Predictive modelling of thermal comfort using physiological sensing

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**PREDICTIVE MODELLING OF THERMAL
COMFORT USING PHYSIOLOGICAL SENSING**

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PREDICTIVE MODELLING OF THERMAL COMFORT USING PHYSIOLOGICAL SENSING

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in partial fulfillment of the requirement for the degree of
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2018

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research and has not been submitted for a higher degree to any other University or Institution.

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Date

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Tanaya Chaudhuri

Abstract

A thermally comfortable building indoor environment is imperative for human health and work productivity. Although the major energy consumption in a tropical building is attributed to its Air-Conditioning and Mechanical Ventilation (ACMV) cooling systems, yet complaints of thermal dissatisfaction is prevalent among occupants. Prediction of the occupant's thermal comfort can be instrumental in bridging this gap by utilizing the predicted thermal state (*Cool-Discomfort/Comfort/Warm-Discomfort*) as a control criterion for the ACMV system. However, the existing thermal comfort prediction methods rely primarily on environmental information. We envision that a possibly simpler approach would be a direct investigation of the human physiological parameters, since the bodily responses are direct consequences of surrounding thermal ambience.

In this study, we investigate the potential of six different physiological parameters to predict thermal state namely, skin temperature, skin conductance, pulse rate, blood oxygen saturation, and systolic/diastolic blood pressure. Human subject experiments were conducted, during which these six physiological responses and four subjective responses (thermal comfort, thermal preference, humidity sensation, airflow sensation) were recorded in conjunction with a thermal sensation survey while environmental conditions were varied. An overall relational study of all the physiological, subjective, and environmental parameters is performed to gain a clearer understanding of human thermal comfort. An index termed as Thermal State Index (TSI) is introduced to quantitatively represent thermal comfort.

A study of skin temperature of the selected hand skin location revealed that it strongly correlates with the overall thermal sensation. It is verified that the rate at which skin temperature changes carries significant information about the thermal state. However, considerable individual differences are revealed. We develop a novel normalization process to address both inter and intra individual differences by incorporating body surface area and clothing insulation, respectively. Based on this normalization process, we develop a TSI predictive model named *Predicted Thermal State* (PTS) model. While non-normalized skin temperature alone could predict only about (60-65)% of thermal states, the PTS model based on the normalized skin features could predict accurately 87% of thermal states. The combination of skin temperature and its gradient carried more predictive potential than the skin temperature alone. Therefore, the temporal profiles of skin temperature could portray adequate information without normalization.

Based on these temporal profiles, we develop another TSI predictive model named the *Temporal Profile based Predicted Thermal State* (TPPTS) model. A 2-D sensor data to visual space domain-transformation process is developed. Based on a deep convolutional neural network, the TPPTS model achieves 93.33% accuracy.

A study of pulse rate response also revealed considerable individual differences. A novel normalization process using logic gate operations is developed to address the differences with gender and BMI as individual factors. Additionally, a new potential feature of pulse rate is extracted using a spectral analysis method. Based on these features and novel processes, we develop another TSI predictive model named the *enhanced Predicted Thermal State* (ePTS) model; it achieves about 97.15% accuracy.

A collective study of all six physiological and four subjective responses revealed significant gender differences in both responses. Hence, a separate comfort study for each gender-group is conducted, where potential predictive features are identified. Derivative features such as change rate and mean squared gradient are also studied. Based on the identified features and a Random Forest algorithm, we develop another TSI predictive model named the *Gender based Predicted Thermal State* (GPTS) model; it achieves 92.86% and 94.29% accuracies for males and females, respectively. A canonical correlation analysis reveals strong relations between physiological and subjective responses. The four proposed TSI predictive models significantly outperform the conventional PMV method. A comparative analysis of the proposed and existing methods is performed. Subsequently, we propose a novel framework for indoor climate control that can provide optimum comfort with minimum energy consumption of the ACMV system. It incorporates a TSI predictive model and a novel optimization algorithm named the OAT algorithm, that provides the optimal operating condition based on the current TSI. The framework exhibits 36.5% energy saving potential.

Additionally, we study four less-explored non-physiological parameters namely, mean radiant temperature (MRT), age, gender and outdoor weather in context of their significance for thermal comfort. As for MRT, we investigate the effect of the common practice of assuming it to be equal to air temperature on comfort assessment, and subsequently develop an alternative model ($R^2 = 0.89$) to estimate MRT. Age, gender, and outdoor effective temperature, which are not included in the existing comfort models, are found to be important factors for thermal comfort. We believe that the findings of this thesis will assist the built environment community with a better understanding of human thermal comfort and associated phenomena.

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Symbols and Acronyms

Symbols

ST	hand skin temperature
ST_{grad}	skin temperature gradient
ST_n	normalized skin temperature
ST_{grad_n}	normalized skin temperature gradient
PR	pulse rate
PR_{grad}	pulse rate gradient
PR_n	normalized pulse rate
PR_{grad_n}	normalized pulse rate gradient
PR_{sp}	pulse rate spectral feature
SC	hand skin conductance
SpO_2	blood oxygen saturation
BP_{sys}	systolic blood pressure
BP_{dia}	diastolic blood pressure
T_a	air temperature
V_a	air speed
MRT	mean radiant temperature
I_{cl}	clothing insulation
A_{Du}	Du Bois and Du Bois body surface area
A_{exp}	exposed body surface area
α	gender coefficient
β	BMI coefficient
f_1	supply-air fan frequency
f_2	water pump frequency
f_3	compressor frequency

$\mathbf{f}$	ACMV operating frequency vector
$\mathbf{f}_{curr}$	current operating frequency vector
$\mathbf{f}^*$	optimal operating frequency vector
T_{curr}	current air temperature
T_a^*	optimal air temperature
E	ACMV energy consumption
E_{ref}	ACMV energy consumption at benchmark operating state
ET_{out}	outdoor effective temperature
T_g	globe temperature
h_g	globe's mean convection coefficient
ϵ	emissivity of globe thermometer
D	diameter of globe thermometer
M	metabolic rate
A	age of occupant
G	gender of occupant

Acronyms

ACMV	Air Conditioning and Mechanical Ventilation
AMV	Actual Mean Vote
ANN	Artificial Neural Network
ANSI	American National Standards Institute
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
aPMV	adaptive Predicted Mean Vote
BMI	Body Mass Index
C	Comfort thermal state
CL	Comfort Level
CLI	Comfort Level Inaccuracy
CNN	Convolutional Neural Network
CoV	Coefficient of Variance
RSS	Residual Sum of Squares
CT	Classification Tree
DC	Discomfort thermal state
ePTS	enhanced Predicted Thermal State
ELM	Extreme Learning Machine

ePMV	extended Predicted Mean Vote
ESP	Energy Saving Potential
FFT	Fast Fourier Transform
FOG	First Order Gradient
GPTS	Gender based Predicted Thermal State
HVAC	Heating Ventilation and Air-Conditioning
KNN	K Nearest Neighbours
LDA	Linear Discriminant Analysis
LR	Logistic Regression
MAPE	Mean Absolute Percentage of Error
MBE	Mean Bias Error
MCI	McIntyre thermal preference vote
MRE	Mean Residual Error
MRT	Mean Radiant Temperature
MSE	Mean Squared Error
MSG	Mean Squared Gradient
NV	Naturally Ventilated
OAT	Optimal Air Temperature algorithm
OLS	Ordinary Least Squares
PMV	Predicted Mean Vote
PTS	Predicted Thermal State
RBF	Radial Basis Function
RF	Random Forest
RMSE	Root Mean Squared Error
RSS	Residual Sum of Squares
SVM	Support Vector Machine
TP	Temporal Profile
TPPTS	Temporal Profile based Predicted Thermal State
TS	Thermal State
TSA	Thermal Acceptability vote
TSI	Thermal State Index
TSV	Thermal Sensation Vote

Dedicated to my dear parents

Chapter 1

Introduction

This chapter provides the motivation and objectives for the research. It defines the hypothesis and outlines the objectives and scope of the research. It also summarizes the major novel findings, outcomes and implications.

1.1 Motivation

A thermally comfortable indoor environment is imperative for human health, work productivity and building sustainability, especially because people generally spend most of their daily time (about 90%) staying indoors [1, 2]. Buildings are responsible for more than one-half of the global electricity use, and the largest building energy consumption, at about 40-60%, is by the Heating Ventilation and Air-Conditioning (HVAC) systems alone [3]. The HVAC systems account for more than 30% of the world's energy consumption [4]. Yet, complaints of thermal dissatisfaction are prevalent among indoor occupants [5]. This widespread disparity between energy efficiency and indoor thermal comfort in buildings is attributed to inadequate thermal environment control schemes, that culminate in over-cooled and over-warmed environment during warm and cool climates, respectively [6, 7].

Over-cooling is a common issue in the air-conditioned buildings in hot and humid climate such as that of Singapore [7]. Located at 1.35°N of equator, Singapore is a country with consistent high temperatures and humidity throughout the year as depicted

by the climatological summary in Figure 1.1a [8]. It is imperative for almost all the residential and commercial buildings in Singapore to be supported with continuous Air Conditioning and Mechanical Ventilation (ACMV) cooling systems. The ACMV systems typically account for about 60% of a building's electricity consumption in Singapore [9] (Figure 1.1b). Yet, over-cooled indoors of a building owing to inefficient controllers result in prevalent complaints of discomfort among the occupants [10]. The resulting frequent transitions between hot outdoors and cold indoors weaken human thermal regulation ability due to large temperature gaps [11, 12]. Besides, the human body is more sensitive to prolonged cooling than heating owing to the higher number (10 times) and the greater depth (5 times) of subcutaneous cold receptors as compared to subcutaneous hot receptors [12, 13]. Thus, over-cooling not only leads to energy wastage but also results in a compromised health. This emphasizes the need for effective and reliable control algorithms for the ACMV systems. Incorporating thermal comfort of the occupant as a control criterion can be a prospective solution in this respect.

Prior knowledge of the occupant's thermal comfort state can facilitate an informed control decision of the ambient thermal-conditioning. Therefore, the prediction of thermal comfort can be an indispensable aid to a better ambient control. The current control algorithms are primarily based on predefined set-points that are derived from the ASHRAE-PMV approach [14], which primarily depends on environmental information such as air temperature, humidity, etc. However, its reliability may be limited by possible discrepancy between the predicted and the actual comfort votes [15, 16]. The subjective nature of thermal comfort and its multiple deciding factors make its quantification further challenging. While it benefits to study the environmental factors, a possibly simpler approach would be a direct investigation of the human physiological parameters, since the bodily responses are the direct consequences of the surrounding thermal ambience.

Figure 1.1: Singapore's typical outdoor weather and building electricity consumption.

1.2 Hypothesis and Problem Statement

As the environmental conditions vary, human thermoregulatory system operates to maintain thermal equilibrium in the body, and this process gets reflected in the physiological responses. Specifically, the somatic nervous system collects sensory data from skin thermoreceptors as well as from the internal organs through the blood stream, evaluates this data based on the psychological state, and yields a thermal comfort response [17]. Thus, physiological parameters can potentially give insight into the thermal state. Six physiological parameters are specifically selected for investigating their ability to indicate thermal comfort:

1. Hand skin temperature
2. Hand skin conductance
3. Pulse rate
4. Blood oxygen saturation
5. Systolic blood pressure
6. Diastolic blood pressure

During thermoregulation, skin temperature and skin conductance represent conductive heat transfer through the skin layer. Pulse rate and blood pressure can represent thermal stimulus on cardiovascular system, while blood oxygen saturation can represent thermal stimulus on the respiratory system. The detailed rationale behind the selection of these parameters is described in the next chapter. Thereafter, the hypothesis and problem statement are defined:

This thesis tests the hypothesis that the thermal comfort of a building occupant can be predicted by sensing primarily six physiological parameters namely, hand skin temperature, hand skin conductance, pulse rate, blood oxygen saturation and systolic/diastolic blood pressure.

Based on the above hypothesis, this thesis also designs four thermal comfort predictive models and one closed-loop framework for indoor climate control to provide optimum thermal comfort with minimum energy consumption of the ACMV system.

1.3 Objectives and Scope

It is important to conduct an overall relational study of all the physiological, subjective, and environmental parameters to gain a clear understanding of human thermal comfort. Therefore, a series of rigorously designed thermal experiments are conducted, where the physiological parameters are measured along with subjective surveys and environmental measurements. An index termed as Thermal State Index (TSI) is introduced to quantitatively represent thermal comfort. Besides physiological factors, it is also important to study the non-physiological factors of thermal comfort. The thesis is outlined in Figure 1.2. The content indicated as *Part A* in Figure 1.2 forms the major crux of the thesis corresponding to the laid hypothesis. The content indicated as *Part B* is an additional reconnaissance study to investigate the importance of certain less-explored non-physiological factors. The thesis objectives are four-fold:

- Study how each of the six physiological parameters and their derivative features respond to thermal stimuli. Observe the patterns in their behaviour, and extract the information that is significantly related to the corresponding thermal comfort state. Consequently, based on the observations, develop a thermal comfort predictive model. It is to be ensured that the model is personalized as well as scalable. Due to morphological dissimilarities, investigate gender differences in physiological responses as well.
- Study the patterns in the various subjective responses corresponding to thermal stimuli. Observe the connections among the subjective parameters and investigate the gender differences. Lastly, study the connections between the physiological and subjective responses.
- Design a closed-loop framework for indoor climate control. The framework would include a TSI predictive model and an optimization algorithm such that optimal comfort can be achieved with minimum energy consumption.
- Study four specific less-explored non-physiological parameters namely, mean radiant temperature (MRT), age, gender and outdoor weather in context of their significance for thermal comfort. As for MRT, investigate the common practice of assuming it to be equal to air temperature, and develop an alternative model to estimate MRT. It is important to study MRT because it is often neglected in comfort studies by the equality assumption. Age and gender are to be studied because their impact on thermal comfort has often been debated in the literature.

Figure 1.2: The Thesis Outline.

1.4 Dissertation Overview

Chapter 1 provides the motivation and rationale for the research. It defines the hypothesis and problem statement and outlines the objectives and scope of the research. It also summarizes the major novel findings, outcomes and implications.

Chapter 2 reviews the relevant seminal and recent literature on thermal comfort prediction, and places the Ph.D. thesis in context.

Chapter 3 describes the experimental set-up and methodology. Demographic details of the human subjects, measurement specification and procedures will be presented. It also provides the rationale for the experimental design and considerations, and enlists all the statistical methods and learning algorithms used during this study.

Chapter 4 presents the results of investigating skin temperature as a TSI biomarker. This chapter studies the relationship between thermal sensation and skin temperature and its gradient feature, both at individual and overall level. Based on the observed characteristics, it also proposes two TSI predictive models (models A and B). Novel normalization and domain-transfer processes will be proposed for the models, and performance comparison with state-of-the-art will be conducted.

Chapter 5 presents the results of investigating pulse rate as a TSI biomarker. This chapter studies the relationship between thermal sensation and pulse rate and its gradient feature. Based on the observed characteristics, it proposes a new TSI predictive model (model C). A normalization process and spectral analysis based method will be proposed to extract significant information. Moreover, the model will be compared with eight different new and state-of-the-art methods.

Chapter 6 presents the results of studying all the six physiological responses both individually, and collectively. Gender differences in both physiological and subjective responses will be discussed. It also identifies the derivative features with predictive potential, and proposes a new TSI predictive model (model D). Moreover, correlation between physiological and subjective responses will be discussed. This chapter also proposes a framework for indoor climate control, that would facilitate optimum comfort with minimum energy consumption. A comparative analysis of all four proposed predictive models will also be presented.

Chapter 7 presents the results of investigating significance of the non-physiological parameters MRT, age, gender and outdoor weather. The impact of the equality assumption

on comfort assessment will be investigated, and a new model to estimate MRT will be developed.

Chapter 8 is devoted to concluding remarks, summarizing the major findings and implications arising from this study. Possible future works to extend this research are also outlined.

1.5 Findings and Originality

To the best of author's knowledge, a full-fledged relational study of all physiological and subjective parameters for thermal comfort prediction has not been done earlier. This research led to several novel findings and outcomes as summarized below:

1. Each of the six physiological parameters except for blood pressure, revealed significant response to thermal stimuli. Certain derivative features of the parameters which reflect how they vary with time, were discovered to be strong biomarkers of TSI. These features sometimes carried more relevant information to translate to the occupant's comfort than the parameters themselves. Significant gender differences were observed in both physiological and subjective responses, which indicates the need for separate comfort study of each gender-group. In addition, the potential of a single body location's skin temperature to predict the overall body thermal state was demonstrated. To the best of author's knowledge, existing literature has generally employed multiple body locations, most of which are intrusive.
2. Based on the response behaviours, four different TSI predictive models were developed. In order to make the model scalable, individual differences should be addressed. Hence, novel normalization processes were developed after identifying significant individual factors. For skin temperature, clothing insulation and Du Bois area, and for pulse rate, gender and BMI were discovered to be the individual factors. In addition, relevant information of skin temperature and pulse rate were extracted using a novel domain transfer process and a spectral analysis, respectively. The first model (A) is based on the skin temperature features and the developed normalization process. After discovering a certain important behaviour of skin temperature, the second model (B) was developed. It proposes a new 2-D to image domain transfer process. The third model (C) extends and enhances the

model A by identifying and appending new significant features related to pulse rate. Finally, the fourth model (D) is developed using a gender specific approach including all six physiological parameters and their features. The four proposed models significantly outperformed the existing conventional methods, achieving up to 97% accuracy in predicting the occupant's thermal state.

3. A framework to control the indoor climate was proposed that aims to provide optimum comfort with minimum energy consumption of ACMV system. The general outline of the framework is shown in Figure 1.3. It incorporates a TSI predictive model and an optimization algorithm that provides optimal operating condition based on predicted TSI. It exhibited up to 36.5% energy saving potential, and an ambient temperature of about 25°C is found to be most optimum for comfort and energy use.
4. An error analysis revealed that the equality assumption of MRT adversely affects thermal comfort assessment, resulting in incorrect conclusion about the occupant health. An alternative MRT estimation model ($R^2 = 0.89$) was developed, that reduces the error by over 65%. Age, gender and outdoor effective temperature, which are not included in conventional methods, were found to be important factors of thermal comfort.

Figure 1.3: The general outline of the proposed indoor climate control framework.

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Chapter 2

Literature Review

This chapter reviews the relevant seminal and recent literature on thermal comfort prediction, identifies existing research gaps, and places the thesis in context.

Thermal comfort has been defined by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) as “the condition of the mind in which satisfaction is expressed with the thermal environment” [1]. There are two different types of approaches for evaluation of thermal comfort namely, the heat balance approach and the adaptive approach [2].

The heat balance approach rests its evaluations based on the heat balance model of human body with the surrounding environment. It is based on the perception of the human body as a dynamic thermoregulation machine which ensures that the body heat is within certain safe limits by exchanging heat with the environment. The most popular thermal comfort prediction method is the PMV method [3], a heat balance approach.

According to the adaptive approach, an occupant’s control over the environment such as ability to close/open the windows, operate and regulate fans, also has a psychological influence on the thermal sensation. Besides, thermal preferences, expectations, and adaptation abilities (physiological, behavioural, psychological) can also influence thermal sensation. These extraneous factors are taken into account by the ePMV and the aPMV methods [4, 5]. These three conventional methods are briefly described in the next section.

2.1 Conventional Prediction Methods

PMV method

The Predicted Mean Vote (PMV) method [3] was developed by P. O. Fanger in the early 1970s. According to this method, thermal comfort depends on six factors mentioned by Macpherson namely, air temperature, relative humidity, air speed, mean radiant temperature, clothing insulation and metabolic rate. The method entails a series of mathematical computations to predict thermal sensation using these six factors as inputs. It predicts the actual thermal sensation using equation 2.1:

$$PMV = (0.303e^{-0.036M} + 0.28)L \quad (2.1)$$

where, M is the metabolic rate and L is a function of the six factors. For detailed description of the PMV method, see [3].

ePMV method

The extended PMV (ePMV) method [4] was developed by P.O. Fanger in 2002. He extended the PMV method by including the adaptive abilities of occupants through an expectancy factor “ e ”. It predicts the actual thermal sensation using equations 2.2-2.3 where, TSV is the actual thermal sensation vote and N is the sample size.

$$ePMV = e \times PMV \quad (2.2)$$

$$e = \frac{\sum_{i=1}^N TSV_i \times PMV_i}{N} \quad (2.3)$$

aPMV method

The adaptive PMV (aPMV) method [5] was developed by Yao *et al.* in 2009. It uses an adaptive coefficient “ λ ” to predict the actual thermal sensation using equations 2.4-2.5:

$$aPMV = \frac{PMV}{1 + \lambda \times PMV} \quad (2.4)$$

$$\lambda = \frac{\sum_{i=1}^N \frac{1}{TSV_i} - \sum_{i=1}^N \frac{1}{PMV_i}}{N} \quad (2.5)$$

2.2 Human Physiological Parameters

The thermoregulatory centre lies in the hypothalamus, a small organ located in the brain [6]. It receives the core temperature by measuring the temperature of the blood passing through the thermoreceptors in brain, and it receives external temperature with the help of thermoreceptors in the skin. Based on these two temperatures, it adjusts the body temperature. Human skin is a mediator of heat transfer; hence *skin temperature* and *skin conductance* play major roles in this thermoregulation process through the vasoconstriction and vasodilation operations using subcutaneous heat receptors [7, 8]. These two parameters are integral to maintaining heat balance at a fixed activity level [3]. Consequently, the predominant reaction under cold and hot environment is lowered skin temperature and increased sweating, respectively.

Skin Temperature

Several researchers such as Xiong *et al.* [9] and Ghahramani *et al.* [10] have investigated the physiological responses of skin to various thermal environments. Xiong's research studied the thermal sensations and physiological responses of the skin temperatures of 7 different body locations to step-change transient thermal environments, while Ghahramani studied skin temperatures of 4 facial locations under thermal stress. Based on the mean skin temperature of 22 body locations, Zhang *et al.* [11] proposed rule-based overall sensation and comfort models. However, Zhang's model validation was focused on an automobile setting which may not be compatible with a building environment. Liu W. *et al.* [12] used the mean skin temperature of 10 body locations to evaluate thermal comfort of a person in a sleeping posture. However, Liu's method strictly defined ranges of skin temperature for each comfort state, which may not address the individual differences in physiological response as a common range cannot be generalized for the entire population [13]. Similarly, Takada's regression model [14] to relate transient thermal sensation with the mean skin temperature of 7 body locations is based on fixed mathematical expressions. While a recent study [13] used the more flexible and adaptive machine learning based data-driven approaches, the locations recommended were intrusive in nature and challenges practical implementation. Sim *et al.* [15] studied four non-intrusive hand locations, however validation of their study was limited by a small sample size.

Skin Conductance

Skin conductance represents both convective heat transfer through circulating blood and conductive transfer by skin layer. In the study [16] of Wang and Hu, sweat activity linearly related to people's thermal sensation and the thermal regulation process of sweat had some impact on the sensation. However, the sweat rates in this study were subjectively reported by the occupants instead of measurement. Thermal adaptive changes have been observed in distribution of regional skin temperature and sweating threshold temperatures as a response to external thermal stimuli [17].

Pulse Rate

Pulse rate is closely linked with the cardiovascular system. Recently, a couple of studies studied the potential of heart rate to indicate thermal sensation. In Choi *et al.*'s study [18], both heart rate and changes in it showed significant variations between warm and cool conditions, while in another study [19], heart rate variability (HRV) indices, which reflect the time variation between successive heartbeats, could evaluate thermal comfort using machine learning algorithms.

Blood Oxygen Saturation

Blood oxygen saturation, also denoted as SpO_2 , is the percentage of haemoglobin binding sites in the bloodstream occupied by oxygen and is commonly measured by pulse oximetry. It is linked with respiration and can indicate the impact of thermal stimuli on the respiratory system. Xiong *et al.* [20] studied the response of SpO_2 to large temperature step-changes ranging (5-15)°C and found no significant behaviour.

Blood Pressure

Blood volume pressure is another important parameter for human health. It is closely linked to the thermoregulation process and can reflect the effect of thermal stress on the cardiovascular system. It is usually expressed as two numbers. Systolic blood pressure (the higher number) measures the pressure in the arteries when the heart beats while diastolic blood pressure (the smaller number) measures the pressure in the

arteries between heartbeats. Systolic pressure can be more responsive to temperature step-changes than diastolic pressure [21].

Xiong *et al.* studied the responses of blood pressure, SpO₂, skin temperature and heart rate to step changes in temperature [20–22]. Study subjects in [22] reported symptoms of accelerated respiration, sweating and heart rate, while [20, 21] revealed that blood pressure, heart rate and skin temperature are sensitive to sudden temperature changes.

2.3 Personal Comfort Systems

The advancement of ubiquitous computing and the internet-of-things in the building domain project a promising future for personal comfort systems in smart building applications [23]. The immense development and current trend of wearable technology has made this integration even easier. For instance, heart rate and accelerometer data extracted from wearable device can be used to compute metabolic rate, and be integrated with PMV thermal comfort model [24]. Besides, sweat rate and skin temperature captured by commodity wearable can be combined with ambient sensors for personalized comfort [25, 26]. However, these studies relied primarily on ambient sensors with very few physiological sensors. There are several challenges in collecting such ambient data and interfacing data from multiple sources can be cumbersome and prone to security issues. We envision a comfort system based on a single wearable with physiological sensors alone; it would require minimum set-up and disruption and be portable too.

2.4 Gender Differences

Gender is a profound individual factor often debated to be linked with thermal perception and comfort requirements. While several studies found no gender difference in comfort perception, the dissimilarities between men and women were evidently significant in several field studies and controlled chamber tests [27–29]. A meta-analysis revealed that females are more likely to express dissatisfaction than males in the same thermal environment [28]. This inconclusive debate on gender difference warrants study of the underlying physiological differences during thermoregulation [30]. Innate differences in physical traits and physiology between men and women is likely to create differences in their thermoregulatory functions. Although few studies have analysed gender difference

in bodily reactions to temperature step-changes [31], similar investigation regarding thermal comfort is required.

2.5 Mean Radiant Temperature

Mean radiant temperature (MRT) is one of the six factors that significantly influence human thermal comfort according to the Fanger's PMV model [3, 32, 33]. MRT is defined as the uniform temperature of an imaginary enclosure in which radiant heat transfer from the human body is equal to those in the actual non-uniform enclosure [34]. Thermal comfort is governed by heat exchange between a person and its surroundings via conduction, convection, radiation, and MRT is a measure of the body's radiant environment, contributing up to 30% of the heat exchange [35]. However, determination of MRT is a classic problem in the field of human bio-climatology because it is one of the most complicated parameters to analyse [36].

Over several decades, various methods to evaluate MRT have been proposed. The measurement methods rely on globe thermometers, two-sphere radiometers, radiative flow sensors or constant air-temperature sensors, while calculation methods require temperatures of surrounding surfaces and angle factors, or plane radiant temperatures [37]. Recently, several methods have been proposed to estimate MRT in urban outdoor spaces [38–41]. Few studies have been conducted to predict indoor MRT as well, such as in office spaces [42] or for a subject exposed to incoming solar radiation [35, 43].

However, it is a widely common practice to assume MRT equal to air temperature (T_a) in indoor spaces [36, 44–50]. This simplistic assumption is based on the hypothesis that, unlike outdoor conditions, where MRT has clear spatial patterns, the indoor surfaces have uniform radiation fluxes and temperatures due to limited solar radiation. Because of uniform flux, it is often assumed that the difference between MRT and T_a would be negligible [51]. This rationale was investigated by an indoor case study, however it was specific for a naturally ventilated building [50]. In spite of this assumption being a widely followed practice with significant influence on human bio-climate and health, little experimental evidence exists in its support. Over or under-assumption of MRT can result in incorrect conclusion about thermal comfort. This warrants a study of the effect of this assumption on thermal comfort assessment:

$$\text{MRT} = T_a$$

2.6 Ph.D. thesis in context of literature

The literature review brings to light several existing research gaps. Firstly, besides skin temperature, other physiological parameters were seldom explored with respect to thermal comfort. Although few studies have analysed several physiological mechanisms under drastically transient thermal environments, these parameters have not been collectively investigated for thermal comfort evaluation. Secondly, gender difference in physiological responses in view of thermal comfort, remains largely unexplored.

Although several research have studied local and mean skin temperatures and local/overall thermal sensations under transient thermal environments, their practical applications for indoor climate control are significantly limited. Firstly, measurements of multiple body locations will require several sensors leading to higher computational load on ACMV control systems and larger hardware costs. Secondly, most of the suggested locations such as shin, back, chest, abdomen, etc are intrusive in nature, which hinders practical applicability. Thirdly, although studies have shown that gender do have influence on how comfort is perceived [29, 52], none of the known past works has considered equal gender distribution in their selection of subjects. Moreover, to the best of author's knowledge, existing literature does not address that physiological responses to thermal changes may vary from person to person. In such cases, a model that performs well on one occupant may not function equally well on another, unless normalized on the basis of personal factors.

Moreover, the conventional PMV method has often shown discrepancy with the actual comfort [53, 54]. Unlike the rigid conventional methods, computational intelligence techniques have the adaptive ability and can be integrated with wearable technology and internet-of-things. In view of these research gaps and leveraging upon the data-driven possibilities, this thesis aims to meet the objectives described in Chapter 1.

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Chapter 3

Experimental Methodology

This chapter describes the methodology of experiments that form the foundation for the analysis, investigation, and validation of the findings of this dissertation. The experiments are designed after a thorough literature review of existing experimental studies, and identification of research gaps. Strict adherence to the latest international standards of ASHRAE/ANSI is maintained while focusing on the main objectives of the thesis. Although the primary aim of the experiments is a thorough understanding of the physiological parameters, nevertheless, the practicalities of the proposed approaches or models are also taken into prior consideration, such as the convenience of data acquisition. Several mock experiments were performed before finalizing the following methodology. The chapter is organized as follows: Section 3.1 highlights some important pre-considerations for the experiments. Section 3.2 presents the demographic information of the participating human subjects. Section 3.3 describes the environmental, the physiological and the subjective measurements taken. Section 3.4 illustrates the experiment procedure, and section 3.5 lists the statistical methods and the learning algorithms that will be used during this study.

3.1 Pre-Considerations

We made some important considerations prior to the experiments as highlighted below:

- Equal gender representation was ensured while recruiting the human subjects for the series of experiments. This is because it has often been debated that gender differences can influence how thermal comfort is perceived [1].
- According to the adaptive thermal comfort model [2], one's thermal experiences and expectations significantly influence perception of thermal comfort. Therefore, the participants were subject to the criterion of residing in Singapore for at least about 3 years, in order to make sure that they were physically (in terms of their thermoregulatory system) and psychologically adapted to the local climate and indoor/outdoor thermal environment patterns.
- It was ensured that all subjects were healthy and were not undergoing any medication. Preliminary evaluation of subjects was conducted to include only those who do not suffer from any cardiovascular/respiratory/skin disease which might interfere with the physiological measurements. Particularly so, because pulse rate and blood pressure are related to cardiovascular health, SpO₂ is related to respiratory health, and skin temperature is related to skin health. In addition, it was ensured that no subject has fever, as that might affect the results, because, skin temperature of a person with fever could be high irrespective of external conditions. The approximate date of last occurrence of fever was noted to make sure it was not recent and does not affect the results anyhow.
- After the final selection of subjects, they were asked to strictly avoid alcohol, smoking and intense physical activity for at least 12 hours prior to the experiments, in order to avoid any influence on the measurements.
- Immediately prior to the experiment, each subject was asked to report his/her stress level on this scale: "Very relaxed/Relaxed/Little stress/Very stressed". This step was taken to note the existence of any psychological issues that might impact the results of the survey.
- It was ensured that the data-acquisition using wearable sensors was convenient and non-intrusive such that it does not interfere with the subject's comfort, and be suitable for practical realization.

- All the experiment protocols were in accordance with the Declaration of Helsinki and the university's ethics committee. Verbal and written consents were obtained from each subject prior to their participation.

3.2 Human Subjects

Twenty subjects (10 males and 10 females) were recruited to take part in the thermal comfort experiments. A sample of 20 subjects in particular is motivated by past relevant studies on skin temperature and thermal comfort using similar number of subjects; Ghahramani's study [3], Zhang's model [4], Liu's method [5], Dai's study [6], Takada's model [7], Sim's method [8] and Choi's study [9] were based on 15, 17, 22, 11, 15, 8 and 16 subjects, respectively (comparative analysis summarised as Table 3.4).

The anthropometric information of the subjects is summarized in Table 3.1. Subjects were free to wear clothing of their choice. However, since Singapore has an equatorial hot and humid climate, the clothing ensembles of the subjects were typical light summer clothing which included T-shirts, thin trousers, walking/short shorts, knee-length dresses/skirts, sandals, and shoes with or without socks. The clothing insulation factor (I_{cl}) of each subject was calculated using ANSI/ASHRAE Standard-55 [10]. The clothing insulations ranged between (0.35-0.58) clo. Additionally, the age, height and weight of the subjects were noted. The body surface area (A_{Du}) of each subject was calculated using the height and weight information based on the Du Bois & Du Bois equation [11]:

$$A_{Du} = \text{Weight}^{0.425} \times \text{Height}^{0.725} \times 0.203 \quad (\text{m}^2) \quad (3.1)$$

where, weight and height are in kg and m, respectively. A statistical means analysis revealed that there were highly significant ($p < 0.001$) gender differences in height, weight and body surface area, while their age and clothing insulations were similar.

Table 3.1: Anthropometric information of the subjects (mean $\pm$ standard deviation).

Gender	Count	Age (years)	Height (cm)	Weight (kg)	A_{Du}^0 (m ²)	I_{cl}^1 (clo)
Male	10	24.0 $\pm$ 2.4	174.9 $\pm$ 5.2	72.0 $\pm$ 12.3	1.87 $\pm$ 0.16	0.46 $\pm$ 0.09
Female	10	22.3 $\pm$ 1.1	160.3 $\pm$ 4.2	51.7 $\pm$ 7.9	1.52 $\pm$ 0.10	0.44 $\pm$ 0.1
Total	20	23.2 $\pm$ 2.0	167.6 $\pm$ 8.8	61.8 $\pm$ 14.5	1.70 $\pm$ 0.22	0.45 $\pm$ 0.09
<i>p</i> -value	-	0.158	< 0.001*	< 0.001*	< 0.001*	0.295

Note: ⁰Du Bois Body Surface Area, ¹Clothing Insulation, *Significant gender difference.

3.3 Measurements

3.3.1 Environmental Measurements

Experiments were conducted in a typical office room located at the Cambridge CARES office in the Nanyang Technological University, Singapore (Figure 3.1). The experiment room was supplied by a centrally located ceiling-mounted ACMV system whose control could be maneuvered from 16°C to 31°C. The indoor air temperature, relative humidity, air velocity, and globe temperature were recorded within close proximity to the subject. The instruments utilized for recording these parameters are summarized in Table 3.2. The table also lists the instrument specifications (accuracy and range). Multi-directional air velocity measurements were taken and the average was computed. The recorded data of air temperature, relative humidity and air velocity were processed using LogData2TM software (TSI Inc., USA.). The indoor mean radiant temperature was computed using a black globe thermometer, while the outdoor air temperature and relative humidity were monitored as per the nearest weather station using *Weather@SG* service provided by the Meteorological Service Singapore (MSS). The globe thermometer was constructed according to the ASHRAE guidelines using a plastic ping-pong ball with a diameter of 0.4 m that was painted black with a paint with emissivity of 0.95. The temperature sensor IC-LM35 was placed at the spherical centre of the black globe. The globe thermometer was thoroughly calibrated using a standard commercial globe thermometer as well as a thermocouple, as described in Table 3.2.

Figure 3.1: Diagram of the test bed: a 6.8m×5.35m×2.71m experiment room located at the Cambridge CARES office in the Nanyang Technological University, Singapore (diagram not drawn to scale). The environmental sensors were located at 1.1m height above the ground. The symbols in the figure denote: T_a —air temperature, V_a —air velocity, and RH —relative humidity.

3.3.2 Physiological Measurements

The following six physiological parameters of each subject were monitored:

1. Hand skin temperature (ST)
2. Hand skin conductance (SC)
3. Pulse rate (PR)
4. Blood oxygen saturation (SpO_2)
5. Systolic blood pressure (BP_{sys})
6. Diastolic blood pressure (BP_{dia})

The specifications of the wearable sensors used for data acquisition are summarized in Table 3.2. Sensor device used for measuring hand skin temperature was calibrated using a standard mercury thermometer with a precision of 0.1 °C. All the sensor probes except that of blood pressure were connected to a micro-controller board (Model: Arduino Uno, Arduino Co., USA) via a sensor shield (Model: e-Health sensor shield V2.0, Libelium Co., Spain), which has an in-built intelligence to translate the captured analog signals to standard units. The micro-controller was programmed for sensor activation and real-time data transfer to a computer for processing.

The sensing devices were attached on specific locations of the non-dominant hand as depicted in Figure 3.2a. The sphygmomanometer was used on the other hand to avoid interference with the remaining sensors. Pulse rate, which is analogous to heart rate was studied due to ease of measurement; it can be sensed from the wrist/finger unlike the intrusive EEG method for measuring heart rate, and hence it is more practically realizable as a wearable device. Figure 3.2b depicts some subjects filling survey during the thermal comfort experiments.

Rationale for ‘Hand’ Skin Temperature

For the skin temperature measurement, we have selected a specific location- the area between the wrist and the fingers on the dorsal side of hand, as depicted in Figure 3.3 (encircled and shaded area). There are several reasons for selecting this location. Firstly, the radial and ulnar arteries, which channel heat loss from the body core to the periphery,

meet at this very region. This makes this region thermally receptive. The hand has a good amount of blood supply because of numerous anastomosis arteries present in the hand. Majority of these arteries function to facilitate heat loss when required. The radial and the ulnar arteries interconnect at the selected measurement location forming two arches called the superficial palmar arch and the deep palmar arch.

Secondly, among all body parts, the skin of hand and fingers have the highest number of AVAs (arterio-venous anastomoses), which are valves that control vasoconstriction and vasodilation with signals directly from the hypothalamus, the centre of thermoregulatory system [12]. This is probably the reason why the experimental studies of Choi *et al.*[9, 13] and Zeiler *et al.*[14] had found hand locations such as the wrist and fingertip, respectively, to have the most significant correlations with thermal sensations. Moreover, the selected location being characterized by thin skin, would allow faster conduction from heat transferring blood vessels, and being an usually unclothed area would render it more responsive to the thermal environment.

Table 3.2: The instrumentation used for the environmental and physiological data acquisition and their specifications.

Parameter	Instrument	Accuracy	Range
Environmental measurements			
Air Temperature	Velocalc 9545, TSI Inc., USA	± 0.3 °C	(−10 - 60) °C
Black Globe Temperature	LM35, TI Inc., USA	± 0.5 °C	(−55 - 150) °C
	^a Thermasgard RPTM2	± 0.5 °C	(50 - 230) °C
	^a Thermocouple Pt1000 HFTM, S+S Regeltechnik, Germany	± 0.5 °C	(50 - 230) °C
Relative Humidity	Velocalc 9545, TSI Inc., USA	± 3 %	(5 - 95) %
Air Velocity	Velocalc 9545, TSI Inc., USA	± 0.015 m/s ^b	(0 - 30) m/s
	Transducer 8455, TSI Inc., USA	± 2 %	(0 - 50) m/s
Physiological measurements			
Skin Temperature	Exacon D-S18JK, Libelium Co., Spain	± 0.1 °C	(0 - 50) °C
Skin Conductance	GSR sensor, Libelium Co., Spain	± 5 %	(0 - 20) μ S
Pulse Rate	Pulsioximeter, Libelium Co., Spain	± 5 %	(25 - 250) ppm
Blood Oxygen Saturation	Pulsioximeter, Libelium Co., Spain	± 2 %	(35 - 100) %
Blood Pressure	Sphygmomanometer, Libelium Co., Spain	± 3 mmHg	(0 - 300) mmHg

Note: ^aFor calibration. ^bor $\pm 3\%$ of reading, whichever is greater.

(a)

(b)

Figure 3.2: (a) A subject during an experiment with the physiological parameters' wearable sensors at specific measurement locations. The ST , SC , PR and SpO_2 sensors were attached on the dorsal side of the non-dominant hand and the BP sensor was attached on the other hand as indicated. (b) Some subjects undergoing the thermal comfort experiments.

Figure 3.3: The location used for skin temperature measurement.

3.3.3 Subjective Measurements

A questionnaire was designed to reflect the respondents' subjective assessment of the indoor thermal environment. Subjects were required to report five subjective responses:

(A) Thermal sensation vote (7-point ASHRAE scale) [15].

(B) Thermal comfort vote (7-point Bedford scale) [16].

(C) Thermal preference vote (3-point McIntyre scale) [17].

(D) Airflow sensation vote.

(E) Humidity sensation vote.

The questionnaire scales (A) to (E) used in the survey are illustrated in Figure 3.4. We used the Bedford scale [16] for recording the thermal comfort vote and the McIntyre scale [17] for recording the thermal preference vote. Taking the Bedford scale as a reference, we designed an airflow sensation scale and a humidity sensation scale to record the airflow sensation vote and humidity sensation vote, respectively. The subject could report how 'breezy' or 'still' the airflow is perceived and how 'dry' or 'humid' the humidity is perceived using the airflow sensation scale and the humidity sensation scale, respectively.

+3 Hot +2 Warm +1 Slightly warm 0 Neutral -1 Slightly cool -2 Cool -3 Cold	+3 Much too warm +2 Too warm +1 Comfortably warm 0 Comfortable -1 Comfortably cool -2 Too cool -3 Much too cool	+1 Prefer warmer 0 No change -1 Prefer cooler	+3 Much too still +2 Very still +1 Slightly still 0 Just right -1 Slightly breezy -2 Very breezy -3 Much too breezy	+3 Much too humid +2 Very humid +1 Slightly humid 0 Just right -1 Slightly dry -2 Very dry -3 Much too dry
(A) Thermal Sensation	(B) Thermal Comfort	(C) Thermal Preference	(D) Airflow Sensation	(E) Humidity Sensation

Figure 3.4: The five voting scales (A), (B), (C), (D) and (E) used for the subjective survey measurements.

As the thermal sensation vote (TSV) is the most widely embraced standard in comfort studies, we adopted this scale (E) to obtain the thermal state of occupants. As shown in Figure 3.5, we categorized the thermal states as follows: *Cool-Discomfort* ($TSV < -1$), *Comfort* ($TSV \in [-1, 1]$), *Warm-Discomfort* ($TSV > 1$). It has been confirmed by past studies that ‘neutral’ is not necessarily the desired thermal sensation always [18]. Rather, people in hot climates might prefer a sensation slightly cooler than neutral, while people in cold climates might prefer a sensation slightly warmer than neutral [18]. Therefore, the three central sensations of ASHRAE scale, namely *Slightly cool*, *Neutral* and *Slightly warm* spanning $[-1, 1]$, form the standard range of “thermal acceptability” and satisfaction [19]. It is to be noted that since this study does not include the case of *Warm-Discomfort*, the term *Discomfort* is used analogously to *Cool-Discomfort* in the rest of the dissertation.

In order to quantify the three thermal states, we propose an index termed as the “Thermal State Index” or “TSI” in abbreviated form. As illustrated in Figure 3.5, we quantified the thermal states as TSI of “-1” for *Cool-Discomfort*, “0” for *Comfort* and “+1” for *Warm-Discomfort*. Throughout this dissertation, the TSI index is used during the mathematical computations for the predictive modelling of thermal state.

Figure 3.5: The categorization of Thermal State from the thermal sensation scale and the quantization of Thermal State as the Thermal State Index (TSI).

3.4 Experiment Procedure

A series of experiments were conducted with one subject per experiment over a period of two months. Considering the diurnal rhythm of physiology and subjective perception, experiments were performed within daylight hours of each day. The experiment protocol is illustrated in Figure 3.6.

In order to simulate the scenario of excessive cooling as discussed in the previous sections, the experimental conditions were designed to generate the two cases of *Cool-Discomfort* and *Comfort*. The temperature control in the experiment room was set at 19°C one hour prior to the start of experiment to achieve a uniform cold/cool environment. Each experiment was of 40 minutes duration. The room remained in cool environment during the first 20 minutes. At the 20th minute, the temperature control was set at 24°C to obtain thermally neutral environment. Thus the first and second halves of the experiment were set at cold/cool and neutral conditions respectively, with the intention to obtain *Cool-Discomfort* and *Comfort* thermal states (Figure 3.6). As observed, the ambient air temperature gradually increased from 18°C to 27°C during the course of the experiment. This range conforms to the typical applied indoor ACMV conditions during summer [20]. The air velocity was maintained at lesser than 0.2 m/s as recommended by ASHRAE Standard-55 [10]. The observed indoor and outdoor environmental parameters are summarized in Table 3.3. While the outdoor relative humidity was high at a mean of 61.8%, the indoor relative humidity remained at 48.8% on average.

The subject was first pre-conditioned to a comfortable temperature (23-24°C) in a separate room for 15 minutes to avoid any bias due to previously exposed environment. During this period, the subject was briefed about the experiment procedure, the anthropometric information was noted, and the physiological sensing devices were attached.

During the experiment, the subject remained seated in a sedentary position and occasionally engaged in office activities such as reading and writing. The subject was prompted to vote on scales (B) to (E) at intervals of 10 minutes, specifically at the 1st, 10th, 20th, 30th and 40th minute, while a continuous thermal sensation survey (per minute) was obtained on voting scale (A). An interval of 10 minute is justified by its adoption in earlier studies as an optimum interval of subject's awareness [13]. Besides, subjects were asked to report their TSV if at any point they felt their current sensation was different from last reported TSV. Unless reported, the current TSV was considered the same as last administered TSV. Thus a continuous thermal sensation survey (per minute) was

obtained. The questionnaire is presented in Figure 3.7. Meanwhile, the environmental and physiological parameters were monitored continuously. Hand skin temperature, hand skin conductance, pulse rate and blood oxygen saturation were measured per second, while the blood pressure was recorded every 10 minute due to the response time limitations associated with a sphygmomanometer. The environmental parameters- air temperature, air velocity, relative humidity and globe temperature were measured every second. The measured physiological parameters were averaged per minute, leading to a total of 800 samples (40 minute $\times$ 20 subjects) of paired physiological values and corresponding thermal states.

Figure 3.6: The experiment protocol.

Table 3.3: Summary of experimental indoor and outdoor environmental parameters.

	Indoor			Outdoor		
	Range	Mean	S.D.	Range	Mean	S.D.
Air temperature (°C)	18.0 – 27.0	22.7	1.6	28.0 – 32.5	29.9	1.0
Relative humidity (%)	40.5 – 60.3	48.8	4.0	45.8 – 75.0	61.8	0.1
Mean radiant temperature (°C)	14.3 – 26.1	19.9	2.6	-	-	-

3.5 Statistical Analyses and Learning Algorithms

As will be discussed in the following chapters, several statistical analyses are performed during this study namely, Pearson's correlation analysis, Spearman's rank correlation analysis, Student's T-test, ANOVA for F-test with nested models, linear regression analysis, Chi-Squared Test of Independence, Two-proportions Z-Test, Marascuillo procedure

How do you feel at this present moment? (Tick inside shaded box when prompted)

	T=1	2	3	4	5	6	7	8	9	T=10	11	12	13	14	15	16	17	18	19	T=20	21	22	23	24	25	26	27	28	29	T=30	31	32	33	34	35	36	37	38	39	T=40	
Cold (-3)																																									
Cool (-2)																																									
Slightly cool (-1)																																									
Neutral (0)																																									
Slightly warm (+1)																																									
Warm (+2)																																									
Hot (+3)																																									

If at any moment you feel your sensation has changed from last vote then indicate your current sensation above.

Figure 3.7: The questionnaire used for thermal sensation survey (voting scale (A)).

of multiple proportions, Thin-plate spline interpolation, k-means clustering algorithm and the canonical correlation analysis.

Normality of data is checked using Shapiro–Wilk test. Two-sample T-tests and the Wilcoxon–Mann–Whitney tests are used for comparison of means for normally and non-normally distributed data, respectively. Besides, several learning algorithms are formulated and implemented namely, Support Vector Machine, Random Forest, Single Layer Feedforward Neural Network, Extreme Learning Machine and deep Convolutional Neural Network.

The significance level is set at 95% ($p < 0.05$) for all analyses. All computations are done using the statistical computing software environment R (version 3.3.2), the data analysis software OriginPro® (version 8.1) and the numerical computing software application MATLAB® (version R2013a).

Table 3.4: Recent literature that used skin temperature to predict thermal comfort.

Year	Authors	Subject Sample Size	TSV Size	Sample	No of Measurement Locations*
2017	Choi and Yeom [9]	16	-		7
2017	Dai <i>et. al.</i> [6]	11	969		18
2016	Ghahramani <i>et. al.</i> [3]	15 (10 males, 5 females)	584		4
2016	Sim <i>et. al.</i> [8]	8 (6 males, 2 females)	840		4
2015	Liu W. <i>et. al.</i> [5]	22 (12 males, 10 females)	88		10
2013	Takada <i>et. al.</i> [7]	15 (all male)	6082		7
2010	Zhang <i>et. al.</i> [4]	17	347 (steady), 3568 (transient)		22
-	Present study	20 (10 males, 10 females)	800		1

Note: TSV = Thermal Sensation Vote, * Skin temperature's measurement location.

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Chapter 4

Skin Temperature as a TSI Biomarker

Skin temperature, through its heat-transferring property, plays a significant role in the thermoregulation principle that governs thermal comfort. This chapter¹ investigates the potential of skin temperature as a biomarker of thermal state, and subsequently develops two novel TSI predictive models. The chapter is organized as follows: Section 4.1 outlines the contributions of this chapter. Section 4.2 highlights the importance of skin temperature for thermoregulation. Section 4.3 studies the relationship between thermal sensation and skin temperature. Section 4.4 studies the gradient of skin temperature. Section 4.5 develops a novel TSI predictive model named as the Predicted Thermal State (PTS) Model. This model is based on a novel normalization process. Section 4.6 develops another novel TSI predictive model named as the Temporal Profile based Predicted Thermal State (TPPTS) Model. This model is based on temporal profiling through a domain transfer process. Section 4.7 compares the two proposed models with the state-of-the-art, and conclusions are drawn in Section 4.8.

¹This chapter published substantially as [1], [2] and partially as [3].

4.1 Outline of Contributions

The main novel contributions of this chapter include:

- Studied the relationship between the overall thermal sensation and skin temperature to investigate its potential to establish thermal comfort of the occupant. Subsequently, proposed two novel TSI predictive models based on skin temperature—the PTS model and the TPPTS model.
- Developed a novel normalization process for the PTS model.
- Developed a novel domain-transformation process from 2-D sensor data to visual space for the TPPTS model.
- Demonstrated potential of a single body location's skin temperature to predict the overall body TSI.
- Emphasized the significance of the gradient feature of skin temperature.

4.2 Importance of Skin Temperature

Skin temperature plays a significant role in the thermoregulation principle that governs thermal comfort by balancing heat flux between a human body and its environment [4]. The body regulates heat through the processes of vasoconstriction and vasodilation, where skin blood flow is used as the medium to transfer heat between the body core and the periphery.

Under warm conditions, the human body channels out heat by increasing blood flow from core to periphery; this phenomenon termed as cutaneous vasodilation increases blood flow to the skin, as a result the skin temperature increases. Under cool conditions, blood flow from the core to periphery decreases to keep core temperature constant; this phenomenon termed as cutaneous vasoconstriction reduces blood skin flow, as a result the skin temperature lowers. This thermoregulation process signifies the skin temperature's potential to indicate the thermal state. The following sections analyse the experimental data of hand skin temperature in context of thermal comfort.

4.3 Relation between Thermal Sensation and Skin Temperature

In general, the skin temperatures ranged between 28.5°C and 34.5°C and averaged around 31.4°C (Table 4.1). Figure 4.1 illustrates the boxplot of the skin temperatures for each subject. No particular pattern or trend is observed in the distribution of the skin temperatures, although for some subjects, the ranges are wider than the others. It can be seen from Figure 4.1 that even though the subjects were exposed to the same thermal environment, each of them generated different skin temperature response. This indicates that every person's physiological response to the same thermal situation differs. It can be inferred that a fixed skin temperature range cannot be generalized per thermal sensation for the general population.

Table 4.1: The range, mean and standard deviation of the hand skin temperature of the experimental human subjects.

Parameter	Range	Mean	S.D.
Skin Temperature (°C)	(28.5 - 34.5)	31.4	1.6
Skin Temperature Gradient (°C/ 5 min)	(-1.3 - 1.7)	0.02	0.4

Figure 4.1: The boxplots of hand skin temperature of each individual subject.

Spearman's rank correlation analysis is performed to investigate the correlation between the skin temperature and the 7-point thermal sensation (3.5) for each individual subject. The correlation results are tabulated in Table 4.2. The table shows that there were significantly strong correlations for most of the subjects ($p < 0.001$) with the highest coefficient being $Rho = 0.88$ (subject 19). The correlations are observed to be strongly positive, which implies that the skin temperature monotonically increases as the thermal sensation changes from the cooler towards warmer levels.

However, three subjects, namely subject 6, 11 and 14 shows negative correlations. To investigate further, an interval plot of the means is generated for each subject as illustrated in Figure 4.2. The figure reveals that there is a definite pattern of direct proportionality between thermal sensations and mean skin temperatures for each individual subject. The negative correlation for the three subjects (6, 11 and 14) can be attributed to their smaller number of votes for warmer levels.

Table 4.2: Spearman's rank correlation coefficient (Rho) and significance (p) for correlations between thermal sensation and skin temperature for each subject.

Subject ID	Spearman Rho	p -value
1	0.77	< 0.001*
2	0.77	< 0.001*
3	0.53	< 0.001*
4	0.69	< 0.001*
5	0.59	< 0.001*
6	-0.77	< 0.001*
7	-0.07	0.651
8	0.35	0.026*
9	0.79	< 0.001*
10	0.22	0.182
11	-0.77	< 0.001*
12	0.46	0.003*
13	0.14	0.378
14	-0.63	< 0.001*
15	0.14	0.380
16	0.87	< 0.001*
17	0.21	0.193
18	0.19	0.251
19	0.88	< 0.001*
20	0.19	0.247

Note: *Statistically significant.

Figure 4.2: Means analysis of the hand skin temperature versus the thermal sensation votes (TSVs) for each subject (Plot: $\text{mean} \pm \text{S.D.}$).

Figure 4.3 shows the interval plot of the average skin temperatures of all 20 subjects with respect to the thermal sensation votes. As the experimental conditions were designed to exclude warm conditions, the reported sensation votes ranged between -3 (*Cold*) to +1 (*Slightly warm*). The average skin temperature appears to gradually increase with the overall thermal sensation. However, this trend is not as distinct as it was in the case of an individual subject. The increments in average skin temperature are significant between (-3) and (-2), and between (-1) and (0) thermal sensation levels.

Figure 4.3: Interval plot of the average hand skin temperature of all the twenty subjects versus the thermal sensation votes (mean $\pm$ 95%C.I.).

4.4 Gradient of Skin Temperature

As few previous studies have discussed the gradient of skin temperature during thermal transitions [5, 6], we incorporate this derivative feature into our analysis. The change of skin temperature over the last five minutes is taken as the skin temperature gradient. Let $ST(t)$ be the skin temperature at time t , then the gradient of skin temperature is calculated as:

$$STgrad(t) = ST(t) - ST(t - 5) \quad (4.1)$$

The mean gradient of skin temperature is found to be 0.02°C , and it ranged between -1.3°C and 1.7°C (Table 4.1).

To investigate the importance of the gradient information, multivariate linear regression analysis is performed for each subject. For each individual subject, two linear regression models are developed, one with skin temperature as the only input (the restricted model) and the other with both skin temperature and the gradient as inputs (the full model). ANOVA² is performed to do an F -test for comparison of the two nested regression models.

Table 4.3 summarizes the results of the linear regressions and ANOVA tests. It is observed from Table 4.3 that for each individual subject the R -sq value, i.e., the coefficient of determination of model (or the model accountability) largely improves on inclusion of gradient as an additional input. For instance, for subject 15, skin temperature can explain only 7.84% accountability, while skin temperature along with its gradient can explain 71.26% of accountability in thermal sensation. According to the F -Test, an F -value greater than 1 or alternatively a low p -value indicates that the full model is significantly better than the restricted model. It can be observed from Table 4.3 that the improvements are significantly remarkable for most of the subjects ($p < 0.05$). Thus, the gradient of skin temperature carries significant information to indicate how an occupant perceives one's thermal sensation in a given thermal environment. It can be further inferred that skin temperature when combined with its gradient, contains significantly more relevant potential to translate to thermal sensation as compared to skin temperature alone.

Table 4.3 also presents the linear regression analysis and ANOVA results for the overall case with the combined population of all subjects. It is to be noted that even though most of the individual models faired significantly well, the overall model fails to describe thermal sensation efficiently (R -sq = 0.07%). This is primarily because under the same thermal environment, different people's skin temperatures were different as seen earlier in Figure 4.1. Thus, a multivariate linear regression model may be sufficient to indicate individual thermal sensation for personal comfort. But, in order to have a robust (scalable) model that can be applicable for the general population, it is crucial to include normalization based on individual factors. The normalization process is important to address the individual differences among the subjects.

²ANOVA (analysis of variance) is a collection of statistical models used to analyse the differences among group means in a sample.

Table 4.3: ANOVA F-test and multivariate linear regression analysis between thermal sensation and skin temperature for investigating importance of the gradient.

Subject ID	Model Input(s)	Model Coefficients		F-value	p-value	R-sq (%)	ΔR -sq (%)
		ST	STgrad				
1	ST	0.87				68.00	
	ST, STgrad	0.95	-1.64	14.24	0.001*	77.85	9.85
2	ST	0.80				61.40	
	ST, STgrad	1.03	-0.75	25.79	< 0.001*	78.63	17.23
3	ST	1.62				50.99	
	ST, STgrad	1.98	0.11	2.71	0.109	54.81	3.82
4	ST	0.93				58.46	
	ST, STgrad	1.08	-0.38	4.37	0.045*	63.45	4.99
5	ST	1.83				54.19	
	ST, STgrad	1.55	0.36	1.63	0.211	56.41	2.22
6	ST	-0.69				31.91	
	ST, STgrad	-0.51	0.93	3.83	0.059#	39.18	7.27
7	ST	-0.06				0.14	
	ST, STgrad	-0.02	0.20	0.25	0.617	0.93	0.79
8	ST	1.43				38.31	
	ST, STgrad	1.22	1.30	59.05	< 0.001*	78.32	40.01
9	ST	0.57				55.06	
	ST, STgrad	0.47	0.37	2.20	0.147	57.96	2.9
10	ST	0.81				29.05	
	ST, STgrad	0.27	1.41	112.38	< 0.001*	84.28	55.23
11	ST	-1.28				37.71	
	ST, STgrad	-1.11	1.28	2.69	0.111	42.54	4.83
12	ST	2.50				21.98	
	ST, STgrad	1.21	2.81	14.51	< 0.001*	46.32	24.34
13	ST	0.08				00.06	
	ST, STgrad	1.30	-0.75	6.78	0.014*	17.52	17.46
14	ST	-0.97				29.29	
	ST, STgrad	-0.93	1.26	5.50	0.025*	39.67	10.38
15	ST	0.12				7.84	
	ST, STgrad	-0.38	0.89	70.62	< 0.001*	71.26	63.42
16	ST	0.79				74.81	
	ST, STgrad	0.95	-0.38	16.81	< 0.001*	83.48	8.67
17	ST	0.26				10.48	
	ST, STgrad	0.17	0.14	0.75	0.393	12.53	2.05
18	ST	0.91				11.87	
	ST, STgrad	0.91	0.65	3.77	0.061#	21.17	9.3
19	ST	1.87				83.99	
	ST, STgrad	1.50	0.63	8.23	0.007*	87.26	3.27
20	ST	2.29				8.97	
	ST, STgrad	2.65	-0.66	0.99	0.326	11.71	2.74
Overall	ST	0.06				0.01	
	ST, STgrad	0.01	0.63	46.08	< 0.001*	0.07	0.06

Note: *Statistically significant at 95% C.I. #Statistically significant at 90% C.I.

4.5 Proposed Model A: PTS Model

As discussed in the previous section, normalization is an important step to build a model that would be scalable for general population. In this section, we propose a novel normalization process which can address the individual differences for scalability. Subsequently, we develop a novel TSI predictive model termed as the ***Predicted Thermal State (PTS) model*** which is based on this normalizing process.

4.5.1 Structure of the PTS Model

The framework for the development of the PTS model is illustrated in Figure 4.4a. Firstly, the occupant's hand skin temperature and real-time thermal sensation survey are recorded simultaneously. Secondly, the recorded skin temperature and its gradient are subjected to a normalization process based on the occupant's two individual factors, namely body surface area (A_{Du}) and clothing insulation (I_{cl}). Meanwhile, the surveyed overall thermal sensations are classified into thermal states according to Figure 3.5. Lastly, the relationships between the normalized skin features and the thermal states are modelled by machine learning algorithms as:

$$TSI = g(ST_n, STgrad_n) \quad (4.2)$$

where, ST_n and $STgrad_n$ are normalized features, which will be introduced later. The developed PTS model can be deployed as depicted in Figure 4.4b for real-time thermal state prediction using sensor-recorded skin temperature and individual factors as the primary inputs. The predicted thermal state can be fed into the ACMV systems for adequate operations according to the thermal demand indicated by the thermal state of the occupant.

As the purpose of the PTS model is to aid in efficient cooling control of ACMV systems, the information of thermal state (*Cool-Discomfort* / *Comfort* / *Warm-Discomfort*) is sufficient for the ACMV systems to take necessary actions. *Cool-Discomfort* indicates heating demand, *Warm-Discomfort* indicates cooling demand, and *Comfort* indicates no change in operation. As mentioned earlier, since this study does not include the case of *Warm-Discomfort*, the term *Discomfort* is used analogously to *Cool-Discomfort* henceforth.

(a) PTS model development

(b) PTS model deployment

Figure 4.4: Framework of the proposed PTS model.

4.5.2 The Normalization Process

4.5.2.1 Normalization Factor

Wang *et al.* [7] had found that the skin temperature was more related to the overall thermal sensation if the subject's clothing was controlled ($R-sq = 0.60$) as compared to when clothing varied ($R-sq = 0.19$). As in our study the clothing varies, it can be interpreted from Wang's finding that the clothing insulation is an individual factor influencing the skin temperatures under different thermal environment. We identify clothing insulation and body surface area as the individual factors. Moreover, these two individual factors are peripheral properties, and therefore, they are apt to represent a peripheral organ such as skin temperature. We introduce normalization with 'exposed body surface area', as discussed below.

Clothing plays an important role in maintaining thermal balance of a body. It is an effective way to control thermal comfort as garments can be added or removed to adjust the thermal sensation. With the air-gap and clothing in between, it adds two layers of insulation between the skin and the environment (Figure 4.5). The heat loss from the body in clothed area (Φ_2) is consequently lesser than heat loss (Φ_1) from unclothed/exposed area (bare skin). The larger the amount of unclothed surface area, the larger would be the total heat loss from the body, and the overall heat loss directly influences the overall thermal sensation.

Figure 4.6 can illustrate this simple phenomenon. When subject X is unclothed, then the whole body surface area ($= 1.95$) is exposed and heat loss is maximum. On wearing a clothing of 0.36 clo, the exposed body surface area and heat loss reduces. Another subject Y with different height and weight will have different whole body surface area (1.77 in this case). So even for the same clothing insulation of 0.36 clo, X and Y have different exposed body surface area. With heavier clothing insulation of 0.57 clo, the exposed area and heat loss are reduced for the same subject Y. Thus, body surface area which is constant for a person, can address inter-individual differences, whereas clothing insulation, which varies for a person, can address intra-individual differences.

In order to incorporate this simple phenomenon, we introduce a normalization factor A_{exp} which indicates the unclothed/exposed body surface area. Given a person with whole body surface area as A_{Du} , and clothing insulation as I_{cl} (< 1), the exposed body surface area can be calculated according to equation 4.3:

$$A_{exp} = (1 - I_{cl}) \times A_{Du} \quad (4.3)$$

Thermal insulation provided by clothing, I_{cl} is numerically expressed in clo unit, where 0 stands for nude unclothed body, and 1 stands for a typical business suit [8]. Typically

Figure 4.5: Heat loss from the area covered with clothing (Φ_2) is less than the heat loss from the uncovered area (Φ_1).

Figure 4.6: The normalization factor A_{exp} addressing the inter-individual and intra-individual differences.

during summer or in tropical countries, clothing insulation varies about 0.30 to 0.50 clo [8]. In this study, the Du Bois & Du Bois equation [9] is used to calculate A_{Du} :

$$A_{Du} = \text{Weight}^{0.425} \times \text{Height}^{0.725} \times 0.203 \quad (\text{m}^2) \quad (4.4)$$

where, weight and height are in kg and m, respectively.

A_{exp} will vary with different person and clothing insulation (Figure 4.6). Thus, by including both the individual factors, A_{exp} can address both inter and intra individual differences. In summary, different combinations of clothing insulation and body build (height/weight) will result in different exposed body surface area, which directly influences the total heat loss from the body, and the total heat loss finally determines the overall thermal sensation. The normalization process is illustrated in Figure 4.7.

The skin temperature and its gradient are normalized with A_{exp} to obtain the normalized skin temperature ST_n and the normalized skin temperature gradient $STgrad_n$ as:

$$ST_n = \frac{ST}{A_{exp}} \quad (4.5)$$

$$STgrad_n = \frac{STgrad}{A_{exp}} \quad (4.6)$$

It is important to note that ST_n should not be considered as skin temperature because its values may not fall within the normal ranges of human skin temperature. It is rather

Figure 4.7: Framework of the proposed normalization process.

a new feature that has been derived from the actual skin temperature.

We have not considered body mass (body fat content) as an individual factor, because studies have shown that it does not have an influence of statistical significance on the thermal sensation for sedentary activities [8, 10]. It may be significant for higher activity levels, though.

4.5.2.2 Normalization Results

Before applying the above normalization method to the entire dataset, we briefly consider the case of an individual subject. As seen in the previous sections, lower the skin temperature, lower is the thermal state index. Therefore, we use the k-means clustering method [11] to analyse if an individual's dataset can be divided into two distinct clusters (*Discomfort* and *Comfort* clusters). The k-means clustering method works by dividing the observations into k distinct clusters depending on the target variable (TSI here), and assigning new observations to the cluster with the shortest Euclidean distance from the cluster centroid. Figure 4.8 shows the clustering result for one subject. Two distinct clusters are formed with centroids (ST , $STgrad$) for the *Discomfort* and *Comfort* states equal to (30.0878, -0.0789) and (32.8751, 0.1358), respectively. It is found that about 90% of the individual data are assigned to the correct thermal state using the k-means clustering approach. The remaining 10% data are overlapped. However, the classification of the entire dataset of all 20 subjects (shown in Figure 4.10a) clearly indicates that the two thermal states cannot be grouped into distinct clusters for general population, although it could be distinctly classified for an individual subject with about

Figure 4.8: The *Discomfort* and *Comfort* cluster assignments of the non-normalized features using k-means clustering method.

90% correction. This further emphasizes the need for normalization that will ensure model scalability across general population.

Figure 4.9 summarizes the mean of skin temperatures and the gradients for the two thermal states prior to and post the normalization process. The actual mean skin temperatures of the two thermal states were not distinct before normalization ($p = 0.1368$). It is observed that the normalization process makes the distinction between the *Discomfort* and *Comfort* states remarkably significant ($p < 0.0001$) in terms of both skin temperature and the gradient.

Although the gradients vary almost equally during both the thermal states, the mean gradient is found to be negative during *Discomfort* and positive during *Comfort* state (Figure 4.9b). This implies that skin temperature tends to increase during warmer conditions and decrease during cooler conditions.

Figure 4.10 demonstrates the detailed classification of the thermal states with respect to paired combinations of skin temperatures and their gradients. Before normalization, the distinction is unclear with several overlapped points (Figure 4.10a). This can explain the low accountability (R -sq) found during the linear regression analysis for the overall case in previous section (Table 4.3). However, as seen in Figure 4.10b, the normalization process manages to successfully push out the *Comfort* cases towards the right, generating

clearer non-linear regions separating the two thermal states. While the division may not be visually distinct on a linear scale, nevertheless the normalization process significantly improves the distinction as compared to the non-normalized case.

(a) Mean skin temperature- before (left) / after (right) normalization

(b) Mean skin temperature gradient- before (left) / after (right) normalization

Figure 4.9: Mean skin temperature and mean skin temperature gradient before and after the normalization process.

Figure 4.10: The classification of thermal states.

4.5.3 SVM and ELM Classification Formulations

As seen in the previous section, normalization improved the stratification of thermal state classes. We further examine the prediction accuracy of the PTS model by using normalized features of skin temperature. The Support Vector Machine (SVM) and Extreme Learning Machine (ELM) classifiers are implemented to model the thermal state index TSI with respect to four cases of model inputs shown in Table 4.4 below:

Table 4.4: The input cases for comparison.

Case 1:	ST
Case 2:	ST_n
Case 3:	ST, ST_{grad}
Case 4:	ST_n, ST_{grad}_n (PTS)

For each of the four input cases, an SVM or ELM classifier $g(\cdot)$ is developed to classify *TSI* based on the respective input features:

For case 1:

$$TSI = g(ST) \quad (4.7)$$

For case 2:

$$TSI = g(ST_n) \quad (4.8)$$

For case 3:

$$TSI = g(ST, STgrad) \quad (4.9)$$

For case 4 (PTS model):

$$TSI = g(ST_n, STgrad_n) \quad (4.10)$$

SVM Formulation

The SVM algorithm is based on the principle of structural risk minimization [12, 13]. *TSI* is classified by generating the optimal hyperplane that separates the two thermal states *Discomfort* and *Comfort*. The hyperplane is obtained by maximizing its margin within tunable constraints. In this study, the radial basis function (RBF) kernel has been used to introduce non-linearity by mapping the input features to a high-dimensional space. Assume that $\mathbf{x}_i = [x_1, x_2, \dots, x_n]^T_i$ is the input vector of n inputs and TSI_i is the target output for the i^{th} training sample, then the criterion for this RBF-SVM classifier can be formulated in Lagrangian dual form as follows:

$$\begin{aligned} & \text{maximize} \left(\sum_i \alpha_i - \frac{1}{2} \sum_{ij} TSI_i TSI_j \alpha_i \alpha_j K(\mathbf{x}_i, \mathbf{x}_j) \right) \\ & \text{subject to: } 0 \leq \alpha_i \leq C, \text{ and } \sum_i \alpha_i TSI_i = 0 \end{aligned} \quad (4.11)$$

where, α is Lagrange multiplier, C is cost, a positive tuning parameter that controls the bias-variance trade-off, and $K(\mathbf{x}_i, \mathbf{x}_j)$ is the RBF kernel where γ is the kernel tuning parameter:

$$K(\mathbf{x}_i, \mathbf{x}_j) = e^{-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2} \quad (4.12)$$

The *TSI* for a new input is then found using the weight vector obtained from the above optimization. The optimal values of the tuning parameters C and γ are located by a grid search operation using 10-fold cross validation.

ELM Formulation

The Extreme Learning Machine (ELM) is a neural network based learning method that caters to a broad range of non-linear problems [14, 15]. It performs a fast training of a Single Layer Feedforward Neural Network (Figure 4.11). The hidden layer parameters are generated randomly and are independent of both the training data and of each other. The output layer weights is of higher importance than the random hidden layer weights and can be trained using a pseudo-inverse technique [16]. As it does not require parameter-tuning during learning, it is rendered an extremely fast learning speed and the problem of tuning different learning rates is eliminated.

Figure 4.11: Structure of an Extreme Learning Machine.

Assume that $\mathbf{x} = [x_1, x_2, \dots, x_n]^T$ is the input vector of n inputs, L is the number of hidden neurons, (a_i, b_i) are the hidden node parameters: a_i is the random weight from input nodes to the i^{th} hidden neuron, b_i is the random bias of the i^{th} hidden neuron, $\beta = [\beta_1, \beta_2, \dots, \beta_L]$ is the weight vector from hidden layer to output node. The ELM training involves three steps: First, the hidden node parameters (a_i, b_i) are randomly assigned. Second, the hidden layer output matrix $\mathbf{H}$ is computed:

$$\mathbf{H} = \begin{bmatrix} h(x_1) \\ h(x_2) \\ \vdots \\ h(x_n) \end{bmatrix} = \begin{bmatrix} h_1(x_1) & h_2(x_1) & \dots & h_L(x_1) \\ h_1(x_2) & h_2(x_2) & \dots & h_L(x_2) \\ \vdots & \vdots & \vdots & \vdots \\ h_1(x_n) & h_2(x_n) & \dots & h_L(x_n) \end{bmatrix}$$

Lastly, the output weight matrix is computed as $\beta = \mathbf{H}^\dagger \mathbf{T}$, where $\mathbf{H}^\dagger$ is the Moore-Penrose generalised inverse of $\mathbf{H}$, and $\mathbf{T}$ is the training target output vector of TSI . The

TSI prediction is then obtained as:

$$TSI = \mathbf{H}\beta \quad (4.13)$$

We implemented ELM as a single-hidden layer network with sigmoid function as neuron's activation function:

$$h(z) = \frac{1}{1 + \exp(-z)} \quad (4.14)$$

The optimal value of hidden neurons is located by grid-search-operation. The weights between hidden-layer and output-layer are determined analytically by solving a Least-Squares problem. The algorithm is implemented for each of the four input cases.

4.5.4 Predictive Performance Results of PTS Model

First, the thermal states are randomly divided into two groups with equal proportion of each state to prevent bias. One group is used for training, and the other is used for validation of the developed prediction model. Tables 4.5 and 4.6 present the cross-validated accuracy results of the SVM and ELM prediction models, respectively for the four input cases.

It is observed from Table 4.5 that using only the skin temperature data, the SVM classifier can correctly predict only 64.6% of the states, while using the normalized skin temperature alone improves the accuracy to 75.4%. Moreover, using both skin temperature and gradient information correctly predicts 77.8% of thermal states. However, the PTS model outperforms the rest with the highest accuracy and minimum training MSE by correctly predicting about 87% of the thermal states. Similar patterns are observed for the ELM model (Table 4.6), however the SVM model could better recognize the non-linear relations in this study at a better accuracy.

The purpose of comparing two different classifiers is to gain perspectives from different classification principles. Though the SVM classifier resulted in higher accuracy, ELM classifiers have the advantage of extremely fast learning speed. In real time implementation, the decision on classifier may be subject to a trade-off between accuracy and speed.

The detailed graphical visualization of the prediction performance of the PTS model using SVM and ELM classifiers are presented in Figures 4.12 and 4.13, respectively. It can be seen in Figure 4.12a that the SVM classifier generates a non-linear class boundary

Table 4.5: Comparison of thermal state prediction performance between four input cases under SVM classifier.

Model Input(s)	Optimal Training Parameters			Prediction Accuracies (%)		
	Cost	Gamma	MSE	Overall	DC	C
ST	8	4	0.35159	64.63	59.76	69.51
ST_n	128	4	0.24616	75.41	74.80	76.02
ST, ST_{grad}	8	4	0.31090	77.85	77.64	78.05
ST_n, ST_{grad_n} (PTS Model)	64	4	0.20731	86.79	86.59	86.99

Note: The best values are highlighted in bold font. MSE-mean squared error, DC-Discomfort, C-Comfort.

Table 4.6: Comparison of thermal state prediction performance between four input cases under ELM classifier.

Model Input(s)	Optimal Training Parameters		Prediction Accuracies (%)		
	Hidden Neurons	MSE	Overall	DC	C
ST	100	9.4×10^{-11}	60.57	58.54	62.60
ST_n	100	5.4×10^{-08}	70.12	71.54	68.70
ST, ST_{grad}	100	7.7×10^{-08}	71.95	73.17	70.73
ST_n, ST_{grad_n} (PTS Model)	100	1.4×10^{-08}	79.67	78.05	81.30

Note: The best values are highlighted in bold font. MSE-Mean squared error, DC-Discomfort, C-Comfort.

based on the RBF kernel to separate the two thermal states. The shaded regions in the figure represent the areas predicted by the SVM classifier pertaining to each thermal state, while the data points represent the actual thermal states: red (*Comfort*), black (*Discomfort*). The optimal tuning parameters are found by 10-fold cross validation with a grid search operation between the following values: cost (2^0 to 2^8), gamma (0.5 to 4), and the number of hidden neurons (10 to 1000). Figures 4.12b and 4.13b demonstrate the best tuning parameter selections subject to minimum cross-validation error for the SVM and the ELM model, respectively.

The confusion matrix, a table that summarizes the accuracy of performance of the classification model is generated. The confusion matrices for the test and the overall data using SVM classifier are presented in Table 4.7 and Table 4.8, respectively, where the left diagonal values indicate the number of correctly predicted thermal states, and the right diagonal values indicate incorrect predictions. The precision and recall values (Table 4.7) indicate that the PTS model performed equally well for each thermal state when implemented on the unseen test data.

Figure 4.12: Predictive performance of PTS model using SVM classifier (Accuracy: 87%). In (a), predicted thermal states are represented by the two non-linear regions; actual thermal states are indicated by the data points- red: *Comfort*, black: *Discomfort*.

Figure 4.13: Predictive performance of PTS model using ELM classifier (Accuracy: 80%).

Given that previous studies achieved good accuracy at indicating thermal comfort by using skin temperature of multiple body locations, attaining similar accuracies using only a single location is evidently challenging. Nevertheless, the advantages of the measurement location and the normalization process significantly enabled the PTS model to attain a good acceptable accuracy of 87% on new occupant data.

Table 4.7: PTS model confusion matrix using SVM classifier- test data.

		Predicted Thermal State		
		Discomfort	Comfort	Recall
Actual Thermal State	Discomfort	213	33	0.866
	Comfort	33	214	0.870
	Precision	0.866	0.870	87%

Table 4.8: PTS model confusion matrix using SVM classifier- overall data.

		Predicted Thermal State		
		Discomfort	Comfort	Recall
Actual Thermal State	Discomfort	213	33	0.866
	Comfort	66	388	0.855
	Precision	0.763	0.922	86%

4.6 Proposed Model B: TPPTS Model

It was observed in the previous sections that the gradient of skin temperature exhibits significant response to thermal comfort. We leverage this behaviour to develop a novel TSI predictive model termed as the *Temporal Profile based Predicted Thermal State (TPPTS) model*. It is based on a deep convolutional neural network (CNN) that associates TSI with images of hand skin temperature's temporal profile.

4.6.1 Structure of the TPPTS Model

The analytical diagram of the TPPTS model is illustrated in Figure 4.14a. The hand skin temperature data is extracted from the wearable sensor, followed by a new domain transfer process, and subsequently trained with a deep Convolutional Neural Network.

The rate at which skin temperature changes i.e. its gradient, carries significant information to indicate thermal state [5, 6]. In fact, the combined information of the skin temperature and its change rate can obtain significantly better accuracy than using skin temperature alone. Another important observation from the previous section is that the change rate is mostly negative for cool-discomfort, and positive for comfort state. Skin temperature decreases during cooler conditions, and remains stable or fluctuates

Figure 4.14: Framework of the proposed TPPTS model.

abruptly under neutral state. We leveraged this interesting property to obtain the temporal profile (TP) of the hand skin temperature over the past 5 minutes. The input to the convolutional neural network is a processed image of TP. For the target output TSI, each 5-minute interval is assigned a TSI based on the majority count, and designated to its respective TP image. The model could be deployed using only a single physiological input as shown in Figure 4.14b.

4.6.2 Domain Transfer Process

The process of obtaining the TP is demonstrated in Figure 4.15. The 2-dimensional sensor data (skin temperature, time) is extracted using wearable sensors (Figure 4.14a). Firstly, a temporal plot of the skin temperature over an interval of 5 minutes is obtained. Secondly, the plot is smoothed using thin plate smoothing spline operation. A thin-plate smoothing spline is the unique spline s that minimizes the following weighted sum:

$$pE(s) + (1 - p)R(s)$$

where, p is the smoothing parameter, $E(s)$ is the error measure and $R(s)$ is the roughness measure. For details on thin plate smoothing splines, see [17].

Thirdly, the plot is enhanced by (a) transformation to grayscale format and (b) Colour complementation, which means reversal of black and white pixels. Colour complementation is important to reduce white space computations because the white pixel value is highest (255) and black pixel value is lowest (0). The plot image is captured and finally, it is resized to a standard size for the CNN input (here, it is resized to $28 \times 28 \times 3$ pixels).

We list some of the sample images as obtained in Figure 4.16. The first row images belong to *Discomfort* category, and second row image belongs to *Comfort* category. Most of the *Discomfort* images had the similar pattern of a descending slope. It indicates the decreasing change rate. For *Comfort* images, the patterns depicted either ascending slope, or concave curves. Since these images do not give the magnitudes of skin temperature, we infer based on our experimental observation that concave curves refer to a stable state, and ascending slopes portray transition from cool to neutral state. It is to be noted that the gradient information gets automatically embedded into the TP image.

Figure 4.15: Temporal Profiling- Domain transfer process from 2-D sensor data to imagery form for CNN input.

Figure 4.16: Some images of the temporal profiles. The first row images belong to *Discomfort* state, the second row images belong to *Comfort* state.

4.6.3 The CNN Architecture for Classification Formulation

The CNN architecture employed in this study is illustrated in Figure 4.17. It resembles a LeNet-5 architecture. The pioneering network of LeNet-5 was first developed by LeCun *et al.* in 1998, and was originally developed for simpler classification tasks such as digit recognition [18]. The TP imageries in this study are simple images, similar to pixel images of digits in grayscale. Therefore, the basic CNN network such as LeNet was adopted in this study. As seen in Figure 4.17, the network consists of two convolutional layers, two pooling layers and two fully connected layers. The first convolutional layer comprises 20 filters each of size 5×5 while the second convolutional layer consists of 50 filters of size 5×5 each. No zero-padding is used in the convolutional layers, and full spanning is ensured with a stride at 1. For downsampling, the pooling layers consist of filters of size 2×2 , and stride of 2, with the max pooling operation. The first fully connected layer consists of 500 hidden nodes, and the second fully connected layer consists of 2 hidden neurons for the two output classes of thermal state.

Figure 4.17: The Convolutional Neural Network architecture. Conv1, Conv2- convolution layers; tanh1, tanh2, tanh3- activation functions; Pool1, Pool2- pooling layers; FC1, FC2- fully connected layers.

The hyperbolic tangent function ($\tanh$) has been chosen as the non-linear activation function:

$$\tanh x = \frac{e^{2x} - 1}{e^{2x} + 1} \quad (4.15)$$

The $\tanh$ function has stronger gradients, as compared to a logistic *sigmoid* function, which has the vanishing gradient problem. The *sigmoid* activation function has the potential problem that it saturates at 0 and 1 while $\tanh$ function saturates at +1 and -1. Another commonly used activation function *ReLU* (rectified linear unit) is very successful in image classification tasks. However, it led to overfitting in our case. Therefore, the $\tanh$ function was sufficient for the simple image classification in this study.

The input image has the dimensions of $28 \times 28 \times 3$ pixels. Given that W, H, D, K, P and S denote width, height, depth, filter size, zero-padding size and stride, respectively; then, the first convolutional layer transforms the input image spatially to a volume of width $(W - F + 2P)/S + 1 = 24$, height $(H - F + 2P)/S + 1 = 24$ and depth $K = 20$; i.e., size $(24 \times 24 \times 20)$. The first pooling layer converts the resultant after activation to a volume of width $(W - F)/S + 1 = 12$, height $(H - F)/S + 1 = 12$, and depth $D = 20$, i.e., size $(12 \times 12 \times 20)$. The 2×2 receptive fields with a stride of 2 discards exactly 75% of the activations in the input volume. Similarly, the second convolutional and pooling layers transform the input volume to $8 \times 8 \times 50$ and $4 \times 4 \times 50$ sizes, respectively. Finally, the fully connected layers, whose neurons have connections to all activations in the previous layer, performs the conclusive reasoning by providing the scores for each thermal state.

4.6.4 Predictive Performance Results of TPPTS Model

The CNN classifier takes the TP images as inputs. The recorded experimental sample size was 800, but as a single image sample comprised 5 minutes, it amounts to a total of 160 samples (images) for TPPTS method. To prevent bias, the samples are randomly selected with equal proportion of each TSI. The data is randomly divided in the ratio 80:20 for training and validation purpose, respectively. The optimal training parameters of the CNN network are summarized in Table 4.9. The training accuracy saturated at 92% at a learning rate of 0.05. The TSI detection performance on the validation dataset is summarized in Table 4.9. The TPPTS model achieved a significant accuracy of 93.33% in overall as well as each TSI. Some advantages of the TPPTS method are:

- **Gradient information included:** Skin temperature gradient is significant contributor to TSI detection, and in this method it is implicitly included in the temporal profile.
- **Robust to normalization:** The images contain only the temporal patterns. They do not carry magnitude information. As skin temperature widely varies from person to person in terms of magnitude, while preserving pattern properties, this makes the method immune to normalization issues.
- **Single input:** Unlike existing methods and the PTS model, it requires only skin temperature data, implying low sensory cost.

Table 4.9: Optimal training parameters and prediction accuracy of the trained CNN classifier.

Optimal Tuning parameters		TSI Prediction Accuracy (%)	
Learning rate	0.05	Overall	93.33
Momentum	0.9	Comfort	93.33
Training accuracy	92%	Discomfort	93.33

4.7 Comparison with the state-of-the-art

The three conventional methods namely, the PMV method, ePMV method and aPMV method are implemented using the validation data for a comparison with the proposed models. The PMV values are computed using equation 2.1. Using the PMV values, the ePMV and aPMV values are computed using equations 2.2 and 2.4, respectively.

The prediction accuracy results are summarized in Table 4.10. The PMV method attains 73.06% overall accuracy, performing better than the ePMV and aPMV methods which obtain 48.95% and 45.21% overall accuracy, respectively. The proposed PTS and TPPTS models outperforms all three conventional methods at 87% and 93.33% overall accuracy, respectively. Detailed comparative analysis of all proposed methods will be covered in Chapter 6.

Table 4.10: Predictive performance comparison with conventional methods.

Model	TSI Prediction Accuracy (%)		
	Overall	Comfort	Discomfort
PTS	84.32	87.99	80.65
TPPTS	93.33	93.33	93.33
PMV	73.06	69.32	76.80
ePMV	48.95	59.54	38.36
aPMV	45.21	47.40	43.02

4.8 Concluding Remarks

Firstly, according to the human subject experimental results, the skin temperatures of the selected hand location strongly correlated with the thermal sensations at individual level. Moreover, the additional information of its 5-minute gradient significantly improved the potential to indicate thermal sensation. It was verified that the rate at which skin temperature changes carries significant information on a person's thermal state.

Secondly, the novel normalization process addressed both inter and intra individual differences by incorporating body surface area and clothing insulation respectively, and resolved the unclothed body surface area, which has a direct influence on the overall heat loss. While non-normalized skin temperature alone could correctly predict only about (60–65)% of thermal states, the PTS model based on the normalized skin features could predict accurately 87% of thermal states of new occupant data.

Thirdly, the combined information of the gradient and the skin temperature carried more significant information than the skin temperature alone. Therefore, the temporal profiles of skin temperature over 5 minutes could portray adequate information to indicate thermal state even without the need for normalization. Based on these temporal profiles, the TPPTS model could accurately predict 93.33% of the mean thermal states.

Lastly, unlike existing literature which employed multiple body locations, the PTS model could achieve sufficiently good accuracy using skin temperature of only a single hand location. The combined knowledge of several physiological inputs may provide better insights which skin temperature alone cannot. Hence, further study of the remaining physiological parameters will be performed in the following chapters.

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Chapter 5

Pulse Rate as a TSI Biomarker

Pulse rate is closely linked to cardiovascular health and can reflect the effect of thermal stress on the cardiovascular system. This chapter¹ investigates the potential of pulse rate as a biomarker of thermal state. The chapter is organized as follows: Section 5.1 outlines the contributions of this chapter. Section 5.2 studies the relationship between thermal sensation and pulse rate and seeks to identify individual factors. Thereafter, a novel TSI predictive model is developed in Section 5.3 that extends and enhances the PTS model. Conclusions are drawn in Section 5.4.

5.1 Outline of Contributions

The main novel contributions of this chapter include:

- Studied the relationship between pulse rate and thermal sensation and identified the individual factors.
- Developed a TSI predictive model based on skin temperature and pulse rate features.

¹This chapter submitted substantially as [1].

- Developed input feature engineering approaches including (a) a novel normalization process that addresses individual differences in pulse rate to expand the model scalability, and (b) a spectral analysis to obtain a new pulse rate feature for TSI prediction.

5.2 Relation between Thermal Sensation and Pulse Rate

In general, the pulse rate ranged between 47.1 bpm and 95 bpm, and averaged around 71.4 ± 9.26 bpm. Figure 5.1 illustrates the boxplot of the pulse rate for each subject. No particular pattern or trend is observed in the distribution of the pulse rates, although for some subjects, the ranges are wider than the others. Interestingly, it is clearly seen that even though the subjects were exposed to the same thermal environment, each of them generated different response, both in the value and the width of range. This indicates that physiological response of pulse rate to the same thermal situation may differ owing to differences in individual factors. It is thus inferred that a fixed pulse rate range cannot be generalized for each TSI. Hence, a normalization process based on individual factors is necessary for model scalability.

Figure 5.1: The boxplots of pulse rate of each individual subject.

It was seen in the previous Chapter 4 that, as human skin is a peripheral organ directly responsive to ambient changes, the skin temperature features were normalized based on peripheral properties such as clothing insulation and body surface area. Pulse rate, on the other hand, is an intrinsic parameter because it is closely linked to a core organ i.e. heart. While the skin has inbuilt heat receptors, the heart keeps the core body temperature stable during thermoregulation. Therefore, we consider that the pulse rate features should be normalized based on intrinsic/core properties. The following two individual factors are selected for normalization of pulse rate features for two main reasons, firstly, their intrinsic nature and secondly, their influence on thermal comfort:

- **Gender:** Owing to different physiology, the thermoregulatory responses in women distinctly differ from that of men leading to gender differences in comfort perception [2].
- **BMI** (body mass index): People with higher BMI are more resistant to cooler condition due to higher fat insulation, and vice versa. Moreover, BMI has shown close connections to pulse rate and its gradient [3]. In this study, BMI is categorised into two groups: Low (L) if $BMI \leq 22$ and high (H) if $BMI > 22$. A BMI of 22 is taken as the separator based on a previous study [3]. In our study, there are 10 subjects in each BMI group.

Henceforth, all the analyses regarding pulse rate will be categorised into BMI and gender groups. Figure 5.2 shows the interval plot of the recorded pulse rate with respect to the thermal sensation votes. Pulse rate shows a clear increasing trend in case of female and low BMI groups. No significant trend is observed in the other two groups.

Along with pulse rate, we also study the gradient of pulse rate. If $PR(t)$ is the pulse rate at time unit t (minute), then pulse rate gradient $PRgrad(t)$ is computed as the change in PR over the last 5 minutes as:

$$PRgrad(t) = PR(t) - PR(t - 5) \quad (5.1)$$

A Spearman's rank correlation analysis is performed to further investigate the relation between thermal sensation and the two pulse rate features. The results are presented in Table 5.1. Significant positive correlations ($p < 0.001$) are observed between PR and thermal sensation in case of females and low BMI groups, indicating that PR increases with warmer sensations. The gradient PR_{grad} of high BMI group shows significant positive correlations ($p = 0.044$). This indicates that pulse rate of heavier people increases rapidly when exposed to warmer environments. Thus there are significant relations between pulse rate features and comfort for certain groups. Based on these preliminary findings, we develop a novel normalization process for pulse rate features, and subsequently propose a new TSI predictive model as described in the next section.

Figure 5.2: Interval plots of pulse rate with respect to thermal sensation.

Table 5.1: Spearman's rank correlation coefficient (Rho) and significance (p) for correlations between thermal sensation and PR/PR_{grad} for different Gender and BMI groups.

		Gender		BMI	
		M	F	L	H
PR	Rho	-0.029	0.199	0.223	0.045
	p -value	0.562	< 0.001*	< 0.001*	0.371
PR_{grad}	Rho	0.054	0.010	-0.026	0.108
	p -value	0.311	0.846	0.622	0.044*

Note: *Statistically significant correlation. F-Female, M-Male, L-Low BMI, H-High BMI.

5.3 Proposed Model C: ePTS Model

As observed in the previous section, normalizing the pulse rate is necessary for model scalability. We thereby develop a new TSI predictive model that incorporates pulse rate features along with the normalized skin temperature features of the PTS model. We name this model as the *enhanced Predicted Thermal State (ePTS) model*.

5.3.1 Structure of the ePTS Model

The analytical diagram of the ePTS model is illustrated in Figure 5.3a. Firstly, ambient air temperature (T_a) is recorded while the hand skin temperature (ST) and pulse rate (PR) are recorded using wearable sensors. Secondly, the gradient of skin temperature ($STgrad$) and pulse rate ($PRgrad$) are obtained from ST and PR , respectively. Thirdly, these four physiological features are normalized based on individual factors namely, clothing insulation (I_{cl}), body surface area (A_{Du}), gender and BMI, while spectral analysis of pulse rate is performed to obtain another new feature (PR_{sp}). The parameters A_{exp} , α , β are normalization factors. This feature engineering process comprising normalization and spectral analysis is done to extract significant information from the basic sensory data. The following input features are generated:

1. Normalized skin temperature (ST_n)
2. Normalized skin temperature gradient ($STgrad_n$)
3. Normalized pulse rate (PR_n)
4. Normalized pulse rate gradient ($PRgrad_n$)
5. Pulse rate spectral feature (PR_{sp})
6. Ambient air temperature (T_a)

Finally, these features are fed to an optimally trained SVM classifier to predict the TSI :

$$TSI = g(ST_n, STgrad_n, PR_n, PRgrad_n, PR_{sp}, T_a) \quad (5.2)$$

(a) The ePTS model development

(b) The ePTS model deployment

Figure 5.3: Framework of the proposed ePTS model.

5.3.2 Input Feature Engineering

Feature engineering is a technique of data preprocessing, whereby significant information is extracted from the otherwise noisy sensor data. The methods used for extracting the six input features are described below:

5.3.2.1 Peripheral property based Normalization Process for Skin Temperature features

The PTS model as described in previous Chapter 4 is adopted here for the normalization of skin temperature features. For clarity, the equations are re-summarized below:

$$\begin{aligned}
 STgrad(t) &= ST(t) - ST(t - 5) \\
 ST_n &= \frac{ST}{A_{exp}} \\
 STgrad_n &= \frac{STgrad}{A_{exp}} \quad (5.3)
 \end{aligned}$$

where, $A_{exp} = (1 - I_{cl}) \times A_{Du}$, $I \in (0, 1)$
and, $A_{Du} = Weight^{0.425} \times Height^{0.725} \times 0.203$

5.3.2.2 Intrinsic property based Logic Gated Normalization Process for Pulse Rate features

As the ePTS model aims to differentiate between *Discomfort* (DC) and *Comfort* (C) thermal states, statistical tests are first performed to investigate the significance of differences in pulse rate features between DC and C. Student's T-test and Wilcoxon-Mann-Whitney tests are performed for normally and non-normally distributed data, respectively, and the results are summarized in Table 5.2. The table enlists the mean and standard deviation values of *PR* and *PRgrad*.

For female gender group and low BMI group, mean *PR* is significantly higher during C state than DC state ($p = 0.009, p < 0.001$). For female group, the mean *PR* is (72.6 ± 7.3) bpm and (75.1 ± 7.7) bpm during DC and C states, respectively. For low BMI group, the mean *PR* is (68.4 ± 8.2) bpm and (73.1 ± 7.8) bpm during DC and C states, respectively. The mean gradient *PRgrad* is significantly different between DC and C for higher BMI people ($p = 0.042$). While the change is negative for DC state at (-0.39 ± 4.87) bpm/5min, it is positive for C state at (0.44 ± 4.57) bpm/5min, indicating that *PR* decreases during discomfort and increases during comfort.

Table 5.2: Results of Student's T-test and Wilcoxon-Mann-Whitney test for difference in PR/PRgrad between *Discomfort* (DC) and *Comfort* (C) states for different Gender and BMI groups.

		Gender				BMI			
		M		F		L		H	
		mean±S.D.	p	mean±S.D.	p	mean±S.D.	p	mean±S.D.	p
<i>PR</i>	DC	69.2±8.6	0.591	72.6±7.3	0.009*	68.4±8.2	<0.001*	71.2±8.2	0.532
	C	67.9±10.5		75.1±7.7		73.1±7.8		70.6±12.2	
<i>PRgrad</i>	DC	-0.26±5.14	0.262	-0.39±3.89	0.589	0.44±3.97	0.206	-0.39±4.87	0.042*
	C	0.33±4.61		-0.09±6.28		-0.31±6.28		0.44±4.57	

Note: *Statistically significant difference, S.D.-standard deviation, *p*-significance value of difference between DC and C.

Overall, three groups exhibit potential for TSI prediction: (F, L) for *PR* and H for *PRgrad*. To incorporate this, a normalization process is developed using NAND logic gate operation as shown in the equation set 5.4. Here, PR_n is the normalized pulse rate, $PRgrad_n$ is the normalized pulse rate gradient, α is defined as the gender coefficient, β is defined as the BMI coefficient, and $(\overline{\alpha \cdot \beta})$ implies logical NAND operation between α and β .

$$\begin{aligned}
 PRgrad(t) &= PR(t) - PR(t - 5), \\
 PR_n &= (\overline{\alpha \cdot \beta}) \times PR \\
 PRgrad_n &= \beta \times PRgrad \\
 \text{where, } \alpha &= \begin{cases} 0, & \text{female} \\ 1, & \text{male} \end{cases} \\
 \text{and, } \beta &= \begin{cases} 0, & \text{low BMI} \\ 1, & \text{high BMI} \end{cases}
 \end{aligned} \tag{5.4}$$

The normalization chart is illustrated in Table 5.3. It can be seen that this normalization method effectively extracts the significant features for prediction during each case.

5.3.2.3 Pulse Rate Spectral Feature Extraction

We consider that the spectral component of *PR* carries useful information for TSI prediction because of the following two reasons: 1) unlike skin temperature which varies

Table 5.3: Normalization chart for pulse rate features.

Case	α	β	$(\overline{\alpha \cdot \beta})$	PR_n	$PRgrad_n$	Features
F-L	0	0	1	PR	0	PR
F-H	0	1	1	PR	$PRgrad$	$PR, PRgrad$
M-L	1	0	1	PR	0	PR
M-H	1	1	0	0	$PRgrad$	$PRgrad$

Note: F-Female, M-Male, L-Low BMI, H-High BMI.

$(\overline{\alpha \cdot \beta})$ denotes logical NAND operation between α and β .

smoothly over time, PR varies erratically in a noisy manner; it is therefore important to extract meaningful data excluding the noise, 2) PR varies in a roughly periodical manner; if PR is considered as a discrete time signal, then this signal would be a superposition of several signals with different frequencies and amplitudes. These underlying signals can potentially carry important information.

The Fast Fourier Transform (FFT) is a popular mathematical procedure used to obtain the spectral component of a discrete signal sequence, and can address both the above matters. The highest magnitude of the ac spectral component of pulse rate (PR_{sp}) is a dominant feature and therefore, it has been selected as an input for the ePTS model. The procedure for PR_{sp} extraction is illustrated in algorithm 1. For each sample (extracted per minute), the discrete sequence of pulse rate over the 60s period is taken, and its 1024-point FFT computed, followed by extracting the highest magnitude. We avoid the zero-frequency magnitude $|X(0)|$ because it is always highest and is basically the average pulse rate in that minute, which is none other than the PR value itself. The search is limited to half the search-spectrum due to the symmetry property of real-valued FFT. The sampling frequency is 1s. Particularly ‘1024’-point FFT is done because it provides good resolution at reasonable computation time.

Subsequently, a Spearman’s rank correlation analysis is performed. It reveals a significant correlation between PR_{sp} and TSI ($Rho = 0.089, p = 0.0185$), validating PR_{sp} as a potential predictor of TSI .

Algorithm 1 Pulse Rate Spectral Feature PR_{sp} Extraction.

Input: $x(n)$ = discrete sequence of pulse rate in seconds
 $= \{x(0), x(1), \dots, x(N-1)\}$, where $N = 60$

Output: PR_{sp}

For each sample:

- 1: $X(m) \leftarrow$ 1024-point FFT of $x(n)$
 $= \{X(0), X(1) \dots X(N-1)\}$
 where,

$$X(m) = \sum_{n=0}^{N-1} x(n) \cdot e^{-j \frac{2\pi n m}{N}}$$

- 2: $PR_{sp} \leftarrow \max\{|X(1)|, \dots, |X(\frac{N}{2})|\}$
- 3: **return** PR_{sp}

5.3.2.4 Ambient Air Temperature

Among all environmental factors of thermal comfort, the ambient air temperature has the highest impact on thermal comfort and it is the most widely used parameter for indoor climate control [4]. Therefore, in this study, we consider it as an input, however, we treat it only as secondary to the physiological inputs.

5.3.3 Model Comparisons for RBF-SVM based TSI Classification

An SVM classifier is developed to model the thermal state index TSI with respect to the above input features. The ePTS model is compared with five other input cases as shown in Table 5.4.

Table 5.4: The input cases for comparison.

Case 1:	$ST_n, STgrad_n$ (PTS)
Case 2:	$ST_n, STgrad_n, PR, PRgrad$
Case 3:	$ST_n, STgrad_n, PR_n, PRgrad_n$
Case 4:	$ST_n, STgrad_n, PR_n, PRgrad_n, PR_{sp}$
Case 5:	$ST_n, STgrad_n, PR_{sp}$
Case 6:	$ST_n, STgrad_n, PR_n, PRgrad_n, PR_{sp}, T_a$ (ePTS)

For each of the four input cases, an SVM classifier $g(\cdot)$ is developed to classify TSI based on the respective input features:

For case 1 (PTS model):

$$TSI = g(ST_n, STgrad_n) \quad (5.5)$$

For case 2:

$$TSI = g(ST_n, STgrad_n, PR, PRgrad) \quad (5.6)$$

For case 3:

$$TSI = g(ST_n, STgrad_n, PR_n, PRgrad_n) \quad (5.7)$$

For case 4:

$$TSI = g(ST_n, STgrad_n, PR_n, PRgrad_n, PR_{sp}) \quad (5.8)$$

For case 5:

$$TSI = g(ST_n, STgrad_n, PR_{sp}) \quad (5.9)$$

For case 6 (ePTS model):

$$TSI = g(ST_n, STgrad_n, PR_n, PRgrad_n, PR_{sp}, T_a) \quad (5.10)$$

The formulation for the RBF-SVM classifier was presented in previous Chapter 4 equations 4.11-4.12. The optimal values of the tuning parameters C and γ are located by a grid search operation using 10-fold cross validation.

5.3.4 Predictive Performance Results of ePTS Model

The data is randomly divided at ratio 80:20 into training and test datasets with equal proportion of each TSI to prevent bias. Models are developed using training dataset and their performances are validated using test dataset. The optimal training parameters are found by grid-search operation using cross-validation of the training data, in the following ranges: Cost C (2^0 to 2^8), gamma γ (0.5 to 5). The parameter tuning map of the ePTS model is illustrated in Figure 5.4. It shows that the minimum error (MSE) or the optimal hyperplane is obtained at the combination ($C = 8$, $\gamma = 5$).

Figure 5.4: SVM tuning parameter map for the ePTS model.

The optimal training parameters and the prediction accuracies on the test dataset are presented in Table 5.5. Firstly, it shows that the ePTS model has the minimum training error. The PTS model which is based solely on normalized skin temperature features achieves 82.32% accuracy (case 1). On adding the non-normalized pulse rate features, the accuracy reduces to 72.36% (case 2). This is because the non-normalized data contains irrelevant information, rendering the model non-scalable. On including the normalized pulse rate features (case 4), the accuracy improves to 87.80%, outperforming the PTS model. On adding the spectral feature PR_{sp} , the accuracy further exceeds 91.6% (case 5). This validates that the spectral feature contains significant predictive information. Therefore, we attempt using only PR_{sp} with the skin temperature features, and it obtains 94.51% accuracy.

However, using all the six input features including air temperature results in the highest accuracy of 97.15% (case 6). The ePTS model also has a balanced prediction for DC (97.97%) and C (96.34%) states unlike the remaining models.

Table 5.5: The optimal training parameters and the comparison of TSI prediction performance of the six input cases.

RBF-SVM Model Inputs	Optimal Training Parameters			Prediction Accuracy (%)		
	Cost	Gamma	MSE	Overall	DC	C
(1) $ST_n, STgrad_n$ (PTS Model)	64	3	0.219388	82.32	87.80	76.83
(2) $ST_n, STgrad_n, PR, PRgrad$	1	3	0.396449	72.36	76.83	67.89
(3) $ST_n, STgrad_n, PR_n, PRgrad_n$	32	5	0.260367	87.80	93.90	81.71
(4) $ST_n, STgrad_n, PR_n, PRgrad_n, PR_{sp}$	1	0.5	0.337265	91.67	95.93	87.40
(5) $ST_n, STgrad_n, PR_{sp}$	2	0.5	0.327224	94.51	98.37	90.65
(6) $ST_n, STgrad_n, PR_n, PRgrad_n, PR_{sp}, T_a$ (ePTS Model)	8	5	0.069143	97.15	97.97	96.34

Note: MSE-mean squared error, DC-Discomfort, C-Comfort.

5.4 Concluding Remarks

Pulse rate and its changes showed significant relation with thermal state for certain combinations of gender and BMI groups. The predictive model developed leveraged primarily on skin temperature and pulse rate features. Further study of the remaining parameters is required to gain an overall understanding. Gender differences are observed in pulse rate, and using gender as individual factor aided normalization. It is therefore important to study the gender differences for other parameters as well.

References

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Chapter 6

Collective Physiological Parameters as TSI Biomarkers and Energy-Saving Framework for Indoor Climate Control

This chapter¹ studies all the six physiological and the five subjective responses. Gender differences in subjective thermal perception and the physiological responses under different thermal states are investigated. The physiological features that have the potential to predict TSI are identified and consequently a new TSI predictive model is developed for each gender group. The chapter is organized as follows: Section 6.1 outlines the chapter contributions. Section 6.2 presents and discusses the subjective response results. Section 6.3 presents and discusses the physiological response results, followed by introduction of a new predictive model in section 6.4. Section 6.5 presents results of canonical correlation analysis between the subjective and physiological responses. Section 6.6 proposes an energy-saving framework for indoor climate control. Section 6.7 presents a comparative analysis of the proposed four different TSI predictive models and conclusions are drawn in Section 6.8.

¹This chapter published substantially as [1] and submitted partially as [2].

6.1 Outline of Contributions

The main novel contributions of this chapter include:

- Primarily investigated the possibility to predict the overall thermal state of an occupant using the collective information of gender-specific physiological parameters and their derived features, taking into consideration subjective psychological patterns.
- In the literature, connection between gender difference and thermal perception has often been debated. In this context, this chapter adopted four objectives as summarized in Figure 6.1 and described below:
 1. Investigated the gender differences in subjective thermal perception based on 4 types of survey responses- thermal comfort, thermal preference, humidity sensation, airflow sensation. See Chapter 3 for a description of these subjective scales.
 2. Investigated the gender differences in all six types of physiological responses under different thermal states, which are skin temperature, skin conductance, pulse rate, oxygen saturation and systolic/diastolic blood pressure. Additionally, the derivative features of each physiological parameter, namely first order gradient and mean squared gradient were studied.
 3. Identified the physiological features of each gender that possess significant potential to predict thermal state.
 4. Established a data-driven TSI predictive model termed as the GPTS model for each gender group using the identified potential features.
- Studied the overall relation between the subjective and the physiological responses based on a canonical correlation analysis.
- Proposed an energy-saving framework for indoor climate control. The control framework comprises TSI predictive model as one of its components.

- Performed a comparative analysis of all the proposed TS predictive models among themselves as well as with state-of-the-art methods.

Figure 6.1: The four-fold objective approach to developing the GPTS model.

6.2 Subjective Responses

As both gender groups were subjected to the same thermal conditions, a study of their subjective responses can indicate whether the females differed from the males in how they perceive their thermal environment.

A Chi-Squared Test of Independence is performed to investigate the gender difference for each of the four subjective scales. The Two-proportions Z -Test is administered as the post-hoc test. Difference between response levels of a subjective scale is analysed using the Marascuillo procedure of multiple proportions. Figure 6.2 illustrates the gender differences in subjective perception.

The tests reveal that there were significant gender effects on the perception of thermal comfort (Figure 6.2a, $p < 0.05$) and ambient humidity (Figure 6.2c, $p < 0.001$). No significant gender difference is observed in thermal preference (Figure 6.2b, $p = 0.530$) and perception of ambient airflow (Figure 6.2d, $p = 0.528$).

Even though both genders were exposed to the same thermal environments, a significantly larger proportion of women reported being *comfortable* as compared to men ($p < 0.01$). 56% of females felt *comfortable* whereas 28% of males felt the same. 48% of males and 30% of females felt *comfortably cool* ($p = 0.101$). A significantly larger proportion of women (76%) found the ambient humidity levels *just right*, as compared to only 34% of men ($p < 0.001$). Majority of men (52%) found the ambient conditions *slightly dry* as compared to only 12% of women ($p < 0.001$). Overall, women portrayed greater adaptability to thermal comfort and humidity conditions.

Overall, majority of women felt *comfortable*, found the humidity and airflow levels *just right* and preferred *no change* in thermal environment. Majority of men found the ambient air *slightly dry* (in humidity) and *slightly still* (in airflow), and yet reported feeling *comfortably cool* and preferred *no change* in conditions. This indicates that although men were sensitive yet they were tolerant of the thermal conditions. These observations are briefly discussed with respect to the existing literature, as follows.

According to a comprehensive review [3] of existing literature, females were more thermally dissatisfied than men under similar ‘conditions’. However, the ‘conditions’ used in these studies were quite diverse and also different from this study. Most of these studies experimented with distinctly set levels of air temperature, or subjected the participants to varying air velocity/turbulence and noise levels/sound qualities. The source of dissatisfaction was therefore unfixed and varied; it could be thermal, noise, draught, etc. In this study, however, subjects were exposed to variations in air temperature, and four types of responses were collected to study each source of dissatisfaction separately (humidity, airflow, comfort), as well as to draw a more complete understanding through overall analysis of all four responses.

As per specific response analysis, males were more thermally dissatisfied in terms of humidity and comfort. This finding was true for another study [4] of Danish subjects exposed to varying temperatures between 20°C and 29°C, where males felt more discomfort than women under the same conditions. No significant gender difference in airflow sensation may be attributed to the lower levels of air velocity ($< 0.2\text{m/s}$). From the perspective of ambient control, thermal preference is perhaps the most important and

conclusive metric, as it can clearly indicate the control action to be taken. The current result of no significant gender difference in thermal preference is consistent with that of earlier studies [5] conducted in Singapore.

As per the overall response analysis, an important observation is made. Most women being thermally satisfied (i.e., prefer no change) is justified by their mostly *comfortable* or *neutral* votes on the other three responses. However, most men reporting being thermally satisfied (i.e., prefer no change) even when they did not find the desirable conditions of humidity and airflow, is noteworthy. This indicates that men are probably more tolerant of their thermal conditions. Conclusions cannot be drawn on tolerance of women as they mostly expressed finding the thermal conditions desirable.

Figure 6.2: Gender differences in subjective thermal perception responses.

6.3 Physiological Responses

Six physiological parameters of each subject namely, hand skin temperature (ST), hand skin conductance (SC), pulse rate (PR), blood oxygen saturation (SpO_2) and blood pressure (BP_{sys}/BP_{dia}) were monitored. Three features of each physiological parameter were examined as described in Table 6.1. Besides the raw value of the parameter itself, FOG which represents parameter change in past 5-min and MSG which indicates fluctuations in parameter, were computed. The change rate FOG may sometimes lose important data if there are positive and negative 1-min gradients cancelling each other out. The MSG prevents losing such data as it averages the squares of 1-min gradients. The MSG can thus effectively represent fluctuations in the parameter. Besides these, some other derivative features were also studied but later excluded such as, moving average (it was redundant with the raw value), and higher order gradients (it was not found to be of significance). The observed physiological parameter values are summarized in Table 6.2. As seen from the table, although the parameter means were in general healthy, owing to thermal stress some of the values marginally crossed the range which is typically considered normal. A detailed discussion is furnished below.

Table 6.1: List of studied features of each physiological parameter.

Feature	Description
Raw value	$f(i)$
First Order 5-min Gradient	$FOG(i) = f(i) - f(i - 5)$
Mean of Square of 1-min Gradients in past 5 min	$MSG(i) = \frac{\sum_{j=i-4}^i \{f(j) - f(j-1)\}^2}{5}$

Table 6.2: Summary of all physiological parameters of the subjects.

	ST (°C)	SC (μS)	PR (bpm)	SpO_2 (%)	BP_{sys} (mmHg)	BP_{dia} (mmHg)
Mean	31.4	9.4	71.4	97.7	109	69
Std. Dev.	1.6	8.26	9.26	1.1	13	10
Min - Max	28.5 - 34.5	0.8 - 33.2	47.1 - 95	93.5 - 99	84 - 137	51 - 92
Normal range	-	2 - 20	60 - 100	94 - 99	90 - 140	60 - 90

Note: Sample size = 800 (ST , SC , PR , SpO_2), 100 (BP_{sys} , BP_{dia}).

6.3.1 Hand Skin Temperature

Females portrayed significantly lower ST than the males under comfort state ($p < 0.001$, Figure 6.3a). Under cold stress (discomfort state), the ST of males significantly lowered, while that of females remained unaltered.

The change rates (FOG) of ST were in general negative and positive during discomfort and comfort state, respectively (Figure 6.3b), demonstrating that in general ST varies in proportion to the perceived ambient temperature. However, no gender difference was observed.

Mean squared gradient (MSG) of women was higher during both thermal states (Figure 6.3c, $p < 0.001$). MSG was significantly greater during discomfort state for both genders, demonstrating that undesirable thermal environment may have onset increased fluctuations in ST .

The lower ST response in women (Figure 6.3a) may be attributed to higher amounts of body fat commonly exhibited by females. Subcutaneous fat affects skin temperature through the conductive heat transfer between the body core and the skin; therefore, higher subcutaneous fat renders women greater surface tissue insulation and consequently cooler skin temperatures [6]. Vasoconstriction induced by cold exposure enhances skin's insulation benefits, and women have added insulation equivalent to a layer of about 4 mm more completely vasoconstricted body fat [6]. This may explain why female ST remained unaltered during cold stress. Skin temperature has been utilized to predict thermal comfort in several existing studies. Our study (Figure 6.3a) however revealed that while it may be a strong predictor for men, the thicker tissue insulation in women can make their hand skin temperature comparatively less sensitive to thermal environment and probably less likely to reflect thermal state. However, its change rate and fluctuations were profoundly different under the two states indicating predictive potential.

6.3.2 Hand Skin Conductance

Males exhibited significantly higher SC than females during cool discomfort state (Figure 6.3d, $p < 0.001$). SC levels were significantly different under the thermal states for both gender group.

Men's FOG had larger variations (standard deviations) although on an average it was close to zero under comfort state, and about $1\mu S$ under discomfort state (Figure 6.3e) because of the sedentary activity level.

Males portrayed higher fluctuation (MSG) and variations under all circumstances ($p < 0.001$, Figure 6.3f). For both genders, MSG was significantly greater during cold stress ($p < 0.05$).

Under comparable stress levels, women generally have been observed to exhibit rates of sweating which average only 30% to 86% those of men [6, 7]. However, these past studies usually focused only on heat stress or higher activity level scenarios. In our study, similar behaviour was observed for cold stress as well, with higher SC in males. While females possess higher number of sweat glands, males are characterized with larger gland size [7]. These physical trait differences could be a possible reason behind the different sweating responses to same thermal stress level.

6.3.3 Pulse Rate

Female hearts beat significantly faster than male hearts under all thermal conditions ($p < 0.001$, Figure 6.4a). Females exhibited significantly lower PR during cold stress as compared to comfort state, while male pulse rates did not show any changes under the stress.

No significant difference was found for PR -FOG (Figure 6.4b). As for MSG (Figure 6.4c), the female PR -MSG was significantly greater than that of males during comfort state ($p < 0.01$), but under cold stress, it significantly lowered ($p < 0.001$) while that of males remained unaltered.

The observation of higher female PR is consistent with that of earlier studies under heat stress conditions [8]. This response is attributed to the smaller heart size in females, which pumps less blood with each beat and therefore, beats faster.

6.3.4 Blood Oxygen Saturation

Females portrayed significantly higher oxygen saturation than males under normal thermal conditions ($p < 0.001$, Figure 6.4d). No gender difference in any SpO_2 feature was found under cold stress. However, males' SpO_2 fluctuations were significantly higher in discomfort state ($p < 0.05$) than in comfort state, probably owing to elevated respiration under thermal stress [9].

Gender difference in SpO_2 values under comfort state could be owing to women on average having a lower diffusing capacity, smaller airway diameter and lung volumes than men [10].

6.3.5 Blood Pressure

Systolic pressure (BP_{sys}) indicates the highest pressure that the heart exerts while beating, and diastolic pressure (BP_{dia}) is the pressure in the arteries between heartbeats. In general, men portrayed significantly higher systolic blood pressure than women (Figure 6.5, $p < 0.001$). However, neither systolic nor diastolic blood pressure exhibited any potential to differentiate thermal state.

Weaker response of diastolic pressure to temperature changes was observed in an existing study [11]. Similar behaviour in our study in respect to thermal comfort validates its exclusion as a probable predictor, although further investigation is preferred due to comparatively smaller BP sample size in this study.

Figure 6.3: Skin Temperature (*ST*) and Skin Conductance (*SC*) responses.

Figure 6.4: Pulse Rate (PR) and Blood Oxygen Saturation (SpO₂) responses.

Figure 6.5: Systolic Blood Pressure (BP_{sys}) and Diastolic Blood Pressure (BP_{dia}) responses.

6.3.6 Gender Differences

The physiological gender differences as observed in Figures 6.3 - 6.5 are summarized in Table 6.3. The table lists the significances (p -value) of gender differences. Except diastolic pressure, at least one feature of each physiological parameter exhibited profound gender difference. No dissimilarity was observed between men and women in terms of change rate FOG, however the MSG in hand skin temperature, hand skin conductance and pulse rate were starkly different in general. Males exhibited distinctly higher BP_{sys} and lower PR than females in general, while under cold stress, women had lower SC than men. Men at comfort state had higher ST and SpO_2 than women but no such difference was observed during cold stress.

In general, it is indicative that women and men thermo-regulate differently not simply due to differences in physical characteristics but due to innate physiologic gender differences as well [7]. The above differences in subcutaneous responses (ST and SC), respiratory

Table 6.3: Gender differences in physiological features under different thermal states. Tabulated are significance p -values (Male vs Female).

	Thermal state: <i>Discomfort</i>			Thermal state: <i>Comfort</i>		
	Raw	FOG	MSG	Raw	FOG	MSG
<i>ST</i>	0.352	0.622	<0.001***	<0.001***	0.473	<0.001***
<i>SC</i>	<0.001***	0.108	<0.001***	0.077	0.444	<0.001***
<i>PR</i>	<0.001***	0.943	0.001**	<0.001***	0.414	0.003**
SpO ₂	0.165	0.240	0.206	<0.001***	0.891	0.659
BP _{sys}	<0.001***	0.481	N/A	<0.001***	0.626	N/A
BP _{dia}	0.410	0.344	N/A	0.776	0.620	N/A

Note: Significant gender difference * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

responses (SpO₂) and cardiovascular responses (*PR* and BP) during thermoregulation, urges the consideration of gender in future comfort studies.

6.3.7 Potential Predictive Features

Features that vary significantly between thermal states are recognized as its potential predictors. The potential predictors as observed in Figures 6.3 - 6.5 are summarized in Table 6.4. The table lists the significances (p -value) of difference in physiological response under different thermal states. As seen in Table 6.4, seven features for males were identified with thermal state predicting potential, specifically *ST*, *ST*-FOG, *ST*-MSG, *SC*, *SC*-FOG, *SC*-MSG and SpO₂-MSG. As for the female gender group, six of the studied features demonstrated predictive potential, namely *ST*-FOG, *ST*-MSG, *SC*, *SC*-MSG, *PR* and *PR*-MSG.

To further validate these findings, Spearman's rank correlation analysis is performed between the features and thermal state. The correlation analysis results are consistent with the findings as reflected by the significantly correlated features in Table 6.5.

As significant gender differences are found, it is imperative that separate analysis is done for each gender. The next step is utilization of the identified potential predictors to develop a thermal state prediction model. Prior to the model development, a Pearson's correlation analysis of the features is performed. Table 6.6 illustrates the correlation

Table 6.4: Potential predictors of thermal state TSI for each gender group. Tabulated are significance p -values (*Discomfort* vs *Comfort*).

	Gender: Male			Gender: Female		
	Raw	FOG	MSG	Raw	FOG	MSG
<i>ST</i>	<0.001***	<0.001***	<0.001***	0.620	0.022*	0.010**
<i>SC</i>	<0.001***	0.024*	0.028*	<0.001***	0.711	0.040*
<i>PR</i>	0.591	0.262	0.705	0.009**	0.589	<0.001***
SpO ₂	0.756	0.772	0.016*	0.832	0.265	0.854
BP _{sys}	0.675	0.995	N/A	0.708	0.734	N/A
BP _{dia}	0.963	0.393	N/A	0.673	0.919	N/A

Note: Significant predictive potential * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 6.5: Spearman's rank correlation coefficient (*Rho*) for correlations between thermal state and physiological features for each gender group.

	Gender: Male			Gender: Female		
	Raw	FOG	MSG	Raw	FOG	MSG
<i>ST</i>	0.286***	0.200***	-0.332***	-0.027	0.123*	-0.138**
<i>SC</i>	-0.183***	-0.121*	-0.118*	0.239***	0.020	0.110*
<i>PR</i>	-0.029	0.082	-0.020	0.140**	0.016	0.319***
SpO ₂	-0.017	-0.016	-0.128*	0.011	0.060	-0.010
BP _{sys}	-0.067	-0.197	N/A	0.019	-0.011	N/A
BP _{dia}	0.114	-0.016	N/A	0.049	-0.014	N/A

Note: Significant correlation * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

matrices of physiological features for male and female gender groups. In general, SpO₂ levels of both genders exhibited strong negative correlations with *ST* and *PR*, which were positively correlated. *SC* of women showed strong positive correlations with their *ST* and *PR*. Most importantly, the tables reveal significant correlations among some of the potential predictor inputs.

Table 6.6: Pearson's coefficient of correlation between different physiological features.

MALE											
Hand Skin Temperature (<i>ST</i>)			Hand Skin Conductance (<i>SC</i>)			Pulse Rate (<i>PR</i>)			Oxygen Saturation (<i>SpO₂</i>)		
	Raw	FOG	MSG	Raw	FOG	MSG	Raw	FOG	MSG	Raw	MSG
<i>ST</i>	Raw	1	0.377***	0.195***	-0.012	-0.110*	0.516***	0.034	0.171**	-0.571***	0.149***
	FOG		1	0.379***	-0.081	-0.064	0.310***	-0.025	0.113*	-0.517***	0.294***
	MSG			1	-0.034	0.087	0.176***	-0.020	0.025	-0.323***	0.486***
<i>SC</i>	Raw			0.282***	0.305***	0.126*	0.100	-0.019	0.126*	-0.054	-0.057
	FOG			1	-0.362***	0.012	0.054	-0.074	-0.043	0.030	-0.037
	MSG				1	-0.189***	-0.012	0.043	0.070	0.109*	-0.040
<i>PR</i>	Raw					0.120*	1	0.253***	0.115*	-0.518***	0.313***
	FOG					0.046	1	0.105	0.020	0.060	0.020
	MSG					1		0.099	0.114*	-0.172**	0.114*
<i>SpO₂</i>	Raw								0.180***	1	-0.416***
	FOG								1	-0.020	-0.020
	MSG									1	1
FEMALE											
Hand Skin Temperature (<i>ST</i>)			Hand Skin Conductance (<i>SC</i>)			Pulse Rate (<i>PR</i>)			Oxygen Saturation (<i>SpO₂</i>)		
	Raw	FOG	MSG	Raw	FOG	MSG	Raw	FOG	MSG	Raw	MSG
<i>ST</i>	Raw	1	0.255***	0.119*	0.248***	-0.194***	0.330***	-0.030	-0.174**	-0.531***	0.086
	FOG		1	0.167**	0.033	-0.436***	0.048	0.067	-0.104	-0.275***	0.067
	MSG			1	0.290***	-0.252***	0.113*	0.084	-0.147**	-0.093	0.130*
<i>SC</i>	Raw				1	-0.056	0.337***	-0.009	-0.201***	-0.010	-0.134*
	FOG					1	-0.075	0.095	0.168**	0.103	0.016
	MSG						0.089	-0.025	0.031	-0.251***	0.078
<i>PR</i>	Raw						1	0.317***	0.039	-0.132*	-0.147***
	FOG							1	-0.062	0.038	0.165**
	MSG								1	0.097	0.081
<i>SpO₂</i>	Raw									1	0.283***
	FOG									1	0.157**
	MSG										1

6.4 Proposed Model D: GPTS Model

Correlated features can often be a hindrance to the predictive performance of data-driven methods. Random Forest algorithm, a data-driven method possess the ability to eradicate the redundancy associated with such correlated input features. Therefore, based on this algorithm and the identified predictive features, we propose a new TSI predictive model, named as the ***Gender based Predicted Thermal State (GPTS) model***. The analytical diagram of the GPTS model is shown in Figure 6.6a. Depending on the occupant's gender, different parameters are sensed and the relevant features are derived. These features are used to model the thermal state index using the Random Forest algorithm.

(a) GPTS model development

(b) GPTS model deployment

Figure 6.6: Framework of the proposed GPTS Model.

6.4.1 Random Forest Algorithm

The Random Forest algorithm [12], an ensemble statistical classifier, is employed to develop the thermal state prediction model. Algorithm 2 illustrates the pseudo-code of the Random Forest procedure.

Random Forest operates by building a multitude of decision trees. It has several advantages over the other existing machine learning classifiers. Its random feature selection property makes it reliable and robust against correlated predictors. A random subset of predictors is used as split candidates for each tree; if not for this property, all trees would be similar and correlated. Secondly, it performs bagging wherein multiple trees are generated using bootstrapped samples and the majority vote is taken. This property reduces variance and is immune to over-fitting as well. Moreover, it can evaluate relative ranking of variable importance i.e. it can estimate which predictors are most important in the classification. Random Forest being a powerful yet moderately interpretable classifier made for a suitable choice in this study.

Algorithm 2 Random Forest Pseudo Code

Given

S : Original Training sample dataset of size n

p : Number of input predictors/physiological features

X : Test observation (new input set of physiological features)

Initially Determine

M : Number of Trees to be generated

v : Number of predictors to be selected as split candidates for each tree (usually

$v \approx \sqrt{p}$)

for $m \leftarrow 1$ **To** M **do**

 Draw a random sample S^* of size n with replacement from S (Bootstrap)

 Grow a tree T_m using S^* through the following loop:

while minimum node size $node_{min}$ is not reached **do**

 For the leave node of the tree

 Randomly select v predictors out of the p predictors

 Select the best pair of split candidates among the v predictors

 Split the node into two daughter nodes

end while

Return Constructed tree $T_m(X)$

end for

Return Prediction for a given new input X as per majority vote $\Leftarrow \frac{1}{M} \sum_{m=1}^M T_m(X)$

{Note: $node_{min}$ is the minimum number of observations at each leaf node}

The datasets pertaining to each gender group are divided into training and validation sets in the ratio 80%:20%. The models are developed using the training dataset. The optimal number (M) of decision trees is found to be about 500 corresponding to the minimum out-of-bag error rate. The predictor subset size $v(= \sqrt{p})$ is equal to 2 for both models (males: $p= 7$, females: $p= 6$).

The performance of each developed model as tested on the validation dataset is demonstrated in Table 6.7. The models could accurately predict 92.86% and 94.29% of thermal states of the male and female subjects, respectively. This confusion matrices which summarizes the accuracy of classification are presented in Table 6.7. The diagonal values denote the number of correct predictions. As indicated in the table, both models achieve good precision and sensitivity. Therefore, the physiological features identified with predictive potential could collectively attain good accuracies of over 90% on new occupant data.

In addition, an evaluation of the relative ranking of the predictors in terms of their importance is performed. Figure 6.7 represents the mean decrease in accuracy when each predictor is excluded from the model. ST and SC appears to be the most important predictor for males and females respectively, accounting for almost 50% of total contribution in thermal state prediction.

A Random Forest generates a large number of classification trees (500 in this study) and takes the average performance of all trees to evaluate its final accuracy. Therefore, it is not feasible to visually represent a random forest with such many trees; therefore, a full size classification tree randomly selected from the Random Forest is presented in Figures 6.8 and 6.9 to demonstrate how a decision tree might have generated principles to classify the thermal states.

Table 6.7: Thermal state prediction accuracy and confusion matrix based on Random Forest algorithm using the identified significant physiological features as inputs. Sample size = 700; No. of trees generated, $M = 500$; No. of random predictors for node split, $v = \sqrt{p} \approx 2$.

Gender	Model Inputs	Prediction Accuracy	Confusion Matrix				
Male	ST	92.86%			Predicted TSI		
	ST -FOG						
	ST -MSG		DC	C	Sensitivity		
	SC		True TSI	DC	29	0	1.000
	SC -FOG						
	SC -MSG			C	5	36	0.878
	SpO_2 -MSG		Precision		0.853	1.000	
Female	ST -FOG	94.29%			Predicted TSI		
	ST -MSG						
	SC		DC	C	Sensitivity		
	SC -MSG		True TSI	DC	18	1	0.947
	PR						
	PR -MSG			C	3	48	0.941
			Precision		0.857	0.979

Figure 6.7: Relative importance of TSI predictors.

(a) Classification Tree structure

```

node), split, n, deviance, yval, (yprob)
* denotes terminal node

1) root 280 384.000 0 ( 0.43929 0.56071 )
2) x.Ts < 32.1343 167 219.200 -1 ( 0.63473 0.36527 )
4) x.Ts_MSG < 0.00271395 55 62.400 0 ( 0.25455 0.74545 )
8) x.SpO2_MSG < 0.169556 47 39.560 0 ( 0.14894 0.85106 )
16) x.SC_MSG < 0.191233 23 28.270 0 ( 0.30435 0.69565 )
32) x.SC_MSG < 0.0863312 12 0.000 0 ( 0.00000 1.00000 ) *
33) x.SC_MSG > 0.0863312 11 14.420 -1 ( 0.63636 0.36364 )
66) x.Ts_FOG < -0.0625833 5 5.004 0 ( 0.20000 0.80000 ) *
67) x.Ts_FOG > -0.0625833 6 0.000 -1 ( 1.00000 0.00000 ) *
17) x.SC_MSG > 0.191233 24 0.000 0 ( 0.00000 1.00000 ) *
9) x.SpO2_MSG > 0.169556 8 6.028 -1 ( 0.87500 0.12500 ) *
5) x.Ts_MSG > 0.00271395 112 105.100 -1 ( 0.82143 0.17857 )
10) x.SC_MSG < 0.347456 46 58.090 -1 ( 0.67391 0.32609 )
20) x.Ts < 31.1285 34 46.660 -1 ( 0.55882 0.44118 )
40) x.Ts_FOG < -0.3695 12 10.810 0 ( 0.16667 0.83333 )
80) x.Ts < 30.7005 7 0.000 0 ( 0.00000 1.00000 ) *
81) x.Ts > 30.7005 5 6.730 0 ( 0.40000 0.60000 ) *
41) x.Ts_FOG > -0.3695 22 23.580 -1 ( 0.77273 0.22727 )
82) x.Ts < 30.9848 17 12.320 -1 ( 0.88235 0.11765 )
164) x.SC_MSG < 0.0382633 5 6.730 -1 ( 0.60000 0.40000 ) *
165) x.SC_MSG > 0.0382633 12 0.000 -1 ( 1.00000 0.00000 ) *
83) x.Ts > 30.9848 5 6.730 0 ( 0.40000 0.60000 ) *
21) x.Ts > 31.1285 12 0.000 -1 ( 1.00000 0.00000 ) *
11) x.SC_MSG > 0.347456 66 35.410 -1 ( 0.92424 0.07576 )
22) x.Ts_FOG < 0.44375 58 10.100 -1 ( 0.98276 0.01724 )
44) x.Ts_MSG < 0.00346605 5 5.004 -1 ( 0.80000 0.20000 ) *
45) x.Ts_MSG > 0.00346605 53 0.000 -1 ( 1.00000 0.00000 ) *
23) x.Ts_FOG > 0.44375 8 11.090 0 ( 0.50000 0.50000 ) *
3) x.Ts > 32.1343 113 95.710 0 ( 0.15044 0.84956 )
6) x.Ts_MSG < 0.00502118 58 0.000 0 ( 0.00000 1.00000 ) *
7) x.Ts_MSG > 0.00502118 55 68.020 0 ( 0.30909 0.69091 )
14) x.SpO2_MSG < 0.358423 34 47.130 0 ( 0.50000 0.50000 )
28) x.Ts < 33.3527 22 25.780 -1 ( 0.72727 0.27273 )
56) x.SC < 10.966 17 7.606 -1 ( 0.94118 0.05882 ) *
57) x.SC > 10.966 5 0.000 0 ( 0.00000 1.00000 ) *
29) x.Ts > 33.3527 12 6.884 0 ( 0.08333 0.91667 ) *
15) x.SpO2_MSG > 0.358423 21 0.000 0 ( 0.00000 1.00000 ) *

```

(b) Principles for classification

Figure 6.8: A randomly selected full grown classification tree for male gender group (accuracy: 85.71%). ‘yval’: -1 (*Discomfort*), 0 (*Comfort*).

(a) Classification Tree structure

```

node), split, n, deviance, yval, (yprob)
* denotes terminal node

1) root 280 317.100 0 ( 0.25357 0.74643 )
2) SC < 2.25867 50 62.690 -1 ( 0.68000 0.32000 )
4) ST_MSG < 0.00126391 16 15.440 0 ( 0.18750 0.81250 )
8) ST_FOG < -0.02875 5 6.730 -1 ( 0.60000 0.40000 ) *
9) ST_FOG > -0.02875 11 0.000 0 ( 0.00000 1.00000 ) *
5) ST_MSG > 0.00126391 34 20.290 -1 ( 0.91176 0.08824 )
10) SC < 1.0085 5 6.730 0 ( 0.40000 0.60000 ) *
11) SC > 1.0085 29 0.000 -1 ( 1.00000 0.00000 ) *
3) SC > 2.25867 230 202.900 0 ( 0.16087 0.83913 )
6) SC < 30.0758 214 137.400 0 ( 0.09813 0.90187 )
12) SC_MSG < 0.327588 146 21.130 0 ( 0.01370 0.98630 )
24) PR < 83.2333 128 0.000 0 ( 0.00000 1.00000 ) *
25) PR > 83.2333 18 12.560 0 ( 0.11111 0.88889 )
50) ST_FOG < 0.0851667 13 0.000 0 ( 0.00000 1.00000 ) *
51) ST_FOG > 0.0851667 5 6.730 0 ( 0.40000 0.60000 ) *
13) SC_MSG > 0.327588 68 80.570 0 ( 0.27941 0.72059 )
26) PR < 65.4583 11 6.702 -1 ( 0.90909 0.09091 ) *
27) PR > 65.4583 57 49.720 0 ( 0.15789 0.84211 )
54) PR_MSG < 24.467 31 37.350 0 ( 0.29032 0.70968 )
108) PR_MSG < 2.13075 6 7.638 -1 ( 0.66667 0.33333 ) *
109) PR_MSG > 2.13075 25 25.020 0 ( 0.20000 0.80000 )
218) SC < 5.13083 8 11.090 0 ( 0.50000 0.50000 ) *
219) SC > 5.13083 17 7.606 0 ( 0.05882 0.94118 ) *
55) PR_MSG > 24.467 26 0.000 0 ( 0.00000 1.00000 ) *
7) SC > 30.0758 16 0.000 -1 ( 1.00000 0.00000 ) *

```

(b) Principles for classification

Figure 6.9: A randomly selected full grown classification tree for female gender group (accuracy: 88.57%). ‘yval’: -1 (*Discomfort*), 0 (*Comfort*).

6.5 Canonical Correlation Analysis between Subjective and Physiological Responses

As the human thermoregulation is a combination of both the physiological and the psychological states, it is of great importance to study the relationship between the physiological state of the body and the corresponding subjective responses. A canonical correlation analysis [13], which provides an overall correlation between two sets of variables, is performed to study this relationship. It generates linear combinations of the variables that maximally correlate, and has an advantage of being robust to multicollinearities. For the analysis, all bodily parameters including BP_{sys}/BP_{dia} , and all subjective perceptions including thermal sensation (TSV) are incorporated.

Let $\mathbf{X}$ be the vector of all five ($p = 5$) subjective responses including thermal sensation (TSV) and $\mathbf{Y} = [ST, PR, SC, SpO_2, BP_{sys}, BP_{dia}]^T$ be the vector of all six ($q = 6$) physiological parameters. Then we define new variables $\mathbf{U}$ and $\mathbf{V}$ via linear combinations of $\mathbf{X}$ and $\mathbf{Y}$.

$\mathbf{U}$ is a set of linear combinations of $\mathbf{X}$ and $\mathbf{V}$ is a set of linear combinations of $\mathbf{Y}$. With $p < q$, there are 5 canonical covariates $(U_1, V_1), \dots, (U_5, V_5)$. The canonical correlation for the i^{th} canonical variate pair is then calculated by:

$$\rho_i = \frac{cov(U_i, V_j)}{\sqrt{var(U_i)var(V_j)}} \quad (6.1)$$

Linear combinations of the $\mathbf{X}$'s and linear combinations of the $\mathbf{Y}$'s that maximize the above correlation are found. Figure 6.10 outlines the results of the canonical correlation analysis, including the whole population. Amongst all, the first canonical variate (U_1, V_1) only passed the significance test. The correlation is found to be statistically significant at $\rho_1 = 0.45$ ($p < 0.05$). The figure also lists the canonical coefficients, which denote contribution of each variable to the first canonical variate. The results reveal a strong connection between the physiological and the subjective responses. Thus, it further emphasizes that information of either response can be studied to interpret the other.

Figure 6.10: Canonical correlation analysis between Subjective responses (R_{sub}) and Physiological responses (R_{phy}).

6.6 Proposed Energy-Saving Framework for Indoor Climate Control

We propose a framework for indoor climate control as detailed in Figure 6.11. It incorporates a TSI predictive model and an optimization algorithm that collectively act as an intelligent autonomous mediator between the occupant and the ACMV system. We term the optimization algorithm as the Optimal Air Temperature (OAT) algorithm.

Firstly, the TSI predictive model takes in the necessary input variable information (physiological, personal, environmental etc. depending on the type of model), and predicts the occupant's current TSI. Secondly, the OAT algorithm provides optimal operating points to the ACMV system based on the current TSI. The OAT algorithm takes as input the predicted TSI along with the current operating state of the ACMV system (T_a, f). Here, T_a refers to the ambient air temperature and f refers to the operating frequency vector (defined in next section). During discomfort states ($TSI = -1, +1$), it locates the optimal operating state (T_a^*, f^*) that will result in comfort with minimum energy consumption. Subsequently, the ACMV system makes necessary adjustments accordingly. The operating state is adjusted to the optimal point such that the desired air temperature T_a^* is achieved. Details of the framework are presented below:

Figure 6.11: Detailed structure of the proposed indoor climate control framework.

6.6.1 Neural Network modelling of ACMV energy consumption

The Air Handling Unit (AHU) of the ACMV system is responsible for circulating and supplying fresh air in the room. It takes in mixed outside and return air, initiates conditioning the mixed air depending on cooling/heating demand, and supplies the fresh conditioned air into the room through the supply-air fan. In the study of Acosta *et al.*, a non-linear predictive controller was proposed that predicts the power consumption of the air-conditioning systems based on estimated cooling loads [14]. In another study, operating frequencies of ACMV components were used to model the ACMV energy consumption [15]. In this study, we model the energy consumption of our ACMV system using operating frequencies of the AHU and the cooling components along with an additional parameter, i.e the ambient temperature in the room.

The ACMV system in the thermal laboratory of the School of Electrical and Electronic Engineering, Nanyang Technological University is used as the test-bed, which comprises the cooling capacity due to year-round tropical climate of Singapore. A general outline is shown in Figure 6.12. It consists of the liquid-dehumidification unit, the AHU, and the water chiller unit. The operating frequencies of the compressor and water pump of the chiller unit, and supply-air fan of the AHU, are recorded along with the indoor ambient air temperature. The reasons for selecting these parameters as model inputs are that, firstly, air temperature is the primary indicator of a thermal environment; secondly, supply-air fan is primary part of the AHU that provides conditioned air into the room;

Figure 6.12: General outline of the ACMV cooling system.

and thirdly, in a cooling system, the water-pump and compressor are responsible for water-circulation and refrigerant-circulation, respectively.

The ACMV energy consumption (E) is modelled as a function of the ambient air temperature (T_a), and the three operating frequencies of the ACMV system components namely, the supply-air fan frequency (f_1), the water pump frequency (f_2) and the compressor frequency (f_3) as shown in 6.2:

$$E(T_a, f_1, f_2, f_3) = E(T_a, \mathbf{f}) \quad (6.2)$$

where, $\mathbf{f} = [f_1, f_2, f_3]$ is the ACMV operating frequency vector. A single hidden layer feedforward artificial neural network (SLFF-ANN) [16] is used for the modelling as shown in Figure 6.13. Assume that $\mathbf{X}^k = (x_1^k \ x_2^k \ x_3^k \ x_4^k) = (T_a^k \ f_1^k \ f_2^k \ f_3^k)$ is the input vector (i.e. operating state) and E^k is the energy for the k^{th} training sample, then the

SLFF-ANN model can be formulated as:

$$V_i^k = \Phi \left(\sum_{j=1}^4 w_{ij} x_j^k - b_i \right) \quad (6.3)$$

$$E^k = \sum_{i=1}^{hn} V_i^k W_i - B$$

where, V_i^k is the output of hidden neuron i , $\Phi(\cdot)$ is the activation function, w_{ij} is the weight parameter of the input layer neuron j to the hidden layer neuron i , b_i is the bias of the hidden neuron i , hn is the number of hidden neurons, W_i is the weight parameter of the hidden neuron i to the output neuron and B is the bias of the output neuron. An SLFF-ANN model that is optimally trained with adequate data will provide the energy consumption at a given operating state. This model will be integral to our novel OAT optimization algorithm which is introduced in the next section.

Figure 6.13: ANN model for energy-consumption of ACMV system.

6.6.2 OAT Algorithm

The OAT algorithm is illustrated as Algorithm 3. It takes in three inputs namely, the current TSI of the occupant as predicted by the TSI predictive model, the current air temperature T_{curr} and the current operating frequency vector f_{curr} . Based on the current TSI, it returns the optimal operating state (T_a^*, f^*) . Search for optimal temperature is constrained within $(22-27)^\circ\text{C}$. If the current TSI is at *Comfort*, then there is no modification in operation. If the current TSI is -1 (*Cool-discomfort*), then the search

space spans $[T_{curr} + \Delta T, 27]$, where ΔT is the modification factor. Similarly, if the current TSI is +1 (*Warm-discomfort*), then the search space spans $[22, T_{curr} - \Delta T]$. A modification factor of $\Delta T = 0.1^\circ\text{C}$ is considered in this study. Then, the optimal point $(T_a^*, \mathbf{f}^*)$ is the one in the optimization search space at which the energy consumption $E(T_a, \mathbf{f})$ is minimum. The search space is iteratively updated depending on the thermal demand, and scanned to locate the optimal point based on a greedy search algorithm.

Algorithm 3 OAT Algorithm

Inputs

TSI : current TSI from TSI Predictive model ($-1, 0$ or $+1$)

T_{curr} : current air temperature

$\mathbf{f}_{curr}$: current operating frequency

Outputs

T_a^* : optimal air temperature

$\mathbf{f}^*$: optimal operating frequency

i.e., $(T_a^*, \mathbf{f}^*)$: optimal operating state

For each update operation:

- 1: **if** ($TSI == 0$) **then**
- 2: $(T_a^*, \mathbf{f}^*) \leftarrow (T_{curr}, \mathbf{f}_{curr})$
- 3: **else if** ($TSI == -1$) **then**
- 4: $(T_a^*, \mathbf{f}^*) \leftarrow \underset{(T_a, \mathbf{f}) \in S}{\operatorname{argmin}} E(T_a, \mathbf{f})$
- $S := \left\{ T_a, \mathbf{f} \mid \begin{array}{l} (T_{curr} + \Delta T) \leq T_a \leq 27 \\ 30 \leq f_i \leq 50 \end{array} \right\}$
- 5: **else if** ($TSI == +1$) **then**
- 6: $(T_a^*, \mathbf{f}^*) \leftarrow \underset{(T_a, \mathbf{f}) \in S}{\operatorname{argmin}} E(T_a, \mathbf{f})$
- $S := \left\{ T_a, \mathbf{f} \mid \begin{array}{l} 22 \leq T_a \leq (T_{curr} - \Delta T) \\ 30 \leq f_i \leq 50 \end{array} \right\}$
- 7: **end if**
- 8: **return** $T_a^*, \mathbf{f}^*$

Note:

S is the optimization search space

ΔT is the modification factor in T_a ($\Delta T = 0.1^\circ\text{C}$)

The Energy Saving Potential (ESP) is defined as:

$$ESP = \frac{E(T_a^*, \mathbf{f}^*) - E_{ref}}{E_{ref}} \times 100\% \quad (6.4)$$

where, E_{ref} is the ACMV energy consumption at nominal benchmark operating conditions ($E_{ref} = E(24^\circ\text{C}, [40, 40, 40] \text{Hz})$).

OAT Algorithm Results

Total 1155 samples of the energy model's input-output parameters were experimentally collected. For training the ANN model, the data was divided in the ratio 70%:15%:15% for training, validation and testing datasets, respectively. The training settings and the optimal training parameters are summarized in Table 6.8. The Log-Sigmoid function is used as the activation function for all hidden neurons. A back-propagation method namely, Levenberg–Marquardt algorithm is employed for the learning of the parameters. The number of hidden neurons, hn , is determined by using a grid search operation with cross validation of the training data. Fig. 6.14 shows the training MSE (mean squared error) corresponding to the hidden neurons, and $hn = 4$ resulted in a sufficiently low MSE.

Operating state changes are demanded only during a DC scenario. The optimal air temperatures and operating states for each of the DC cases were located using the OAT algorithm. Subsequently, the corresponding energy values $E(T_a^*, \mathbf{f}^*)$ were obtained. The optimal air temperatures T_a^* and corresponding ESP values for these DC cases are plotted in Figure 6.15. Firstly, it is seen that ESP is always positive, implying that all the output optimal energy values $E(T_a^*, \mathbf{f}^*)$ are lower than the reference E_{ref} . Secondly, the mean optimal air temperature is observed to be 24.99°C . The ESP is highest at this temperature and reduces on moving farther away from it. The mean ESP is observed to be 36.5%. Thus the OAT algorithm exhibited a mean energy saving potential of 36.5%, and approximately 25°C should be the preferable ambient air temperature to maintain thermal comfort with minimum energy use, according to our findings.

Table 6.8: Training parameters of the energy ANN model $E(T_a, \mathbf{f})$.

Optimal Parameters		Settings	
Neurons	$hn = 4$	Algorithm	Levenberg-Marquardt
Iterations	570	Sample size	1155
MSE	0.000044	Activation function	$\Phi(\cdot) = \text{Log-sigmoid}$

Figure 6.14: Training MSE vs hidden neurons for the ANN energy model $E(\cdot)$.

Figure 6.15: Energy Saving Potential ESP vs optimal air temperature T_a^* .

6.7 Comparative Analysis of the Proposed TSI Predictive Models

Table 6.9 summarizes all the four TSI predictive models proposed in this study (as described in the previous and current chapters) and the existing conventional methods. The table lists the primary input features i.e. the basic data that needs to be acquired and fed to the predictive model, the number of input features, the TSI prediction accuracies and the ESP s of each method. The models are compared based on their sensor and computational costs, predictive performances and energy saving potentials:

Table 6.9: Comparative analysis of the proposed and existing TSI predictive models.

Method	Input(s)	No. of inputs	TSI Prediction Accuracy (%)			ESP (%)
			Overall	DC	C	
Model A: PTS	ST, I_{cl}, A_{Du}	3	86.79	86.59	86.99	30.7
Model B: TPPTS	5-minute TP of ST	1	93.33	93.33	93.33	34.0
Model C: ePTS	ST, PR, I_{cl}, A_{Du} , Gender, BMI, T_a	7	97.15	97.97	96.34	35.4
Model D: GPTS	Male: ST, SC, SpO_2	3	92.86	100.00	87.70	33.90
	Female: ST, SC, PR	3	94.29	94.70	94.10	34.4
PMV	$T_a, MRT, V_a, RH, I_{cl}, M$	6	73.06	69.32	76.80	-
ePMV	$e, T_a, MRT, V_a, RH, I_{cl}, M$	7	48.95	59.54	38.36	-
aPMV	$\lambda, T_a, MRT, V_a, RH, I_{cl}, M$	7	45.21	47.40	43.02	-

Sensor and Computational Cost

Amongst all, the TPPTS model has the least sensor cost, requiring only skin temperature data. It is already inclusive of the gradient information. It also does not require any individual factor because it is immune to a need for normalization process as the temporal profile is independent of the skin temperature's magnitude. However, the image-processing based domain transfer process can make it computationally expensive. The PTS, TPPTS and GPTS models are all based on physiological sensors alone. As all the physiological inputs are accessible from hand locations, a single wearable integrating all sensors can be realizable. The ePTS model requires an additional ambient sensor for T_a . Interfacing information from such multiple sensor sources can be cumbersome, and prone to security issues as well.

Predictive Performance

The ePTS model attains the highest prediction accuracy at over 97%. Each of the four proposed models outperformed the conventional methods which achieved accuracies ranging around (45-73)%. They also attained balanced performance for each thermal state unlike the conventional methods. All four models require the information of at least the past 5 minutes to predict the current thermal state. However, while PTS, ePTS

and GPTS models provide thermal state of the present minute based on the past data, the image-input based TPPTS model can detect the mean thermal state over 5 minutes based on the temporal profile.

Energy Saving Potential

In the previous section, the *ESP* of the OAT algorithm was computed for the true thermal states. The *ESP* of 36.5% is thus the highest potential it could achieve. Here, we compute the *ESP* with each predictive model in the control framework (Table 6.9). The ePTS model attains the highest *ESP* (35.4%) because it has the highest predictive accuracy. Nevertheless, all four models attained over 30% *ESPs*, which can translate to considerable energy-saving of the ACMV system.

6.8 Concluding Remarks

Firstly, women portrayed greater satisfaction in terms of comfort and humidity. No gender difference existed in thermal preference and airflow sensation. While women exhibited greater adaptability, men were more sensitive yet tolerant of the thermal conditions.

Secondly, significant gender differences were observed in most physiological features, mainly the raw values and the MSGs. This indicates that due to morphology differences, males significantly differ from females in their thermoregulatory responses under similar thermal stress. Therefore, it may benefit from studying each gender group separately during comfort studies.

Thirdly, several physiological features exhibited potential to indicate thermal state. In case of males, there were 7 features, namely SpO_2 -MSG, *ST*, *ST*-FOG, *ST*-MSG, *SC*, *SC*-FOG, and *SC*-MSG. In case of females, there were 6 features, namely *ST*-FOG, *ST*-MSG, *SC*, *SC*-MSG, *PR* and *PR*-MSG. Thus, the temporal behaviour (change rate and fluctuation) of certain parameters can provide vital insights into one's thermal state.

Behavioural observations for a span of 5 minutes deemed sufficient for the prediction. The collective information of the identified features could accurately estimate 92.86% and 94.29% of thermal states of males and females, respectively.

Fourthly, proposed framework to control ambient climate exhibited up to 36.5% energy saving potential. An ambient air temperature of about 25°C deemed ideal for optimum comfort with minimum energy consumption of the ACMV system. A comparison between the proposed and the conventional methods revealed their strengths and weaknesses. The next chapter will focus on some non-physiological factors of thermal comfort.

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Chapter 7

Non-Physiological Factors of Thermal Comfort

The previous chapters explored physiological factors of thermal comfort. In this chapter¹, we use a data-driven approach to explore the significance of some non-physiological factors namely, the indoor mean radiant temperature (MRT), the occupant's age, the occupant's gender and the outdoor weather with respect to indoor thermal comfort. The chapter is organized as follows: Section 7.2 investigates the effects of the common practice of assuming MRT to be equal to air temperature on indoor thermal comfort assessment. Section 7.3 develops an alternative MRT estimation model. The methodology for the model development is outlined in Section 7.3.1, and described in Sections 7.3.2-7.3.4. Section 7.3.5 presents the MRT estimation model's performance results and its impact on thermal comfort assessment. Section 7.4 investigates the significance of age, gender and outdoor weather using a data-driven approach. Finally, conclusions are drawn in Section 7.5.

¹This chapter published substantially as [1] and [2] and submitted partially as [3].

7.1 Outline of Contributions

The major novel contributions of this chapter include:

- Investigated the effect of assuming indoor MRT to be equal to air temperature on thermal comfort assessment by PMV modelling. The study is based on a large worldwide database categorised by climate types.
- Developed an alternative MRT estimation model using state-of-the-art modern regression algorithms.
- Evaluated the impact of the MRT estimation model on comfort assessment as compared to the simplistic equality assumption.
- Investigated the significance of three factors namely, age, gender and outdoor weather on thermal comfort perception, with the study categorised according to building type namely, air-conditioned buildings and naturally ventilated buildings.

7.2 On the equality assumption of $MRT = T_a$

7.2.1 Dataset Processing

For this study, we have used the ASHRAE's publicly available worldwide database named RP-884 [4]. This database is based on an extensive study of human thermal comfort carried out by ASHRAE in 160 different buildings across 4 continents (including countries UK, Australia, Canada, Greece, Singapore, Indonesia, Pakistan, Thailand and USA), amounting to about 21000 people being surveyed. The data is collected from 15 field experiments. For each person surveyed, it contains indoor and outdoor environmental data, personal physiological data, and thermal comfort survey results.

The database contained field studies for three types of buildings: centrally air conditioned (ACMV), naturally ventilated (NV) and mixed mode. We extracted the data for the ACMV buildings alone, which amounted to about 12000 entries. We classified this

Table 7.1: Field studies for each climate zone.

Climate zone	Locations
Tropical Savanna	Hawaii (USA); Townsville, Darwin (Australia); Bangkok (Thailand)
Continental Subarctic	Montreal (Canada)
Humid Subtropical	Brisbane, Sydney (Australia)
Westcoast Marine	South Wales (UK)
Mediterranean	SF Bay Area, San Ramon, Antioch, Auburn (USA)
Hot Arid	Kalgoorlie (Australia)
Humid Midlatitude	Grand Rapids (USA)
Wet Equatorial	Singapore
Temperature Marine	Melbourne (Australia)

extracted data into several climatic zones and seasons as shown in Table 7.1. After excluding entries with missing values, the final dataset amounted to 9356 entries for PMV based study, and 9333 entries for AMV based study.

***MRT* Calculation**

There are several existing methods to measure and calculate *MRT* which are consistent with negligible difference [5], [6]. However, the basic principle concept for *MRT* evaluation is that the amount of radiant heat gained/lost by the human body is determined by the radiation flux exchanged by the body with the surrounding surfaces in the room. It is calculated from the temperatures of surrounding surfaces and their position with respect to the occupant. This is mathematically represented by equation 7.1:

$$MRT^4 = T_1^4 F_{p-1} + T_2^4 F_{p-2} + \dots + T_m^4 F_{p-m} \quad (7.1)$$

where, T_m is the temperature of surface ‘ m ’ (in Kelvins); F_{p-m} is the angle factor between the person and the surface ‘ m ’.

However, the difficulty in measuring angle factors mainly for non-standard geometries, makes it a complicated procedure. Hence, the most popular method is using the globe temperature, as explained by Kuehn and Stubbs [7]. Globe temperature gives a direct evaluation of the radiative thermal load on the occupant [6]. Globe temperature, along

with air velocity and air temperature are used to calculate MRT according to equation 7.2 (by ISO standard 7726 [8]). In this study, we have calculated MRT using equation 7.2.

$$MRT = \left[(T_g + 273)^4 + \frac{h_g(T_g - T_a)}{\epsilon D^{0.4}} \right]^{\frac{1}{4}} - 273 \quad (7.2)$$

where,

h_g = globe's mean convection coefficient

$$= 1.100 \times 10^8 \times V_a^{0.60} \quad (\text{for black globe})$$

$$= 1.335 \times 10^8 \times V_a^{0.71} \quad (\text{for gray globe})$$

MRT = mean radiant temperature ($^{\circ}\text{C}$)

T_g = globe temperature ($^{\circ}\text{C}$)

V_a = air velocity (m/s)

ϵ = emissivity of the globe

D = diameter of the globe (m)

T_a = air temperature ($^{\circ}\text{C}$)

PMV Calculation

The database contained information about metabolic and clothing insulation, air temperature, humidity, air velocity, and globe temperature. The globe temperature values were used to calculate MRT by equation 7.2 and subsequently, we calculated PMV using all the six parameters by equation 2.1 as described in ASHRAE Standard 55 [9]. To investigate the effect of the assumption $MRT = T_a$ on comfort assessment, PMV was computed for the following two cases:

- PMV_1 : Here, both air temperature T_a and mean radiant temperature MRT , are separately measured and used in PMV calculation. It is the true PMV value.
- PMV_2 : Here, MRT is assumed to be equal to T_a ($MRT = T_a$).

7.2.2 PMV Error Analysis

The error in PMV values caused by the assumption $MRT = T_a$ are discussed in this section. The PMV error is the difference between the ideal case PMV_1 and the assumption case PMV_2 . The statistical results are shown in Figure 7.1. The mean absolute error is low, but the maximum error ($=1.54$) is quite high. Such high error can easily adversely affect the determination of comfort level on the thermal comfort scale (Figure 3.5) which has a short range from around -3 to +3. The distribution of error ($PMV_1 - PMV_2$) and its descriptive statistics are presented in Figure 7.2 and Table 7.2 respectively. It is observed from Table 7.2 that the distribution is slightly negatively skewed and has a high kurtosis. Thus the error ($PMV_1 - PMV_2$) is mostly positive, that is, PMV_1 is mostly greater than PMV_2 . This means that the assumption $MRT = T_a$ is more likely to underestimate the true PMV value. Such incorrect PMV values can lead to misleading results about other related indices such as PPD as well.

Figure 7.1: PMV error analysis.

7.2.3 Effect on thermal comfort assessment

As there are 7 thermal comfort levels (CL) according to the ASHRAE scale (Figure 3.5) ranging from *cold* to *hot*, each comfort level represents a range of PMV values. In this study, we have found comfort levels for all the PMV values for both PMV_1 and

Table 7.2: Descriptive statistics for PMV error ($PMV_1 - PMV_2$).

Mean	0.02
Std. Dev.	0.12
Minimum	-1.26
Maximum	1.54
Skewness	-0.1
Kurtosis	32

Figure 7.2: PMV error distribution.

PMV_2 , and calculated the inaccuracy caused in comfort level determination due to the assumption $MRT = T_a$.

We introduce Comfort Level Inaccuracy (CLI) as a measure of the error in thermal comfort level caused by the assumption. We define the CLI as the number of cases with incorrect comfort levels divided by the total number of cases, where, $CL(PMV_1)$ and $CL(PMV_2)$ are the comfort levels corresponding to PMV_1 and PMV_2 , respectively on the thermal comfort scale:

$$CLI = \frac{\text{No. of cases} \left(CL(PMV_1) \neq CL(PMV_2) \right)}{\text{Total no. of samples}} * 100 \quad (7.3)$$

We have defined $(\% \Delta T_m)$ as the mean absolute percentage difference between T_a and MRT according to equation 7.4:

$$\% \Delta T_m = \left\langle \frac{|T_a - MRT|}{T_a} \right\rangle \quad (7.4)$$

Table 7.3: Climate zone-wise Comfort Level Inaccuracy (CLI) for PMV₂.

Climate zone	Season	Samples	% ΔT_m	CLI(%)
Tropical savanna	Dry	1820	2.80	8.08
	Wet	2578	2.76	8.61
Humid subtropical	Summer	564	2.79	6.38
	Winter	83	2.35	2.41
Mediterranean	Summer	769	1.17	3.51
	Winter	524	0.92	2.29
Westcoast marine	Summer	80	3.24	6.25
	Winter	38	3.52	5.26
Hot Arid	Summer	589	2.57	4.92
	Winter	614	1.44	2.77
Continental subarctic	Summer	443	2.65	4.97
	Winter	426	3.54	7.28
Humid midlatitude	Winter	85	0.32	2.35
Wet equatorial	Summer	234	7	14.96
Temperature marine	Summer	509	3.76	10.41
Overall Worldwide	-	9356	2.6	6.7

We have grouped the dataset according to nine climatic zones and further regrouped them into four seasons. The results of the calculated temperature differences of these zones and their corresponding inaccuracies are presented in Table 7.3. It is observed that a small temperature difference of 2.6% leads to 6.7% CL inaccuracy (in the overall worldwide database). 6.7% of the total database of 9356 people implies 644 people. Thus the comfort levels of a large number of people (644) are incorrectly determined because of the simplistic assumption $MRT = T_a$.

The CL inaccuracies are plotted against the temperature differences in Figure 7.3. It is seen that the inaccuracy increases almost linearly with increase in temperature difference. A linear fit of ($y = 2.01x + 0.55$) with high goodness of fit ($r^2 = 80.4\%$) implies that a certain temperature difference can cause an error/inaccuracy almost double its value. Thus the assumption $MRT = T_a$ adversely affects comfort level determination, and can lead to misleading conclusions in indoor thermal studies, even for small temperature difference between MRT and T_a .

Figure 7.3: CL Inaccuracy (%) vs. $\% \Delta T_m$ for PMV_2 ($MRT = T_a$).

Temperature differences between different climate zones

The temperature differences $\% \Delta T_m$, between the air temperature and the mean radiant temperature can be attributed to the nature of the climate zone they belong to. The climate zones mentioned here are according to the Köppen climate zone classification [10]. It is observed in Table 7.3 that the temperature differences are higher in summer than in winter for Humid subtropical, Mediterranean and Hot Arid climate zones. The reason behind the higher temperature difference in summer could be that these three climate zones are characterized by hot summers and cool to cold winters, thus having major temperature differences between the two seasons, summer and winter. Hot summers are characterized by higher solar radiation. Higher radiation in the outdoors leads to higher MRT in the indoors. As a result, the MRT differs more from the indoor air temperature. This leads to a higher temperature difference $\% \Delta T_m$ during summers.

On the other hand, the Continental subarctic climate zone is dominated by winter season that has short clear days, low humidity and bitter cold period [10]. Clear winter days are characterised by strong solar radiation, unlike the summer days. Higher radiation leads to higher MRT compared to air temperature. This may result in the higher temperature difference in winter.

However, the Westcoast marine climate zone is characterized by almost constant temperature throughout the year. The ocean keeps the air over land cool in summer and warm in winter, thus maintaining a narrow annual temperature range [10]. This could possibly be the reason behind similar temperature difference in summer and winter, as seen in Table 7.3. Humid midlatitude winters are mild but frosty, and Wet equatorial summers have consistent high temperature, precipitation, and humidity. The Tropical savanna climate comprises two seasons- dry and wet; however, the temperature is almost consistent throughout [10]. This could explain the similar temperature differences in dry and wet season in Table 7.3.

CL Inaccuracies between different climate zones

It is observed in section 7.2.3 that comfort level inaccuracy almost linearly increases with temperature difference. Humid midlatitude winters are mild and frosty, and study shows it has the minimum temperature difference of 0.32%. Therefore it's corresponding CL inaccuracy is also the minimum at 2.35%. The highest CL inaccuracy is observed for Wet equatorial summer, which has the highest temperature difference of 7%. The wet equatorial summer has very little annual temperature variation, with high temperatures, and high humidity all year round. Thus the variation in temperature difference $\% \Delta T_m$ depends on the nature of the climate zone it belongs to, while the variation in CL inaccuracy depends on the temperature difference, irrespective of the sample size studied.

7.2.4 *MRT* and Actual Mean Vote (AMV)

While PMV is a predicted vote of the occupant's comfort because it is determined by calculations, comfort indices such as AMV, TSA, MCI are based on direct feedback from occupant. Actual Mean Vote (AMV) is an important comfort index and it is the value on the thermal scale (in Figure 3.5) directly mentioned by the occupant. This value is used as the ground truth comfort level of the occupant.

As discussed earlier, the six Fanger's factors that influence thermal comfort are *MRT*, T_a , air velocity, humidity, metabolic rate and clothing insulation [11]. A comparative

Table 7.4: Spearman's rank correlation coefficient (ρ) and significance (p) values between AMV and Fanger's factors.

Parameters	ρ	p -value
Mean radiant temperature	0.3253	< 0.001*
Air temperature	0.2773	< 0.001*
Air velocity	-0.1150	< 0.001*
Relative humidity	-0.1083	< 0.001*
Metabolic rate	0.0331	0.0014*
Clothing insulation	0.0807	< 0.001*

analysis of Spearman's rank correlation between these six factors and AMV has been performed. Spearman's rank correlation is applied because AMV is a categorical parameter. The results are presented in Table 7.4. All the values are at 95% confidence level. The significance values are mostly close to zero ($p < 0.001$) which means all the factors are highly significant for AMV. However, MRT exhibits the highest correlation with AMV. This portrays that MRT can have a stronger influence on thermal comfort as compared to the other factors. Heat stress due to the surrounding radiant temperature influences how the occupants report sensation on the thermal scale.

7.2.5 MRT and Thermal Acceptability Vote (TSA)

Thermal acceptability (TSA) is the vote reported by the occupant as a reply to the following survey question:

'At the present time, is this thermal environment acceptable to you or not?'

The voting options are numbered as:

- 1- *unacceptable*
- 2- *acceptable*

The responses reported by the occupants in the worldwide study are accumulated and studied. An analysis of PMV error with the acceptability vote TSA is done. Results are presented in Figure 7.4. It is observed that the error in PMV is higher in case of

Figure 7.4: Absolute PMV error vs. Thermal Acceptability Vote.

TSA=1, i.e., when the occupant reports the thermal environment as unacceptable. Thus a higher PMV error is associated with the occupant feeling uncomfortable. This implies that the assumption $MRT = T_a$ is more likely to affect comfort level determination in the uncomfortable range (*cold, cool, warm, hot*).

7.2.6 MRT and Thermal Preference Vote (MCI)

The most common thermal preference scale is the McIntyre scale [12], which we refer as MCI here. Thermal Preference Vote (MCI) is the vote reported by occupant as a reply to the following survey question:

‘At this point in time, would you prefer to feel warmer, cooler, or no change?’

The voting options are numbered as:

- ☐ 1- *Want cooler*
- ☐ 2- *No change*
- ☐ 3- *Want warmer*

When thermal environment is unacceptable (TSA=1), occupant usually prefers a change in the sensation. So we have studied the preference vote MCI only when TSA=1. The results are presented in Figure 7.5. It is seen that majority of people, about 63% prefer

Figure 7.5: Absolute PMV error vs. Thermal Preference Vote for TSA=1.

cooler sensation. The absolute PMV error is highest in case of people preferring cooler sensation, which means error is higher in case of comfort level on the higher end of the thermal scale (towards +3). Therefore, the assumption $MRT = T_a$ is more likely to affect comfort level determination of people experiencing warmer sensation in the uncomfortable range (*warm, hot*).

Effect on Building operation

One of the main functions of building operation is to maintain a thermally comfortable indoor environment for the occupants. This objective is met by performing indoor thermal study such as PMV modelling, which quantifies the thermal comfort of the occupants by calculating several indices: PMV, AMV, TSA and MCI. Such quantification of thermal comfort portrays whether the building conditions are within the acceptable comfort limits recommended by ASHRAE international standards. It is seen above how all of these thermal indices are adversely affected when MRT is neglected during PMV modelling. The simplistic assumption $MRT = T_a$ has lead to

- Underestimation of PMV value.
- Wrong interpretation of comfort level on thermal scale.
- Health and comfort of people feeling warm/hot being compromised.

Such misinterpretations are a hindrance to effective building operation. In the next section, we attempt to develop a new MRT estimation model based on our experimental data described in Chapter 3.

7.3 Proposed MRT Estimation Model

MRT is related to air temperature and air speed according to the globe thermometer method. We develop an alternative model to estimate MRT using readily measurable parameters of air temperature and air speed excluding the globe temperature data, with the help of modern regression algorithms. The model is developed based on the data collected through our thermal experiments described in Chapter 3.

Section 7.3.1 outlines the methodology of model development and sections 7.3.2-7.3.4 describe the methodology in detail. Section 7.3.5 presents the model performance results and compares the developed model with the equality assumption regarding their impacts on thermal comfort assessment.

We adopted the globe thermometer method to obtain the ground truth MRT value (equation 7.2) [7, 8]. The primary reasons for selecting this method are: firstly, it allows direct assessment of the radiative thermal load on the subject, making it the most widely used method; secondly, it was initially developed for primarily indoor measurements [13]. Moreover, recent comprehensive studies have revealed that all existing MRT evaluation methods are consistent in their results with negligible differences [6]. However, to avoid any possible uncertainties in measurement, the black globe thermometer instrument used in this study was calibrated using the standard angle factor method with a thermocouple (model: HFTM, S+S Regeltechnik) and further calibrated using another globe thermometer (model: RPTM2, S+S Regeltechnik).

Figure 7.6: Block diagram of the model development approach.

7.3.1 Model Development Methodology

The overall analytical approach of model development is presented in Figure 7.6. The initial step is to identify the set of features from among T_a , V_a , RH that can best describe the target variable MRT ; the next step is to find the best combination of the selected features, i.e. an appropriate mathematical model to evaluate MRT .

A three-step approach is used to develop the model as shown in Figure 7.6:

Step-1 Firstly, a combination of Pearson's correlation analysis and Taylor's expansion is applied to obtain the initial feature set F .

Step-2 Secondly, the obtained set F is delivered as an input to six different modern regression algorithms. Each algorithm generates multiple predictive models depending on the algorithm principles. The best models are identified based on the minimum 10-fold cross validated error.

Step-3 Finally, the resultant six models are compared on the validation data under three performance criteria to obtain the final MRT prediction model.

These three steps are described in detail in the following sections.

7.3.2 Step 1 - Selection of Initial Feature Set

Feature selection is imperative for developing a prediction model as it eliminates non-significant and redundant input features. Pearson's correlation coefficient (r) and coefficient of determination (r^2) between MRT and the prospective features are summarized in Table 7.5. It is observed that both T_a and V_a are significantly correlated with MRT ($p < 0.001$). While T_a strongly positively correlated at $r = 0.72$, V_a has a strong negative correlation of -0.77 with MRT . However, RH has a negligible correlation of -0.04 with a poor r^2 value of 0.001 only. Therefore, RH is excluded from the feature set.

Figure 7.7 demonstrates the temporal variations of T_a , MRT and V_a for one of the experiments. Non-linearity present in the model can be addressed by the quadratic effect and the interaction effect which represent the response of curve surfaces and the synergy between the variables, respectively. To include quadratic effects, features T_a^2 and V_a^2 are introduced. To include interaction effect, feature $T_a V_a$ is introduced. All three non-linear terms are seen to be strongly correlated with MRT (Table 7.5).

Quadratic approximation in multiple variables by Taylor's series expansion is given by

$$f(x, y) \approx f(a, b) + f_x(a, b)(x - a) + f_y(a, b)(y - b) + \frac{1}{2!}[f_{xx}(a, b)(x - a)^2 + 2f_{xy}(a, b)(x - a)(y - b) + f_{yy}(y - b)^2] \quad (7.5)$$

Table 7.5: Correlation coefficients and accountability between MRT and prospective features; r = Pearson's correlation coefficient, r^2 = coefficient of determination; sample size, $n = 800$.

	Feature	r	r^2
Main effects	T_a	0.72	0.51
	V_a	-0.77	0.59
	RH	-0.04	0.001
Quadratic effects	T_a^2	0.73	0.53
	V_a^2	-0.67	0.45
Interaction effect	$T_a V_a$	-0.75	0.56

Note: All values are at 95% confidence interval.

Figure 7.7: Temporal profiles of T_a , MRT and V_a for one experiment.

in a neighbourhood of $(x, y) = (a, b)$. Considering variables (x, y) as (T_a, V_a) , and assuming $T_g = cT_a$ momentarily with c as a positive constant, applying the approximation (equation 7.5) to MRT equation 7.2, it is found that the coefficient of quadratic term T_a^2 is equal to zero, irrespective of the point (a, b) , and coefficients of the other features $(T_a, V_a, V_a^2, T_a V_a)$ are significantly non-zero. This indicates that in quadratically approximated form, the feature T_a^2 is not significant, irrespective of the point (a, b) . Hence T_a^2 is excluded as a feature. Thus the initial feature set is:

$$F = \{T_a, V_a, V_a^2, T_a V_a\}$$

7.3.3 Step 2 - Model Training by Modern Regression Algorithms

Ordinary least squares (OLS) is the most common approach used for regression. Say m is the number of features and n is the number of training samples. For a multivariate linear model as

$$y \approx \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_m x_m \quad (7.6)$$

where, y is the dependent factor, $\{x_1, x_2, \dots, x_m\}$ are the features and $\{\beta_0, \beta_1, \dots, \beta_m\}$ are the coefficients, then the OLS method generates estimates of the coefficients as $\{\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_m\}$.

.. $\hat{\beta}_m$ to predict y as $\hat{y}$ by minimizing the residual sum of squares, RSS :

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \dots + \hat{\beta}_m x_m \quad (7.7)$$

$$RSS = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (7.8)$$

Given $X = [X_1^T, X_2^T, \dots, X_n^T]^T$ where, $X_j = [x_{j1}, x_{j2}, \dots, x_{jm}]^T, j = 1$ to n , and $Y = [y_1, y_2, \dots, y_n]^T$, then the coefficient estimates are given as:

$$\hat{\beta} = (X^T X)^{-1} X^T Y \quad (7.9)$$

In this study, y denotes MRT and $n = 800$. As per the obtained set F , the remaining values are: $m = 4$, and $\{x_1, x_2, x_3, x_4\} = F = \{T_a, V_a, V_a^2, T_a V_a\}$.

However, models developed by traditional OLS can be substantially improved in terms of prediction accuracy by the modern regression methods as they have several advantages over OLS, such as subset selection, regularization, stability under data perturbations, bias-variance trade-off, reduced multicollinearity effect and better interpretation. The following six modern regression algorithms were implemented in this study. The initial feature set F is fed to each of these algorithms to further refine the feature set.

Best Subset Selection

In Best Subset Selection method, separate OLS regression is performed for each possible combination of m features [14]. In this study, all $\binom{m}{k}$ models with exactly k features were fitted, and the ones with highest R^2 were selected. The best model among the 2^m models was then selected using 10-fold cross validation.

Forward Stepwise Selection

The Forward Stepwise Selection method starts with a null model, and adds one feature at a time until all m features are added to the model [14]. In this study, for $k = 1, 2, \dots, m-1$, all $m-k$ models that augment the features with one additional feature were considered,

and the ones with highest R^2 were selected. The best model among the $1 + m(m+1)/2$ models was then selected using 10-fold cross validation.

Backward Stepwise Selection

The Backward Stepwise Selection method starts with a model containing all m features, and iteratively removes the least useful feature for each step [14]. In this study, for $k = m, m-1, \dots, 1$, all k models that contain all but one of the features were considered, and the ones with highest R^2 were selected. The best model among the $1 + m(m+1)/2$ models was then selected using 10-fold cross validation.

Ridge Regression

The Ridge Regression method is similar to OLS except that it estimates the coefficients by minimizing

$$RSS + \lambda_2 \sum_{j=1}^m \beta_j^2 \quad (7.10)$$

$$\implies \hat{\beta} = (X^T X + \lambda_2 I)^{-1} X^T Y$$

where $\lambda_2 \geq 0$ is a tuning parameter [15]. Each value of λ_2 produces a different set of estimates, so finding the optimal λ_2 is crucial. In this study, the optimal λ_2 was obtained from among 100 randomly selected values between 10^{-2} to 10^{10} by performing 10-fold cross validation.

Lasso

The Lasso method [16] estimates the coefficients by minimizing

$$RSS + \lambda_1 \sum_{j=1}^m |\beta_j| \quad (7.11)$$

$$\implies \hat{\beta} = \underset{\beta}{\operatorname{argmin}} \left(\|y - X^T \beta\|^2 + \lambda_1 \|\beta\|_1 \right)$$

where $\lambda_1 \geq 0$ is a tuning parameter, and $\|\beta\|_1$ is the l_1 norm of coefficient vector β . In this study, the optimal λ_1 was obtained from among 100 randomly selected values between 10^{-8} to 10 by performing 10-fold cross validation.

Elastic Net

Elastic Net method [17] combines the effects of ridge regression and lasso. It estimates the coefficients by minimizing

$$\begin{aligned} & \|y - x^T \beta\|^2 + \lambda_2 \|\beta\|_2^2 + \lambda_1 \|\beta\|_1 \\ \Rightarrow \hat{\beta} = \underset{\beta}{\operatorname{argmin}} & \left(\|y - x^T \beta\|^2 + \lambda \left(\alpha \|\beta\|_2^2 + (1 - \alpha) \|\beta\|_1 \right) \right) \end{aligned} \quad (7.12)$$

where, $\alpha = \frac{\lambda_2}{\lambda_1 + \lambda_2} \in [0, 1]$. The optimal λ and α were found by 10-fold cross validation. The basic elastic net suffers from double shrinkage. This was corrected as $\hat{\beta}_{corrected} = (1 + \lambda_2) \hat{\beta}$.

7.3.4 Step 3 - Model Validation

The experiment database was used for model development. However, for model validation a completely new and broader dataset was generated to substantiate the developed model on unseen data.

Validation Dataset

The validation dataset with N=1000 samples was generated as follows:

1. T_a , RH , V_a and I_{cl} samples were randomly selected from a uniform distribution of values in the range $[16, 32]^\circ\text{C}$, $[20, 70]\%$, $[0, 0.20]$ m/s and $[0.35, 0.70]$ clo respectively. Metabolic rate, M was kept equal to one.
2. For every value of T_a , a corresponding globe temperature value T_g was obtained as $T_g = T_a + \rho(a, b)$, where $\rho(a, b)$ is a random number from a uniform distribution

in range $[a, b]$. The values of a and b were obtained from experimental data by curve fitting.

3. The MRT values were obtained from the above generated T_a , T_g , and V_a samples using equation 7.2 with $D = 0.04$ m and $\epsilon = 0.95$.

Table 7.6 and Figure 7.8 illustrate the generated validation dataset. This dataset allows good model validation because it efficiently covers the variety of combinations that occur between the parameters.

Table 7.6: Range of parameters of validation dataset.

Parameter	Range
Air temperature	(16-32) °C
Mean radiant temperature	(7-28.5) °C
Air velocity	(0-0.2) m/s
Relative humidity	(20-70) %
Clothing insulation	(0.35-0.70) clo

Note: Number of samples, $N = 1000$.

Figure 7.8: Input-output distribution of parameters of validation dataset; number of samples, $N=1000$.

Performance Metrics

The models were assessed based on the following three criteria:

1. Mean Absolute Percentage of Error (MAPE): This metric indicates percentage of error per prediction. It is a commonly used measure of prediction accuracy and is defined as

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^N \frac{|y_i - \hat{y}_i|}{y_i} \times 100 \quad (7.13)$$

where, N is the number of test samples, y_i is the actual MRT value and $\hat{y}_i$ is the predicted MRT value.

2. Mean Bias Error (MBE): This metric indicates how likely a particular model is to over-estimate or under-estimate the actual MRT value. An MBE closest to zero is preferred, which this means the model does not favour a particular trend in its prediction. It is defined as

$$\text{MBE} = \frac{1/(N-1) \sum_{i=1}^N (y_i - \hat{y}_i)}{\bar{y}} \times 100 \quad (7.14)$$

where, $\bar{y}$ is the mean of actual MRT .

3. Coefficient of Variance (CoV): It is a measure of how much the prediction error differs from the mean of actual MRT . The lower the CoV, the lesser is the error. It is defined as

$$\text{CoV} = \frac{\sqrt{\frac{1}{N-1} \sum_{i=1}^N (y_i - \hat{y}_i)^2}}{\bar{y}} \times 100 \quad (7.15)$$

7.3.5 Model Performance

The initial feature set F was further augmented by the regression algorithms. Table 7.7 presents the best feature set of each algorithm's best model, their corresponding optimal tuning parameters and the total number of models tested by each algorithm. The performance results of the six best models on the validation data are presented in Table 7.8. It is seen from Table 7.8 that ridge regression results in the minimum error

in MAPE and CoV. The MBE errors for ridge regression, lasso, and elastic net are close to zero. Therefore, ridge regression outperforms the rest under all criteria and delivers the best prediction model which is,

$$MRT = 0.78T_a - 19.67V_a - 21.94V_a^2 - 1.17T_aV_a + 4.27 \quad (7.16)$$

The model coefficients are consistent with the correlation results in Table 4.2. The error and fit statistics are presented in Table 7.9. The model has a mean residual error MRE (mean difference between actual and predicted MRT), of only -0.3°C and a RMSE (root mean squared error) of 1.5°C . The coefficient of multiple correlation or the coefficient of determination value is $R^2 = 0.89$, which implies that the model very well describes the variance in the validation data. All error statistics are within the ISO 7726 recommended instrument accuracy limits i.e. $\pm 2^\circ\text{C}$ [18]. The plot of the predicted versus the observed values is demonstrated in Figure 7.9.

Table 7.7: Summary of best model of each regression algorithm post training phase.

Algorithm	Best Feature Set	Optimal Parameters	Models Tested
Best Subset Selection	$\{T_a, V_a, T_a V_a\}$	-	32
Forward Stepwise Selection	$\{T_a, V_a, (V_a)^2, T_a V_a\}$	-	11
Backward Stepwise Selection	$\{T_a, V_a, (V_a)^2, T_a V_a\}$	-	11
Ridge Regression	$\{T_a, V_a, (V_a)^2, T_a V_a\}$	$\lambda_2 = 0.2167$	100
Lasso	$\{T_a, (V_a)^2, T_a V_a\}$	$\lambda_1 = 0.0004$	100
Elastic Net	$\{T_a, V_a, (V_a)^2, T_a V_a\}$	$\lambda = 0.0212, \alpha = 0.5$	100

Note: Number of samples, $n = 800$.

Table 7.8: Performance metrics results on the validation dataset.

Algorithm	MAPE (%)	MBE (%)	CoV (%)
Best Subset Selection	30.86	7.51	37.57
Forward Stepwise Selection	32.47	10.74	41.56
Backward Stepwise Selection	32.47	10.74	41.56
Ridge Regression	13.96	0.47	15.41
Lasso	14.28	0.55	15.80
Elastic Net	14.38	-0.13	15.56

Note: Number of samples, $N = 1000$. Best values are highlighted in bold font.

Table 7.9: Model error and Fit statistics.

	Validation Data	Training Data
R^2	0.89	0.77
MRE	-0.3°C	0.2°C
RMSE	1.5°C	1°C

Figure 7.9: Predicted MRT versus Observed MRT .

Any model in nature has some amount of inherent non-linearity. The way to check whether applying linear regression to this study is suitable is by checking whether the prediction model abides by the underlying assumptions of linear regression. These assumptions are linearity of relationships, multivariate normality, no or little multicollinearity, and homoscedasticity. Firstly, the selected feature sets included non-linearity into the model in form of quadratic and interaction terms. Multicollinearity if present were taken care of by the ridge regression method, which adjusts the weights of collinear terms. The model exhibits homoscedasticity with no particular trend or pattern in the residuals, and a homogeneous error variance. The residuals are scattered around zero error and show no specific pattern with respect to the value of the independent variable. This proves that the model prediction has no significant drift, meaning there is not going to be any specific drift in future predictions. Thus the prediction model holds all the assumptions of linear regression, indicating its suitability to this study. The detailed error analysis proves that the model has a good accuracy in prediction ability. Polynomials are flexible because they can fit a wide range of curvature, but they sometimes are not valid outside

the range of the training data. However in this study, the data used to validate the model covered a wide range of environmental parameters of indoor ACMV built environment.

Effect on Thermal Comfort Assessment

To investigate the effect of the assumption $MRT = T_a$ on comfort assessment, PMV_1 , PMV_2 and CLI are calculated. Table 7.10 shows the resultant errors. The assumption of $MRT = T_a$ leads to large errors of 68.60% and 45.38% on the validation data and experiment data respectively. The proposed prediction model results in CLI error of only 23.90% and 20.13%, significantly reducing the errors by (55.64-65.16)%. Figure 7.10 shows the increment in comfort level accuracy at each comfort level for the validation data. It is the number of cases where comfort level is correctly determined out of all cases. Overall, the accuracies for the proposed model ranged between 60% to 100% across the comfort levels.

Table 7.10: CLI error when $MRT = T_a$ and error reduction by the proposed model.

	CLI (%)		Error Reduction (%)
	$MRT = T_a$	Proposed Model	
Validation Data (N=1000)	68.60	23.90	65.16
Experiment Data (n=800)	45.38	20.13	55.64

Note: N,n are sample size of validation(test) data and experiment(training) data, respectively.

Figure 7.10: Comfort level prediction accuracy at each thermal comfort level.

7.4 Identifying non-physiological factors

The previous sections focussed on indoor mean radiant temperature, and re-emphasized its significance for thermal comfort evaluation. However, thermal comfort is a very subjective term as it depends on miscellaneous factors ranging environmental, personal, psychological, behavioural, etc. In this section, we investigate three such extraneous factors that are not included in the PMV model: (a) Age, (b) Gender and (c) Outdoor weather condition.

Metabolic ability decreases with age and so it changes the person's sensitivity to heat or cold [19]. In case of gender, women have lower metabolic rate and hence lower evaporative heat loss as compared to men. The previous chapters have revealed that gender differences can have significant impact on thermal perception. Several works have studied the impact of age and gender, but resulting in different conclusions [11, 19–21]. Outdoor weather can have a psychological effect on the perception of thermal comfort in air-conditioned buildings, and a direct effect on thermal comfort in naturally ventilated buildings. This section investigates the importance of these three factors (age, gender and outdoor weather) on thermal comfort in building indoors. A data-driven approach is used to model individual thermal comfort using several environmental and human factors including the six Fanger's factors and these three proposed factors.

The overview of the approach is presented in Figure 7.11. The first step is the selection of the best classifier. Each classifier takes in several environmental and human factors as input, and the actual comfort level; trains itself, and its accuracy is tested on new/test dataset. The classifier with the minimum classification error is selected as the best. The selected classifier with its optimal tuning parameters forms the prediction model, which can be implemented in real-time. The predicted comfort level can be sent as a signal to the ACMV controller in air conditioned buildings, or in case of naturally ventilated buildings, it can be displayed and used by the occupant to manually control the cooling device such as fans etc.

Figure 7.11: Data-driven approach for Comfort Level classification.

7.4.1 Dataset Processing

As seen in Table 7.3, the Wet equatorial climate zone had the highest CLI error and temperature difference. The database for Wet equatorial climate zone comprised only the studies based in Singapore. Moreover, all our experimental studies in previous chapters are based on Singapore. Therefore, for the current analysis, we use only the Singapore database.

It comprises thermal comfort experiments performed in Singapore by de Dear *et al.*, which is publicly available as part of the ASHRAE RP-884 project [4]. A total of 818 people were surveyed about their thermal sensation, across several buildings in Singapore. There were two types of buildings used in the survey: air-conditioned (ACMV) and naturally ventilated (NV) buildings. A total of 235 occupants were surveyed across 12 different air-conditioned office buildings. These were all high-rise buildings with open plan design, with centrally controlled ACMV system. For naturally ventilated buildings, a total of 583 residents were surveyed across 4 public residential buildings. These buildings were high-rise as well, and the mode of thermal control consisted mainly of manually operating ceiling fans and standing fans. For each occupant, the following measurements were taken during the experiments among others: indoor and outdoor environmental parameters (air temperature, air velocity, mean radiant temperature, relative humidity), personal parameters (gender, age, metabolic rate, clothing insulation), and thermal comfort questionnaire.

For our study, we are interested in the data of Fanger's six parameters, thermal sensation vote, gender, age and outdoor weather. Hence, the datasets that had any of these missing values were excluded. This amounted to 229 datasets and 583 datasets for ACMV and NV buildings respectively. The following factors are included in the input feature set:

- PMV parameters: The six PMV parameters are well established as definite factors of thermal comfort: air temperature (T_a), mean radiant temperature (MRT), relative humidity (RH), air speed (V_a), clothing insulation (I_{cl}), and metabolic rate (M).
- Outdoor effective temperature (ET_{out}): The effective temperature indicates the combined effect of air temperature and relative humidity. Thus it better represents overall outdoor weather, as compared to using only outdoor air temperature. In the database, it represented arithmetic average of 6 a.m. and 3 p.m. outdoor effective temperatures.
- Age (A)
- Gender (G)

To study the importance of the three new factors ET_{out} , A and G on thermal comfort, we created two different feature sets, one including and one excluding these three factors.

For NV case, the feature sets are:

$$f_{NV_wo} = \{T_a, MRT, V_a, RH, M, I_{cl}\}, \text{ and}$$

$$f_{NV_w} = \{T_a, MRT, V_a, RH, M, I_{cl}, A, G, ET_{out}\}.$$

However, information about occupant's age were not available for the ACMV buildings, hence the feature set for ACMV case are:

$$f_{ACMV_wo} = \{T_a, MRT, V_a, RH, M, I_{cl}\}, \text{ and}$$

$$f_{ACMV_w} = \{T_a, MRT, V_a, RH, M, I_{cl}, G, ET_{out}\}.$$

The ratio of gender proportion in ACMV case was: 61% (male), 39% (female); and for NV case it was 49.2% (male) and 50.8% (female). The ages were divided into four groups in the NV case. The proportion of ages were: 15% (17-20 years old), 41.3% (21-40 years old), 28.3% (41-60 years old), and 15.4% (>60 years old). The target output

was the thermal state grouped from the thermal sensation votes as: *Cool-discomfort* [-3,-1], *Comfort* [-1, 1], *Warm-discomfort* (1, 3].

7.4.2 Classification Algorithms

Several classification algorithms are implemented and to avoid scaling issue, all the feature data were standardized by normalizing them to a mean of zero and standard deviation of one, prior to learning. Each sample consisted of a feature set and its corresponding thermal comfort level. The datasets were then divided into training and testing sets in the ratio 70%:30%. Thus there were 160 samples for training and 69 samples for testing in ACMV case ($n=229$); and 408 samples for training and 175 samples for testing in the NV case ($n=583$); where, n is the total number of samples. However, for Artificial Neural Network, the datasets were divided into three sets: training, validation, and testing in the ratio 70%: 15%: 15%. Thus the numbers of samples in each case were: training (161), validation (34) and testing (34) for ACMV case; and training (409), validation (87), and testing (87) for NV case. We have tested the following six different machine learning classifiers on the datasets of each type of building and repeated for each of the two feature sets per building type:

Support Vector Machine (SVM)

In this study, we have experimented with different types of kernels [22], and Radial basis Function (RBF) worked best among them. The best tuning parameters of cost (C) and gamma (γ) are found using 10-fold cross-validation. The values are: ($C = 1, \gamma = 0.1$) for f_{ACMV_wo} , ($C = 1, \gamma = 0.1$) for f_{ACMV_w} , ($C = 1, \gamma = 0.5$) for f_{NV_wo} , and ($C = 1, \gamma = 0.1$) for f_{NV_w} . We have used a C-type classification (C-SVC) with one-versus-one approach.

Artificial Neural Network (ANN)

In our study, we have used a single hidden layer feed forward ANN [23], with sigmoid function as activation function for hidden and output neurons. Scaled conjugate gradient backpropagation has been used to train the network. The optimal number of neurons is found to be 20 for all four models.

Logistic Regression (LR)

Logistic Regression uses maximum likelihood method to fit the data according to a logistic function model. Once the coefficients are estimated, it can calculate the probabilities of the observation belonging to each class. LR then predicts the class according to the highest probability [14].

Linear Discriminant Analysis (LDA)

LDA is similar to Logistic Regression in the aspect that it also produces linear decision boundaries, and takes a probabilistic approach to classification. However, unlike LR, LDA estimates the coefficients using estimated mean and variance from a normal distribution, using the least squares method [14].

K-Nearest Neighbours (KNN)

The KNN classifier is one of the simplest yet powerful classifiers [14]. It requires a user-input constant K. It first identifies K number of points in the training data that are closest to the test observation, estimates the conditional probability of each class as a fraction of points among the K points belonging to that class. KNN then classifies the test observation to the class with the highest probability using Bayes rule. K=1 gives the optimal result in this study.

Classification Trees (CT)

CT classifier is a decision tree that is grown using recursive binary splitting [14]. The leaves are the class labels and the branches are the feature subsets leading to the class label. CTs are built using either classification error rate, Gini index or cross entropy as the criterion for making the splits. This classifier is popular for its strong interpretation abilities.

7.4.3 Findings

Air conditioned buildings

Table 7.11 presents the results of the predictive performance of the six machine learning classifiers on the test dataset of air conditioned buildings. The first and second column presents the classification accuracies for feature sets f_{ACMV_wo} and f_{ACMV_w} , respectively. The Fanger's PMV method reaches an accuracy of 65.5%. It is observed that all the classifiers studied outperforms the PMV method at predicting the actual thermal state, with SVM performing the best at 79.7% and ANN performing the best at 85.3% for each feature set, respectively. Also, it is observed that the feature set that includes gender and outdoor effective temperature along with the six PMV parameters results in improved accuracies for all the methods. This implies that gender and outdoor weather environment are important factors for thermal comfort in ACMV buildings.

Naturally ventilated buildings

Table 7.11 presents the results of the predictive performance of the six machine learning classifiers on the test dataset of naturally ventilated buildings. The third and fourth column presents the classification accuracies for feature sets f_{NV_wo} and f_{NV_w} , respectively. The PMV method reaches an accuracy of 41.68%. PMV method gives better results in air-conditioned buildings, which is consistent with previous studies that the PMV model is better suited to ACMV case compared to NV case [24]. It is observed that

Table 7.11: Prediction accuracies (%) with and without the new factors.

	f_{ACMV_wo}	f_{ACMV_w}	f_{NV_wo}	f_{NV_w}
SVM	79.70	81.20	71.43	73.14
ANN	79.40	85.30	70.10	72.40
LR	76.81	79.71	70.28	73.14
LDA	73.91	76.81	61.14	64.00
KNN	72.46	75.36	56.00	61.71
CT	72.46	75.36	62.86	64.57
PMV	65.50		41.68	

all the classifiers studied outperforms the PMV method at predicting the actual comfort level, with SVM performing the best at 71.43%, and both SVM and LR performing the best at 73.14% for each feature set respectively. It is evident that inclusion of the proposed features improves the prediction accuracies. This implies that gender, age and outdoor weather are important factors of thermal comfort in NV buildings.

The confusion matrices for SVM and LR are presented in Table 7.12. To decide which method performs better, we have calculated Positive Predictive Value (PPV) or Precision for each of the thermal state. PPV is the ratio of the true positives to the sum of true positives and false positives. A PPV of 0.8 implies that out of the times a class was predicted, 80% of the time the prediction was correct. Both SVM and LR perform equally well on overall accuracy. But PPV results show that SVM performs better at each comfort level, with almost equal and balanced precision for each state unlike LR which is biased towards *Comfort* state.

Naturally ventilated buildings may/may not have open windows, which allow wind and solar radiation to enter and influence the indoor climate. Thus it is intuitive to believe that in such buildings, outdoor weather have influence on indoor climate. However, adaptive model says that the occupant's control over the environment such as ability to close/open the windows, operate and regulate fans, also have a psychological influence on the thermal sensation in naturally ventilated buildings. Beside thermal control, thermal preferences, expectations, and adaptation abilities (physiological, behavioural, psychological), can also influence thermal sensation. These factors are not taken into

Table 7.12: Confusion matrix and Positive Predictive Value (PPV) for SVM and LR.

		SVM				LR		
		<i>Predicted Comfort Level</i>						
		-1	0	+1		-1	0	+1
<i>True Comfort Level</i>	-1	8	15	0		8	2	0
	0	2	97	7		17	87	18
	+1	0	23	23		0	10	33
PPV (Precision)		0.8	0.7	0.8		0.3	0.9	0.6

consideration by the Fanger's PMV model, which may explain its low prediction accuracy. In order to include these extraneous factors, the modified PMV models i.e. the ePMV and aPMV models were developed specifically for naturally ventilated buildings. The model coefficients are found to be $e = 0.6$ and $\lambda = -0.3217$. The extended PMV model obtains 61.75% accuracy, performing almost two times better than the adaptive PMV model at 35.51%. Taking into consideration the occupants' adaptive abilities helps in modelling their comfort better (61.75%) as compared to using only the six PMV factors (41.68%). However, considering the occupants' age, gender and the outdoor effective temperature along with the PMV factors further improves the modelling (73.14%). This could be because adaptive abilities such as altering or regulating windows and fans etc., is directly related to the outdoor weather. While the six PMV parameters represent the environmental and personal factors, the outdoor effective temperature represent the adaptive behavioural and psychological factors, and the age and gender partially represent the physiological factors.

7.5 Concluding Remarks

Firstly, this chapter analysed the effect of considering MRT to be equal to air temperature during indoor thermal studies by PMV modelling. It is found that this assumption, even for small temperature differences in MRT and T_a , can lead to incorrect determination of PMV and comfort level. Larger the temperature difference, larger is the inaccuracy (almost double). Highest correlation of MRT with AMV signifies the importance of MRT . Study of TSA and MCI indices show that the assumption is more likely to affect

comfort level determination in the uncomfortable range. Hence, it is recommended to avoid assumption of $MRT = T_a$ as it can result in misleading conclusions in indoor thermal comfort studies, and can compromise the occupant's thermal comfort and health.

Secondly, a model is developed to estimate indoor MRT . Multiple regression analysis using six modern regression algorithms have been implemented for model development. Rigorous feature selections using a combination of correlation analysis, Taylor's approximation and the regression algorithms, have rendered air temperature and air velocity as the input parameters. The model is extensively well validated against a new wider dataset conforming to the typical range of indoor parameters and evaluated with respect to three performance criteria. The model demonstrates excellent performance with a low mean residual error of 0.3°C , RMSE of 1.5°C and R^2 of 0.89. A comparative analysis emphasizes the advantages of the proposed model over the simplified equality assumption.

Thirdly, age, gender, and outdoor weather, which are not included in the PMV model, are found to be important factors for thermal comfort. The outdoor effective temperature may represent the adaptive behavioural and psychological factors of thermal comfort in naturally ventilated buildings.

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Chapter 8

Conclusion and Future Work

This chapter concludes and discusses the findings of this research with respect to the original hypothesis and objectives. Section 8.1 summarizes the key findings and inferences. Section 8.2 briefly addresses practical implications of the study. Section 8.3 outlines possible future works to extend this research.

8.1 Thesis Summary and Inferences

In this thesis, we have performed an overall relational study of the physiological, subjective, and environmental parameters for gaining a clearer understanding of human thermal comfort in order to develop predictive models for occupant's thermal state. We have primarily tested and proved the hypothesis that thermal comfort can be predicted by sensing certain physiological parameters. In this respect, six different physiological parameters have been studied namely, hand skin temperature, hand skin conductance, pulse rate, blood oxygen saturation, systolic blood pressure and diastolic blood pressure.

The relational study of the physiological and subjective responses have provided several significant insights on thermal comfort, which we believe can contribute remarkably to thermal comfort research. Each of the six physiological parameters except for blood

pressure is discovered to be a strong biomarker of TSI, albeit depending on the occupant's gender. Utilising the observations from our relational study, we have developed four different TSI predictive models based on physiological inputs. Our models take care of the inter and intra individual differences including gender dissimilarities, using novel normalization methods developed in this thesis. These models cater to personalized comfort prediction, and perform significantly well as compared to the existing conventional methods.

Singapore being a tropical country comprising mainly the cooling systems in buildings, the disparity between indoor thermal comfort and building energy efficiency is getting widespread due to ineffective cooling control mechanisms. In this thesis, we have developed a framework for indoor climate control that optimises both the thermal comfort and the energy consumption of the ACMV cooling system. It incorporates the developed TSI predictive models along with a novel optimization algorithm to ensure thermal comfort for occupants with the minimum energy use. The framework demonstrates application of TSI predictive models in improving building energy efficiency.

Besides the above physiological parameters studied in this thesis, and the subjective and environmental parameters that are usually studied in thermal comfort research, there are several non-physiological factors that are less-explored in this field, but are often debated to be linked to thermal comfort. Two such factors namely, occupant's age and gender along with outdoor weather and indoor MRT, have been studied in this thesis. Also, the common assumption of equating MRT to air temperature has been investigated, and an alternative model to predict MRT has been developed. We have substantiated all the findings of this study by conducting extensive human thermal comfort experiments elaborated in Chapter 3. To be more specific, the key findings from this thesis are summarized below:

1. Physiological and Subjective Responses:

- Each of the six physiological parameters except for blood pressure, revealed significant response to thermal stimuli. Certain derivative features of the parameters which reflect how they vary with time, are discovered to be strong biomarkers of

TSI. They include the change rate (FOG) and the fluctuations (MSG) of a parameter. These derivative features sometimes carried more relevant information to translate to the occupant's comfort than the parameters themselves. An interval of 5 minutes deems sufficient for observing the temporal behaviour to predict TSI.

- In addition, we demonstrated the potential of a single body location's skin temperature to predict the overall body thermal state. To the best of author's knowledge, existing literature has generally employed multiple body locations, most of which are intrusive. We selected a specific hand location for skin temperature measurement. We identified how this location favours heat transfer and how it could be strategic for analysis and prediction of overall thermal state.
 - Significant gender differences were observed in both physiological and subjective responses, which indicates the need for separate comfort study of each gender-group. Women portrayed greater satisfaction in terms of comfort and humidity. No gender difference existed in thermal preference and airflow sensation. While women exhibited greater adaptability, men were more sensitive yet tolerant of the thermal conditions. Significant gender differences were observed in most physiological features, mainly the raw values and the MSGs. This indicates that due to morphology differences, males significantly differ from females in their thermoregulatory responses under similar thermal stress. Therefore, it is imperative to study each gender group separately during comfort studies. Strong correlation between the physiological and the subjective responses were found.
2. **TSI Predictive Models:** Based on the response behaviours, we proposed four novel TSI predictive models. In order to make a model scalable, individual differences should be addressed. Hence, novel normalization processes were developed after identifying significant individual factors. For skin temperature, clothing insulation and Du Bois area, and for pulse rate, gender and BMI were discovered to be the individual factors. In addition, relevant information of skin temperature and pulse rate were extracted using a novel domain transfer process and a spectral analysis, respectively. The proposed models are:

- [A] **PTS model-** We developed a normalization process that addressed both inter and intra individual differences by incorporating body surface area and clothing insulation respectively. The normalization factor A_{exp} resolved the unclothed body surface area, which has a direct influence on the overall heat loss. While non-normalized skin temperature alone could correctly predict only about (60–65)% of thermal states, the PTS model based on the normalized skin features could predict accurately 87% of thermal states.
- [B] **TPPTS model-** The combined information of the skin temperature and its gradient carried more significant information than the skin temperature alone. The temporal profiles of skin temperature portrayed adequate information to indicate thermal state even without the need for normalization. Based on these temporal profiles, the TPPTS model could accurately predict 93.33% of the mean thermal states.
- [C] **ePTS model-** The PTS model is enhanced with additional information of pulse rate features and air temperature to form the ePTS model. We developed two input feature engineering approaches including (a) a novel normalization process that addresses individual differences in pulse rate to expand the model scalability, and (b) a spectral analysis to obtain a new pulse rate feature for TSI prediction. The ePTS model achieved over 97% accuracy.
- [D] **GPTS model-** Through a gender-based study of the physiological features, we identified 7 male and 6 female features that has potential to indicate thermal state. Based on the collective information of these identified features, the GPTS model could accurately estimate 92.86% and 94.29% of thermal states of males and females, respectively.

These proposed models significantly outperformed the existing conventional methods which achieved between (45-73)% accuracies only. A comparative analysis of the proposed and existing methods on grounds of sensor and computational cost, predictive performance and energy saving potential is covered in Chapter 6.

3. Indoor climate control framework:

- We have proposed a framework to control the indoor climate. It aims to provide optimum comfort with minimum energy consumption of an ACMV system. It incorporates a TSI predictive model and an optimization algorithm termed as the OAT algorithm that provides optimal operating condition based on the predicted TSI.
- We have modelled the ACMV energy consumption as a non-linear function of the ambient air temperature and three operating frequencies namely, of supply-air fan, compressor and water pump. A single layer feedforward neural network is used for the energy model.
- We have proposed the OAT algorithm to locate the optimal operating state of the ACMV system, and introduced a parameter named *ESP* to measure the energy saving potential of the framework.
- The framework exhibited up to 36.5% *ESP*. An ambient temperature of about 25°C is found to be most optimum for comfort and energy use, especially in tropical climates like that in Singapore.

4. Non-physiological factors: We investigated the significance of four less-explored non-physiological factors for indoor thermal comfort namely, MRT, age, gender and outdoor weather.

- As for indoor MRT, we investigated the impact of assuming it to be equal to air temperature on comfort assessment. An error analysis revealed that the equality assumption of MRT adversely affects thermal comfort assessment, resulting in incorrect conclusion about the occupant health.
- We propose an alternative MRT estimation model ($R^2 = 0.89$), that reduces the error by over 65%. The model is developed using a ridge regression algorithm, and is extensively validated.
- Age, gender and outdoor effective temperature, which are not included in the existing PMV method, were found to be important factors of thermal comfort. The outdoor effective temperature may represent the adaptive behavioural and psychological factors of thermal comfort in naturally ventilated buildings.

From the thesis findings, it can be inferred that it is important to explore the physiological parameters to better understand the thermal state. These physiological responses are interlinked with the subjective responses, mirroring each other, and hence they provide significant insights. Along with other fields, thermal comfort research is also witnessing a paradigm shift towards personalized systems. This is largely due to the developments in learning-based technology, and better connectivity through the Internet of Things. Another important factor is the onset of hardware that has immense capacity to collect and store data. This encouraged the use of adaptive algorithms in this study. These learning based algorithms have been carefully curated depending on the type of dataset and the desired goal of the model. As for PTS model, the two popular methods based on completely different principles were chosen; while SVM is hyperplane-based, ELM is neural network based. As for ePTS model, RBF-SVM was used because it proved effective for PTS model and the ePTS model was an extension of the PTS model. As for the TPPTS model, the input data was visual image. Therefore, CNN was used which is applicable for image input, unlike other algorithms. As for GPTS model, the input data had significant correlations among them, which can often be a hindrance to the predictive performance. Random Forest was chosen because it can eradicate the redundancy associated with such correlated input features. As for the MRT model, multiple linear regression was used because a fixed mathematical model was desired unlike the machine learning algorithms that have black-box structure.

8.2 Practical Implications

The findings of this study can be practically realized by leveraging on three technological domains: ***Wearable Sensing Technology***, ***Personal Comfort Models***, and the ***Internet of Things***. Computational intelligence techniques are largely popular for their adaptable nature unlike static comfort models which are not suitable for transient conditions. Due to these advantages, *personal comfort system* is a new promising paradigm of thermal comfort research. It leverages the Internet of Things and machine learning to learn individuals' comfort requirements directly from the data collected in their everyday environment [1]. However, the existing personal comfort methods rely mainly on

ambient sensors. This study, on the other hand, leverages sufficiently on biometric sensors. These sensors can be integrated into a single wearable device as all parameters were measured from the hand location; therefore, besides being effective, the proposed approach can be portable, convenient to use, computationally cheaper than using a host of ambient sensors, and most importantly, can provide an individualized feedback on thermal comfort. The models' practicalities were covered under a comparative analysis in Chapter 6.

The physiological features are non-intrusively obtainable. Given the immense development of wearable sensing technology today, the proposed approaches may be realized as a wearable solution. They may be further integrated with the Internet of Things for strategic control of building ACMV systems to balance energy-efficiency and indoor thermal comfort of occupants using the proposed control framework. Therefore, with the advancement of personal and environmental sensing techniques and the development of various advanced machine learning algorithms, the ideas demonstrated in this thesis can have promising applications.

8.3 Future Work

- **Control frameworks:** The control framework proposed in this thesis is an example of how a TSI predictive model can be incorporated into building energy control. Several such frameworks can be formulated in diverse ways. The classical PMV approach can be combined with the personal comfort systems for better prediction. The PMV method could be further improvised with additional parameters, and the problem could be formulated as:

$$TSI = f_{PMV}(T_a, MRT, RH, V_a, I_{cl}, M) + f_{phy}(ST, SC, PR, BP, SpO_2)$$

In our future work, we aim to study the above problem using hierarchical tree-based algorithms. It could provide a doubly-verified feedback on both general and individualized level.

- **Comfort spectrum:** As this study is motivated by the over-cooling problem in buildings of tropical climates, all analyses have been done for *Cool-Discomfort* and *Comfort* states i.e. cold/cool/neutral conditions. A parallel analysis for warmer situations including *Warm-Discomfort* state needs to be performed. It is important to study the complete comfort spectrum ranging *cold* to *hot*. The behavioural findings of the physiological features in this study may not stand true for the warmer spectrum. It is expected that skin conductance will play a significant role during *Warm-discomfort* state due to increased sweating in warmer conditions. Moreover, in this study, the direction effect is not studied. Here, we have analysed neutral-to-cool-to-neutral transitions. It would be interesting to observe other variations in transitions such as cool-to-warm, warm-to-cool, cool-neutral-warm etc. Direction effects had been observed in certain physiological response to large temperature step-changes in earlier studies [2]. Will there be similar finding in other such scenarios?
- **Age-group:** This study employed only the young adult population which forms the majority of end-users. With increasing age, human physiology changes and metabolic ability degrades. An elderly person's sensitivity to heat or cold would be lower than that of a younger person [3]; this can directly impact the physiological responses to thermal stimuli as well. It has been observed in Chapter 7 that the age of a person may influence one's thermal perception [4]. Therefore, the findings in this study may not hold true for other age-groups such as the children and the elderly. Hence, similar relational study including other age-groups could be performed. Similarly, the effects of several other non-tactile potential factors could be explored such as socio-economic background, mental state, building environment setting (workplace, home, play-area, music room) etc.
- **Activity level:** This study concentrated on sedentary subjects engaged in usual office activities such as reading, writing and typing. Metabolic rates are different for different activity levels [5]. As metabolic rate is a significant factor of thermal comfort [6], perception of thermal comfort can significantly change with different activity levels [7]. Moreover, the physiological parameters change with different activity levels such as increased skin conductance and pulse rate with higher activity levels like running

or dancing. The findings of this study hold true only for sedentary occupants. It would be beneficial to perform similar study for higher activity levels.

- **Thermal comfort during sleep:** Thermal comfort of the sleeping environment could have a significant influence on an occupant's sleep quality. A good sleep quality is beneficial for health and work productivity. Therefore, thermal comfort during sleep is an important research area [8]. The conventional method of collecting questionnaire is infeasible in sleeping posture, and the proposed predictive approach through physiological sensing can be particularly useful in this case. However, the physiological responses would vary from those under sedentary awake conditions, e.g., pulse rate and blood pressure are likely to dip lower during an asleep state. Therefore, the predictive principles that work under awake state may not hold true during sleep for the same occupant. A similar study during sleep could be performed.
- **Further physiological study:** Although six different physiological parameters were studied in this research, examined blood pressure samples were less as compared to the other parameters. This could have contributed to their non-responsiveness to thermal stimuli. Studies such as [2, 9] had found blood pressure to be responsive to sudden large temperature step-changes. Further study of blood pressure is thus required. Other physiological parameters such as respiration rate [10] and EEG based heart rate variability indices [11] might also provide additional insights and could be included in future studies.

Thermal comfort perception is a very subjective concept. How a thermal situation is perceived differs from one individual to another. But, physiological features are the closest and most personal parameter that can be sensed, and what better way than sensing the closest indicator of comfort when technologically it has become convenient? There are immense possibilities for studying the physiological parameters. In our opinion, there lies several significant information in each parameter that waits to be extracted and applied for the service of mankind. A thermally comfortable living environment with reduced energy use is what we envision for a better future.

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- J4. **Tanaya Chaudhuri**, Yeng Chai Soh, Hua Li and Lihua Xie, "Feedforward neural network based control framework for thermal comfort and energy-saving in buildings". (Submitted).
- J5. **Tanaya Chaudhuri**, Yeng Chai Soh, Hua Li and Lihua Xie, "RBF-SVM based enhanced Predicted Thermal State (ePTS) model for building occupants using physiological sensing through wearable technology". (Submitted).
- J6. **Tanaya Chaudhuri**, Yeng Chai Soh, Hua Li, and Lihua Xie, "Ridge regression based modelling indoor mean radiant temperature for thermal comfort". (Submitted).

Conference Proceedings

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