Individualised Dynamic Model-Based Monitoring of Occupant's Thermal Comfort for Adaptive HVAC Controlling

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ABSTRACT

Thermal comfort and sensation are important aspects of the building design and indoor climate control as modern man spends most of the day indoors. Conventional indoor climate design and control approaches are based on static thermal comfort/sensation models that views the building occupants as passive recipients of their thermal environment. Assuming that people have relatively constant range of biological comfort requirements, and that the indoor environmental variables should be controlled to conform to that constant range. The (r)evolution in modern sensing and computing technologies (price, compact size, flexibility and stretchability) is making it possible to continuously measure signals in real-time from human body using wearable technologies and smart clothing. Many advanced and accurate mechanistic thermoregulation models, such as the 'Fiala thermal Physiology and Comfort' model, are developed to assess the thermal strains and comfort status of humans. However, the most reliable mechanistic models are too complex to be implemented in real-time for monitoring and control applications. Additionally, such models are using not-easily or invasively measured variables (e.g., core temperatures and metabolic rate), which are often not practical and undesirable measurements for monitoring during varied activities over prolonged periods. The main goal of this paper is to develop dynamic model-based monitoring system of the occupant's thermal state and their thermoregulation responses under two different activity levels. In total, 25 test subjects were subjected to three different environmental temperatures, namely 5°C (cold), 20 °C (moderate) and 37 °C (hot) at two different activity levels (at rest and cycling). Metabolic rate, heart rate, average skin temperature, skin heat flux and aural temperature are measured continuously during the course of the experiments. The results have shown that a reduced-ordered (second-order) MISO-DTF including three input variables (wearables), namely, aural temperature, heart rate, and average skin heat flux, is best to estimate the individual's metabolic rate (non-wearable) with average mean-absolute-percentage-error of 8.7%. A general classification model based on least-squares-support-vector-machine (LS-SVM) technique is developed to predict the individual's thermal sensation. For a 7-classes classification problem, the results have shown that the overall model accuracy of the developed classifier is 76% with a F1-score value of 84%. The developed thermal-state prediction model is promising to estimate the occupant's thermal sensation/comfort status in real-time for better demand controlled HVAC systems.

KEYWORDS

Thermal sensation, thermal comfort, machine learning, HVAC, adaptive controlling

1   INTRODUCTION

Thermal comfort (TC) is an ergonomic aspect determining the satisfaction about the surrounding environment and is defined as 'that condition of mind which expresses satisfaction with the thermal environment and is assessed by subjective evaluation' (ASHRAE, 2004). The effect of thermal environments on occupants might also be assessed in terms of thermal

sensation (TS), which can be defined as 'a conscious feeling commonly graded into the categories cold, cool, slightly cool, neutral, slightly warm, warm, and hot' (ASHRAE, 2004). Thermal sensation and thermal comfort are both subjective judgements, however, thermal sensation is related to the perception of one's thermal state, and thermal comfort to the evaluation of this perception (ISO-10551, 1995). The assessment of thermal sensation has been regarded as more reliable and as such is often used to estimate thermal comfort (Koelblen et al., 2017).

Human thermal sensation is mainly depends on the human body temperature (core body temperature), which is a function of sets of comfort factors (Enescu, 2019; Parsons, 2014). These comfort factors are including indoor environmental factors, namely mean air temperature around the body, relative air velocity around the body, humidity, and mean radiant temperature to the body (Parsons, 2014). Additionally, some personal (individual-related) factors, namely, metabolic rate or internal heat production in the body, which vary with the activity level and clothing thermos-physical properties (such as clothing insulation and vapour clothing resistance), are included. It should be mentioned that the individual thermal perception is deepening, as well, on psychological factors include naturalness (an environment where the people tolerate wide changes of the physical environment), expectations and short/long-term experience, which directly affect individuals' perceptions, time of exposure, perceived control, and environmental stimulation (Nikolopoulou and Steemers, 2003). The most considered way to have an accurate assessment of TS is to ask the individuals directly about their thermal sensation perception (Enescu, 2019; Parsons, 2014). Thermal sensation mathematical models have been developed in order to overcome the difficulties of direct enquiry of subjects. The development of such models is mostly depending on statistical approaches that by correlating experimental conditions (i.e., environmental and person-related variables) data to thermal sensation votes obtained from human subjects (Koelblen et al., 2017; Parsons, 2014). Most of these models (e.g., PMV) are static in the sense that they predict the average vote of a large group of people based on the seven-point thermal sensation scale, instead of individual thermal comfort, they only describes the overall thermal sensation of multiple occupants in a shared thermal environment. To overcome the disadvantages of static models, adaptive thermal comfort models aims to provide insights in increasing opportunities for personal and responsive control, thermal comfort enhancement, energy consumption reduction and climatically responsive and environmentally responsible building design (De Dear and Brager, 1998; Lu et al., 2019). The idea behind adaptive model is that occupants and individuals are no longer regarded as passive recipients of the thermal environment but rather, play an active role in creating their own thermal preferences (De Dear and Brager, 1998). Besides regression analysis, thermal sensation prediction can also be seen as a classification problem where various classification algorithms can be implemented (Lu et al., 2019). Recently, number of research work (e.g., Chaudhuri et al. 2017; Dai et al. 2017; Farhan et al. 2015; Huang, Yang, and Newman 2015; Kim et al. 2018) have demonstrated the possibility of using machine learning techniques, such as support vector machine (SVM), to assess and predict human thermal sensation. It can be concluded based on the published work (see the recent literature review by Lu et al., 2019) that classification-based models have performed so well as regression models. Current HVAC control systems can be divided into two types: air temperature regulator (ATR) and thermal comfort regulator (TCR). Most TCR controllers use static models, mainly PMV, as a performance criterion.

This paper is aiming to develop an individualised and adaptive model for monitoring occupant's thermal sensation based on easily measured variables that suitable for adaptive demand controlled HVAC.

2   MATERIALS AND METHODS
2.1   Experiments and experimental setup
- *Climate chambers (Body & Mind Room)*

The "*Body & Mind Room*" is consisting of three climate-controlled chambers (A, B and C) designed and built to investigate the dynamic mental and physiological responses of humans to specific indoor climate conditions. The Body & Mind Rooms are experimental facilities at the M3-BIORES laboratory (Animal and Human Health Engineering Division, KU Leuven). The three rooms are dimensionally identical; however, each room is designed to provide different ranges of climate conditions as shown in Table 1.

Table 1.The different temperature and relative humidity ranges that can be provided by the different Body & Mind (A, B and C).

Room	Air temperature range (ºC)	Relative humidity range (%)
A	+23 - +37	50 - 80
B	+10 - +25	50 - 80
C	-5 - +10	40 - 60

The three rooms are equipped with axial fans to simulate wind velocities between 2.5 and 50 $km.h^{-1}$.

- *Experimental protocol*

The experimental protocol used in the present study is designed in such way to investigate the subjects' thermal and physiological responses to predefined three different temperature (*low*, *normal* and *high*) that under two levels of physical activities (*low* and *high*). The three predefined temperatures (*low* = 5ºC, *normal* = 24ºC and *high* = 37ºC) are chosen based on the *thermal-comfort-chart* of the ASHRAE-55 (2017) and the effects on health according to the Wind Chill Chart for cold exposure (National Weather Service of the US) and for hot temperatures exposure according to (Dewhirst et al., 2003). The conducted experiments are consisted of two phases (Figure 1, upper graph), namely, low activity and high activity phases. During the first experimental phase, low activity phase, the test subjects (while being seated = low activity) are exposed, during 55 minutes, to three levels of temperatures in the following order: normal, low, high and normal again (Figure 1). During the high activity phase, the test subjects is exposed to a 15 minutes of light physical stress (80W of cycling on a fastened racing bicycle). During the course (75 minutes) of the active phase, each test subject is exposed to the predefined three temperature levels (Figure 1, lower graph). During each temperature level, starting from the normal level (24 ºC), the test subjects are performed 15 minutes of cycling (with 80 W power) and followed 4 minutes of resting (seated). During the course of conducted experiments, the clothing insulation factor (Col) is kept constant at Col = 0.34, which accounts for a cotton short and t-shirt as a standard clothing for all test subjects. The experimental protocol is approved| by the SMEC (Sociaal-Maatschappelijke Ethische Comissie), on the 16th of January with number G-2018 12 1464.
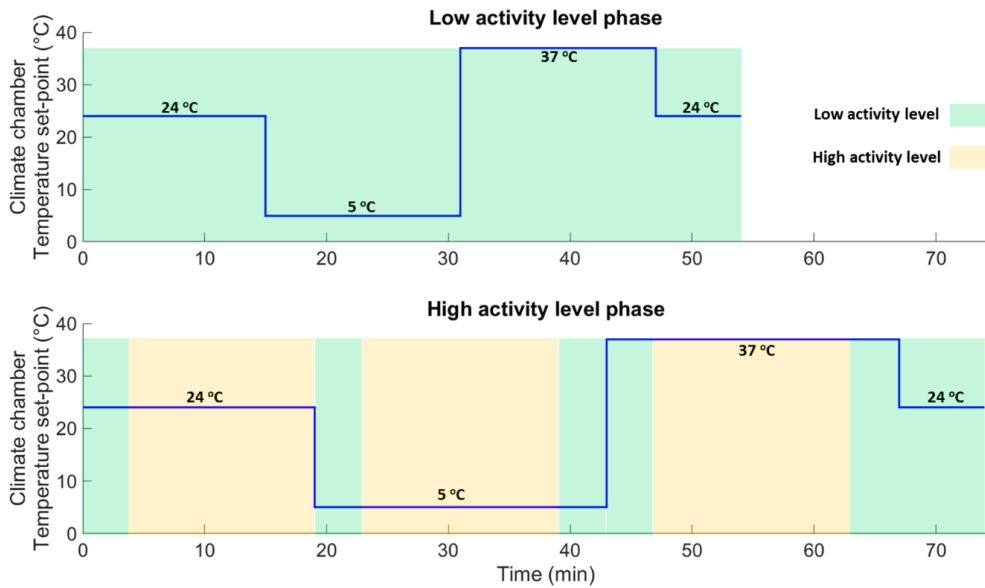
Figure 1. Plots showing the climate chambers' set-point temperatures programed during the 55 minutes low activity phase (upper graph) and the 75 minutes high activity phase (lower graph).

- *Test subjects*

In total 25 healthy participants (6 females and 19 males), between the age of 25 and 35 (average age 26 ±4.2) years, with average weight and height of 70.90 (±12.70) kg and 1.74 (±0.10) m, respectively, are volunteered to perform the aforementioned experimental protocol.

- *Measurements and gold standards*

During the course of the experiments, participants' heart rate, metabolic rate, average skin temperature, heat flux between the skin and the ambient air, core body temperature represented by the aural temperature are measured continuously. The heart rate monitoring is performed using the Polar H7 ECG strap that is placed under the chest, with a sampling frequency of 128 Hz. The metabolic rate of each test subject is calculated based on indirect calorimetry using MetaMAX 3B spiroergometer sensor. The average skin temperature is calculated based on measurements from three body-placed, namely, scapula, chest and arm (Figure 2). The skin temperature measurements are performed using one Shimmer temperature sensor and two gSKIN® bodyTEMP patches. Two heat flux gSKIN® patches are placed on both the chest and the left arm (Figure 2. The skin temperatures and heat flux measurements are acquired at sampling frequency of 1 Hz. Core body temperature is estimated based on aural temperature measure measurements, which is performed using in-ear wireless (Bluetooth) temperature sensor (Cosinuss One) with a sampling rate if 1Hz. At the end of each applied temperature level during the course of both experimental phases, a thermal sensation questionnaire, based on ASHRAE 7-poins thermal scale, is performed for each test subject.
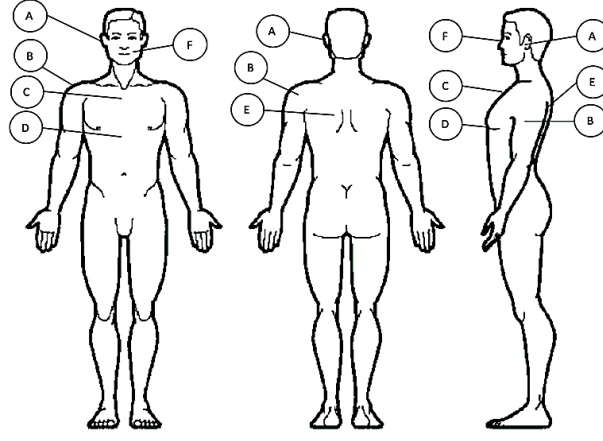
Figure 2. Sensor placement. (A) Ear channel for aural temperature measurement via the Cosinuss One, (B) upper arm where skin temperature and heat flux are measured with the gSKIN patch, (C) middle upper chest where skin temperature and heat flux are measured with the gSKIN patch, (D) lower chest where heart rate is measured with the Polar H7, (E) Scapula where skin temperature is measured with the shimmer, (F) mouth and nose where metabolic rate is measured via the MetaMAX 3B spiroergometer sensor.

2.2   Modelling and classification

For the sake of present study, the measured variables are divided into *wearables*, which are easily measured variables using wearable sensors and *gold-standards* (reference) variables, which are not suitable for wearable technologies. The wearables are including heart rate H_R, aural temperature T_{er}, average skin temperature $\bar{T}_{sk}$, skin heat flux q_{sk} and ambient air temperature T_∞. On the other hand, the gold standards are consisting of the core temperature T_c, which is driven from the aural temperature $[T_c = f(T_{er})]$, metabolic rate M_r and personal thermal sensation votes TS. The ultimate goal of this work is to develop an adaptive classification model to predict the individual thermal sensation depending, solely, on the wearables or estimated variables. Hence, both of the metabolic rate and core body temperature are estimated using online dynamic modelling approach (Figure 3). Then, the individual thermal sensation is predicted using a classification model (classifier) whose inputs are the wearables and estimated the metabolic rate and core body temperature (Figure 3).

   - *Dynamic modelling*

Although the system under study (occupant's thermoregulation) is inherently a non-linear system, the essential perturbation behaviour can often be approximated well by simple linearized Transfer Function (TF) models (Young, 1989, 1993; Youssef et al., 2018). For the purposes of the present paper, therefore, the following liner, Multi-input, single-output (MISO) discrete-time-systems are considered to estimate metabolic rate and core body temperature (Young, 1993),

$$y(k) = \sum_{r=1}^{r=R} \frac{B_r(z^{-1})}{A_r(z^{-1})} u_r(k - \delta_r) + \xi(k), \tag{1}$$

where k denotes the value of the asscociated variable at the kth sampling instant; $y(k)$ is the output variable; $u_r(k)$, $r = 1,2,\dots,R$ are input variables, while $A(z^{-1})$ and $B(z^{-1})$ are appropriately defined polynomials in the backshift operator z^{-1}, i.e., $z^{-i}y(k) = y(k - i)$ and $\xi(k)$ is additive noise, a serially uncorrelated sequence of random variables with variance σ^2 that accounts for measurement noise. The <u>S</u>implified <u>R</u>efined <u>I</u>nstrumental <u>V</u>ariable (SRIV) algorithm was utilised in the identification and estimation of the models (model parameters and model structure) (Young and Jakeman, 1980).Two main statistical measures were employed to determine the most appropriate model structure. Namely, the coefficient of determination R_2^T, based on the response error; and YIC (Young's Information Criterion), which provides a combined measure of model fit and parametric efficiency, with large negative values indicating a model which explains the output data well and yet avoids over-parameterisation

(Young et al., 1991). Additionally, the estimation performance of the selected models is evaluated used the mean-absolute-error (MAE) value.
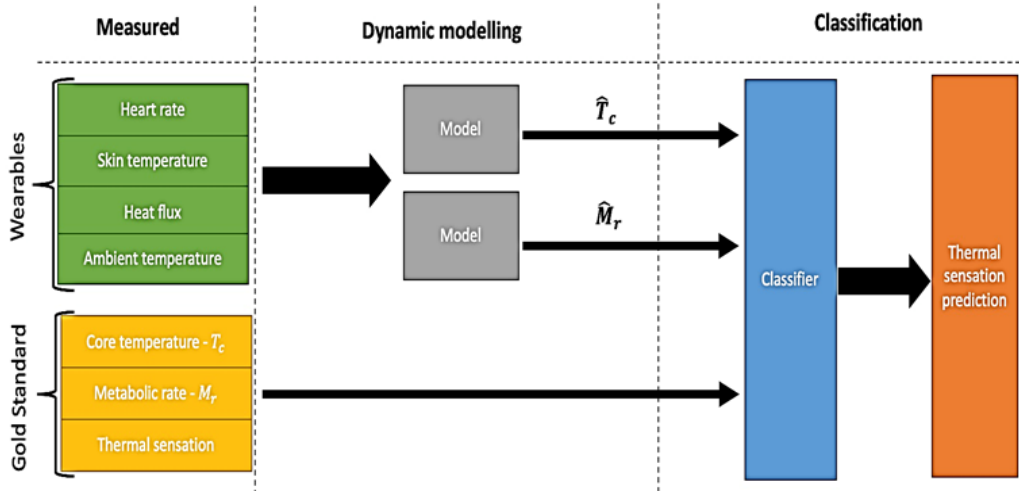

Figure 3. Overview of the main steps to predict the individual thermal sensation.

- *Classification model*

To predict the individual thermal sensation, a classification model (classifier) is developed and trained based on the wearables and estimated variables (metabolic rate and core body temperature) that together with the thermals sensation votes (gold standard). A modified support vector machine (SVM) technique, namely, least-squares support vector machine (LS-SVM) is used to develop and train the thermal sensation classifier (Suykens et al., 2002; Suykens and Vandewalle, 1999). SVMs are originally presented as binary classifiers (Suykens et al., 2002) that assign each data instance $X \in \mathbb{R}^d$ to one of two classes described by a class label $y \in \{-1,1\}$ based on the decision boundary that maximises the margin $2/\|w\|_2$ between the two classes. Generally, a feature map $\phi: \mathbb{R}^d \Rightarrow \mathbb{R}^p$ is used to transform the geometric boundary between the two classes to a linear boundary $L: w^T \varphi(x) + b = 0$ in feature space, for some weight vector $w \in \mathbb{R}^{p \times 1}$ and $b \in \mathbb{R}$. The class of each instance can then be found by $y = sign(w^T \varphi(x) + b)$, where $sign$ refers to the sign function. Due to some computational complexities of standard SVM because of the quadratic programming problem, least squares support vector machines (LS-SVM) is presented to overcome such problem. LS-SVM, in contrast with standard SVM, relies on least squares cost function as follows:

$$\min_{w,b; e} \frac{1}{2} w^T w + \gamma \sum_{i=1}^{N} e_i^2 \ ,$$

such that; $y_i(w^T \varphi(x_i) + b) \geq 1 - e_i \ and \ e_i \geq 0, i = 1, 2, \ldots, N,$

where e_i errors such that $1 - e_i$ is proportional to the signed distance of x_i from the decision boundary, and γ represents the regularisation constant. In LS-SVM, instead of solving the quadratic programming problem a set of linear equations to be solved is sufficient to find the optimal solution of the classifier.

3 RESULTS AND DISCUSSIONS

3.1 Dynamic modelling and estimation of individual's metabolic rate

Different combinations of inputs variables (wearables) are tested for best estimation of individual's metabolic rate. The SRIV algorithm, combined with YIC and R_2^T selection criteria, suggested that a second-order MISO discrete-time TF with heart rate (H_R), average skin heat flux ($\bar{q}_{sk}$) and aural temperature (T_{er}) as input variables is the best (with average $R_2^T = 0.89$ ± 0.04 and $YIC = -13.62 \pm 2.33$) to describe and estimate the dynamic behaviour of the individual's metabolic rate. More specifically, the SRIV algorithm identified the following general MISO discrete-time TF model structure,

$$\widehat{M}_r(k) = \begin{bmatrix} \frac{B_1(z^{-1})}{A(z^{-1})} & \frac{B_2(z^{-1})}{A(z^{-1})} & \frac{B_3(z^{-1})}{A(z^{-1})} \end{bmatrix} \cdot \begin{bmatrix} T_{er}(k - \delta_1) \\ H_R(k - \delta_1) \\ \bar{q}_{sk}(k - \delta_1) \end{bmatrix} + \xi(k), \qquad (2)$$

where $\widehat{M}_r(k)$ is the estimated metabolic rate and the numerator polynomials B_1, B_2 and B_3 are of the following orders (number of zeros) 2, 3 and 2, respectively. While the system delays δ_1, δ_2 and δ_3 are varied from person to another (inter-personal) with average values of 1.4, 0.20 and 0.21 minutes, respectively. The estimation performance of the selected general MISO-DTF (2) is evaluated based on the mean-absolute-percentage-error ($MAPE = \frac{100\%}{N} \sum_{k=1}^{N} \left| \frac{\widehat{M}_r(k) - M_r(k)}{M_r(k)} \right|$) value. The results have shown that the developed general model is shown, for all test subjects, a higher average MAPE value (10 ±2.2 %) during the low activity phases than the average MAPE value (7.6 ±2.6 %) resulted during the high activity phases.

Table 2. Average R_2^T, YIC, model delays and MAPE for the selected MISO-DTF model to estimate the individual's metabolic rate obtained from the 25 test subjects during low and high activity phases.

	Average R_2^T ±std	Average YIC ±std	Model delays Average [δ_1 δ_2 δ_3]	Average $MAPE$ ±std
Low activity phase	0.85 ±0.02	-12.32 ±3.4	[1.5 0.3 0.25] min	10 ±2.2 %
High activity phase	0.94 ±0.03	-14.43 ±2.8	[1.2 0.18 0.20] min	7.6 ±2.6 %

The general estimation performance of the suggested general MISO model can be enhanced by using the online adaptive form of the SRIV algorithm (Garnier et al., 2009). The online adaptive (closed-loop) SRIV algorithm is providing the possibility to personalise the developed general model by retuning the model parameters and model delays based on the streaming data acquired from the wearable sensors.

3.2 Classification model and prediction of individual's thermal sensation

The classification model for predicting the individual's thermal sensation is developed, based on LS-SVM approach, by training the classifier on 80% of the data points, while the rest of the data (20%) is used for testing. The model accuracy, sensitivity F1-score and overall confusion matrix are computed to evaluate the performance of the developed classifier. A feature space including all the measured and estimated input variables, namely, T_{er}, H_R, $\bar{q}_{sk}$, $\bar{T}_{sk}$, $\Delta \bar{T} = T_{er} - \bar{T}_{sk}$ and $\widehat{M}_r$. Additionally, other features are extracted by computing the variance, min, max, root mean squares (RMS) and first derivative of the aforementioned measured and estimated variables. The age and gender of the test subjects are also included in the feature spaces. A feature selection procedure is employed to develop the most reduced-dimension model with highest error performance. The feature selection step is based on an iterative procedure over all possible feature combinations and compare the error performance of the resulted model in each iteration. The feature selection step is resulted in a feature space

including 25 features as shown in Table 3. The resulted confusion matrix from the developed classification model based on the selected feature space is shown in Figure 4.

Table 3. An overview of the selected feature space including the measured and estimated variables (six variables) and some operations on these variables (× = selected).

	Variance	min	max	RMS	$\frac{d}{dt}$
T_{er}	×	×	×	×	-
H_R	×	×	×	×	-
$\bar{q}_{sk}$	×	×	×	×	×
$\bar{T}_{sk}$	×	-	-	×	-
$\Delta\bar{T}$	×	×	×	×	-
$\hat{M}_r$	-	-	-	-	-

	-3	-2	-1	0	1	2	3
-3	0	0	0	0	0	0	0
-2	2	0	1	0	0	0	0
-1	0	1	6	1	0	0	0
0	0	0	0	14	2	0	0
1	1	0	0	1	8	0	0
2	0	0	0	1	0	3	1
3	0	0	0	0	0	1	1

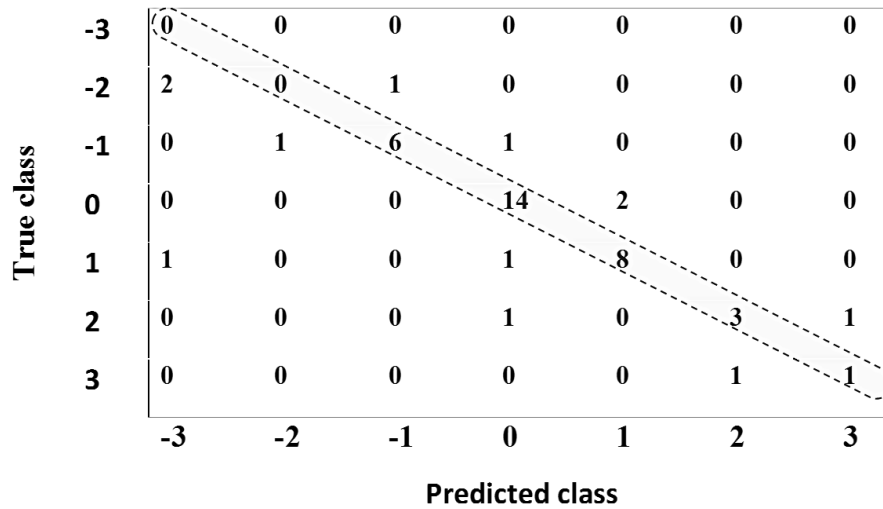(True class / Predicted class)

Figure 4. The resulted confusion matrix from testing the developed LS-SVM classifier. The diagonal represents the correctly classified data points.

The overall performance results of the developed classification model are presented in Table 4. For a 7-classes classification problem, the developed classifier have shown an overall accuracy of 76% to predict the individual's thermal sensation. The developed classifier have shown a high (84%) F1-score, which reflects low false positive and negative.

Table 4. Overall performance of the developed classification model

Measure	Value
Accuracy	0.76
Sensitivity	0.82
Precision	0.87
F1 score	0.84

SVM is used in recent studies to assess occupant's thermal demands (Dai et al. 2017), and to predict thermal comfort/sensation (Farhan et al. 2015). In these studies, the results have shown that SVM is able to predict thermal comfort/ sensation with an accuracy of 76.7%. However, these results is only obtained by reducing the 7-classes classification problem to a 3-classes problem. Hence, we believe that reducing the number of classes will improve our suggested general model performance. Moreover, based on streaming data obtained from wearable sensor technologies, a personalised adaptive classification model, based on the same extracted features, will enhance the model performance to predict the individual's thermal sensation.

4 CONCLUSIONS

In this present paper, 25 participants are subjected to three different environmental temperatures, namely 5°C (cold), 20 °C (moderate) and 37 °C (hot) at two different activity

levels, namely, at low level (rest) and high level (cycling at 80 W power). Metabolic rate, heart rate, average skin temperature (from three different body locations), heat flux and aural temperature are measured continuously during the course of the experiments. The thermal sensation votes are collected from each test subject based on ASHRAE 7-points questioner. The results have shown that a reduced-ordered (second-order) MISO-DTF including three input variables (wearables), namely, aural temperature, heart rate, and average heat flux, is best to estimate the individual's metabolic rate (non-wearable) with average MAPE of 8.7%. A general classification model based on LS-SVM technique is developed to predict the individual's thermal sensation. For a 7-classes classification problem, the results have shown that the overall model accuracy of the developed classifier is 76% with a F1-score value of 84%. It is suggested in this paper that the model overall performance of the model can be enhanced by using a personalised adaptive classification algorithm based on streaming data from wearable sensors.

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