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Sensitivity study for the PMV thermal comfort model and the use of wearable devices biometric data for metabolic rate estimation

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A B S T R A C T

This paper studies the sensitivity of the Predicted Mean Vote (PMV) thermal comfort model relative to its environmental and personal parameters of a group of people in a space. PMV model equations, adapted in ASHRAE Standard 55–Thermal Environmental Conditions for Human Occupancy, are used in this investigation to conduct parametric study by generating and analyzing multi-dimensional comfort zone plots. It is found that personal parameters such as metabolic rate and clothing have the highest impact. However, as these parameters are difficult to estimate or measure, they are usually assumed to be default values (rest conditions and light clothing). In this work, we show the application of the human-in-the-loop sensor data of wearable devices to provide a continuous feedback for the averaged metabolism value of building occupants to be used in the PMV calculation. Moreover, we motivate the use of these sensor data to develop a new personalized comfort model.

1. Introduction

Achieving higher performance at work is of high interest. Thermal comfort that is strongly related to productivity has recently received a great deal of attention. Thermal comfort is a subjective matter and may vary from person to person. There have been multiple attempts to develop a unified and widely accepted thermal comfort model that can be received and adopted by large audiences. The most popular model is the Predicted Mean Vote model (PMV model), which was constructed by P. O. Fanger [1] and was later adapted into the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) Standard 55–Thermal Environmental Conditions for Human Occupancy. This model meant to estimate the "average" thermal sensation that a group of people would report when occupying a given space. For that matter it correlates multiple environmental parameters (air temperature, air velocity, relative humidity, and radiant temperature) and the average of personal parameters of group of people (metabolism and clothing) to different levels of comfort based on a rating between −3 and 3, where −3 means the body thermal sensation is very cold and 3 means the body thermal sensation is very hot. Typically, the goal is to control environmental factors in order to keep the PMV value between −0.5 and 0.5, where the body is believed to be thermally satisfied. Since the environmental parameters are relatively easy to measure, they have received a great deal of attention in the literature. Personal parameters, on the other hand, are more difficult to estimate or measure and, therefore, are usually assumed to be constant default values for a group of people (e.g. rest condition [2–5] and summer clothing [2,3,6]), thus missing the opportunity to accommodate comfort variation due to clothing and metabolism. Multiple tables were created to map the metabolic rate and clothing conditions based on occupants activity level and clothing styles [7,8], however, as most buildings don't include any measurement feedback loop from the occupants, one level of activity (metabolism) and one clothing insulation of the occupants is assumed.

Much recent work has adapted variable metabolic rate in the PMV calculation. For example, in Ref. [9] the metabolic rate was accurately measured using the medical Vmax encore™ station. It was shown that the metabolic rate of an occupant would change at different ambient temperatures without any change in activity. Ref. [10] studied the effect of thermal, visual, and acoustic factors on the overall comfort. In their case study, the metabolic rate and clothing values were considered by observation and in reference to metabolic rate and clothing tables. High cost and relying on human observations and surveys may limit the use of these methods to estimate metabolism in real time. In this work, we show the use of wearable devices data to provide a continuous feedback of

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occupants' metabolism value.

The PMV value can be directly calculated using a system of highly nonlinear and iterative equations, which were later adapted in the ASHRAE Standard 55 [8]:

$$PMV = \left(0.028 + 0.3033e^{-0.036M}\right) \times L \tag{1}$$

$$\begin{aligned} L = {} & (M - W) - 3.05 \times 10^{-3}(5733 - 6.99(M - W) - Pa) \\ & - 0.42(M - W - 58.15) \quad - \ 1.7 \times 10^{-5}(5867 - Pa) \\ & - 0.0014M(34 - t_a) - f_{cl}h_c(t_{cl} - t_a) \quad - 3.96 \\ & \times 10^{-8} f_{cl}\left[(t_{cl} + 273)^4 - (\bar{t}_r + 273)^4\right] \end{aligned} \tag{2}$$

where L defines the overall heat transfer around a single occupant in W/m^2, M is the metabolic rate in W/m^2, W is the work emitted by the occupant in W/m^2, Pa is the water vapor pressure, $\bar{t}_r$ is the mean radiant temperature in °C, t_a is the air temperature in °C, f_{cl} is the clothing insulation factor defined as the percentage of the total body surface area covered by clothing, I_{cl} is the clothing insulation in CLO and h_c is the convective rate heat transfer coefficient in $W/m^2\,K$ given by:

$$h_c = \begin{cases} 2.38(t_{cl} - t_a)^{0.25}, if \ \ 2.38(t_{cl} - t_a)^{0.25} > 12.1\sqrt{V} \\ 12.1\sqrt{V}, \ if \ \ 2.38(t_{cl} - t_a)^{0.25} > 12.1\sqrt{V} \end{cases} \tag{3}$$

where V is the air velocity in ms^{-1}, and t_{cl} is the clothing temperature in °C, which can be calculated based on the conditions of the body using the following simple heat balance equation:

$$\begin{aligned} t_{cl} = {} & 35.7 - 0.028(M - W) - 0.155I_{cl}\Big\{3.96 \times 10^{-8} \\ & \times f_{cl}\left[(t_{cl} + 273)^4 + (\bar{t}_r + 273)^4\right] + f_{cl} \times h_c(t_{cl} - t_a)\Big\} \end{aligned} \tag{4}$$

A heat balance approach is adapted in the PMV model to infer human thermal comfort [1]. For example, Equations (1) and (2) were obtained by balancing the following heat modes: (1) heat generation due to metabolism $(M - W)$, (2) heat transfer by convection $0.0014M(34 - t_a)$, (3) heat transfer through the skin $3.05 \times 10^{-3}(5733 - 6.99\,(M - W) - Pa)$, (4) heat transfer through latent respiration $1.7 \times 10^{-5}(5867 - Pa)$, (5) heat transfer by dry respiration $0.0014M(34 - t_a)$, and (6) heat transfer by radiation $3.96 \times 10^{-8} f_{cl}[(t_{cl} + 273)^4 - (\bar{t}_r + 273)^4]$. Also in equation (2), clothing temperature is estimated based on the heat generated by metabolism and heat transfer by way of convection and radiation. To solve for the clothing temperature t_{cl} in equation (4), ASHRAE incorporated an iterative process to continuously update the clothing temperature until the difference between the current and previous iteration is within a predefined margin.

Evaluating PMV equations is computationally intensive and requires iterative processes. Hence, many approximations were made. For example, in Ref. [3], an artificial neural network (ANN) model was employed to capture the dynamics of the PMV model equations and then use them to evaluate the PMV value for any given thermal parameters set. Also, Zhang and You [11] introduced a sequential approximation to nonlinear equations, not only to simplify the calculation but also to find the "air temperature, relative humidity" pair that leads to maximum energy savings (inverse problem solution).

Most human comfort research work has focused on studying the comfort effect of air temperature, which is widely accepted as the most important parameter in thermal comfort models, coupled with a few other environmental factors, such as air velocity and relative humidity [8]. Less work has dealt with the effects of comfort and sensitivity to metabolism and clothing, which are personal parameters. This may reflect the fact that personal parameters are underestimated, or difficult to quantify and measure. In fact, metabolism and clothing thermal resistance play a vital role in defining the optimal thermal comfort conditions. While metabolism increases the rate of heat generation in the human body and decreases the desirable comfort temperature, clothing helps to tolerate colder conditions. Assuming clothing and metabolism to be constant values may lead to a false PMV calculation.

Focus in this paper will be given to metabolism and its direct effect on the PMV model. MET is the unit of metabolism in the PMV model. A single MET is equivalent to the heat a body produces while it inhales 3.5 ml of oxygen (O_2) per kg of weight each hour (H); ($\frac{ml\ O_2}{Kg.\ H}$) [12]. Also, MET can be thought of as multiples of the resting metabolic rate for the occupant while he or she is engaged in a physical (or mental) activity [13]. Accurate measurement of metabolism requires knowing the amount of oxygen the body inhales or the amount of carbon dioxide and nitrogen waste were produced from the cellular breathing process [14]. This task is not trivial, as it involves using devices such as mask calorimeters to measure the gas intake and outtake. Other devices can also be used to estimate the metabolic rate, such as pedometers, load transducers (also known as foot-contact monitors), accelerometers, and heart rate monitors. Those sensors individually provide an indirect estimate of the metabolic rate and often result in numerous errors. Recent advancement in smart wearable devices has made it possible to fit most of these sensors into a single smart band, thus allowing an accurate and continuous estimation of the metabolic rate. In this paper, in order to estimate the metabolic rate, we will use the Fitbit Charge HR™ smart wearable device that is equipped with a pedometer, an accelerometer, and a heart rate sensor.

In this work, we first conduct a parametric study for the various PMV environmental and personal parameters and highlight the PMV model sensitivity to these parameters. Next, we focus on the use of a wearable fitness device to acquire the metabolic rate for occupants during normal life activities. The organization of this paper is as follows. In Section 2, we simulate the PMV parameters interaction and their effect on the comfort zone using multi-dimensional plots. Next, in Section 3, we monitor the metabolic rate of two occupants for a day and identify those errors that could result from taking the MET value as a constant value. In Section 4, we summarize the paper and provide some conclusions. Finally, in Section 5 we introduce some of our ongoing and future work for the use of wearable device data in the development of personalized comfort mode.

2. Parametric studies of the PMV parameters and their effects on the comfort zone

There has been an increasing interest in studying the combined effect of temperature, humidity, and air velocity on PMV values, but less attention has been paid to the effect of metabolism and clothing. In this section, we follow a general approach in studying the interaction of these factors. First, we plot and discuss multiple areas of comfort under the 10% dissatisfaction criteria, i.e., PMV value is between −0.5 and 0.5, while varying the thermal comfort parameters (including the personal parameters) a pair at a time. Then, we construct plots showing comfort zones as a surface while varying three different PMV parameters. In the remainder of this paper, unless otherwise stated, the radiant temperature is assumed to be equal air temperature [3,15], and any parameter that does not vary in the simulation is assumed to be constant as follows: clothing = 0.65 CLO (clothing condition), relative humidity (RH) = 50%, MET = 1.0 [3,4](metabolism conditions), and air velocity = 0.5 ms^{-1}.

2.1. Parametric study and interactions of environmental thermal conditions

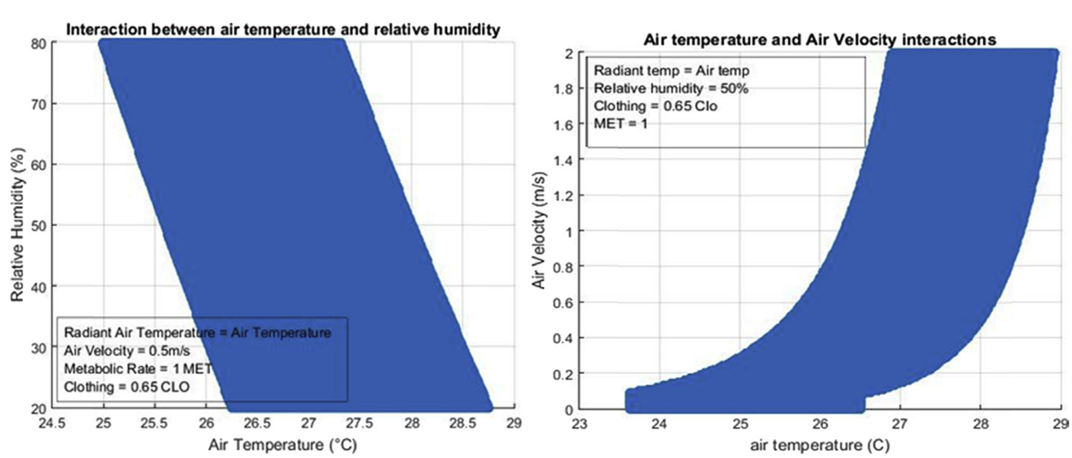
The comfort area (PMV value is between −0.5 and 0.5) as a function of temperature and humidity is depicted as a trapezoid in Fig. 1(a). This plot can be used to explain the relative humidity effect on comfort. On a dry (low humidity) day, air has extra capacity to hold water compared to moist (high humidity) day. Hence, a body, through evaporative and latent respiration cooling, can lose heat faster, thus making it feel colder at the same ambient temperature. This phenomenon explains, for example, why in Fig. 1(a) the pair ($t_a = 28°\mathrm{C}$, RH = 30%) lies within the comfort zone, while the pair ($t_a = 28°\mathrm{C}$, RH = 60%) does not. For the same reason, high relative humidity means high vapor content in the air. Hence, the generated heat from a human body is trapped and cannot be rejected to the surrounding air by evaporative cooling. Fig. 1(a) can be used as a guideline for a thermostat logic to maintain occupants' comfort based on temperature and humidity control.

Air velocity helps in maintaining comfort at high temperatures by increasing the heat-rejection rate through force convection. Fig. 1(b) shows the comfort zone as a function of air velocity and temperature. It is apparent from this figure that an occupant might tolerate higher temperatures as the air velocity increases. For example, even though the air temperature of 28.5°C is considered to be uncomfortable for all possible relative humidity values above 30%, as shown in Fig. 1(a), it is within the comfort zone once the air velocity exceeds $1.^{5\ \mathrm{ms}^{-1}}$. This argument necessitates the need for a 4D plot showing the comfort domain (fourth dimension) as a function of humidity, temperature, and air velocity, as shown in Fig. 2(a). This plot shows the humidity-temperature trapezoid comfort area shift to the left (higher temperature) as air velocity increases. Fig. 2(a) was obtained by merging at least three 3D plots, shown in Fig. 2 (b), (c), (d), that simulate the multiple three parameters pairs' combination on the PMV value.

2.2. Parametric study and interactions of environmental thermal and personal parameters

Fig. 3(a) shows the comfort zone area as a function of temperature and clothing, indicating that the comfort zone is very sensitive to clothing. An interesting extremely high sensitivity is noticed when CLO is around 0.5. This value lies between 0.36 CLO, the CLO value of wearing a short-sleeved shirt and shorts, and 0.57 CLO, the CLO value of wearing a short-sleeved shirt with trousers. This behavior occurs around a clothing point where a comfortable human body changes from a hot to cold feeling. However, this behavior could be due to the use of two discrete equations in the PMV model to calculate the 'clothing area factor'. Fig. 3(a) confirms the naive observation that two people under similar thermal conditions can feel differently because of their clothing. More specifically, higher clothing values make the body tolerant to lower temperatures. For example, an occupant at 17°C air temperature and 2 CLO is predicted to be comfortable. This is true because clothing partially isolates the human body and helps to decrease the rate of heat rejection to the outside. On the other hand, high CLO values can quickly move a person out of his/her comfort zone at mild/high temperatures. In that case, body heat becomes trapped inside, creating an extreme feeling of warmth and thermal dissatisfaction. Fig. 3(a) also shows that low CLO values result in people tolerating higher ambient temperatures and being very sensitive to mild ambient temperatures. For example, at 0.4 CLO, a human body can tolerate an ambient condition of over 30°C air temperature and humidity ratio of 50%, but the same body can feel cold with ambient temperatures under 28°C. From this discussion, it can be concluded that clothing is very critical to thermal comfort and should not assumed in a building to be a constant.

Metabolism is related to heat generation in the human body. As the metabolism (MET) of an occupant increases, the heat generation rate of his/her body increases, leading to a warmness sensation. Metabolism is one of the personal factors in the PMV model that is difficult to estimate and is usually assumed to be constant in most proposed PMV comfort model applications. In a perfect world and if metabolism is measured, a heating, ventilation, and air-conditioning (HVAC) system needs to compensate for an increase in the metabolic rate by controlling the ambient environmental conditions such as decreasing the air temperature, increasing the air velocity, or reducing the relative humidly. Fig. 3(b) shows the comfort zone as a function of metabolic rate in METs and air temperature. As expected, the figure shows better comfort results at low air temperature as the metabolic rate increases. This can be explained by the fact that lower ambient temperatures are needed to reject the internal heat through natural or forced convection. At a high metabolic rate, the body is highly intolerant to high and even mild temperatures. For example, as shown, at a metabolic rate of 1.5 MET, an occupant is thermally uncomfortable at 26 °C, a temperature that is well within the comfort zone with a metabolic rate of 1.0 MET. This 1.0 MET, according to ASHRAE Standard 55 tables, is the metabolic equivalent of a person sitting at rest without



(a) (b)

Fig. 1. Interaction of air temperature: (a) with relative humidity, (b) with air velocity, and resultant comfort zones.

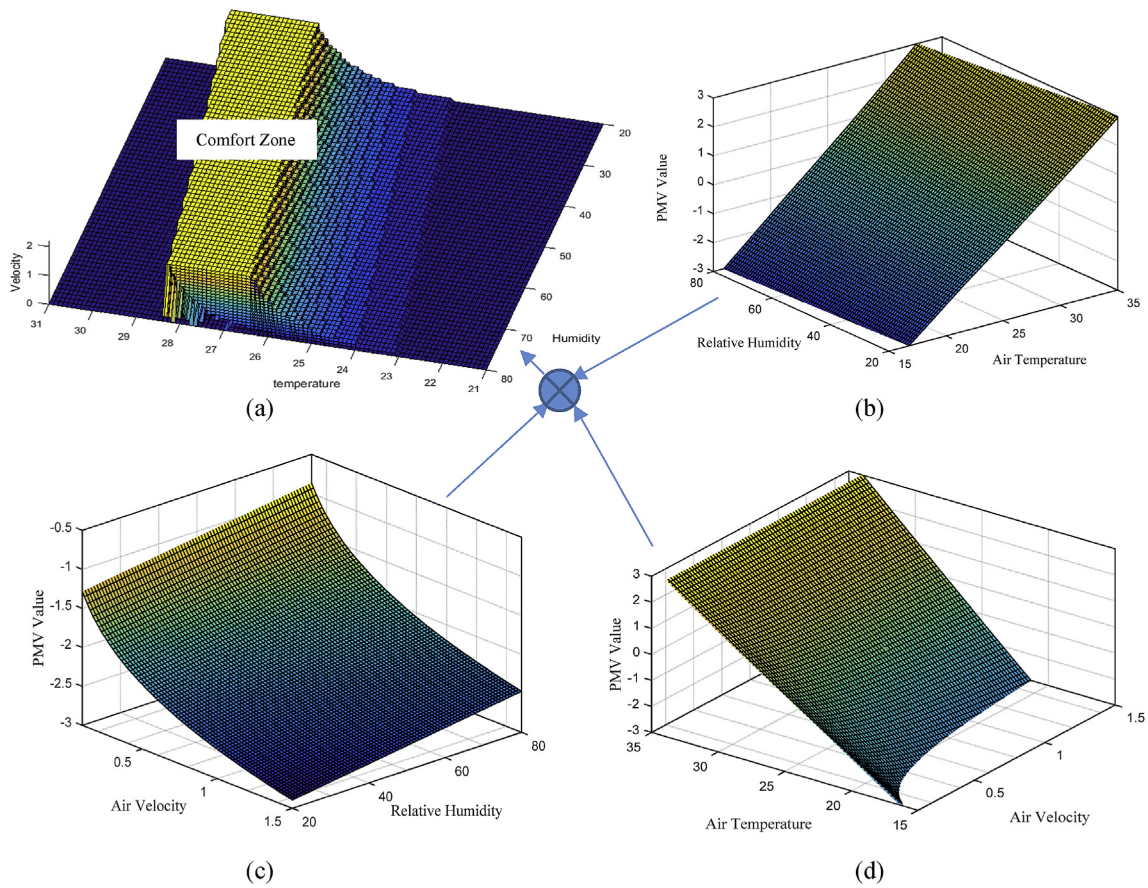


Fig. 2. (a) 4D plot of interaction between air temperature, humidity, and air velocity, and resultant comfort zone. In this plot, the surface represents all points where the PMV value is between −0.5 and 0.5 (comfort zone) and its color is insignificant, (b), (c), (d) are 3D plots that were used to generate the 4D plot, simulating all three parameters pairs' combination on the PMV value.

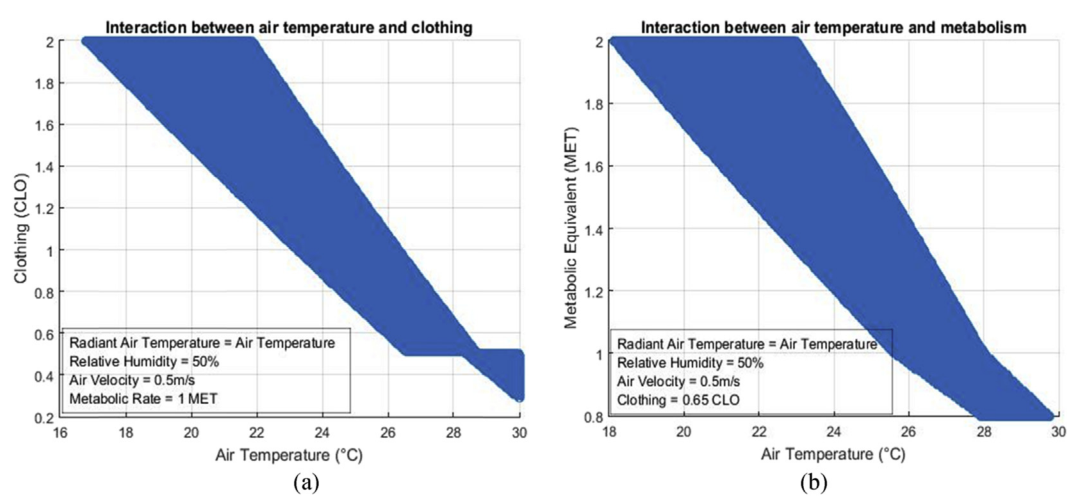


Fig. 3. Interaction of air temperature: (a) with clothing, (b) with air metabolism, and resultant comfort zone.

engaging in any physical and mental activities, and is widely accepted to represent metabolism in the PMV equations when they are used to model comfort in buildings [3,4]. In this paper, however, we show the use of smart wearable devices to accommodate building occupants' metabolic rate variation in the PMV model calculation.

Fig. 4(a) shows the metabolism from a different angle, by displaying its interactions with air temperature and relative humidity. As the metabolic rate increases, the body requires a means to reject the heat/gain cooling in order to stay thermally comfortable. One option is to lower the relative humidity (i.e., air has the capacity to absorb water vapor) in order to provide more cooling through latent respiration and/or sweating. Another option is to increase the heat-rejection rate due to radiation, convection, and

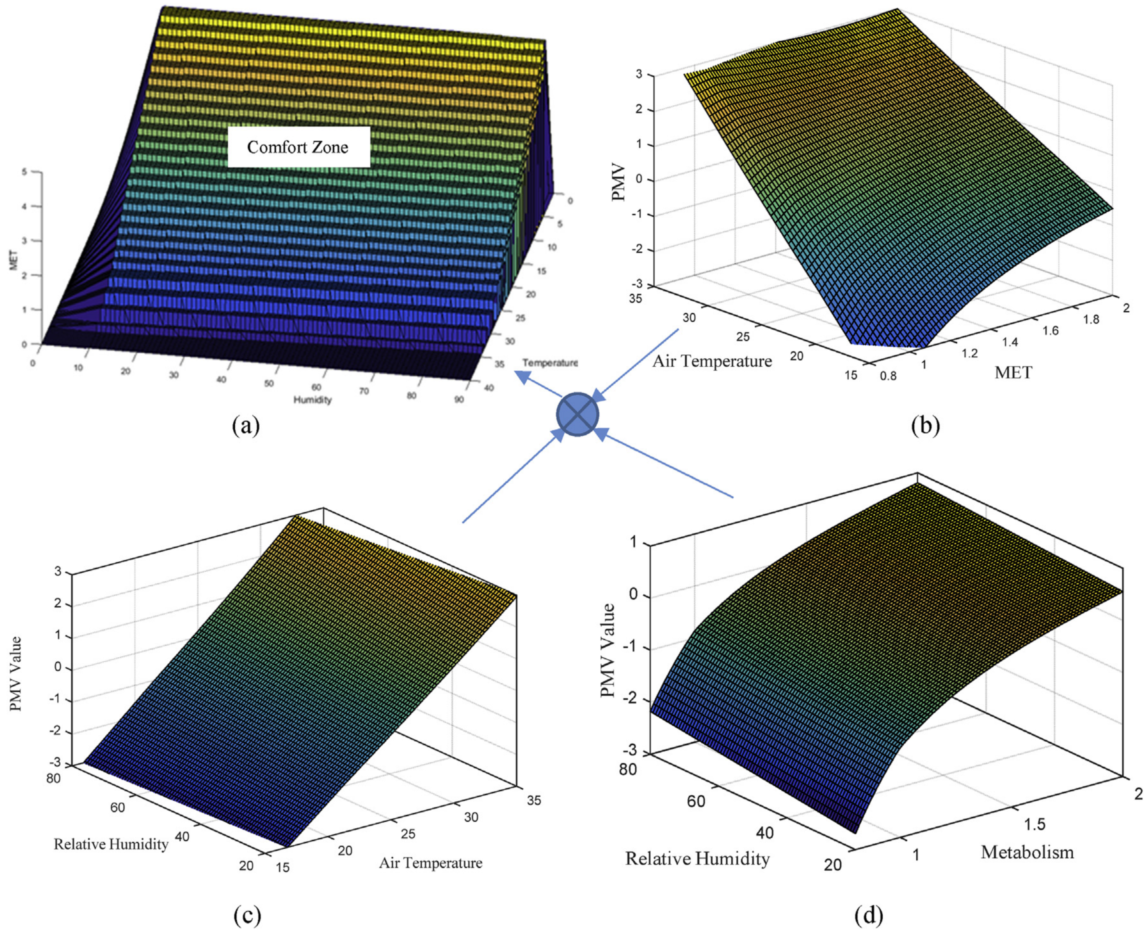


Fig. 4. (a) 4D plot of interaction between air temperature, humidity, and metabolism, and resultant comfort zone. In this plot, the surface represents all points where the PMV value is between −0.5 and 0.5 and its color is insignificant, (b), (c), (d) are 3D plots that were used to generate the 4D plot, simulating all three parameters pair's combination on the PMV value.

dry respiration by lowering the ambient temperature. The generated comfort surface shows a very high sensitivity to metabolism compared to relative humidity and temperature (i.e., surface gradient is higher in MET axis than in direction of relative humidity axis). The sensitivity analysis is discussed in great details in the next section. The low-curve gradient in the direction of the relative humidity axis may reflect the fact that sweating and latent respiration alone are not fast enough to reject heat from the body at a higher metabolic rate.

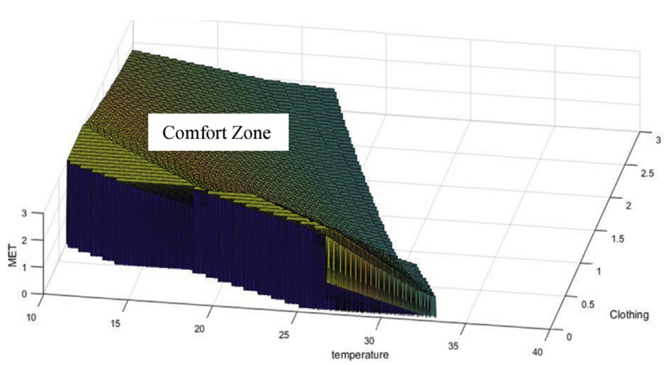


Fig. 5. Comfort region surface relating to interaction between air temperature, clothing, and the metabolic rate.

We close our discussion by presenting Fig. 5, which indicates the effects of varying air temperature, clothing, and metabolism on the comfort zone. In general, this figure shows that metabolism has a larger effect on an occupant's thermal sensitivity comfort compared to clothing. However, as shown in Fig. 3(a), the effect of clothing is more dominate for lower CLO values.

2.3. Sensitivity analysis of the PMV environmental thermal and personal parameters

In this section we study the PMV sensitivity to its thermal and personal parameters. Sensitivity is defined as the partial change in a dependent variable (PMV value) due to the change in one of its independent variables. Mathematically, it is defined as:

$$S_x[f(x,y,z)] = \frac{\partial f(x,y,z)}{\partial x} \tag{5}$$

where S_x is the sensitivity with respect to parameter x, the independent variable. Forward finite difference equation is used to numerically evaluate the partial derivative as follows:

$$f'(x_i) = \frac{(f(x_i) - f(x_{i-1}))}{x_i - x_{i-1}} \tag{6}$$

Sensitivity gives a good indication about the magnitude of change in the PMV model value relative to one of its parameters.

Some of the lowest-hanging fruit of this analysis, from an energy perspective, is the determination of the most effective control parameters to achieve comfort in a building.

A complete sensitivity analysis for the PMV model is very complex due to the strong interaction between its parameters and is beyond the scope of this paper. Focus will be given to PMV sensitivity to metabolism. Fig. 6 shows 3D plots for the PMV sensitivity to the metabolism value at different air temperature values (Fig. 6(a)), different clothing values (Fig. 6(b)), different air velocity values (Fig. 6(c)), and different humidity values (Fig. 6(d)). Fig. 6(a), for example, was obtained by applying the partial derivative Equation (6) over the data in Fig. 4 b. The figures demonstrate that the PMV sensitivity to metabolism is not constant and it varies according to the following observations: (1) PMV value is more sensitive to metabolism at lower metabolism values, (2) PMV sensitivity to metabolism decreases at higher clothing and air temperature values, (3) humidity and air velocity has the least impact on the PMV sensitivity to metabolism. For more illustration

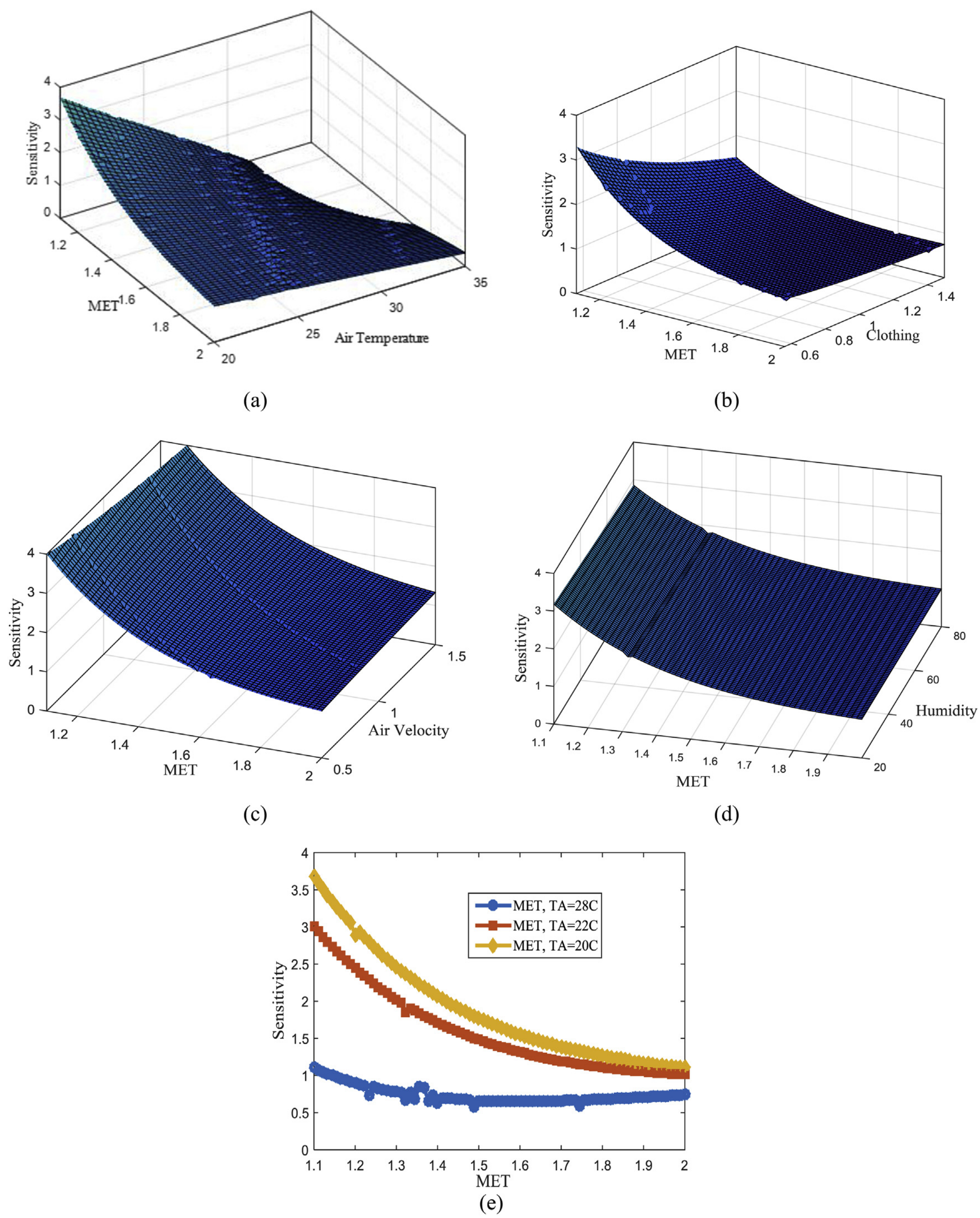


Fig. 6. 3D plots for the PMV sensitivity to the metabolism value at different (a) air temperature, (b) clothing conditions, (c) air velocity, (d) humidity values, and (e) shows 2D slices of the PMV sensitivity to metabolism at air temperature (AT) = 20, 22, and 28C. The plot shows higher PMV sensitivity to metabolism at lower metabolism values and low ambient temperatures.

on observations 1 and 2, we show multiple 2D slices of Fig. 6(a) at different air temperature values in Fig. 6(e). Fig. 6(e) shows that a sensitivity up to 3.5 MET^{-1} (i.e. one MET difference can cause up to 3.5 change in the PMV scale) can be obtained at air temperature = 20C° at low MET values compared to 1.4 MET^{-1} at higher MET values. Moreover, the same figure shows that the sensitivity is around 1.0 MET^{-1} even for low MET values when air temperature = 28 C°. It should be noted here that PMV calculations will yield exaggerated results at high metabolic rates due to heat compensation by sweating as shown by Ref. [16].

Fig. 7 compares the PMV model sensitivity against five of its parameters (metabolism, air velocity, humidity, clothing, and air temperature). For each parameter, the sensitivity was calculated while the rest of the parameters were held at the constant default values that were listed at the beginning of the paper.

Due to clothing discontinuity issues around 0.5, the PMV sensitivity to clothing were plotted only for clothing values above 0.55. The figure confirms our early conclusion that PMV model is highly sensitive to the personal parameters. Moreover, the figure shows a very interesting behavior. The absolute PMV sensitivity value (PMV sensitivity to air velocity has the only negative sign as an air velocity increase (cooling effect) should reduce the PMV value) exponentially converges for all parameters, but not humidity and air temperature, to a low value as the PMV parameters increases. Air temperature and humidity are the only two parameters that the PMV sensitivity to them almost hold constant. Worth to mention that the sensitivity values in the figure represent the rate of change of the PMV value rather than the actual PMV value. Hence even the figure shows a very small constant sensitivity value for humidity (~0.007 RH^{-1}), over the full expected humidity range (0%–100%) the PMV value changes by up to 0.7. This value is way much less than the expected change of the PMV value of 5.78 over air temperature range of (15 C°- 32 C°), assuming an average PMV sensitivity to air temperature of 0.34°C^{-1}. 5.78 is almost near the full range of the PMV scale '6'. In other words, changes in air temperature by itself can drive the thermal sensation of an occupant from very cold to very hot. We close our PMV model sensitivity analysis with Table 1, where summarized the PMV sensitivities to its parameters in Fig. 7 are averaged and summarized.

3. Metabolism estimation using smart wearable device

Metabolism is difficult to measure and is usually assumed to be a constant value for occupants in a building (e.g. rest condition [3]). However, due to the ever-increasing popularity and advancement of wearable fitness devices, the estimation of metabolism becomes much easier and more convenient. In this paper, we have used Fitbit Charge HR™ band data to estimate metabolism as a case study. Recent Fitbit® wearable devices were shown to have an accuracy level up to 95% [17]. However, other wearable devices with more sensors and that are known to have higher accuracy could be used instead in this investigation. Fitbit® can be easily configured to share the metabolic rate, heart rate, and activity level of occupants to a computing unit in real time. These pieces of information are updated every minute to enable, if needed, a fast response. However, to accommodate that the PMV model was designed assuming steady thermal conditions, a simple averaging was applied on these measurements.

3.1. Fitbit® metabolism calculation

The metabolism of a Fitbit® user is calculated as a multiple of the basal metabolic rate (BMR), which is defined as the minimum rate of energy expenditure per unit time by an endothermic human at rest [18]:

$$BMR = \left(\frac{10m}{1\ Kg} + \frac{6.25h}{1\ cm} - \frac{0.5a}{1\ year} + s\right)\frac{Kcal}{day} \tag{7}$$

where m is the mass of the body in kilograms, h is the height of the body in cm, a is the age in years, and s is a factor relating to sex, as follows:

$$s = \begin{cases} +5 & for\ \ males \\ -161 & for\ \ females \end{cases} \tag{8}$$

Fitbit® also uses a built-in accelerometer to infer the activity level of the wearer [2]. It uses this information to calculate the estimated the wearer's energy requirement (EER), which is related to the age, sex, weight, height, and physical activity of the user. For males, the EER is

$$\text{EER} = 864 - 9.72\ \ a(years) + PA(14.2\ m(kg) + 503\ \ h(meters)) \tag{9}$$

and for females, the EER is

$$\text{EER} = 387 - 7.31\ a(years) + PA(10.9m(kg) + 660.7h(meters)) \tag{10}$$

where PA is the physical activity level that is related to the motion of the person and is measured by Fitbit®'s built-in accelerometer as well as the physical properties of the wearer. The PA is calculated

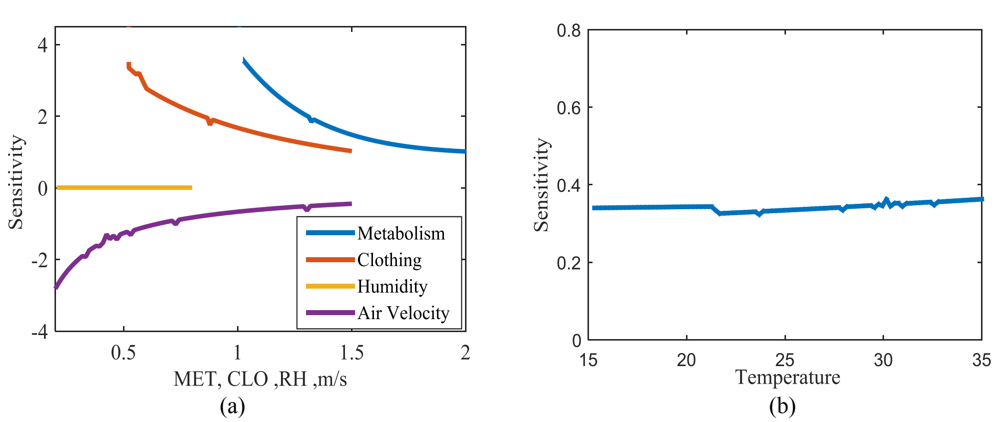


Fig. 7. PMV model sensitivity to (a) metabolism, air velocity, humidity, and air temperature, (b) and to air temperature. The figure show that PMV model is very high sensitive to the personal parameters, and its sensitivity to metabolism, clothing, and air velocity, changes with these parameters values and hold constant for air temperature and humidity.

Table 1
PMV sensitivities to its parameters summary obtained from Fig. 7.

Parameter		Sensitivity (mean)	Sensitivity (range)
Air temperature (t_a)		$S_{AT} \cong 0.34°C^{-1}$	0.04
Humidity (RH)		$S_{RH} \cong 0.007\ RH^{-1}$	~0
Clothing (CLO>0.5)		$S_{CLO} = 1.3\ CLO^{-1}$	1.22
Clothing (CLO<0.5)		$S_{CLO} = 5.53\ CLO^{-1}$	2.8
Air velocity ($V > 0.5$)		$S_{AV} = -0.72\ m^{-1}s$	0.87
Air velocity ($V < 0.5$)		$S_{AV} = -2.2\ m^{-1}s$	2.9
Metabolism ($MET > 1$)	$t_a = 20\ °C$	$S_{MET} = 2.09\ MET^{-1}$	3.37
	$t_a = 22\ °C$	$S_{MET} = 1.6\ MET^{-1}$	2.0
	$t_a = 28\ °C$	$S_{MET} = 0.79\ MET^{-1}$	1.25

for men as [19].

$$PA = \begin{cases} 1\ , & 1.0 < PAL < 1.4\ (Sedentary) \\ 1.12, & 1.4 < PAL < 1.6 (Low\ \ active) \\ 1.27, & 1.6 < PAL < 1.9 (Active) \\ 1.54, & 1.9 < PAL < 2.5 (Very\ \ active) \end{cases} \tag{11}$$

and for women as

$$PA = \begin{cases} 1\ , & 1.0 < PAL < 1.4 (Sedentary) \\ 1.14, & 1.4 < PAL < 1.6 (Low\ \ active) \\ 1.27, & 1.6 < PAL < 1.9\ (Active) \\ 1.45, & 1.9 < PAL < 2.5 (Very\ active) \end{cases} \tag{12}$$

$$PAL = ((I-1)[(1.15/0.9) \times D(minutes)]/1440))/(BEE/[0.0175 \times 1440 \times w(kg)]) \tag{13}$$

where I and D are the activity intensity (inferred from heart rate and accelerometer measurements) and duration, respectively, and BEE is the basal energy expenditure, given by

$$BEE = \begin{cases} 2933.8 \times a(years) + 456.4 \times h(meters) + 10.12 \times w\ (kg), Men \\ 2472.67 \times a(years) + 401.5 \times h(meters) + 8.6 \times w(kg),\ \ Women \end{cases} \tag{14}$$

Once EER and BMR are calculated, the metabolic can be calculated as

$$MET = \frac{EER}{BMR} \tag{15}$$

From Equation (15), MET is actually the ratio between the energy generated while performing some activity to the rest of the body's metabolic rate. This MET is used to estimate the amount of calories burned by the human within the equation of the PMV model. Next, we show results for MET values monitored over time for two occupants.

3.2. Data capturing using Fitbit

The Fitbit sensor data are stored in Fitbit cloud service after synchronizing the wearable device with a pair device (e.g. mobile or PC). The OAuth 2.0 protocol, supported by the Fitbit cloud service, was used to connect to the Fitbit cloud service. To accesses the Fitbit data, an application was built using the Flask micro framework. Flask is a python library to implement a lightweight micro framework based on Werkzeug and Jinja2. This implementation is accessible via every Internet browser. A user may initiate, using the application, a data request that is then forwarded to Fitbit cloud page for authentication. After a successful authentication, a callback service in flask will be triggered to request the data. Finally, a link to the extracted data as a comma-separated value file (CSV) would be shown on web page. These steps are summarized in Fig. 8 and could be applied simultaneously for a group of occupants in a building to arrive to an average metabolism value that can be used in the PMV calculation.

3.3. Monitoring metabolic rate during normal day activates

In this section, we investigate the effect of metabolism on the comfort level for building occupants while performing normal life activates. As a proof of concept, a simple experiment was conducted on a 22-year-old and 35-year-old male graduate students for more than a half day. These students were asked to carry a wireless HOBO MA1101 data logger to record their indoor environmental conditions (ambient temperature and humidity) while wearing a Fitbit® device to monitor their heart rate, activity level, and rate of caloric consumption per minute. Moreover, the students were asked to mark their clothing status through a smart phone application. The Fitbit wearable device data, the HOBO data, and the clothing status were all joined using a python based application. These data were used to determine the students PMV values every minute and then averaged for each 30 min. In this experiment, the two students were asked to perform similar normal life activities while working at office or at home. More experiments are planned to involve bigger human subject experiment size and to compare accuracy between different wearable devices.

Fig. 9(a) and (b) show plots for the measured MET values using the Fitbit® device along with the corresponding PMV value and the assumed PMV value (i.e., using a constant metabolic rate of 1.0 MET [2–5]). These plots show that the MET value keeps changing throughout the entire day. For example, in Fig. 7(a), for the younger student, the metabolic rate was consistently over 1.0 MET throughout the entire day, the lowest being 1.09 around 1:00 p.m. Even at its lowest value, the metabolic rate was higher than the assumed value of 1.0 MET. The figure also shows a very large increase in the MET value, and consequently PMV value, during the student's study-hours at home between (3:00 p.m.–5:00 p.m.) and (7:00 p.m.–9:00pm), while it decreases during the student's relax hours between (5:00 p.m. and 7:00 p.m.). Throughout most of the

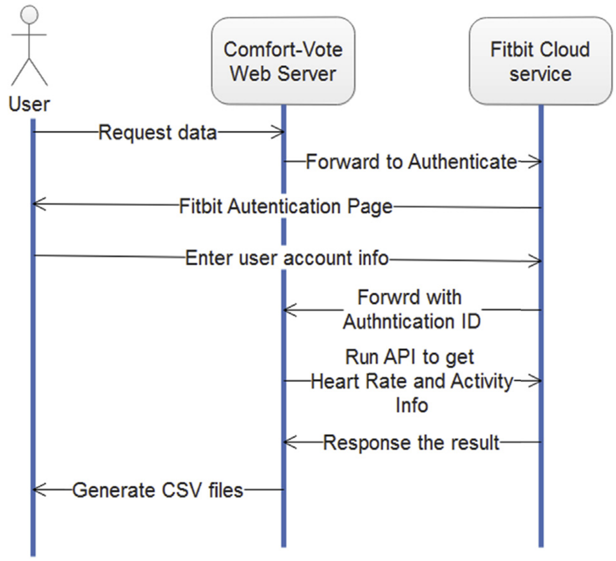


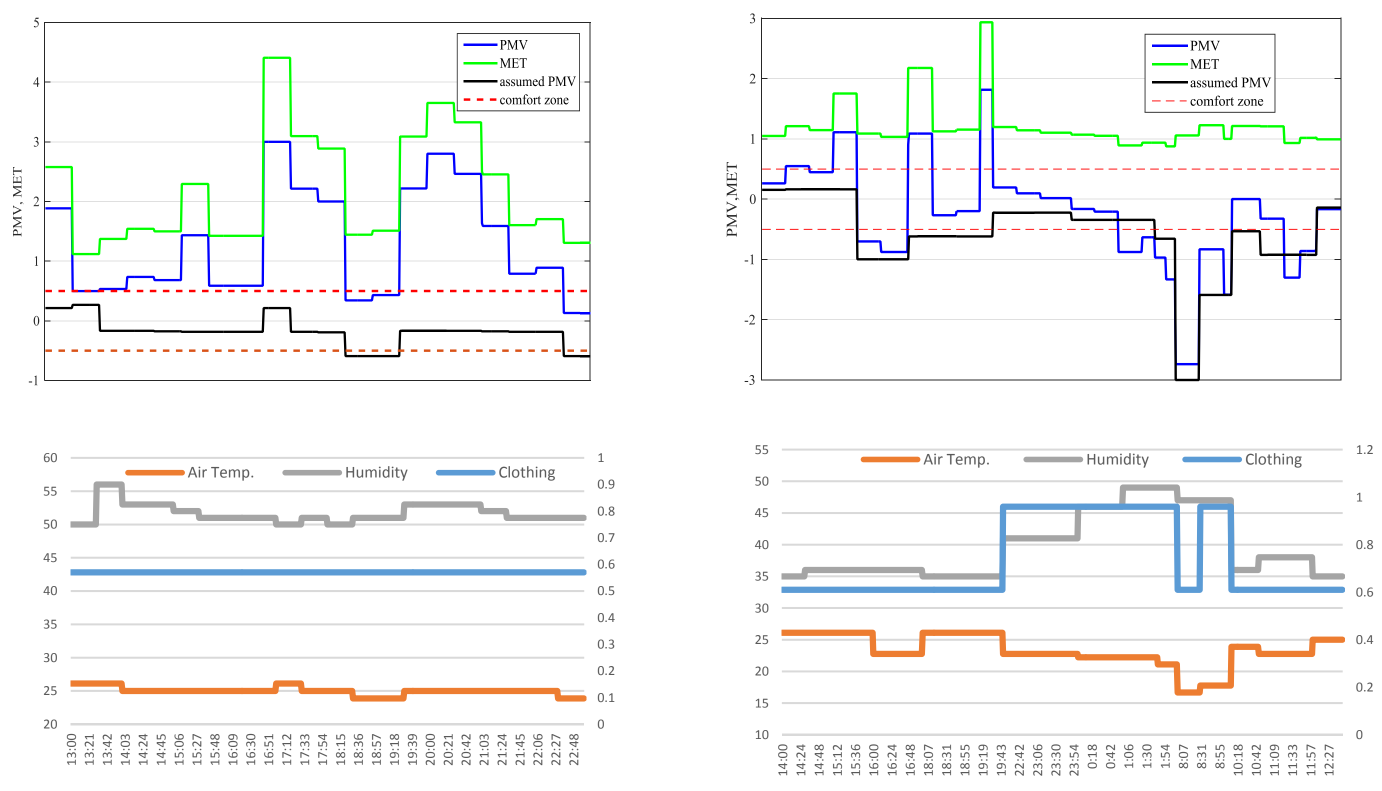
Fig. 8. A chart explains the built application processes to accesses Fitbit data.

studying period, the student was thermally dissatisfied, feeling hot, with an average PMV value of 2.5, while the assumption is that he should be comfortable with a PMV value of less than −0.2 (assuming a constant MET value of 1.0). Even though the student was not involved in physical labor, the plots show that mental work and simply standing and walking around seem to increase the MET value to an average of greater than 3.0. From our earlier findings about the PMV model's high sensitivity to metabolism, as shown previously in Figs. 4 and 5, this should explain the very large error between the assumed and actual PMV calculation.

Fig. 9(b) shows similar higher metabolic rate during daily normal activities for the 34-year-old student. These activates include typing (office) and eating (home). The figure shows that the MET value was sometimes less than 1.0 at complete rest (sleeping). Fig. 9 confirms that not only the MET value may vary over time for an occupant, but may also vary among occupants preforming similar daily activates. Hence a single constant value, such 1 MET or any other value, can't be used to represent the metabolic value in the PMV model.

4. Conclusions

The PMV value of an occupant is calculated based on multiple thermal environment and personal parameters. While it is not a perfect model, the best case should provide an 80% accuracy level, assuming that all input parameters are accurately measured. In this study, the quantitative sensitivity of the PMV value to its parameters is defined. We show that the effect of the personal parameters far exceeds that of the environmental factors within the normal parameter ranges. The PMV model simulation analysis performed in this work can help to prioritize measurements with the highest sensitivity. For example, the relative humidity has low thermal comfort sensitivity expect if it exceeds an extreme range (less than 30% and more than 60% [20,21]. Hence, humidity is rarely in need of monitoring, whereas metabolism sensitivity is much higher and



(a) 22-year-old male student (b) 35-year-old male student

Fig. 9. MET and PMV values, clothing, and indoor environmental conditions recorded for two students. The figure shows a big difference in the PMV value when the actual metabolism is used in the calculation instead of the assumed value of 1.0 MET. Also this difference is shown to be higher for the younger student. Data while students were not inside a building are ignored.

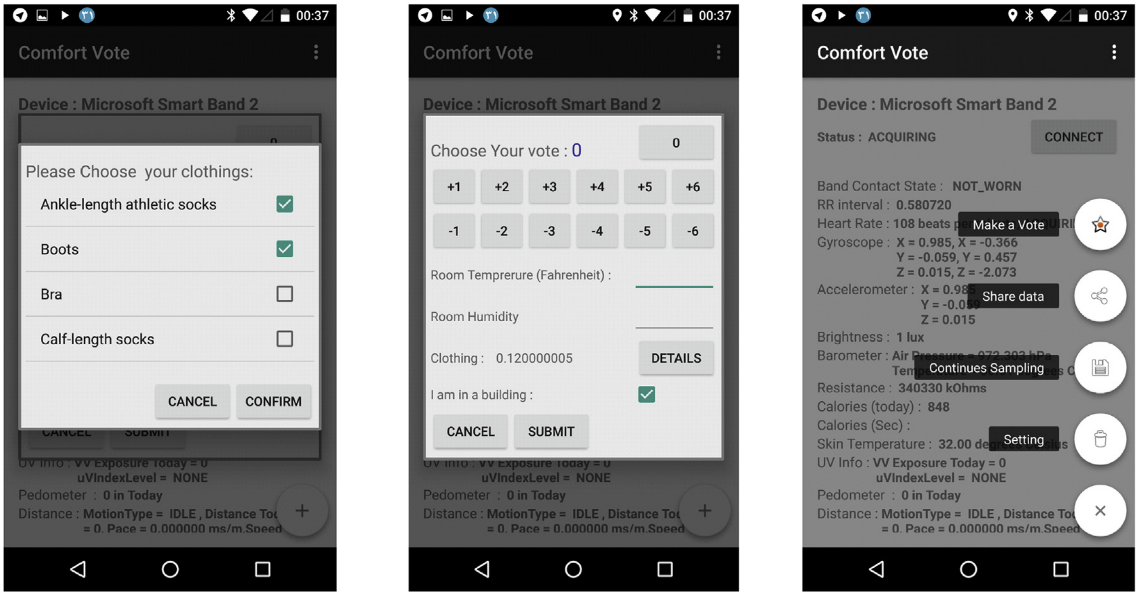


Fig. 10. Smart watch user app prototype for mobile device.

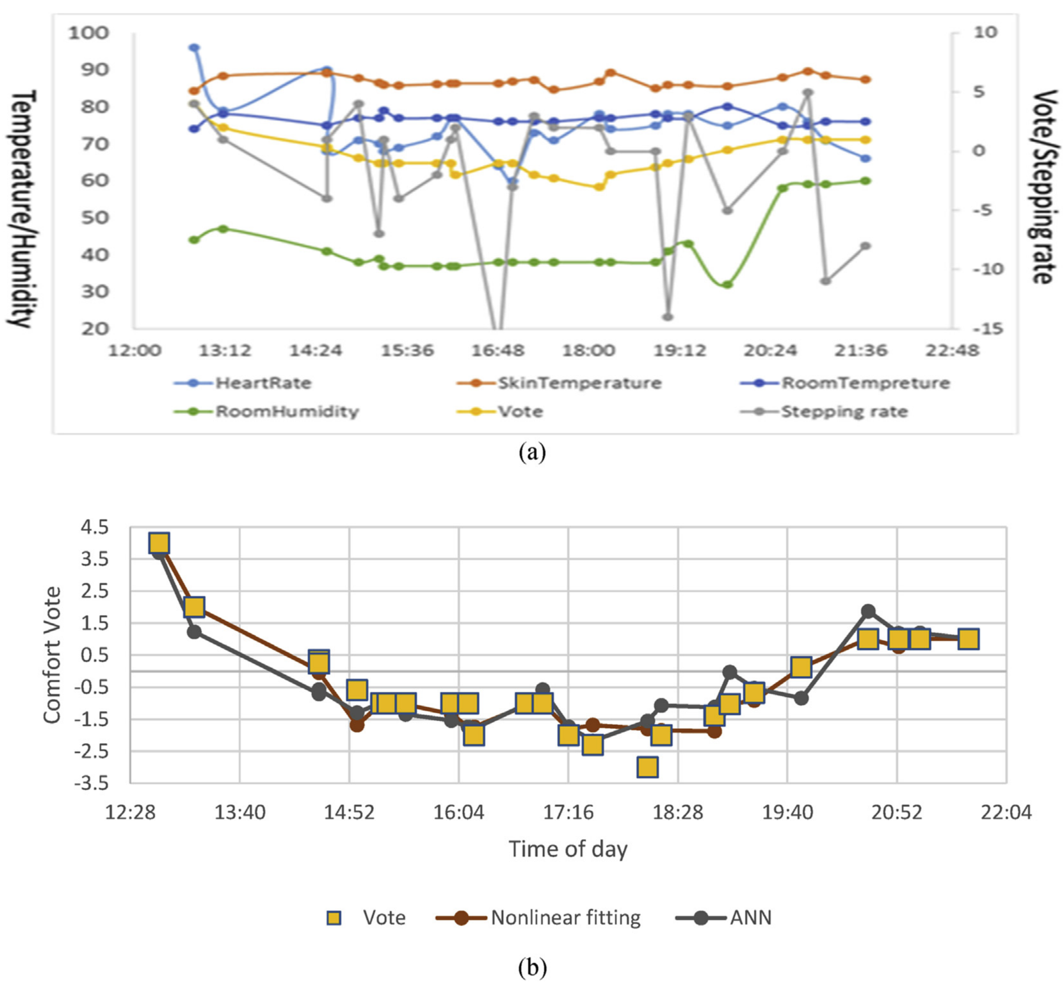


Fig. 11. (a) An occupant wearable device biometrics data along with his comfort feedback, (b) ANN Model and Non-linear fitting model compared with actual occupant vote.

needs to be closely and continuously measured to assure reliability of the PMV comfort model. The metabolic rate is continuously changing over time, even without performing any notable physical activities. For example, this paper shows that simple mental activities and doing regular tasks might lead to some increase in the MET value, which can lead to thermal discomfort.

The metabolic rate, which is assumed to be constant in real building throughout most of the literature, is now easy to estimate using wearable devices. We have shown, in our case study using a commercial wearable device, that a person who is not fully at rest will potentially have high MET value and may experience discomfort during the majority of working hours. The high sensitivity to the metabolic rate was apparent in our case study plots as the deviation between the estimated and actual PMV value is large. This shows the importance of measuring the metabolic rate in buildings to assure the reliability of the PMV model. Accurately measuring the metabolic rate of an occupant can extend the area of application of the PMV model to those who might be engaged in physical activities, such as waiters and waitresses in a restaurant, or people working out in gyms. And while it is practically impossible to make everyone comfortable, taking into account the individual differences in peoples' metabolism can help achieving the 80% true satisfaction rate that is expected from the PMV model.

5. Future work

Because the PMV model relies on steady state heat equations, it cannot be used for transient comfort computation. This further limits the use of this model. Due to the obvious limitations of the PMV model, future plans are to investigate the development of a personalized comfort model based on biometric data from wearable devices and other environment conditions such as ambient temperature and humidity. A user interface application to receive an occupant's Microsoft Smart Band 2™ biometric data and his direct feedback on comfort conditions is developed and is shown in Fig. 10. The Microsoft Smart Band 2™ was chosen due to its high accuracy and the abundance of its biometric sensors (i.e. skin temperature sensor, heart rate sensor, metabolic rate sensor, and skin resistance sensor). Fig. 11 (a) shows sample of the app collected data for an occupant. In our current study, five students were given the Microsoft Band along with the HOBO MA1101 data logger to measure temperature and relative humidity. The students were asked to share their comfort level periodically and whenever they felt thermal discomfort. The study took place over the course of summer 2016. Students' data was stored in a database for future analysis. The goal of this study is to investigate the development of a personalized comfort model for every user where the model would take into account the subjective nature of thermal comfort.

Different machine learning algorithms and nonlinear fitting are planned for training the best model to correlate the biometric data with occupant feedback. Sample preliminary work that are shown in Fig. 11 (b), shows promising results. In the figure, the two lines represent the models; a 30–1 feedforward-back-propagation artificial neural network (ANN) and a non-linear curve fitting model, and the yellow blocks are the actual occupant's vote. Issues such as model over-fitting is planned to be investigated with bigger sample test size.

Nomenclature

a	Age, years
BEE	Basal Energy Expenditure, Kcal/day
BMR	Basal Metabolic Rate, Kcal/day
D	Duration of Activity, minutes
EER	Estimated Energy Requirement, Kcal/day
f_{cl}	Clothing Factor
h	Height, cm
h_c	Convective Heat Transfer Coefficient, W/m^2 K
I	Activity Intensity
I_{cl}	Clothing Insulation, CLO
L	Overall Heat Transfer around occupant, W/m^2
M	Metabolic Rate, W/m^2
MET	Metabolic Equivalence, MET
m	mass, Kg
P_a	Partial Pressure of Water, KPa
PA	Physical Activity Level
PAL	Physical Activity Level Factor
PMV	Predicted Mean Vote
RH	Relative Humidity
S	Sensitivity, unitˆ−1
s	BMR Sex Factor
t_a	Air Temperature, °C
t_{cl}	Clothing temperature, °C
$\overline{t_r}$	Mean Radiant Temperature, °C

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