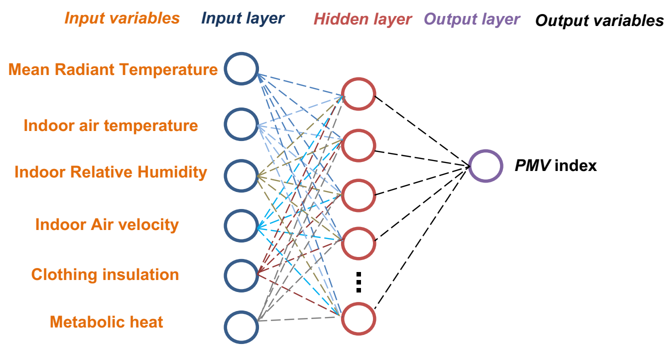

Fig. 10. Structure of an ANN to predict the *PMV* index.

model is more accurate than the static model in predicting the indoor air temperature.

5.2.2. Autoregressive and hybrid autoregressive-ANN models

A number of papers have carried out comparisons between linear ARX and ARMAX models and non-linear NNARX. The results consistently show that the NNARX model is better than ARX, as it is able to capture some non-linearities appearing in the prediction of the indoor air temperature. The literature contributions deal with different types of buildings.

A *residential* building is considered in [216] for carrying out the prediction. In [217] the comparisons involving non-linear ANN model and linear ARX-ARMAX refer to the operation temperature for residential and laboratory buildings, evaluated by means of different variables like the indoor and outdoor temperatures, the electrical power use in the room, the wall temperatures, the ventilation flow rates and the time of day.

For an *office* building, the models used in [218] are effective over long periods without calibrating the parameters very often, as observed by the simulations results. Office buildings are considered also in [219], by using weather data from internal and external locations to dry bulb temperature and relative humidity forecast at different time steps in the range 30 min - 3 h with ARX and NNARX. It is indicated that NNARX performs better than ARX, as temperature and relative humidity depend on non-linear diffusion equations, whose non-linearities are not captured by the linear models. The NNARX and NNARMAX models addressed in [220] exhibit good performance in the prediction of indoor air temperature and relative humidity of an open-plan office. In [166] an NNARX model is used for an office building, by highlighting the optimal selection of the model parameters.

For a *factory* building, Thomas and Soleimani–Mohseni [221] present the results of a comparative analysis to predict the indoor air temperature with ARX, ARMAX and ANNs. This investigation concludes that non-linear ANN models present more accurate temperature predictions compared with the linear ARX model. The prediction is improved by taking into account more signals into the models (e.g., in the case of ANN models the predictions are improved considering the day time as a fifth input signal).

University buildings are addressed in [222] by using the NNARX algorithm with RBF as the neural network, with two different models used in summer (cooling mode) and in winter (heating mode), and in [223] with good results obtained from a NNARX.

ARX, ARMAX and non-linear ANN models are used in [224] to simulate indoor room temperature under *tropical* conditions. The results show that the NNARX models perform better than the ARX and ARMAX models. The analysis of the relevance of the various parameters shows that the most significant parameter is the external temperature, while the less significant parameter is the solar radiation.

5.2.3. Fuzzy model

Non-linear fuzzy modelling based on modified Takagi–Sugeno with two inputs (global solar radiation, outdoor temperature) and one output (indoor air temperature) is used in [225]. A number of cases is analysed, and the best results are obtained when the variables are divided into three membership functions. Temperature control is addressed in [226] with a new approach based on fuzzy logic taking into account the indoor air temperature, the outdoor temperature and humidity, obtaining significant energy saving.

5.2.4. Hybrid ANN-fuzzy model

The combination of ANNs with fuzzy logic models has been developed in order to predict the indoor air temperature considered as output variable of the building model. Some references [166,227] indicate the lack of a comprehensive literature about utilisation of these hybrid models.

A control system useful for modelling and controlling the greenhouse indoor temperature is presented in [179], by applying various control techniques (proportional-integral, fuzzy logic, ANN control and ANFIS). The response of the ANFIS controller results to be very fast and more effective than the response of the other controllers.

The ANN model shown in [166] is used for predicting the indoor air temperature useful to feed a fuzzy controller, which aims at maintaining the indoor conditions in the acceptable comfort range. The results point out the efficiency of the hybrid neuro-fuzzy approach and the positive effect of the temperature regulation provided by the coupling of ANN with the fuzzy logic controller. The neuro-fuzzy approach for HVAC systems is proposed in [227], obtaining better results in comparison with the approach of [166]. The proposed controller can change dynamically the membership functions by obtaining an optimum thermal comfort for the two cases analysed.

In the ANFIS application described in [180] for residential building applications, the data sampling is performed at different timings (initially 10 min, then reduced to 5 min), obtaining accurate predictions from a computationally effective approach.

5.3. Prediction of the PMV index

The *PMV* index is useful in controlling HVAC systems [228]. The *PMV* index computation is an implicit relationship very complicate and iterative, which depends on environmental parameters (dry bulb temperature, air velocity, relative humidity and mean radiant temperature) and personal parameters (clothing insulation, metabolic heat) that affects the thermal sensation.

The *PMV* index dependence on iterative solutions could be difficult for real-time control [229]. The conventional *PMV* index is determined by means of tables indicated in [55] and [230]. A computer model developed to calculate the *PMV* index taking into account the iterative step is presented in [231]. Considering that the iterative step and the tables of conventional *PMV* index are not appropriate for real-time control, some simplified *PMV* models are suggested in [232]. Furthermore, Federspiel and Asada [233] show a user-adaptable comfort controller in which the thermal sensation model depends on a simplified *PMV* index and the model parameters are regulated taking into account the thermal sensation of human subjects.

Various researches were carried out both for identification and control of HVAC system models, because most of them are variable and non-linear [234]. The following subsections deal with the models used to predict the *PMV* index, considering ANN, fuzzy logic, neuro-fuzzy, and other models. Some references deal with *PMV* variations (indicated with ΔPMV).

5.3.1. Artificial Neural Networks

The input variables of the ANN model to obtain the *PMV* index are environmental and personal parameters. Fig. 10 shows an example of ANN structure indicating a set of input parameters [235]. The ANN

Table 9
Models and input data to predict the *PMV* index.

Article	Models	Number of	Total number	Input data														
(first author and reference)	ANN: model (training) Fuzzy: model / type of membership functions	hidden neurons	of input neurons	Solar Radiation	Outdoor Air Temperature	Outdoor Relative Air Humidity	Wet Bulb Temperature	Globe/Mean Radiant Temperature	Methabolic Rate	Clothing Insulation	Indoor Relative Air Humidity	Indoor Air Temperature	Indoor Relative Air Velocity	Water vapour pressure	Room Occupancy	Gender	Age	Position (horizontal, vertical)
Moon [192]	BP (LM)	17	8		2*	2*					2*	2*						
Moon [193]	BP (LM)	17	8		2*	2*					2*	2*						
Ruano [222]	RBF (LM)	2–30	3					1			1	1						
Atthajariyakul [234]	BP (gradient descent)	5,8	6				1	1		1		1	1					
Liu [237]	BP (gradient descent)	5	4					1			1	1	1					
Li [239]	BP (LM)	21	6					1	1	1	1	1	1					
Castilla [240]	BP (gradient descent)	50	4					1			1	1	1					
Garnier [241]	BP (LM)	18–24	8	1	1			1				1			1			
Buratti [242]	BP (LM)	35,75	9		1				1	1	1	1				1	1	2
Jian [243]	BP (gradient descent)	5	6				1	1		1		1	1					
Ferreira [245]	RBF (LM)	2–30	3					1			1	1						
Ruano [246]	RBF (LM)	2–30	3					1			1	1						
Ruano [247]	RBF (LM)	2–30	3					1			1	1						
Hamdi [177]	triangular	–	–					1	1	1	1	1	1					
Stephen [248]	Mamdani/triangular	–	–					1	1	1	1	1	1					
Duan [249]	triangular	–	–					1				1	1					
Homod [250]	Takagi-Sugeno/ trapezoidal	–	–					1**	1**	1**	1**	1	1**					
Ciabattoni [251]	Mamdani/ trapezoidal	–	–					1	1	1	1	1	1					
Gouda [252]	Mamdani/triangular	–	–					1			1	1						
Huang [253]	Adaptive/triangular	–	–					1	1	1	1	1	1					
Calvino [254]	Takagi-Sugeno/ triangular	–	–						1	1				1				
Luo [255]	ANFIS/Gaussian functions	–	–					1	1	1	1	1	1					
Chen [256]	GeneticAlgorithm/ Gaussian	–	–					1	1	1	1	1	1					

* 2 values (absolute value and change of the variable in a predefined period);
** input considered to be constant.

models with good reliability and accuracy in the prediction of the *PMV* index are BP and RBF. Table 9 summarises the ANN modelling structure, with indication of the hidden nodes and of the input variables useful to predict the *PMV*.

5.3.1.1. ANN with BP. The BP model has very strong input-output mapping ability and is useful for approximation of *PMV* and psychrometric variables (dry bulb temperature, wet bulb temperature, dew point temperature, relative humidity, humidity ratio, specific humidity, absolute humidity, specific volume, and enthalpy) [236]. The BP algorithm can assess thermal comfort levels when is applied to the thermal comfort [237]. Liang and Du [238] present the design and implementation of a direct neural controller based on the BP algorithm with two inputs and one output for HVAC systems, which predicts the highest comfort level considering the *PMV* index as a control objective. The results show that, using this controller, high thermal comfort and energy saving are simultaneously obtained.

Most applications refer to the determination of the *PMV* index. Atthajariyakul and Leephakpreeda [234] illustrate a BP model to obtain the *PMV* index by means of the human and environmental variables for a HVAC system. In this case, the proposed ANN model depends on the wet bulb temperature, the human activity, the indoor air temperature, the globe thermometer temperature, the relative air velocity, and the thermal resistance of clothing. This model approximates a non-linear relation as long as in the hidden layer there are enough non-linear neurons. The results demonstrate a good correlation between the *PMV* values obtained from neural network, *PMV* model and the conventional *PMV* model of Fanger.

Liu et al. [237] present a model for individual thermal comfort. The results report an adequate fit with the real thermal sensation of subjects. Li et al. [239] propose a new thermal comfort index control using BP, taking into account as the input data the environmental and personal parameters that affect the thermal sensation. They obtain an adjustment of the air-conditioning control coefficient due to the modifications in *PMV* index to obtain the best comfort state.

Castilla et al. [240] propose two models (polynomial and BP) for approximating the *PMV* index. The conclusion reports that better results with similar number of configurable parameters are obtained by using the BP model. Garnier et al. [241] carry out the predictive control of the multi-zone HVAC systems in non-residential buildings. The ANN model is used to determine the temperature used, together with other variables to assess the PMV. Buratti et al. [242] show the results of experiments carried out in two different periods for obtaining the input data useful for the network training, as well as for validating the trained ANN. The results show that the mean *PMV* values obtained due to the simulation with ANN are near to the values found from questionnaires during the experimental analysis.

Considering the references dealing with *PMV* variations, Moon and Kim [192] describe three structurally identical BP models to approximate ΔPMV. The results show that *PMV* control with ANN has better performance than *PMV* control without ANN, and that ANN models create more pleasant thermal conditions in the HVAC systems compared to current thermostat systems. Jian and Jin [243] propose a BP model to predict the *PMV* index. The results show good concordance with the ones based on the conventional *PMV* with mean absolute error below 5%. Moon [193] uses three BP models with the same structure and the same input, hidden, output layers in order to obtain ΔPMV. The results demonstrate that predictive and adaptive control logics are more advantageous for controlling air temperature, humidity, or *PMV* more comfortably than the conventional models.

5.3.1.2. ANN with the RBF model. The RBF model, considered as a function approximator to the *PMV* index, can predict complex non-linear mappings directly from the input-output relations [244]. Ferreira et al. [245] use the RBF model with parameters identified by MOGA to approximate the *PMV* index necessary for real-time control. The dynamic environment parameters are divided from the human parameters considered constant in order to simplify the input-output structure. The results report good estimation, accuracy as well as good coverage of the thermal sensation scale. An improved version of the model is presented in further papers [222,246,247] where improvements are reported in estimations and forecasts for both indoor air temperature and *PMV* index.

5.3.2. Fuzzy models

Various papers in the literature deal with the prediction of the *PMV* indicator by using fuzzy rules. The interest in using fuzzy rules depends on the fact that the fuzzy calculation of *PMV* does not require iterative solutions. In addition, the calculations are easily adjustable on the basis of the thermal sensation of the users [177]. Thereby, the *PMV* index is useful to be incorporated into HVAC control systems, and the *PMV* controller is able to provide better control of the thermal comfort with respect to a temperature controller [248].

The HVAC control strategy applied in [177] adopts a comfort model with a fuzzy *PMV*, calculated on the basis of six input variables, showing the good accuracy of the fuzzy *PMV* model. The *PMV*-based fuzzy control algorithm proposed in [249] obtains energy saving by increasing or decreasing the indoor air temperature due to the variable ambient conditions in a room. The thermal comfort of the individuals is maintained by controlling the temperature and relative air velocity of the room, keeping the *PMV* index fixed at a constant value. A fuzzy *PMV*/*PPD* model is used in [250] to obtain a reference signal for the HVAC system closer to the thermal sensation than the temperature signal. An experimentally tested fuzzy controller for an HVAC system is presented in [251], developed to avoid the usage of the temperature setpoint.

Some contributions compare the fuzzy controller with a traditional conventional Proportional Integral Derivative (PID) controller. Gouda et al. [252] propose a *PMV*-based fuzzy logic controller to assess *PMV* level for a specified comfort range. The *PMV* model based on fuzzy logic is applied for building spaces and its heating system. The fuzzy controller is compared with the PID controller and the results reveal that the *PMV*-based fuzzy logic controller is more robust than the PID controller.

In the fuzzy model control strategy presented in [253] to characterise the energy performance and thermal comfort in a laboratory, the *PMV* index is introduced as the controlled variable. The *PMV* results demonstrate that the adaptive fuzzy controller obtains much better results than the PID controller. Calvino et al. [254] propose a fuzzy-PID controller useful for assessing the HVAC system in a University building. The *PMV* is the driving index for the control procedure. The simulation results show a *PMV* value close to zero in the comfort range, with very low overshoots. Luo et al. [255] combine a fuzzy model that uses prior knowledge on the working condition with an ANFIS model to improve the prediction accuracy.

CFD is applied in [256] to simulate the environmental data for accurately depicting the *PMV* index for an air-conditioned room in a laboratory during the summer. The fuzzy modelling method is used to represent the dynamics of *PMV* in an efficient way.

5.3.3. Other models

The Least Square Support Vector Machines (LSSVM) model has been analysed to approximate accurately the non-linear relationship between input variables and output variables. In this regard, Kumar and Kar [228] analyse how to model the *PMV* index modelling and the psychrometric variables, by using the LSSVM model in order to approximate accurately the non-linear expressions between input data and output data. The results show the best accuracy in approximating the *PMV* index and some psychrometric variables in the absence of noise. The LSSVM model has also a good robustness against single as well as multi-input noises to predict the *PMV* index.

6. Conclusions

This paper has presented an extensive overview of the most applied thermal comfort indicators, their variants and their applicability in various thermal environments. Then, it has discussed the usage of thermal comfort models to predict relevant variables such as the air temperature and the *PMV* index in indoor environments.

Three main approaches (physiological, psychological, and rational) as well as the ambient and personal parameters have been recalled as key aspects in assessing the thermal comfort applications for indoor environments. Next, the paper has addressed the applications of the *PMV* index, as the most used thermal comfort indicator. Starting from the characteristics of the *PMV* index, further modifications aimed at providing dedicated results in specific environments have been reviewed. Since the *PMV* has not been deemed to be adequate in hot and humid climates, the *aPMV* has been introduced to provide better performance in these cases, considering the psychological and heat balance approaches together. The *ePMV* is useful for naturally ventilated buildings in humid climates where the indoor air temperature rises significantly. It has a greater acceptability in regions with long summer. The *nPMV* is useful in HVAC buildings for equilibrating the difference between the *PMV* predictions and the thermal sensation of the occupants. The *AMV* is useful in tropical zones, taking into account the behaviour and psychology of the individuals. Furthermore, the *PPD* index and a few of its variants useful in transient conditions and non-uniform environments have been illustrated, highlighting their applications as indicated in recent literature contributions.

Moreover, this paper has presented a comprehensive view on the prediction of the main indicators used to define appropriate control strategies in indoor environments – the indoor air temperature and the *PMV* index. The prediction of these indicators is a key asset to deploy intelligent building control in present and future energy management systems. Among the various models used, ANNs and hybrid ANN-fuzzy have emerged as the most used ones. A detailed synthesis of the input parameters used to run these models has highlighted the presence of several parameters used in different applications. A specific assessment of the importance of these parameters in different contexts remains a challenging task for future research. The outcomes of such an assessment highly depend on the non-linear interactions among the variables, and on the suitability of the models to capture these non-linearities during time in different operating conditions.

Further developments are expected in the future research, with the proposal of refined adaptive comfort models to be included in specific control systems aimed at taking into account the customer preferences. These models will enable the progress of the studies referring to energy system analysis and optimisation, energy management in smart energy buildings, as well as demand side management including customer-oriented direct control of the thermal units in indoor environments.

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