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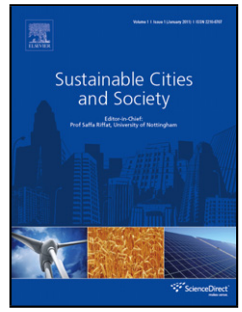


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# Improving Predicted Mean Vote with Inversely Determined Metabolic Rate

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## Highlights

- Metabolic rate is inversely determined to improve PMV.
- Effects of physiological adaptation on metabolic rate are taken into account.
- Variable metric algorithm reduces deviation between PMV and thermal sensation vote.
- Proposed PMV is a grey-box model using model calibration.
- Proposed PMV outperforms original PMV and machining learning based PMV.

## Abstract

Inaccurate thermal comfort prediction would lead to thermal discomfort and energy wastage of overcooling/overheating. Predicted Mean Vote (PMV) is widely used for thermal comfort management in air-conditioned buildings. The metabolic rate is the most important input of the PMV. However, existing measurements of the metabolic rate are practically inconvenient or technically inaccurate. This study proposes a method to improve the PMV for the thermal sensation prediction by inversely determining the metabolic rate. The metabolic rate is expressed as a function of the room air temperature and velocity considering the effects of the physiological adaptation, and inversely determined using an optimizer (variable metric algorithm) to reduce the deviation between the PMV and thermal sensation vote. Experiments in environmental chambers configured as a stratum ventilated classroom and an aircraft cabin and field experiments in a real air-conditioned building from the ASHRAE database validate the proposed method. Results show that the proposed method improves the accuracy and robustness of the PMV in the thermal sensation prediction by more than 52.5% and 41.5% respectively. Essentially, the proposed method develops a grey-box model using model calibration, which outperforms the black-box model using machine learning algorithms.


**Keywords:** Predicted Mean Vote; Metabolic rate; Physiological adaptation; Inverse determination; Model calibration; Grey-box model

## 1. Introduction

Thermal comfort is the condition of mind that expresses satisfaction with the thermal environment [1]. Indoor thermal comfort also significantly affects building occupants' health and productivity [2]. To provide thermal comfort, air conditioning systems are widely used in modern buildings. However, the air conditioning systems account for a large portion of energy consumption [3, 4]. An accurate thermal comfort evaluation is the premise of the proper design and operation of the air conditioning systems [5]. Biases in the thermal comfort evaluation would cause problems of thermal discomfort, large initial and operation costs, and low energy efficiency [2, 6].

Predicted mean vote (PMV) is the most widely used thermal comfort evaluation model for the energy-efficient thermal comfort management of air-conditioned buildings [1, 2, 5, 7]. For example, Hwang and Shu [8] investigated the building envelope regulations of glass façade buildings on thermal comfort and energy saving using a PMV-based comfort control. Zhang et al. [9, 10] optimized the room air temperature of stratum ventilation to maximize energy efficiency with the desired thermal comfort level (i.e., the desired PMV value/range). Xu et al. [11] proposed a PMV-based event-trigger mechanism to improve building energy efficiency under uncertainties. However, the deficiency of PMV has been evidenced by compared with the subjective thermal sensation votes [2, 12]. The PMV could overestimate or underestimate the thermal sensation [13-16]. Humphreys and Nicol [17] confirmed that the biases in PMV exceeded 0.25 scale frequently and reached as much as one scale through meta-analysis. Such large biases indicate the PMV could fail to predict the thermal sensation.

The deficiency in the PMV for the air-conditioned buildings is mainly explained by the errors in its inputs [2]. The PMV calculation requires the inputs of four environmental variables (i.e., air temperature, mean radiant temperature, air velocity and relative humidity) and two occupants-related variables (i.e., the metabolic rate and clothing insulation) [1]. Among the six variables, sensitivity analysis reveals that the metabolic rate plays the most important role in determining the PMV [18-20]. The high sensitivity of PMV to the metabolic rate has been demonstrated that changing the metabolic rate by ±10% resulted in a variation in PMV from -0.16 scale to 0.14 scale [18]. It has been experimentally confirmed that an accurate input of the metabolic rate can efficiently improve the PMV for the thermal sensation prediction [12, 13, 19, 21].

However, when calculating the PMV for practical applications, the metabolic rate is normally estimated roughly from the tables given by standards (e.g., the activity diary in ASHRAE 55 [1] or ISO 8996 [22]) with relatively low accuracy [23]. The activity diary defines a fixed metabolic rate for a given activity. But, for a given activity, the metabolic rate is a variable because it is also affected by body characteristics (e.g., genders, ages, ethnicities and body compositions) and related to the environmental parameters due to the physiological adaptation [24-26]. Luo et al. [27] experimentally found that the metabolic rate was high at low air temperature and low at high air temperature to mitigate the cold and hot discomfort. Fanger commented that a researcher might rate a typical office task as 1.2 met which in fact was 0.9 met [2]. Luo et al. [23] found that the metabolic rate of sitting varied around from 1 met to 3 met in literature. The metabolic rate is probably the most fundamental but least accurately assessed variable in the thermal comfort research and practice [28].

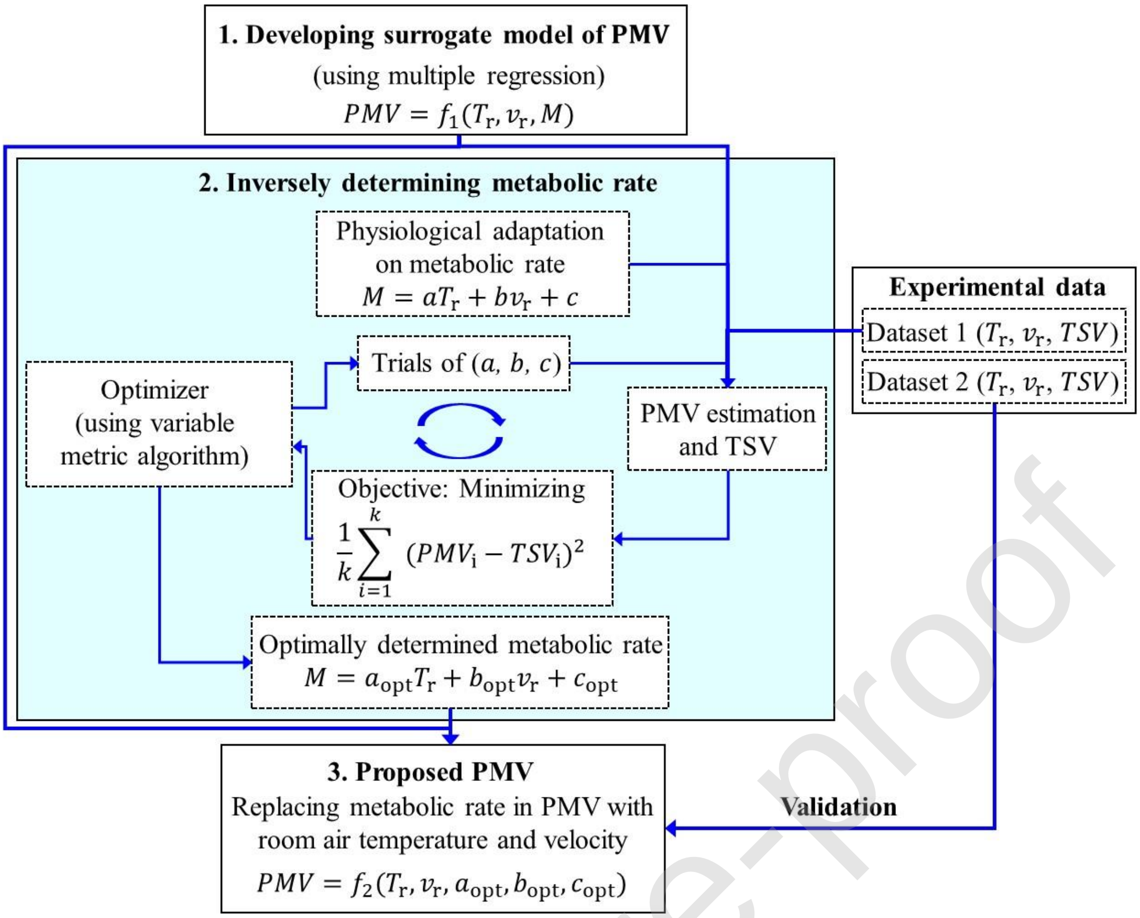
The measurement technologies of the metabolic rate generally include the direct calorimetry and indirect calorimetry [28]. The direct calorimetry measures the total amount of heat released directly from the body to the environment with complex equipment and complicated operations [29]. Because of its inconvenience, the direct calorimetry is seldom used in thermal comfort research and practice [22]. The indirect calorimetry calculates the metabolic rate from the inhaled oxygen and exhaled carbon dioxide [30]. Since the indirect calorimetry requires people to wear uncomfortable masks, it is also inconvenient for practical applications [26, 31]. Recently, wearable or portable devices have been developed to measure the mean blood pressure [12] or heart rate [19] for the metabolic rate calculation. But, their accuracy requires to be improved for thermal comfort evaluation [32]. Both the practical convenience and technical accuracy are imperative requirements for the development of new measurement technologies of the metabolic rate [28].

Considering the importance of the metabolic rate to the PMV and the challenges in the accurate measurement of the metabolic rate, this study proposes a method to improve the PMV for thermal sensation prediction by inversely determining the metabolic rate, which requires no measurements on the metabolic rate. The proposed method will be introduced in detail in Section 2.1, and validated by the experiments in environmental chambers configured as a stratum ventilated classroom (Sections 2.2 and 3.1) and an aircraft cabin (Sections 2.3 and 3.2), and field experiments in a real air-conditioned building from the ASHRAE database (Section 3.3). Four advantages of the proposed method for the convenient implementation in practice, as well as the further improvement of PMV for future studies, are discussed in Section 4.

## 2. Methodology

### *2.1 Method for PMV improvement*

The proposed method mainly includes three parts (Figure 1). Part 1 is to develop a surrogate model of the PMV. It is assumed that the mean radiant temperature is the same as the room air temperature, which is acceptable for the most indoor thermal environment [1, 33]. The relative humidity is assumed to be a fixed value, i.e., 50% [34, 35]. The clothing insulation could be obtained from tables in standards. For example, the typical summer clothing insulation of Hong Kong according to ASHRAE 55 is 0.57 clo [33, 36]. Thus, given different room air temperatures, room air velocities and metabolic rates, the associated PMVs can be calculated according to ASHRAE 55 [1]. Based on the data of the room air temperatures, room air velocities, metabolic rates and the calculated PMVs, the PMV is modelled as a polynomial function of the room air temperature, room air velocity and metabolic rate using multiple regression (i.e., $f_1$ in Figure 1). The procedure of the PMV calculation given in ASHRAE 55 [1] is computationally inconvenient due to the complicated heat transfer process [11, 37]. The obtained surrogate model of the PMV is polynomial and computationally efficient [9]. The computationally efficient surrogate model of the PMV benefits the repeated calculations of the PMV in Part 2 of Figure 1.




*Note: PMV is the Predicted Mean Vote; TSV is the thermal sensation vote; $T_r$ is the room air temperature (°C); $V_r$ is the room air velocity (m/s); M is the metabolic rate (met); $f_1$ and $f_2$ denote the functions; a, b, c are the constants; i is the $i^{th}$ data and the total data number is k; Subscript opt indicates the optimal value.*

**Fig.1.** Method for PMV improvement based on inversely determined metabolic rate.

Part 2 shown in Figure 1 determines the metabolic rate inversely. For a given activity, the metabolic rate is expressed as a function of the room air temperature and velocity in Equation 1, which is explained as follows. The indoor thermal environment (e.g., the room air temperature and velocity) can be the driver of thermal adaptations [27, 38, 39]. Luo et al. [27] correlated the metabolic rate to the room air temperature using a quadratic model when the room air temperature varied in a wide range from around 16°C to 32°C, and for the general thermal environment in an air-conditioned indoor environment the metabolic rate was approximately correlated to the indoor air temperature linearly. Schweiker and Wagner [25] also found that a linear model was adequate to quantify the relationship between the metabolic rate and the environment parameter. The linear relationship between the metabolic rate and the indoor air temperature is resulted from the physiological adaptation. Using the information entropy analysis of a large database, Jing et al. [40] found that the physiological adaptation was linearly related to the indoor air temperature approximately. Since the air velocity (> 0.2 m/s) also has cooling effects [41] and is encouraged for the thermal preference and energy saving [6], Equation 1 correlates the metabolic rate to both the room air temperature and velocity linearly. Equation 1 is also consistent with Fanger and Toftum [5]. Fanger and Toftum [5] linearly correlated the metabolic rate to the PMV. Since the PMV can be approximately linearly correlated to the room air temperature and velocity [9], the metabolic rate can be linearly correlated to the room air temperature and velocity.

$$M = aT_{\mathrm{r}} + bv_{\mathrm{r}} + c \tag{1}$$

where *a*, *b* and *c* are the three constant coefficients; *M* is the metabolic rate (met); $T_{\mathrm{r}}$ is the room air temperature (°C); $v_{\mathrm{r}}$ is the room air velocity (m/s).

With the determined values of *a*, *b* and *c*, Equation 1 and the surrogate model of the PMV (i.e., $f_1$ in Figure 1) together can be used to calculate the PMV by inputting the room air temperature and velocity. The direct determination of Equation 1 requires the metabolic rate but it is challenging practically to measure the metabolic rate accurately (Section 1). It is proposed that *a*, *b* and *c* in Equation 1 can be inversely determined using an optimizer to minimize the deviation between the PMV and thermal sensation vote. The optimizer searches the optimal values of *a*, *b* and *c* to achieve the least square difference between the PMV and thermal sensation vote (Equation 2). Optimization algorithms, e.g., the generic algorithm and variable metric algorithm, can be used in the optimizer to locate the trials of *a*, *b* and *c*. In this study, the variable metric algorithm is adopted because of its good convergence and particular efficiency for small-and-moderate-size dense problems [42, 43]. The variable metric algorithm fits the objective (i.e., Equation 2) to a quadratic function of all independent variables (i.e., *a*, *b* and *c*), and then the quadratic function is differentiated and set to zero to locate the trials of *a*, *b* and *c*. More details about the variable metric algorithm can be found in

Klein (2018) [42].

$$e = \frac{1}{k}\sum_{i=1}^{k} (PMV_{\mathrm{i}} - TSV_{\mathrm{i}})^2 \tag{2}$$

where $e$ is the square difference; $i$ indicates the $i^{th}$ experiment and $k$ experiments in total are used for quantifying $a$, $b$ and $c$; $PMV$ is the Predicted Mean Vote; $TSV$ is the thermal sensation vote.

In Part 3, the metabolic rate in the surrogate model of the PMV (i.e., $f_1$ in Figure 1) is represented by the room air temperature and velocity (Equation 1) with the optimal values of $a$, $b$ and $c$ determined in Part 2. As a result, the PMV is given as a function of the room air temperature and velocity (i.e., $f_2$ in Figure 1), and termed as the proposed PMV. The proposed PMV is further validated by experiments independent from those used for the inverse determination as shown in Part 2. The mean absolute error (Equation 3) and the standard deviation of the absolute errors (Equation 4) are used to evaluate the accuracy and robustness of the PMV for the thermal sensation prediction respectively. A smaller mean absolute error and a smaller standard deviation of the absolute errors indicate that the PMV is more accurate and more robust respectively [44].

$$MAE = \frac{\sum_{j=1}^{m}\left|PMV_{\mathrm{j}} - TSV_{\mathrm{j}}\right|}{m} \tag{3}$$

$$SD = \sqrt{\frac{\sum_{j=1}^{m}\left(\left|PMV_{\mathrm{j}} - TSV_{\mathrm{j}}\right| - \frac{1}{m}\sum_{j=1}^{m}\left|PMV_{\mathrm{j}} - TSV_{\mathrm{j}}\right|\right)^2}{m-1}} \tag{4}$$

where $j$ is the $j^{th}$ experiment; $m$ is the number of experiments; $MAE$ is the mean absolute error; $\left|PMV_{\mathrm{j}} - TSV_{\mathrm{j}}\right|$ is the absolute error of the Predicted Mean Vote (PMV) compared with the thermal sensation vote (TSV); $SD$ is the standard deviation of the absolute errors.

It should be noted that the proposed PMV based on the inversely determined metabolic rate is specific for a given type of activity. For different activity types, the proposed procedure needs to be repeated to re-develop the PMV. Thus, the proposed method can be regarded as the calibration of the activity diary in ASHRAE 55 [1].

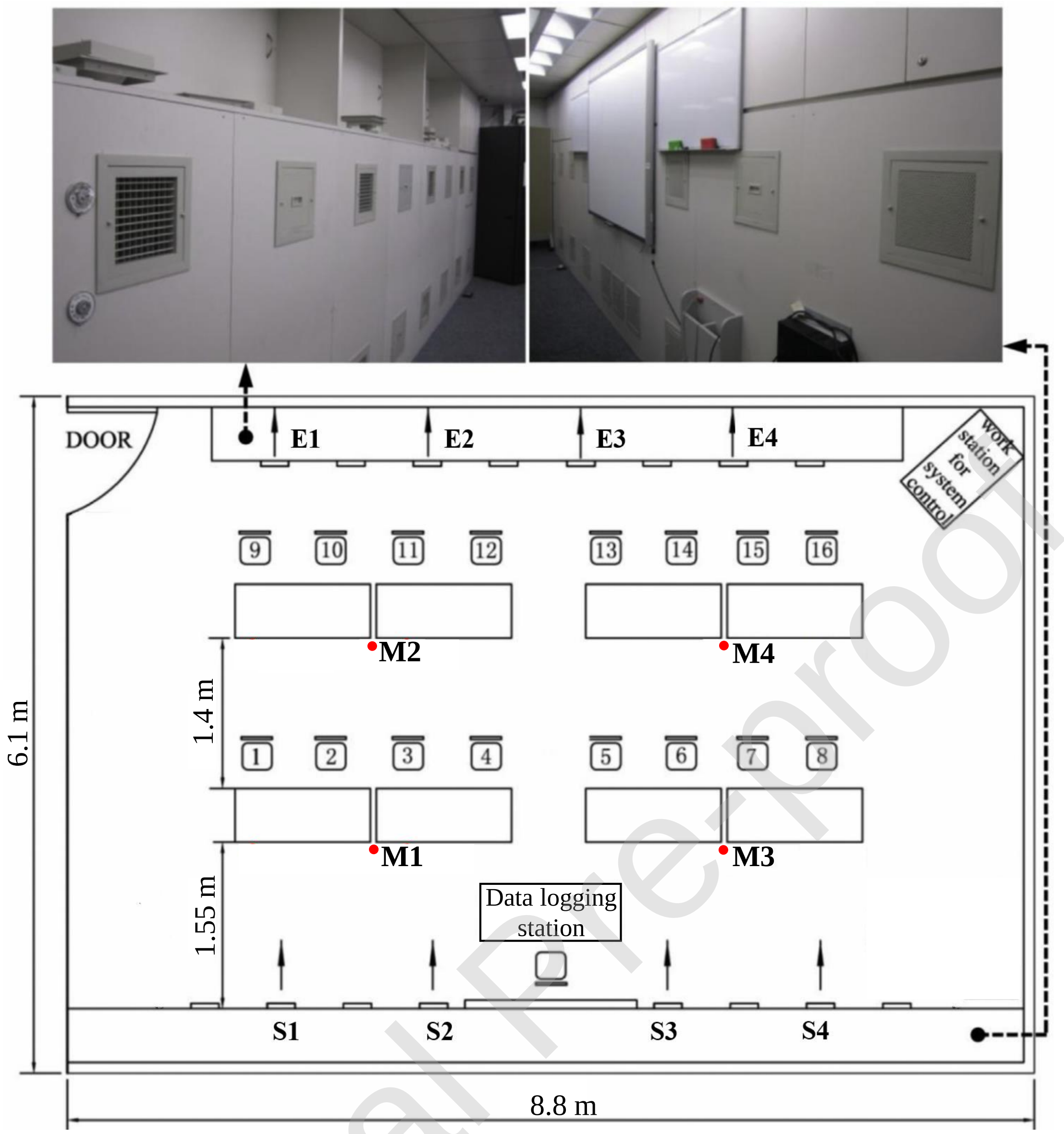
That activity diary determines a specific value of the metabolic rate for a specific activity type. In recent practice, for operation management of one indoor environment, one activity type is generally adequate, e.g., 1.1 met for office buildings and institution buildings [1]. Thus, given an indoor environment, the proposed procedure generally does not need to be repeated for different activity types.

It should also be noted that the proposed PMV is essentially a grey-box model. It takes the advantages of the physical model of human body heat transfer included in the PMV given by ASHRAE 55[1], and uses the data-driven method to inversely determine the metabolic rate for the accuracy improvement of the PMV. The proposed method is similar to the model calibration for existing buildings [45]. The model calibration (also known as calibrated simulation) refers to the process of tuning input parameters of the model to decrease the deviation between the model prediction and the real-monitored data [46]. Some input parameters (e.g., thermal resistance and capacitance, heat loss coefficient, equipment power density, and fan efficiency and pressure rise) in the building energy model are important to the model accuracy but are challenging to be measured accurately [47]. Generally, the model calibration conducts sensitivity analysis first to identify the most important parameters to the building energy performance, and then determines the identified parameters inversely to minimize the error in the building energy prediction [45-47]. Since only the effects of the most important input parameters are considered, the model calibration reduces the model error efficiently, but is unable to eliminate the model error [45-47]. Similarly, the proposed method aims to reduce the deviation between the PMV and the thermal sensation vote by inversely determining the metabolic rate (the most important input to the PMV [18-20]), and it is unable to make the PMV equal the thermal sensation vote.

When implementing the proposed method, data of the room air temperature, room air velocity, and thermal sensation vote need to be collected (Figure 1). Compared with the data-driven thermal comfort models using machine learning algorithms, e.g., classification tree model, Gaussian mixture model, support vector machine, random forest and Q-learning algorithm [48-50], the proposed method requires fewer data and thus is more efficient and convenient to be implemented. Machine learning based thermal comfort models are getting more and more attention for two reasons: Firstly, they take thermal comfort as a black box and do not require looking into the complexities of thermal comfort; secondly, they have been proven to obtain high prediction accuracy. However, as black-box models, they generally require a big database to train the models for sufficient accuracy [49]. In contrast, the proposed PMV is a grey-box model. It takes the advantages of the PMV given by ASHRAE 55, which is based on the physical model of human body heat transfer [1]. With the help of the included physical model, the grey-box model requires fewer data to train the model compared with the black-box [51, 52]. The advantages of the proposed method over the machine learning based thermal comfort models are further discussed in Section 4.

### *2.2 Experiments in environmental chamber configured as stratum ventilated classroom*

Stratum ventilation is an energy-efficient air distribution for small-to-medium sized rooms [33]. It supplies cooled air directly into the occupied zone from the side walls/columns (Figure 2). An air layer of fresh air is formed in the breathing zone so that stratum ventilation can efficiently provide air quality [9]. Around the head level, the room air temperature is lowest and the room air velocity is the highest. The synergistic cooling effects of the low room air temperature and high room air velocity on the most sensitive body part of thermal comfort (i.e. head) make stratum ventilation provide thermal comfort efficiently [9]. Compared with mixing ventilation, stratum ventilation can save energy for cooling annually by at least 44% [53]. Moreover, due to the elevated supply air temperature (higher than 20°C) [54], stratum ventilation is particularly compatible with solar cooling systems (e.g., absorption cooling and ejector cooling) to utilize the solar energy efficiently [55]. Although the thermal environment of stratum ventilation is vertically non-uniform [9], it has been experimentally validated that PMV at the height of 1.1 m above the floor can be used for the thermal sensation prediction for sedentary occupants [33].




*Note: E and S indicate the exit louver and supply diffuser respectively; M denotes the measurement point at the height of 1.1m above the floor.*

**Fig.2.** Configuration of environmental chamber: Stratum ventilated classroom [9].

The environmental chamber of the stratum ventilated classroom is located at City University of Hong Kong. It has dimensions of 8.8 m (length) × 6.1 m (width) × 2.4 m (height) and serves 16 students in two rows. The conditioned air is supplied from the four diffusers S1-S4 on the front wall at the height of 1.3 m above the floor and exhausted from the four lovers E1-E4 on the rear wall at the same height. Four measurement points M1-M4 of the room air temperature and velocity are evenly distributed in the occupied zone at the height of 1.1 m above the floor. The mean room air temperature and velocity at the four measurement points are used for the calculation of the PMV (Section 2.1).

SWEMA omnidirectional hot-wire anemometers are used to measure the air temperature and velocity. The measurement accuracy for the air temperature is ±0.2°C between 10°C and 40°C, and that for the air velocity is ±0.02 m/s between 0.07 m/s and 0.5 m/s and ±0.03 m/s between 0.5 m/s and 3 m/s. The supply airflow rate is the sum of the measurements at the four diffusers S1-S4 by an ALNOR balometer capture hood EBT731 with a measurement accuracy of ±3% of the reading. Students of City University of Hong Kong are recruited for the subjective surveys of the thermal sensation. The thermal sensation is assessed in terms of the 7-point scale of ASHRAE 55 [1]: -3 cold, -2 cool, -1 slightly cool, 0 neutral, +1 slightly warm, +2 warm and +3 hot. The students wear typical summer clothing (i.e., short-sleeved shirts, long trousers, underwear, socks and shoes) with the clothing insulation of 0.57 clo according to ASHRAE 55 [1]. For each case (Table 1), the experiment is repeated for two or three times and thus there are at least 32 students participating in the subjective surveys. The mean value of their votes of thermal sensation is used as the thermal sensation vote of that case.

Nine cases (Series 1 in Table 1) are designed for the development of the proposed PMV (i.e., Dataset 1 in Figure 1). For generalization, the 9 cases cover a wide range of the thermal environment with the supply airflow rate from 7 ACH to 15 ACH and room air temperature between around 23.5°C and 28°C [54]. The resulted room air velocity is around from 0.1 m/s to 0.3 m/s. Ten more cases (i.e., Series 2 in Table 1) are designed to validate the proposed PMV further (i.e., Dataset 2 in Figure 1). In the 10 cases, the supply airflow rate varies from 7 ACH to 17 ACH and the room air temperature is from around 25°C to 26.5°C. The resulted room air velocity ranges from around 0.1 m/s to 0.3 m/s. Thus, the thermal environment of Series 2 is covered by Series 1 and generally thermally comfortable. For all the cases, the indoor air quality is acceptable which is indicated by the reasonable indoor $CO_2$ concentration [54]. More details about the experiments can be found in Zhang et al [9].

**Table 1.** Supply airflow rate ($V_s$), room air temperature ($T_r$) and room air velocity ($v_r$) in environmental chamber configured as stratum ventilated classroom.

| Cases | | $V_s$ (ACH) | $T_r$ (°C) | $v_r$ (m/s) |
|---|---|---|---|---|
| Series 1 | 1 | 7 | 23.9 | 0.08 |
| | 2 | 10 | 23.7 | 0.13 |
| | 3 | 15 | 23.6 | 0.21 |
| | 4 | 7 | 26.4 | 0.08 |
| | 5 | 10 | 26.4 | 0.19 |
| | 6 | 15 | 26.2 | 0.29 |
| | 7 | 7 | 28.1 | 0.08 |
| | 8 | 10 | 27.8 | 0.20 |
| | 9 | 15 | 28.2 | 0.30 |
| Series 2 | 10 | 7 | 26.5 | 0.08 |
| | 11 | 8 | 26.2 | 0.12 |
| | 12 | 10 | 25.7 | 0.19 |
| | 13 | 11 | 26.0 | 0.21 |
| | 14 | 13 | 26.3 | 0.20 |
| | 15 | 13 | 26.0 | 0.23 |
| | 16 | 15 | 26.3 | 0.25 |
| | 17 | 15 | 24.8 | 0.25 |
| | 18 | 17 | 26.1 | 0.30 |
| | 19 | 17 | 25.4 | 0.31 |

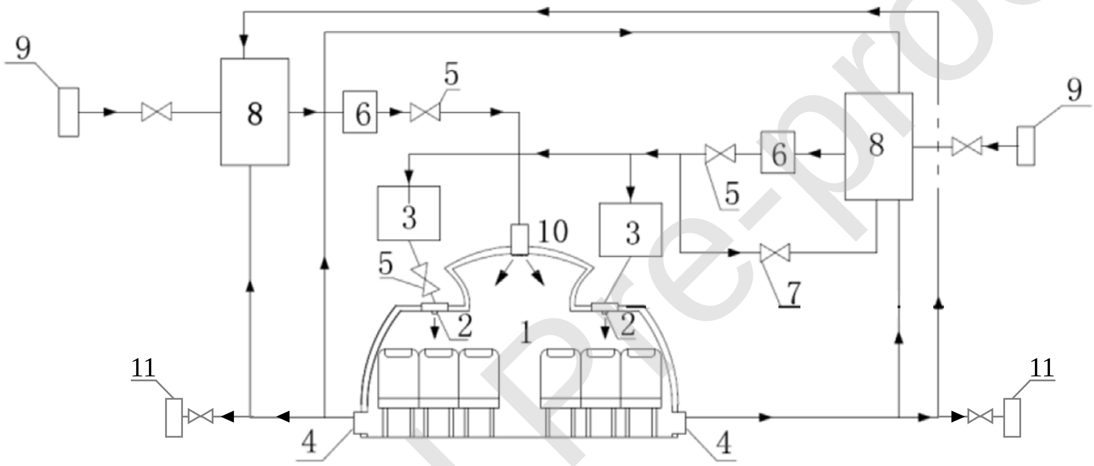
*2.3 Experiments in environmental chamber configured as aircraft cabin*

To validate the proposed method further, the experiments in an environmental chamber configured as an aircraft cabin [34] are selected from the literature for two reasons. Firstly, the data are adequately detailed for the development and validation of the proposed PMV, covering a wide range of the thermal condition (with the room air temperature from 22°C to 28°C and the room air velocity from around 0.05 m/s to 0.9

m/s in Table 2). Secondly, the heating mode is concerned (with the clothing insulation of 1.23 clo) while Section 2.2 focuses on the cooling mode. It is a three-row aircraft cabin with 18 seats simulating an Airbus A320 aircraft (Figure 3). It has dimensions of 4.9 m (length) ×3.9 m (width) × 2.35 m (height) and is located at Chongqing University. The air is supplied from the nozzles above the occupants. The relationship between the supply airflow rate and the room air velocity around the occupants can be estimated by Equation 5 [34, 56].

$$v_{\mathrm{r}} = 0.56V_{\mathrm{s}} + 0.05 \tag{5}$$

where $v_{\mathrm{r}}$ is the room air velocity around the occupants (m/s); $V_{\mathrm{s}}$ is the supply airflow rate (L/s).




*Note: 1 is the aircraft cabin; 2 is the nozzle; 3 is the static pressure tank; 4 is the air return outlet; 5 is the valve; 6 is the fan; 7 is the bypass valve; 8 is the air conditioning unit; 9 is the fresh air inlet; 10 is the air supply inlet; 11 is the exhausted air outlet.*

**Fig.3.** Configuration of environmental chamber: Aircraft cabin [34].

LSI (BSU102) is used to measure the air temperature and velocity. The measurement accuracy for the air temperature is ±0.1°C between -25°C and 150°C, and that for the air velocity is ±0.04 m/s between 0 m/s and 1 m/s. Students of Chongqing University are recruited for the subjective surveys of thermal sensation under the sedentary activity. The thermal sensation is assessed by the 7-point scale of ASHRAE 55 [1].

For each case (Table 2), 40 students participate in the subjective surveys, and the mean value of their votes of thermal sensation is used as the thermal sensation vote of that case. Nine cases (Series 3 in Table 2) are used for the development of the proposed PMV. Seven cases (Series 4 in Table 2) are used for the further validation of the proposed PMV. For both Series 3 and 4, the supply airflow rate is from 0 L/s to 1.5 L/s and the room air temperature is from 22°C to 28°C. The resulted room air velocity is from around 0.05 m/s to 0.9 m/s. More details of the experiments are found in Wu et al [34].

**Table 2.** Supply airflow rate ($V_s$), room air temperature ($T_r$) and room air velocity ($v_r$) in environmental chamber configured as aircraft cabin.

| Cases | | $V_s$ (L/s) | $T_r$ (°C) | $v_r$ (m/s) |
|---|---|---|---|---|
| Series 3 | 20 | 0.0 | 22 | 0.05 |
| | 21 | 0.5 | 22 | 0.33 |
| | 22 | 1.5 | 22 | 0.89 |
| | 23 | 0.0 | 26 | 0.05 |
| | 24 | 0.5 | 26 | 0.33 |
| | 25 | 1.5 | 26 | 0.89 |
| | 26 | 0.0 | 28 | 0.05 |
| | 27 | 0.5 | 28 | 0.33 |
| | 28 | 1.5 | 28 | 0.89 |
| Series 4 | 29 | 1.0 | 22 | 0.61 |
| | 30 | 1.0 | 26 | 0.61 |
| | 31 | 1.0 | 28 | 0.61 |
| | 32 | 0.0 | 24 | 0.05 |
| | 33 | 0.5 | 24 | 0.33 |
| | 34 | 1.0 | 24 | 0.61 |
| | 35 | 1.5 | 24 | 0.89 |

## 3. Results

*3.1 Environmental chamber configured as stratum-ventilated classroom*

The original PMV [1] with the typical summer clothing (i.e., 0.57 clo) is modelled as Equation 6 by the room air temperature, room air velocity and metabolic rate (i.e., $f_1$ in Figure 1). Equation 6 is applicable to the general thermal environment (PMV from -1 to 1) for classroom and office activities under cooling mode, with the room air temperature from 23°C to 29°C, room air velocity from 0.05 m/s to 0.6 m/s and metabolic rate from 0.9 met to 1.3 met [1]. Equation 6 is determined with a coefficient of determination ($R^2$) of 0.99. The terms in Equation 6 with p-values higher than 0.05 indicating statistical insignificance are removed (e.g., $v_{\mathrm{r}}M$) [9]. Thus, Equation 6 is statistically significant and reliable. Figure 4 shows that Series 1 (Table 1) covers a wide thermal condition with the thermal sensation vote from around -1 to 0.75. Based on the experimental data of Series 1, the proposed PMV is developed as Equation 7 using the proposed method (Section 2.1).

$$PMV = 1.7199{v_{\mathrm{r}}}^2 - 4.2082M^2 - 0.0441T_{\mathrm{r}}v_{\mathrm{r}} - 0.3062T_{\mathrm{r}}M + 0.6604T_{\mathrm{r}} - 1.6561v_{\mathrm{r}} + 19.4698M - 24.1733 \quad (6)$$

$$PMV_{\mathrm{p,SV}} = 0.0011{T_{\mathrm{r}}}^2 + 0.4437{v_{\mathrm{r}}}^2 - 0.1956T_{\mathrm{r}}v_{\mathrm{r}} + 0.3073T_{\mathrm{r}} + 4.3290v_{\mathrm{r}} - 8.6710 \quad (7)$$

where $PMV_{\mathrm{p,SV}}$ is the proposed PMV (Predicted Mean Vote) for the environmental chamber configured as the stratum ventilated classroom (Figure 2); $M$ is the metabolic rate (met); $T_{\mathrm{r}}$ is the room air temperature (°C); $v_{\mathrm{r}}$ is the room air velocity (m/s).

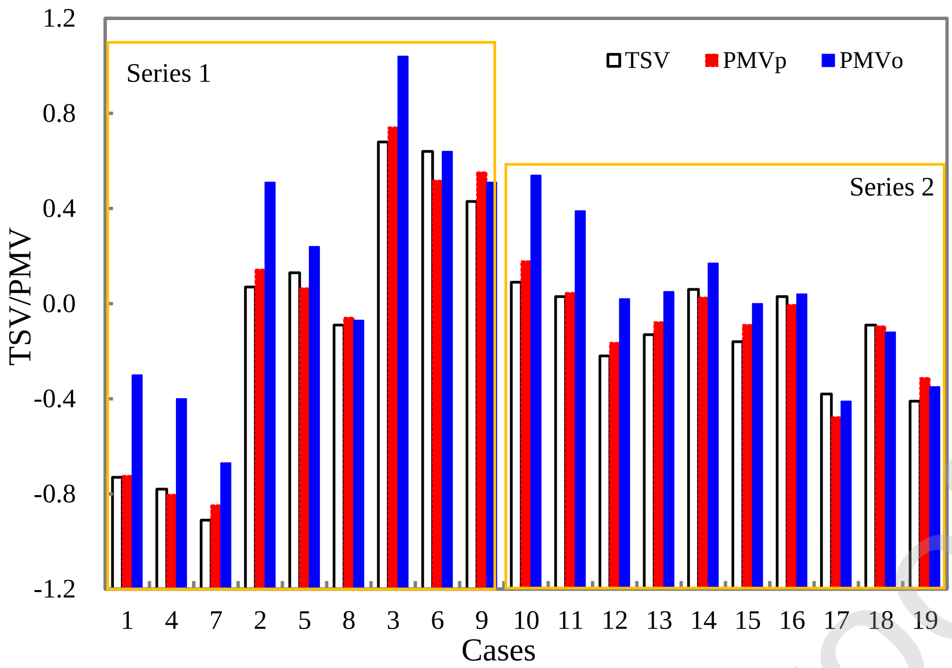



**Fig.4.** Comparisons of original PMV ($PMV_o$), proposed PMV ($PMV_p$) and thermal sensation vote (TSV): Stratum ventilated classroom.

Figure 5 shows with the metabolic rate assumed to be 1.1 met [34], the original PMV from ASHRAE 55 [1] generally overestimates the thermal sensation, with a function between the original PMV and thermal sensation vote above the diagonal function of $y = x$. The $R^2$ of the function between the original PMV and thermal sensation vote is less than 0.9 (i.e., 0.85). Thus, the original PMV can be further improved. In contrast, the proposed PMV is almost at the diagonal function of $y = x$ with the thermal sensation vote, and the $R^2$ is high at 0.98, indicating that the proposed PMV accurately and robustly predicts the thermal sensation. Figure 4 shows for both Series 1 and Series 2, the proposed PMV is generally closer to the thermal sensation vote as compared with the original PMV. The maximal error of the original PMV is 0.45 scale (Case 10), while that of the proposed PMV is reduced to 0.12 scale (Case 9). Overall, compared with the original PMV, the proposed PMV improves the accuracy and robustness in the thermal sensation prediction by 69.5% and 77.9% respectively by reducing the mean absolute error (Equation 3) from 0.19 scale to 0.06 scale and the standard deviation of the absolute errors (Equation 4) from 0.16 scale to 0.04 scale respectively.

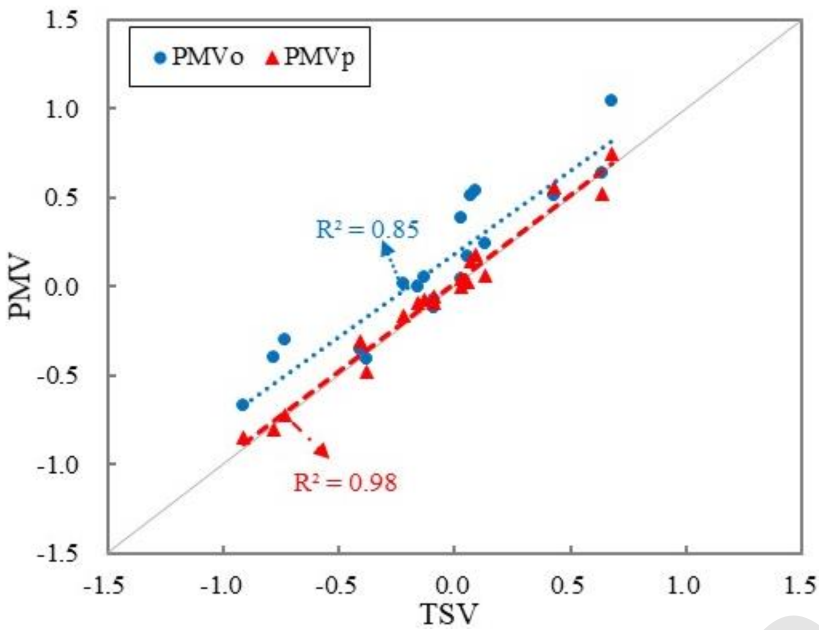



**Fig.5.** Original PMVs ($PMV_{\mathrm{o}}$) and proposed PMVs ($PMV_{\mathrm{p}}$) corresponding to thermal sensation votes (TSV): Environmental chamber configured as stratum ventilated classroom.

*3.2 Environmental chamber configured as aircraft cabin*

The original PMV [1] with the winter clothing (1.23 clo) is modelled as Equation 8 (i.e., $f_1$ in Figure 1). Equation 8 covers a wide thermal environment with the room air temperature from 22°C to 28°C, room air velocity from 0.05 m/s to 0.9 m/s and metabolic rate from 0.8 met to 1.5 met [34]. The p-values of the terms included in Equation 8 are all less than 0.05 indicating statistical significance. And $R^2$ of Equation 8 is 0.99. Thus, Equation 8 is statistically accurate. Figure 6 shows that the thermal sensation vote of Series 3 (Table 2) varies from around -1.5 to 2, indicating a wide range of thermal condition. Based on Series 3, the proposed PMV for the aircraft cabin is developed as Equation 9 using the proposed method (Section 2.1).

$$\begin{aligned}\mathrm{PMV} = {} & 0.9488{v_{\mathrm{r}}}^2 - 3.0344M^2 - 0.2138T_{\mathrm{r}}M + 0.1549v_{\mathrm{r}}M + 0.4656T_{\mathrm{r}} \\ & - 1.8956v_{\mathrm{r}} + 13.9087M - 16.3918 \qquad (8)\end{aligned}$$

$$\begin{aligned}PMV_{\mathrm{p,aircraft}} = {} & -0.0152{T_{\mathrm{r}}}^2 + 0.6159{v_{\mathrm{r}}}^2 + 0.1541T_{\mathrm{r}}v_{\mathrm{r}} + 1.0170T_{\mathrm{r}} - 5.9140v_{\mathrm{r}} \\ & - 14.7300 \qquad (9)\end{aligned}$$

where $PMV_{\mathrm{p,aircraft}}$ is the proposed PMV for the environmental chamber configured as the aircraft cabin (Figure 3); $M$ is the metabolic rate (met); $T_r$ is the room air temperature (°C); $v_r$ is the room air velocity (m/s).

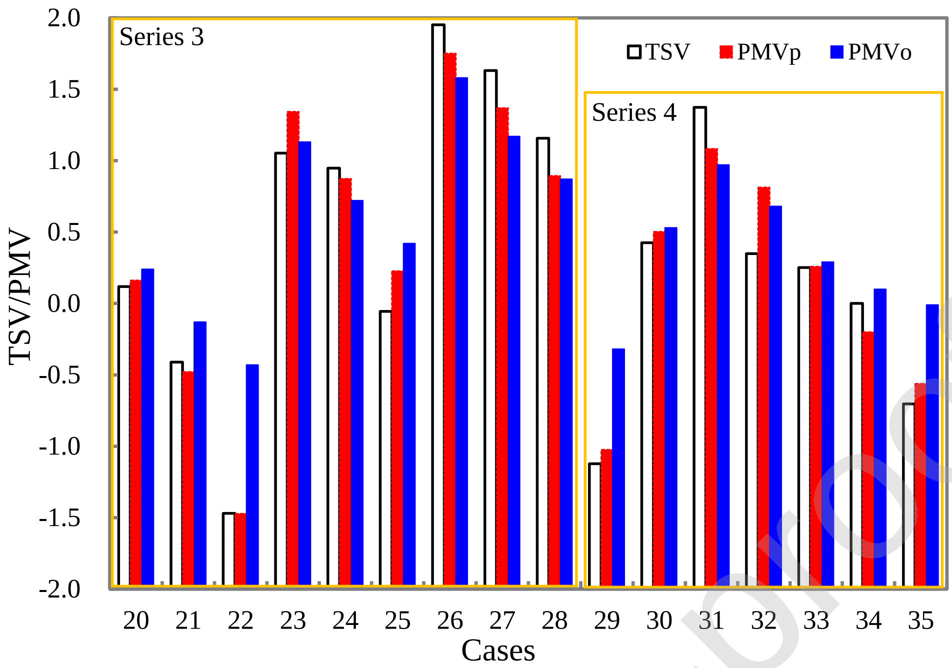



**Fig.6.** Comparisons of original PMV ($PMV_o$), proposed PMV ($PMV_p$) and thermal sensation vote (TSV): Environmental chamber configured as aircraft cabin.

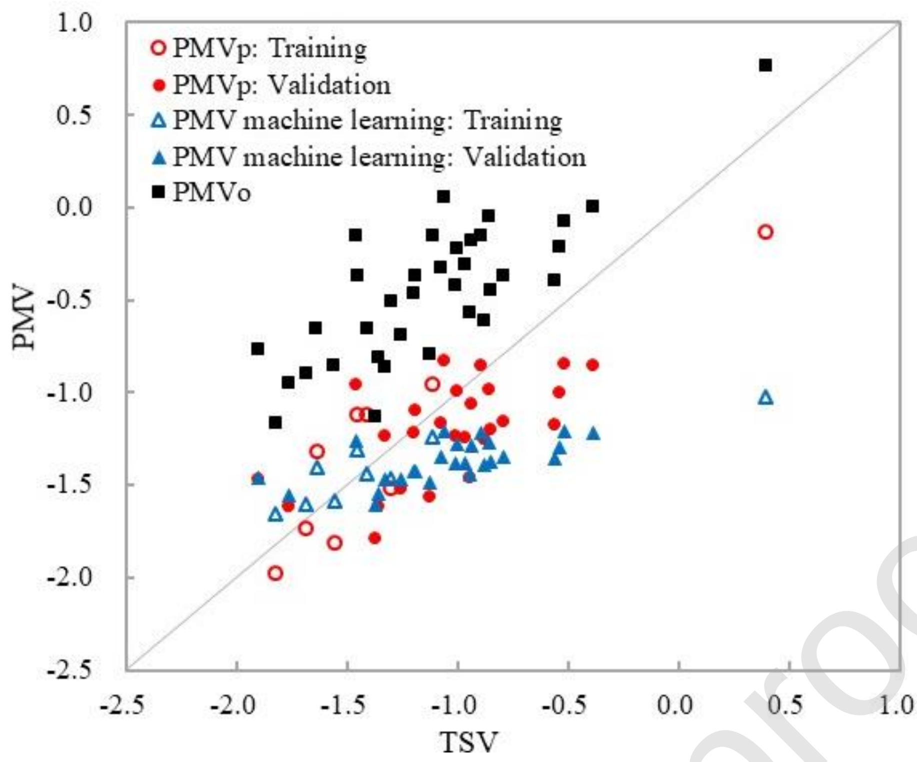
It can be seen from Figure 6 that the original PMV (with metabolic rate of 1.1 met [34]) would lead to a large error in the thermal sensation prediction, particularly in the cold thermal environment with the thermal sensation vote less than -0.5 (i.e., Cases 22, 29, and 35). In contrast, for both Series 3 and Series 4 (Table 2), the proposed PMV improves the thermal sensation prediction generally. For example, the errors in the thermal sensation prediction by the original PMV for Cases 22 in Series 3, and Cases 29 and 35 in Series 4 are 1.04 scales, 0.80 scale, and 0.69 scale respectively, while those by the proposed method are zero scale, 0.1 scale and 0.14 scale respectively. Overall, compared with the original PMV, the proposed PMV improves the accuracy in the thermal sensation prediction by 52.5% with the mean absolute error (Equation 3) reduced from 0.36 scale to 0.17 scale, and improves the robustness in the thermal sensation prediction by 54.1% with the standard deviation of the absolute errors (Equation 4) reduced from 0.28 scale to 0.13 scale.

*3.3 Field study in real air conditioned building*

Data from the ASHRAE database, i.e., RP-884 50_EXL, are used to demonstrate the advantage of the proposed PMV. RP-884 50_EXL refers to the field experiments in an air-conditioned building in the hot season of the tropical savanna climate zone. RP-884 50_EXL includes 40 different thermal conditions, and for each thermal conditions around 18 subjective surveys are collected (with 703 subjective surveys in total). After excluding the outliers using the box-plot method, the original PMV and thermal sensation vote from RP-884 50_EXL are presented in Figure 7. The thermal conditions in the air-conditioned building are generally cold with the thermal sensation vote less than 0. However, the original PMV overestimates the thermal condition which is above the diagonal function of *y* = *x*. The proposed PMV is determined as Equation 10. Compared with the original PMV, the proposed PMV improves the accuracy and robustness in the thermal comfort prediction by 58.4% (with the mean absolute error reduced from 0.66 to 0.27) and 41.5% (with the standard deviation of the absolute errors reduced from 0.28 to 0.16) respectively.

$$PMV_{\mathrm{p,RP-884\ 50\_EXL}} = 0.0031T_{\mathrm{r}}^{2} + 1.2570v_{\mathrm{r}}^{2} - 0.0622T_{\mathrm{r}}v_{\mathrm{r}} + 0.1915T_{\mathrm{r}} - 0.0277v_{\mathrm{r}} - 7.3300 \tag{10}$$

where $PMV_{\mathrm{p,RP-884\ 50\_EXL}}$ refers to the proposed PMV for the real air-conditioned building from the ASHRAE database RP-884 50_EXL.




*Note: Data of TSV and original PMV ($PMV_o$) are from ASHRAE database, i.e., RP-884 50_EXL; and the support vector machine with linear kernel function is used as the machine learning algorithm.*

**Fig.7.** Variations of proposed PMV ($PMV_p$), machine learning based PMV and original PMV ($PMV_o$) with thermal sensation vote (TSV): A real air-conditioned building.

## 4. Discussion

The proposed PMV is convenient for practical applications for four reasons. Firstly, it does not require the measurement of the metabolic rate (Sections 2 and 3). Secondly, the proposed PMV is computationally efficient. The calculation of the original PMV is complicated because it is non-linear and iterative [2]. The complicated calculation would hinder the practical applications, particularly for the control of the supply air parameters where the thermal environment needs to be evaluated frequently [10, 11, 57]. To use the PMV for control, methods like piecewise linearization and fuzzy PMV have been proposed [11, 37]. The proposed PMV (e.g., Equations 7, 9 and 10) is the simple polynomial function of the room air temperature and velocity. The simple polynomial function is the most computationally efficient model [5, 10]. Thirdly, the proposed PMV can be expressed by the room air temperature and supply airflow rate which can be conveniently measured/monitored in practice [10]. The elevated room air velocity (> 0.2 m/s) plays an important role in thermal comfort [1]. However, it is challenging to measure the room air velocity accurately in engineering applications [9]. Since the room air velocity can be correlated to the supply airflow rate (e.g., Equation 5) [9, 34, 58], the proposed PMV can be transferred to be a function of the room air temperature and supply airflow rate, e.g., Equation 11 for the environmental chamber configured as the aircraft cabin.

$$PMV_{\mathrm{p,aircraft}} = -0.0152{T_{\mathrm{r}}}^2 + 0.1931{V_{\mathrm{s}}}^2 + 0.0863T_{\mathrm{r}}V_{\mathrm{s}} + 1.0250T_{\mathrm{r}} - 3.2770V_{\mathrm{s}} - 15.0200 \quad (11)$$

where $PMV_{\mathrm{p,aircraft}}$ is the proposed PMV (Predicted Mean Vote) for the environmental chamber configured as the aircraft cabin (Figure 3); $T_{\mathrm{r}}$ is the room air temperature (°C); $V_{\mathrm{s}}$ is the supply airflow rate (L/s).

Fourthly, as explained in Section 2.1, the proposed PMV is a grey-box model, and thus requires less training data for sufficient accuracy compared with the black-box model using machine learning algorithms. The black-box model requires a large database for sufficient accuracy. Taking the field study in Section 3.3 as an example, among the machine learning algorithms of the linear regression models, regression trees, support vector machines and Gaussian process regression models [58], the support vector machine (with linear kernel function) is selected for developing the machine learning based PMV because of its highest accuracy (Figure 7). Compared with the machine learning based PMV, the proposed PMV improves the accuracy and robustness in the thermal comfort prediction by 23.9% (with the mean absolute error reduced from 0.36 to 0.27) and 41.7% (with the standard deviation of the absolute errors reduced from 0.28 to 0.16) respectively. These results confirm that compared with the machine learning based model, the proposed PMV, as a grey-box model, requires fewer data to realize sufficient accuracy.

The proposed method can also be extended to inversely determine the other occupants-related parameter for the PMV calculation, i.e., the clothing insulation, which is also difficult to be measured accurately in practice [17]. It should be noted that although the above results show that the proposed method effectively improves PMV for the thermal sensation prediction, more efforts are required to improve PMV further. As explained in Section 2.1, using the model calibration [45-47], the proposed method aims to reduce the error of PMV and is unable to eliminate the error of PMV (Figures 4, 6 and 7). There are mainly two ways to improve PMV for the thermal sensation prediction, i.e., accurately determining the inputs and modifying the model itself [2]. The proposed method can be regarded as the efforts of accurately determining the inputs. There are some existing efforts of modifying the model itself, e.g., the extended PMV [5] and the adaptive PMV [59]. It is recommended for future studies to develop a method combining the two ways to further improve PMV for the thermal sensation prediction.

## 5. Conclusions

This study proposes a method to improve the PMV for thermal sensation prediction based on the inversely determined metabolic rate. Firstly, the original PMV of AHSRAE 55 is modelled as a function of the room air temperature, room air velocity and metabolic rate using multiple regression. Secondly, the metabolic rate is considered as a function of the room air temperature and velocity due to the physiological adaptation, and inversely determined using an optimizer (the variable metric algorithm) to reduce the deviation between the PMV and thermal sensation vote. Thirdly, the proposed PMV is obtained by replacing the metabolic rate in the original PMV using the room air temperature and velocity.

Experiments in environmental chambers configured as a stratum ventilation classroom and an aircraft cabin and field experiments in a real air-conditioned building from the ASHRAE database have been used to demonstrate the effectiveness of the proposed PMV. Results show that compared with the original PMV, in terms of the thermal sensation prediction for both cooling and heating modes, the proposed PMV reduces the mean absolute error and the standard deviation of the absolute errors by more than

52.5% and 41.5% respectively.

The proposed PMV is convenient for practical applications for four reasons: 1) it does not need to measure the metabolic rate; 2) it is computationally efficient; 3) it can avoid the measurement of the room air velocity when the elevated room air velocity (> 0.2 m/s) is concerned; and 4) as a grey-box model, the proposed PMV requires less training data for sufficient accuracy when compared with the black-box model (the machine learning based PMV). Due to the improved accuracy and robustness and ease of implementation, the proposed PMV can contribute to the thermal comfort management for low energy buildings.

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