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Sensitivity Analysis for the PMV Thermal Comfort Model and the Use of Wearable Devices to Enhance Its Accuracy

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Sensitivity Analysis for the PMV Thermal Comfort Model and the Use of Wearable Devices to Enhance Its Accuracy

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ABSTRACT

This paper studies the sensitivity of the Predicted Mean Vote (PMV) thermal comfort model relative to its environmental and personal parameters. PMV model equations, adapted in the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) Standard 55–Thermal Environmental Conditions for Human Occupancy, are used in this investigation to generate two-dimensional (2D) and three-dimensional (3D) comfort zone plots for different combinations of parameters. It is found that personal parameters such as clothing and metabolic rate, which are usually ignored or simply assumed to be constant values, have the highest impact. In this work, we demonstrate the use of smart wearable devices to estimate metabolic rate. The metabolic rate for an occupant during normal life activities is recorded using a Fitbit® wearable device. This example is used to do the following: (1) demonstrate the PMV expected error range when personal parameters are ignored, and (2) determine the potential of using a wearable device to enhance PMV comfort model accuracy.

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 (1970) and later adapted into the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) Standard 55–Thermal Environmental Conditions for Human Occupancy. This model correlates multiple environmental parameters (air temperature, air velocity, relative humidity, and radiant temperature) and personal parameters (metabolism and clothing) to different levels of comfort based on a rating between –3 and 3, where –3 means the body is very cold and 3 means the body 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 constants, thus missing the opportunity to accommodate comfort variation for occupants experiencing the same environmental conditions.

The PMV value can be directly calculated using a system of highly nonlinear and iterative equations, which were later adapted in the ASHARE Standard 55 (ASHRAE, 2013):

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

$$\begin{aligned} L = {} & (M - W) - 3.05x10^{-3}(5733 - 6.99(M - W) - Pa) - 0.42(M - W - 58.15) \\ & - 1.7x10^{-5}(5867 - Pa) - 0.0014M(34 - t_a) - f_{cl}h_c(t_{cl} - t_a) \\ & - 3.96x10^{-8}f_{cl}[(t_{cl} + 273)^4 - (\bar{t}_r + 273)^4] \end{aligned} \tag{2}$$

where L defines the overall heat transfer around a single occupant, M is the metabolic rate in Watt/m^2, W is the work excreted by the occupant in Watt/m^2, Pa is the humidity level, $\bar{t}_r$ is the mean radiant temperature, t_a is the air temperature, I_{cl} is the clothing insulation factor defined as the ratio of the area of the clothed body to the area of the nude body, and h_c is 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 m/s, and t_{cl} is the clothing temperature, which can be calculated based on the conditions of the body using the following simple heat balance equation:

$$t_{cl} = 35.7 - 0.028(M - W) - 0.155 I_{cl}\,\{3.96x10^{-8} \times f_{cl}[(t_{cl} + 273)^4 + (\bar{t}_r + 273)^4] + f_{cl} \times h_c(t_{cl} - t_a)\} \tag{4}$$

A heat balance approach is adapted in the PMV model (Balaras et al., 2007) to infer human thermal comfort. 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 $3.05x10^{-3}(5733 - 6.99(M - W) - Pa)$, (4) heat transfer through latent respiration $1.7x10^{-5}(5867 - Pa)$, (5) heat transfer by dry respiration $0.0014M(34 - t_a)$, and (6) heat transfer by radiation $3.96x10^{-8} f_{cl}[(t_{cl} + 273)^4 - (\bar{t}_r + 273)^4]$. Also in equation (2), clothing temperature is estimated based on the heat generated by metabolism and heat transfer by way of conduction, convection, and radiation. To solve for the clothing temperature t_{cl} in equation (4), ASHERE 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 the work of Ku et al. (2015), 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 (2014) 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 (ASHRAE, 2013). 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. Ignoring clothing and metabolism or simply assuming them to be constant values may lead to a false PMV calculation.

The focus in this paper is on 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 per kg of weight each hour ($\frac{ml\ O_2}{Kg.H}$) (Jette et al., 1990). 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 (Institute of Medicine, 2005). It has been found that the body produces 5 Kcal/L of oxygen per inhale, meaning that a man weighing 70 kg would consume 1.2 Kcal/min if his metabolism is equal to 1 MET. Accurate measurement of metabolism requires knowing the amount of oxygen the body inhales or the amount of carbon dioxide and nitrogen waste are produced from the cellular breathing process (Ferrannini, 1990). 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® smart wearable device that is equipped with a pedometer, an accelerometer, and a heart rate sensor.

In this work, we first highlight the PMV model sensitivity to various environmental and personal parameters, and then we study their interaction. Next, we focus on the use of a wearable fitness device to acquire the metabolic rate of an occupant during multiple activities and its impact on his/her comfort level. 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 2D and 3D plots. Next, in section 3, we study the variation in MET values during different controlled physical activities. Later in that section 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.

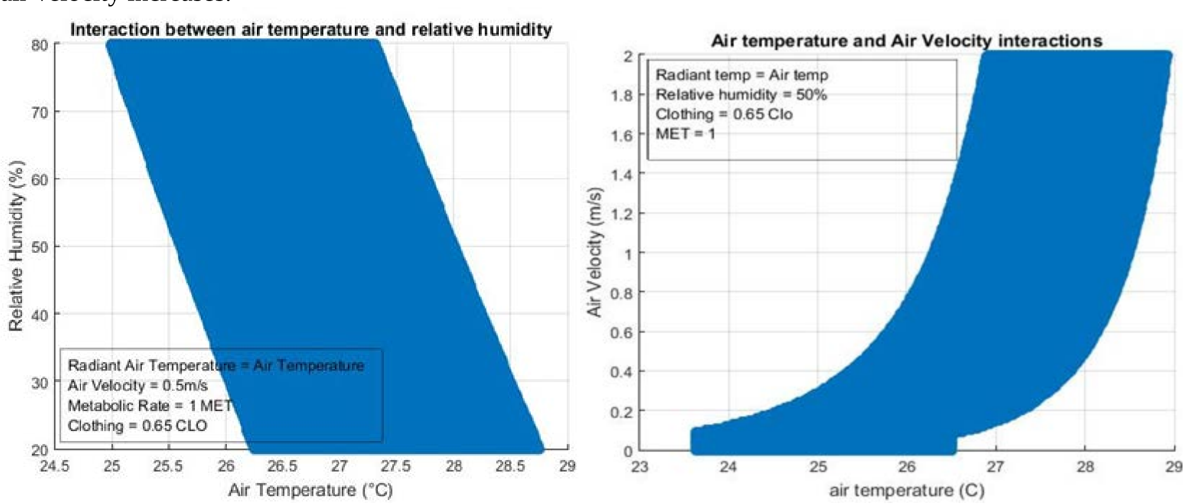
2. PMV PARAMETER INTERACTIONS

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 3D plots showing comfort zones as a surface. In the remainder of this paper, unless otherwise stated, the radiant temperature is assumed to be equal air temperature, 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 = 50%, MET = 1.0 (metabolism conditions), and air velocity = 0.5 m/s.

2.1 Interactions of environmental thermal conditions

The comfort area as a function of temperature and humidity is depicted as a trapezoid in Figure 1(a), a popular plot in the literature that 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 phenomena explains, for example, why in Figure 1(a) the pair (TA = 28^{o}C, RH = 30%) lies within the comfort zone, while the pair (TA = 28^{o}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. Figure 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. Figure 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^{o}C is considered to be uncomfortable for all possible relative humidity values above 30%, as shown in Figure 1(a), it is within the comfort zone once the air velocity exceeds 1.5 m/s. This argument necessitates the need for a 3D plot showing the comfort domain as a function of humidity, temperature, and air velocity, as shown in Figure 2. This plot shows the humidity-temperature trapezoid comfort area shift to the left (higher temperature) as air velocity increases.



(a) (b)

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

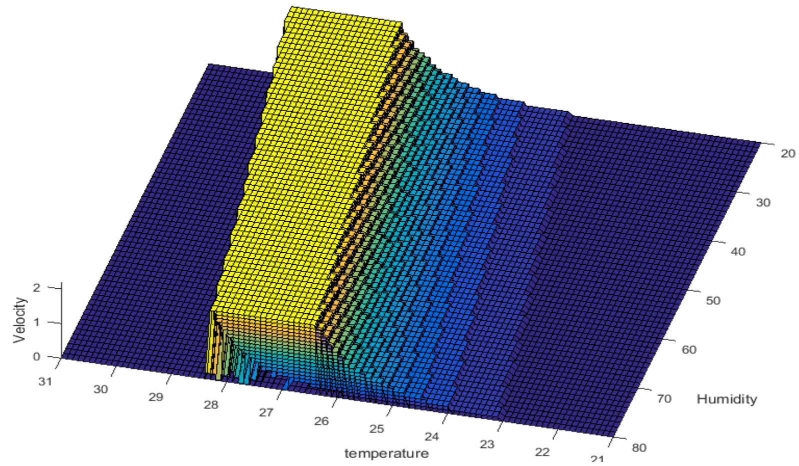
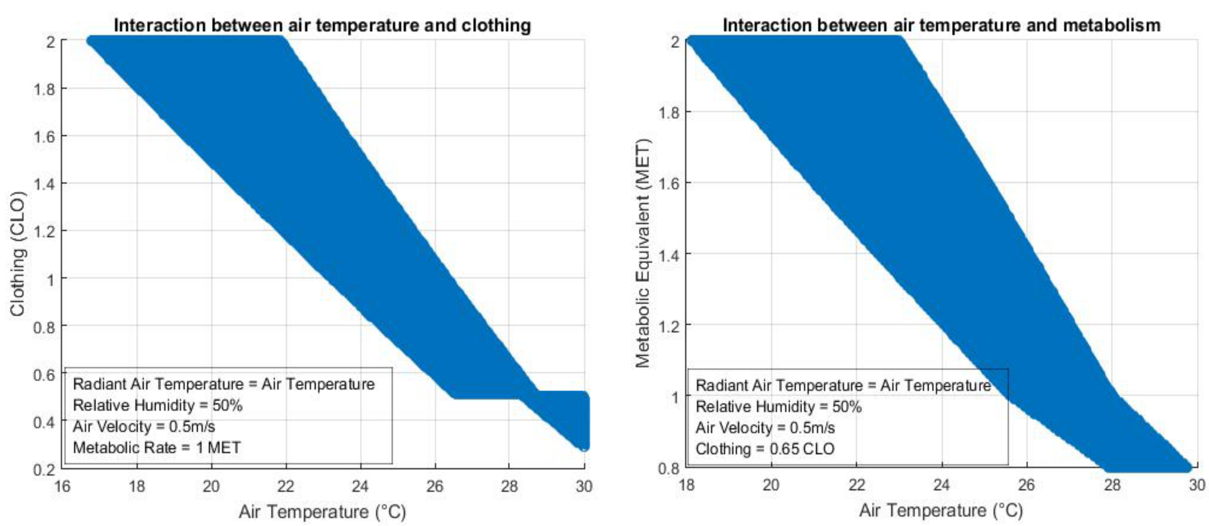


Figure 2: 3D plot of interaction between air temperature, humidity, and air velocity, and resultant comfort zone

2.2 Interactions of environmental thermal and personal parameters

Figure 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. Figure 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 a very wide range of 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. Figure 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 be taken as a constant; otherwise, large errors in calculating the PMV value and the comfort level may be imminent.



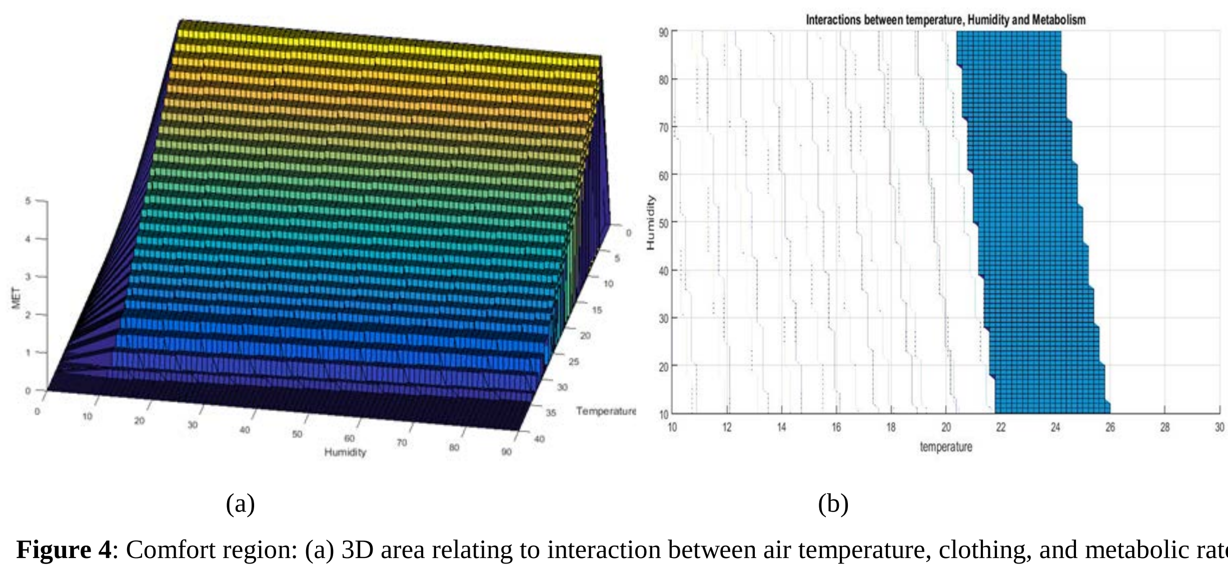
(a) (b)

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

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 the PMV calculation. 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. Figure 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 conviction. 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 ASHARE Standard 55 tables, is the metabolic equivalent of a person sitting at rest without engaging in any physical and mental activities, and is widely accepted to represent metabolism in the PMV equations. In this paper, however, using smart wearable devices data, we show that the metabolic rate may vary for a person even while maintaining minimum activity levels or vary between two persons performing similar activity.

Figure 4(a) shows the metabolism from a different angel, 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 dry respiration by lowering the ambient temperature. The generated 3D 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 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. As shown in Figure 4(b) for MET = 1.5, Figure 4(a) is sliced to find the temperature-relative humidity comfort zone at a given metabolic rate. Figure 4(b) resembles Figure 1(a) but with a different optimal ambient temperature range.

We close our discussion about clothing and metabolism effect by presenting Figure 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 Figure 3(a), the effect of clothing is more dominate in the area around 0.5 CLO, which makes a quick jump in the comfort zone.



(a) (b)

Figure 4: Comfort region: (a) 3D area relating to interaction between air temperature, clothing, and metabolic rate, (b) slice of 3D region at MET = 1.5

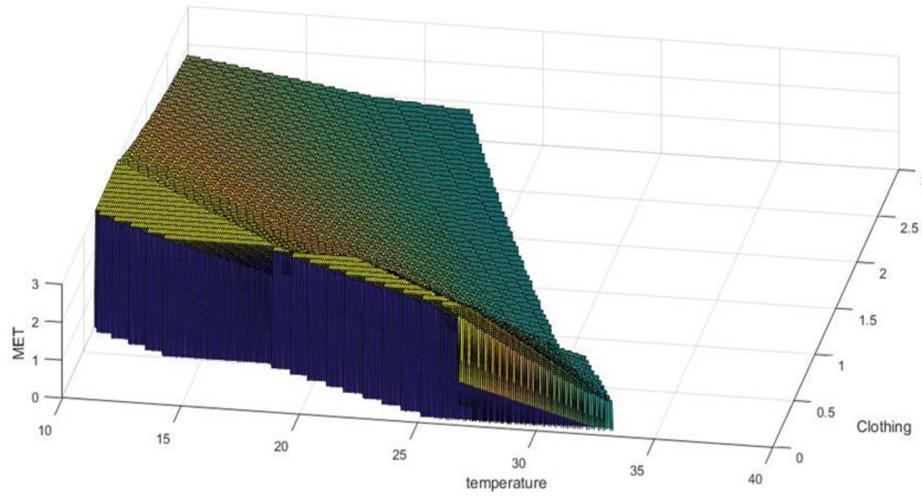


Figure 5: 3D comfort region relating to interaction between air temperature, clothing, and the metabolic rate

3. METABOLISM ESTIMATION USING SMART WEARABLE DEVICE

As mentioned previously, metabolism is difficult to measure and is usually assumed to be constant in the PMV model calculation. 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® band data to estimate metabolism. Fitbit® can be easily configured to share the metabolic rate, heart rate, and activity level to a computing unit in real time. These pieces of information are updated every minute to enable a fast response, if needed.

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 (Mifflin et al. 1990):

$$BMR = \left(\frac{10m}{1\ Kg} + \frac{6.25h}{1\ cm} - \frac{0.5a}{1\ year} + s\right)\frac{Kcal}{day} \tag{5}$$

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:

$$s = \begin{cases} +5 & for\ males \\ -161 & for\ females \end{cases} \tag{6}$$

Fitbit® also uses a built-in accelerometer to infer the activity level of the wearer (Lam et al., 2013). 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

$$\text{EER} = 864 - 9.72\ a\,(years) + PA\,\big(14.2\, m(kg) + 503\ h\,(meters)\big) \tag{7}$$

and for females, the EER is

$$\text{EER} = 387 - 7.31\ a\,(years) + PA\,\big(10.9\, m(kg) + 660.7\ h\,(meters)\big) \tag{8}$$

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 for men as (Gerrior et al. 2006)

$$PA = \begin{cases} 1\,,\ 1.0 < PAL < 1.4\ (Sedentary) \\ 1.12,\ 1.4 < PAL < 1.6\ (Low\ active) \\ 1.27,\ 1.6 < PAL < 1.9\ (Active) \\ 1.54,\ 1.9 < PAL < 2.5\ (Very\ active) \end{cases} \tag{9}$$

and for women as

$$PA = \begin{cases} 1\,,\ 1.0 < PAL < 1.4\ (Sedentary) \\ 1.14,\ 1.4 < PAL < 1.6\ (Low\ active) \\ 1.27,\ 1.6 < PAL < 1.9\ (Active) \\ 1.45,\ 1.9 < PAL < 2.5\ (Very\ active) \end{cases} \tag{10}$$

$$PAL = ((I - 1)\ [(1.15/0.9) \times D\ (minutes)]/1440))/\ (BEE/[0.0175 \times 1440 \times w\ (kg)]) \tag{11}$$

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

$$BEE = \begin{cases} 2933.8 \times a\ (years) + 456.4 \times h(meters) + 10.12 \times w\ (kg),\ Men \\ 2472.67 \times a\ (years) + 401.5 \times h(meters) + 8.6 \times w(kg),\ Women \end{cases} \tag{12}$$

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

$$MET = \frac{EER}{BMR} \tag{13}$$

From equation (13), 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 an occupant.

3.1 Monitoring metabolic rate during physical activities

In this section, we investigate MET during real physical activities and its effect on the PMV value. Here, we conducted an experiment where a student ran on a treadmill at different speeds while wearing a Fitbit® device. Figure 6 shows the MET and PMV curves for the experiment, as well as the following different periods of the experiment:

- Period 1: started at 9:52 (592 minutes) am and ended at 10:02 am; student ran at a speed of 1 mph
- Period 2: started at 10:02 am and ended at 10:08 am; student rested at that time.
- Period 3: started at 10:08 am and ended at 10:18 am; student ran at a speed of 2 mph.
- Period 4: started at 10:18 am and ended at 10:25 am; student rested
- Period 5: started at 10:25 am and ended at 10:35 am; student ran at a speed of 3 mph.
- Period 6: started at 10:35 am and ended at 10:43 am; student rested
- Period 7: started at 10:43 am and ended at 10:52 am; student started running at a speed of 0.5 mph and increased speed 0.5 mph every minute

The MET value of the student was recorded by the minute, and the actual PMV value was computed for every MET value and then averaged to provide one value per period. To remove noise, a low pass filter was applied over the MET values. Figure 6 reveals some interesting behaviors. For example, looking at the active periods (1, 3, 5, and 7), the MET value increases over time as the student starts to breathe more erratically and his heart rate increases as he starts to show signs of exhaustion. At these times, the MET value rises, due to the increase in the amount of oxygen intake. Period (7) illustrates the relationship between the metabolic rate and the intensity of the exercise. The MET value appears to increase as the speed of the treadmill increases. Moreover and as expected the figure shows that the averaged PMV value is way much higher than the assumed PMV value (MET=1.0), while exercising

As shown in Figure 6, resting periods (2, 4, and 6) show an equally interesting phenomena where the metabolic rate does not immediately match the BMR in the resting condition. Instead, it gradually decreases over time and settles at an MET near 2.0. This indicates that physical exercise has a lingering effect on the metabolic rate, because the body continues to breathe at a higher rate, even after exercise is over, in order to supply sufficient oxygen to the body. This phenomena explains why occupants arriving at their work places by foot often set the air conditioning temperature to a relatively low value, causing discomfort to other employees who arrive by car. As the body performs physical labor, its metabolic rate increases; however, once the body stops, this does not immediately return the heart and breathing rates to normal, causing the body to maintain a higher metabolic rate for a period of time before going back to a MET of around 1.0. Another interesting phenomena happens during rest time is the average PMV value decreases and the metabolism rate converges faster to lower value as the intensity of the exercise increases, before resting. This might be because the more intense is the exercise, the easier is to reject the internal body heat through sweating.

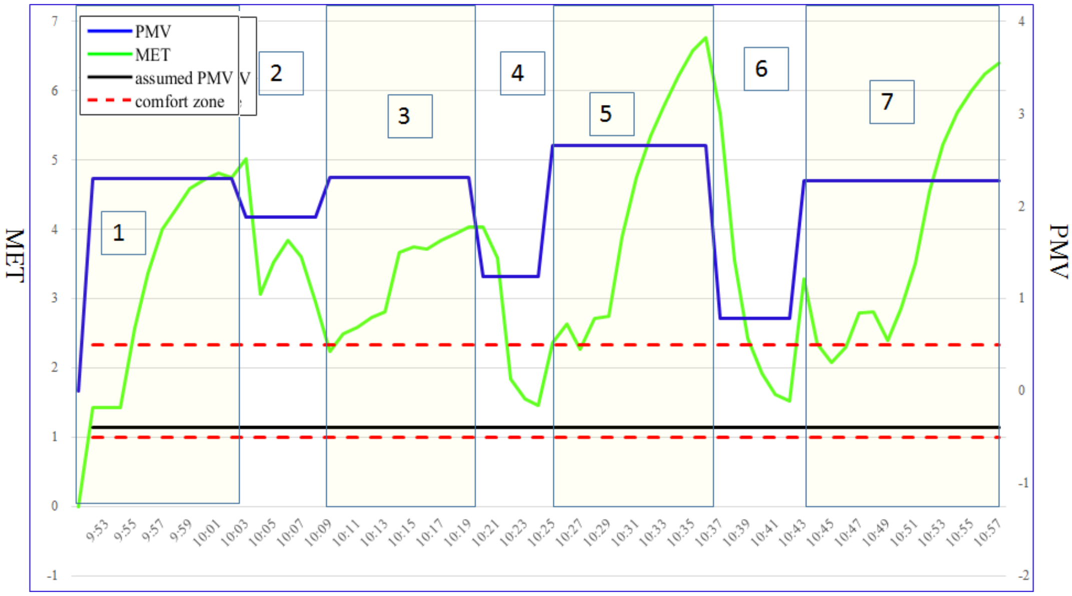


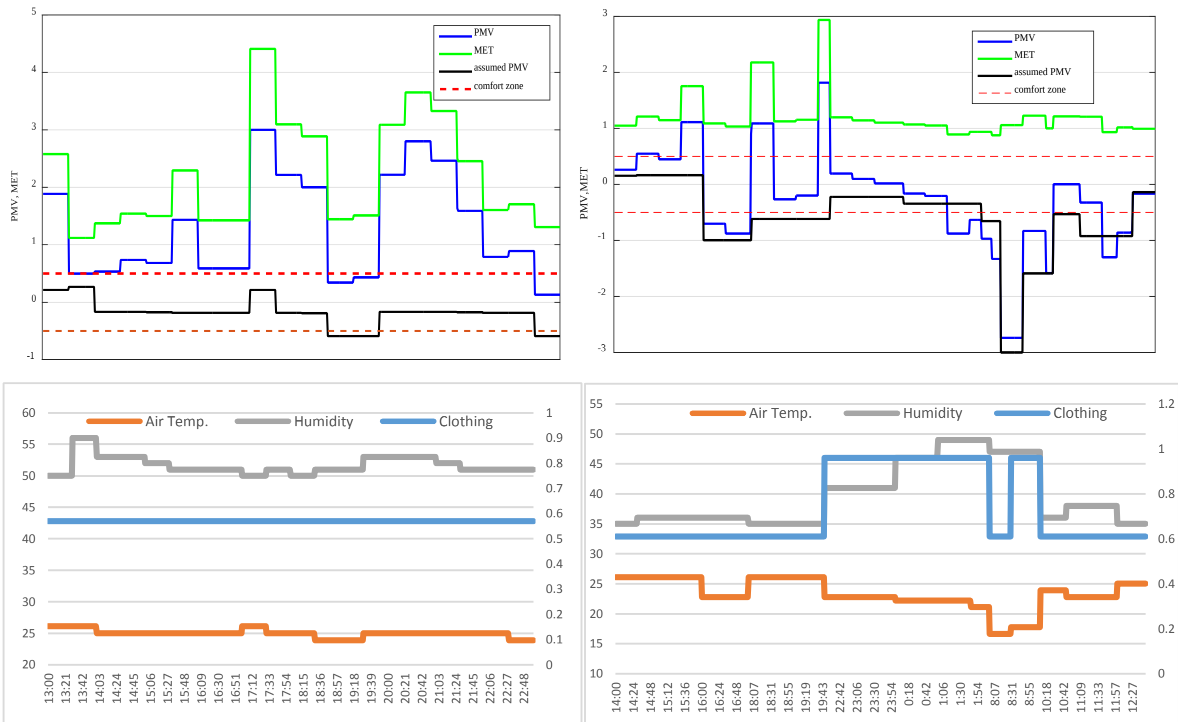
Figure 6: Metabolic rate and PMV values during training periods: periods (1), (3), and (5) are at treadmill speed of 1, 2, and 3 mph; periods (2), (4), and (6) are resting periods; and period (7) is a variable-speed treadmill, starting at 0.5 mph and increasing at a rate of 0.5 mph every minute. The assumed PMV values are calculated with MET=1.0.

3.2 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. An experiment was conducted on a 22-year-old and 35-year-old male graduate students (the first and last authors of this paper) for more than a half day and a full day, respectively. These students have recorded their indoor environmental conditions and clothing every 30 minutes while wearing a Fitbit® device to monitor their heart rate, activity level, and rate of caloric consumption per minute. The wearable device data were used to determine their MET and PMV values every minute and then averaged for each 30 minutes. In this experiment, the two students were asked to perform similar normal life activities while working at office or at home.

Figures 7(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., metabolic rate of 1.0 MET is assumed). These plots show that the MET value keeps changing throughout the entire day. For example in Figure 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 pm. 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 pm – 5:00 pm) and (7:00 pm – 9:00pm), while it decreases during the student's relax hours between (5:00 pm and 7:00 pm). Throughout most of the 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 Figures 4 and 5, this should explain the very large error between the assumed and actual PMV calculation.

Figure 7(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). Figure 7 confirms that not only the MET value may vary over time for an occupant, but may also vary among occupants preforming similar daily activates.



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

Figure 7: 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.

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, it was found that humidity, compared to other factors, has a minimum effect on thermal comfort, while metabolic rate and clothing have a very profound effect. The metabolic rate, which is assumed to be constant throughout most of the literature, is now easy to estimate using wearable devices. We have shown that a person who is not fully at rest will potentially have a MET value considerably higher than 1.0 MET and hence may experience discomfort during the majority of working hours. 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, where the estimated MET value differs greatly from the 1.0 MET.

The PMV model simulation analysis performed in this work can help to prioritize measurements with the highest sensitivity. For example, the relative humidity might cause some "partial discomfort," only if its value exceeds a certain range (less than 30% and more than 60% (Balaras et al. 2007; Wolkoff and Kjaergaad, 2007). Hence, humidity is rarely in need of monitoring, whereas metabolism sensitivity is much higher than relative humidity sensitivity and needs to be closely and continuously measured to assure reliability of the PMV comfort model. The metabolic rate continuously changes over time, even without performing any notable physical activities. 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.

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