# Realtime Multi-factor Dynamic Thermal Comfort Estimation for Indoor Environments

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**Abstract.** Thermal comfort models are mathematical representations that simulate the thermal environment and predict human comfort based on various factors such as air temperature, air velocity, relative humidity, and radiation heat transfer. These models are used to design and evaluate heating, ventilation, and air conditioning systems, buildings, and outdoor spaces. The main issue when exploiting predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) and model for thermal comfort estimation is how to estimate clothing insulation and metabolic rate as accurately as possible. In this paper, a novel approach for calculating thermal comfort is presented that combines algorithms to enhance the precision of existing approaches. Experimental results showcase the suggested method is more accurate than other approaches.

**Keywords:** Thermal comfort · Indoor environmental conditions · Personal factors

## 1 Introduction

Looking at people's daily lives, their timeless connection with the residence they have chosen to live in may be observed. One of the main factors influencing this interaction's quality is the thermal sensation inside the residence. In recent years, the factors that influence the internal temperature of a building and how they are taken into account to give us thermal comfort have been studied to a


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large extent [1]. The importance of thermal comfort is extended even in early building stages like the design phase till further stages like renovation.

Thermal comfort, as defined by ISO standard 7730 [2], is the state of being satisfied with one's thermal environment. Thermal comfort models are mathematical representations that simulate the thermal environment and predict human comfort based on various factors such as air temperature, air velocity, relative humidity, and radiation heat transfer. These models use different methods and algorithms to estimate thermal comfort and are used to design and evaluate heating, ventilation, and air conditioning (HVAC) systems, buildings, and outdoor spaces. Some common thermal comfort models include the PMV (Predicted Mean Vote) and PPD (Predicted Percentage of Dissatisfied), the Adaptive model, and the Transfer Function model [3].

The research community is continually seeking the best thermal comfort model for estimating the ideal living conditions in buildings. Fanger's $PMV$ model ($PredictedMeanVote$) is widely considered one of the most comprehensive and accurate thermal comfort models available. There are several reasons why the $PMV$ model is considered better than other models [4]:

- Accounts for many factors that affect thermal comfort, such as air temperature, air velocity, relative humidity, and clothing insulation. This makes the $PMV$ model more accurate and relevant compared to models that consider only a few factors.
- It is widely used and accepted in the residential sector and is established as the standard for the prediction of thermal comfort under the International ISO 7730 standard [2].
- It is relatively easy to use, with clear instructions for estimating the $PMV$ index and thermal comfort based on index values.
- Has been proven to reliably estimate human thermal comfort in a wide range of situations, making it a dependable tool for evaluating and planning HVAC systems, buildings, and outdoor spaces.

These elements combine to make $PMV$ an effective and trustworthy tool for forecasting thermal comfort, and these are some of the reasons why it is seen to be superior to other models. Based on ASHRAE, a fast and high-accuracy function has been developed that calculates the predicted mean vote ($PMV$) and the predicted percentage of satisfied (PPD) [5,6].

The input variables of the model, such as dry bulb air temperature, mean radiant temperature, average air speed, and relative humidity, can be measured accurately through sensor installation. However, there are no standard real-time methods to calculate the metabolic rate and clothing insulation of people habiting inside the building. The temperature inside a building greatly affects the type of clothing one wears [7]. Furthermore, the variation in clothing insulation values is attributable to the fact that what we wear is influenced by factors other than temperature, such as gender, age, and cold and heat tolerance [7]. In addition, temperature plays an important role in the determination of metabolic rate [7]. The behavior of building occupants is difficult to predict, model, or calculate due to the complexity of humans. Furthermore, the absence of established standards and protocols for data collection, as well as the precision of data, pose difficulties in the field of building occupant research [8].

As a result, the main issue when exploiting the $PMV$ and $PPD$ model for thermal comfort estimation is how to estimate clothing insulation and metabolic rate as accurately as possible. Within this context, the aim of this paper is to present a novel approach by fusing widely used methodologies [7], one for the determination of clothing insulation and one for the determination of metabolic rate. The main objective is to mitigate the error in estimating personal factors by taking into account as many factors as possible, such as indoor and outdoor conditions.

The remainder of this paper is organized as follows: In Sect. 2 the way the thermal comfort is estimated is suggested, highlighting a novel approach for estimating the personal factors. Section 3 presents the experiment set up along with the results. Finally, in Sect. 4, conclusions are drawn.

## 2 Methodology

In this section, a novel approach for calculating thermal comfort is presented that combines algorithms to enhance the precision of existing approaches. A tool that would provide real-time, practical, and accurate thermal comfort estimation is suggested.

### 2.1 Thermal Comfort Inference

As addressed in the Introduction, Fanger's Predicted Mean Vote ($PMV$) and Predicted Percentage of Dissatisfied ($PPD$) model is widely used to estimate thermal comfort. The models are specified through a set of equations that are outlined below [9,10]:

$$PPD = 100 - 95 \cdot e^{-(0.03353 \cdot PMV^4 + 0.2179 \cdot PMV^2)} \tag{1}$$

$$PMV = (0.303 \cdot e^{-0.036 \cdot M} + 0.028) \cdot L \tag{2}$$

$$L = M - W \tag{3}$$

$$M - W = C + R + E_{sk} + (C_{res} + E_{res}) \tag{4}$$

$$C = f_{cl} \cdot h_c \cdot (T_{cl} - T_a) \tag{5}$$

$$R = \sigma \cdot \varepsilon_{cl} \cdot f_{cl} \cdot F_{vf} \cdot \left[ (T_{cl} + 273.15)^4 - (T_r + 273.15)^4 \right] \tag{6}$$

$$\begin{aligned} C_{res} + E_{res} = {} & 0.014 \cdot M \cdot (34 - T_a) \\ & +0.0173 \cdot M \cdot (5.87 - P_a) \end{aligned} \tag{7}$$

$$E_{sk} = 3.05 \cdot (5.73 - 0.007 \cdot M - P_a) + 0.42 \cdot (M - 58.15)) \tag{8}$$

All the used variables are briefly explained in Table 1 [13]. Finally, to estimate the thermal comfort based on the above equations the factors needed to estimate real-time PMV are [12]:

$$PMV = f(T_a, RH, I_{cl}, M), \tag{9}$$

where $T_a$ refers to room temperature, $RH$ refers to room humidity, $I_{cl}$ and $M$ refer to clothing insulation and metabolic rate respectively.

Room environmental conditions (i.e., $T_a$, $RH$) may be retrieved from indoor temperature and humidity sensors while estimating the personal factors may be proven to be a thorny problem [12]. Even though values for the personal factors may be retrieved from the ASHRAE table, an estimation of $I_{cl}$ and $M$ values based solely on the ASHRAE table may generate a significant mistake during thermal comfort estimation [14,15]. As a result, another approach for estimating personal factors should be followed.

**Table 1.** PMV and PPD variables

| Variable | Meaning | Unit |
|---|---|---|
| $W$ | external work | $W/m^2$ |
| $M$ | metabolic rate (internal energy production) | $W/m^2$ |
| $C$ | heat loss by convection | $W/m^2$ |
| $R$ | heat loss by thermal radiation | $W/m^2$ |
| $E_{sk}$ | heat loss by evaporation from the skin | $W/m^2$ |
| $C_{res}$ | sensible heat loss due to respiration | $W/m^2$ |
| $E_{res}$ | heat loss by evaporation from the skin | $W/m^2$ |
| $T_{cl}$ | clothing surface temperature | $^o$C |
| $T_a$ | ambient air temperature (indoor) | $^o$C |
| $h_c$ | heat transfer coefficient | $W/m^2 \cdot K$ |
| $V_a$ | air velocity | $m/s$ |
| $f_{cl}$ | clothing area factor | $clo$ |
| $\varepsilon_{cl}$ | emmisivity of clothing | |
| $F_{vf}$ | view factor between the body and the surrounding | |
| $\sigma$ | Stefan Boltzmann constant [11] | $W/m^2 \cdot K^4$ |
| $T_r$ | radiant temperature | $^o$C |
| $P_a$ | partial vapour pressure | $P_a$ |
| $RH$ | relative humidity | % |
| $I_{cl}$ | thermal insulation of clothing | $clo$ |

### 2.2 Clothing Insulation Estimation

Indoor temperature is an essential factor in clothing worn inside buildings, as suggested by the non-linear regression relationship between clothing insulation and indoor temperatures based on feedback observations in [7]. In this paper [7], an equation is used to calculate the insulation of clothing based on the temperature inside a room:

$$Cl_{T_{in}} = f(T_a) = 89.279(T_a)^{-1.592} \tag{10}$$

Additionally, the influence of season on clothing insulation is significant in determining thermal comfort, as individuals require different levels of insulation in their clothing to maintain comfort in different seasons [18]. During colder seasons, individuals require more insulation to keep warm, while during warmer seasons, individuals require less insulation to avoid overheating [21]. There are some standard values that correspond to each season, such as the 'Typical summer indoor clothing' equal to 0.5 and the 'Typical winter indoor clothing' equal to 1.0. A year is separated into four periods on the basis of seasonality. Each season is represented by average clothing insulation and the clothing insulation by season $Cl_s$ is depicted in Fig. 1.


**Fig. 1.** $Cl_s$: Average clothing insulation by season values

The insulation value of clothing can also be expressed as representative of a particular clothing ensemble as a function of the outdoor temperature [18].

$$Cl_{T_{out}} = 2.1 \cdot 10^{-5} T_{out}^3 + 8 \cdot 10^{-4} T_{out}^2 - 0.0282 T_{out} + 0.8167 \tag{11}$$

where $T_{out}$ is the outdoor temperature expressed in $^o$C. This equation is determining the Icl insulation of clothing based on real-time values.

There is a method that combines the $Cl_{T_{in}}$ and the $Cl_s$ to estimate total clothing insulation as [12]:

$$I_{cl} = wCl_s + (1 - w)Cl_{T_{in}}, \tag{12}$$

this method was tested in real-life environments and has proven to be accurate enough. Nonetheless, this method may produce a significant error during periods of time when the outdoor temperature is extremely high or low than the average seasonal outdoor temperatures (e.g., during spring outdoor temperatures can be more than 25 $^oC$ or less than 10 $^oC$). As a result, in this paper, we suggest a new method that will "correct" this specific error by combining all temperature factors. The insulation value of clothing is:

$$I_{cl} = aCl_s + bCl_{T_{in}} + (1 - a - b)Cl_{T_{out}}. \tag{13}$$

During an experimental phase, the values of $a$ and $b$ were set to $a = 0.5$ and $b = 0.25$.

Finally, when estimating the clothing insulation of a person in motion, it is important to account for the dynamic nature of the insulation, which is affected by both the individual's activity level and the air speed around them. As per the ISO 7730 standard, it is necessary to correct for these factors [2]. Similarly, the ASHRAE 55 Standard provides a correction equation for body movement for activities with a metabolic rate of 1.2 met or higher, expressed as:

$$I_{cl} = I_{cl}(0.6 + \frac{0.4}{met}), \tag{14}$$

## 2.3 Metabolic Rate

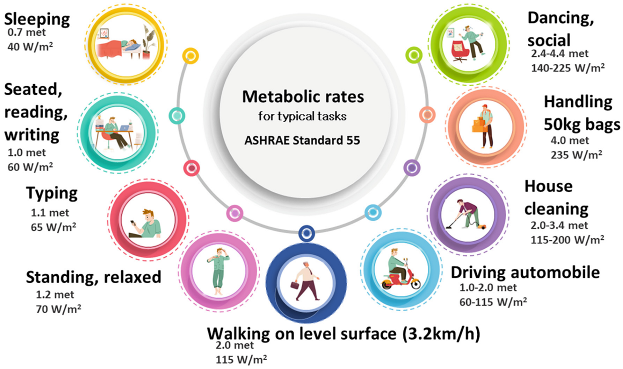


**Fig. 2.** Metabolic rates for typical tasks ASHRAE Standard 55 [17]

The metabolic rate that corresponds to the ideal level of comfort ranges from 84.8 $W/m^2$ to 89.9 $W/m^2$. This range is determined based on occupants' feedback who reported feeling thermally comfortable during a survey [16]. According to the ASHRAE metabolic rate table in Fig. 2, this range of activity is classified as low-level activity, similar to activities such as standing or relaxing. It appears that low-level activities are more feasible in a household setting, while more strenuous activities such as cleaning the house are not so frequent [16]. As a result, the metabolic rate could be set to low-level activities (that is, 70–80 $W/m^2$ or 1.2 $met$), such as standing and relaxed activities. During the night, the activity can be set to sleep (that is, 40 $W/m^2$ or 0.7 $met$).

### 2.4 Overall System

The overall conceptual architecture of the system suggested in Sect. 2 is depicted in Fig. 3. The sensors push real-time indoor environmental conditions to be utilized for both thermal comfort and clothing insulation estimation. The date and time are utilized for the estimation of metabolic rate and clothing estimation. In addition, outdoor conditions are utilized for clothing insulation. It may be observed how clothing insulation is estimated through a multifactor process.

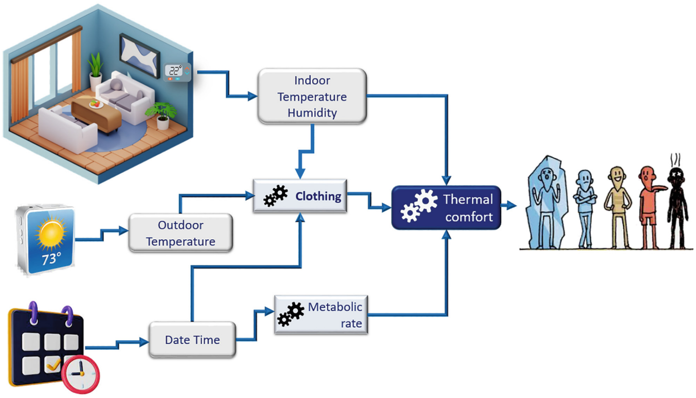


**Fig. 3.** Thermal comfort estimation conceptual architecture

## 3 Results

In this section, the results of the suggested methodology of thermal comfort estimation will be presented. Initially, how the experiment was set up will be discussed. Finally, experimental results will be showcased in the last subsection.

### 3.1 Experiment Set up

To test the suggested methodology as described in Sect. 2, data from the CERTH.ITI smart-home were exploited [19]. Data from a temperature humidity sensor (i.e., [20]) were retrieved. Values from a specific room for a year (i.e., temperature, humidity) were utilized for the tests (Fig. 4).

The average values during the tested period are presented in Table 2.

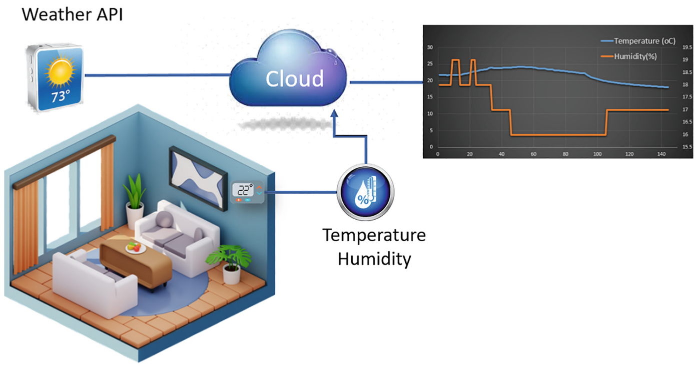


**Fig. 4.** Thermal comfort set up experiment

**Table 2.** Data-set average values

| Month | Average Indoor Temperature °C | Average Indoor Humidity % | Average Outdoor Temperature °C |
|---|---|---|---|
| January | 17.96 | 28 | 8.5 |
| February | 18.23 | 29.11 | 10.7 |
| March | 20.23 | 30.3 | 14.3 |
| April | 22.5 | 27.5 | 18.6 |
| May | 22.5 | 32.3 | 17.3 |
| June | 25.1 | 34.5 | 17.9 |
| July | 26.2 | 33.6 | 20.1 |
| August | 28.1 | 38.8 | 20.8 |
| September | 27 | 23.8 | 18.5 |
| October | 24.3 | 20.5 | 17.3 |
| November | 22.96 | 27.1 | 15.7 |
| December | 23.4 | 28.6 | 10.1 |

### 3.2 Experimental Results

In this section, some indicative results will be presented, one for each season. In the following graphs, real-time values of indoor and outdoor temperatures from the CERTH.ITI smart-home [19], along with the values of the $PMV$ calculated with the two methods will be presented. $PMVold$ value based on Equation (12) and the $PMVnew$ value based on Eq. (13). The graph for each of the four seasons (i.e., Spring, Summer, Fall, and Winter), depicts a representative day from each season. When analyzing the following graphs two facts must be considered. First, the indoor temperature tends to stay more constant than the outdoor temperature and therefore closer to the average seasonal temperature, for reasons such as insulation of the building, heating and cooling systems, and solar radiation. Second, in terms of the thermal sensation scale in Fig. 5, as the $PMV$ value is closer to 0 there is a better thermal sensation, and it is expected that in the summer season, it tends to go higher, where in the winter season it is lower.

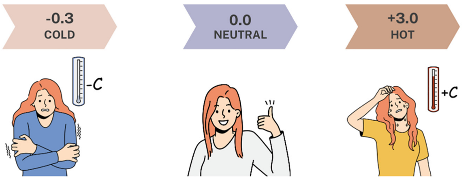


**Fig. 5.** Thermal Sensation Scale

Figure 6 depicts values from April 13th, 2022 during the spring season. Outdoor temperatures may be observed to fall below average spring temperatures (e.g., average below 12 $^{o}$C). As a result, the line of the PMV value calculated with the new equation is lower than the other, meaning that the resident is feeling colder. While the outdoor and indoor temperature increases, the deviation between the two PMV values is smaller.

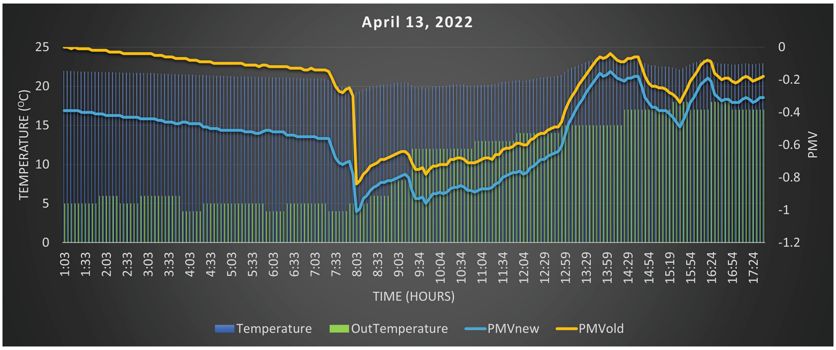


**Fig. 6.** Thermal comfort comparison for Spring

Figure 7 shows values from July 13th, 2022 during the summer season. On this day, outdoor temperatures are very close to indoor ones. So, here the fact that the PMV values calculated with the new equation are closer to 0, means that there is a better thermal sensation compared to the old one, as expected.

Following up, in the winter season, Fig. 8 depicts the data values for the day of December 28, 2022. The first thing that becomes apparent is that the line based on the old equation takes values higher than 0, which is in contrast to previous acknowledgments.

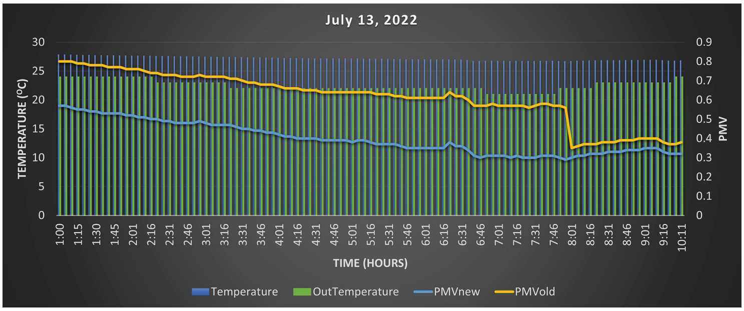


**Fig. 7.** Thermal comfort comparison for Summer

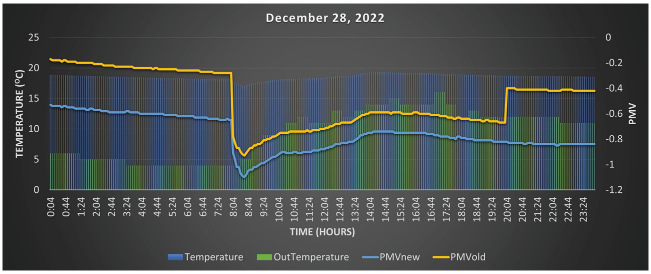


**Fig. 8.** Thermal comfort comparison for Winter

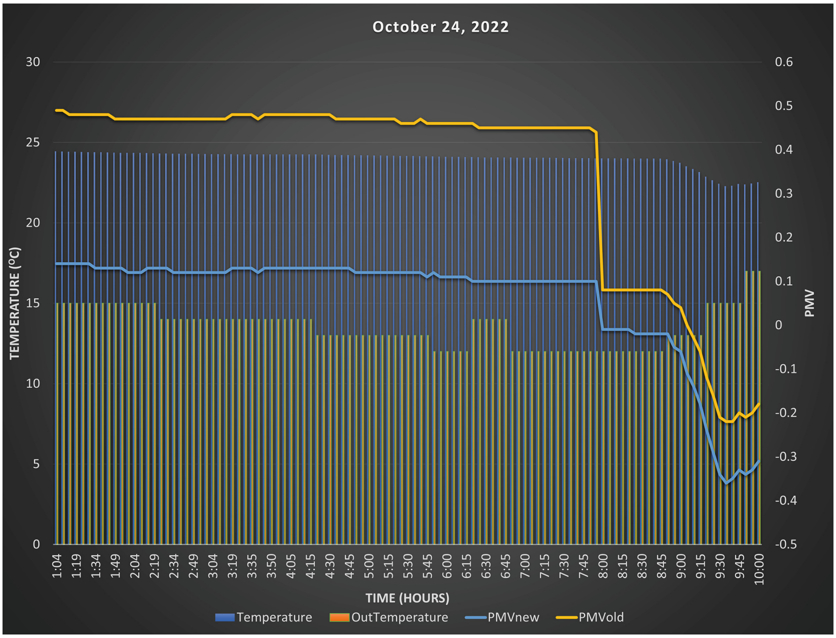


**Fig. 9.** Thermal comfort comparison for Fall

Finally, during the fall season, Fig. 9 depicts the values from October 24th, 2022. In this case, outdoor temperature values are far below the indoor ones and this leads to the conclusion that the line base on the new equation is more accurate.

## 4 Conclusions

In general, thermal comfort is an important factor in building occupants' behavior, which is difficult to predict, model, or calculate due to the complexity of humans. In this paper, a novel approach for calculating thermal comfort was presented that combines algorithms to enhance the precision of existing approaches. The proposed methodology was tested in real-time environments and has proven to be accurate enough.

The analyses of the graphs lead to the conclusion that when the outdoor and indoor temperatures are close, the new PMV values are more comparable to the optimum thermal sensation. Furthermore, the old method may produce a significant error in the thermal comfort calculation when the outdoor temperature is extremely higher or lower than the average seasonal outdoor temperature and consequently the indoor temperatures.

In summary, the proposed approach has shown promising results and could have significant implications for improving building occupant comfort and energy efficiency. However, to further improve the accuracy and applicability of the method, additional steps such as conducting validation tests in different settings, integrating the methodology with building automation systems, incorporating other factors that impact thermal comfort, and considering user feedback and perception should be taken into account.

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