Machine Learning based Prediction of Thermal Comfort in Buildings of Equatorial Singapore

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***Abstract*—Majority of energy consumption in Singapore buildings is due to air-conditioning, because of its hot and humid weather. Besides attaining a healthy indoor environment, a prior knowledge about the occupant's thermal comfort can be beneficial in reducing energy consumption, as it can save energy which is otherwise spent in extra cooling. This paper proposes a data-driven approach to predict individual thermal comfort level ('cool-discomfort', 'comfort', 'warm-discomfort') using environmental and human factors as input. Six types of classifiers have been implemented- Support Vector Machine (SVM), Artificial Neural Network (ANN), Logistic Regression (LR), Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), and Classification Trees (CT), on a publicly available database of 817 occupants for air-conditioned and free-running buildings separately. Results show that our approach achieves prediction accuracies of 73.14-81.2%, outperforming the traditional Fanger's PMV (Predicted Mean Vote) model, which has accuracies of only 41.68-65.5%. Age, gender, and outdoor effective temperature, which are not included in the PMV model, are found to be important factors for thermal comfort. The proposed approach also outperforms modified PMV models- the extended PMV model and the adaptive PMV model which attain accuracies of 61.75% and 35.51% respectively.**

Keywords— thermal comfort; smart building; PMV model; adaptive model; machine learning

I. INTRODUCTION

Singapore is a hot and humid country due to its close proximity to the equator at 1.3521° N, and is characterized by uniformly high temperatures and humidity throughout the year. About 50% of the electricity consumption in Singapore is due to buildings, and about 60% of the electricity consumption in buildings is due to cooling [1]. Hence substantial amount of energy and capital resources is spent every year in cooling to achieve a thermally comfortable environment in buildings. Maintaining a healthy indoor climate is crucial to prevent health hazards to the occupants such as thermal stress and hypothermia [2]. A healthy indoor environment also improves productivity at work. A prior knowledge of the occupant's thermal comfort level can help to control how much energy is to be spent in cooling, thus limiting the energy consumption as per requirement. Prediction of thermal comfort can therefore, not only maintain a favorable indoor climate but also aid in reducing energy consumption. It can bring about an optimal balance between energy use and thermal comfort- a vital objective of smart city buildings.

The most widely adopted method to predict thermal comfort is the Fanger's PMV (Predicted Mean Vote) Model [2]. According to this model, a person's thermal comfort depends upon six factors – air temperature, mean radiant temperature, relative humidity, air speed, clothing rate (clothing insulation of the person), and metabolic rate (activity level of the person). The PMV model uses these six factors as inputs to predict actual thermal comfort by an index termed PMV. The PMV index ranges on a scale of -3 (Cold) to +3 (Hot), according to the ASHRAE thermal comfort scale (Fig. 1), where *neutral* is the desirable level [3]. However, previous works have revealed discrepancies between the predicted vote PMV and the actual thermal sensation vote reported by the occupants [4, 5]. This could probably be because certain other factors such as age, gender and the outdoor climate conditions are not included in the PMV model.

Metabolic ability decreases with age and so it changes the person's sensitivity to heat or cold [6]. In case of gender, women have lower metabolic rate and hence lower evaporative heat loss as compared to men. It is found that women usually prefer higher air temperature [7]. Several works have studied the impact of age and gender, but resulting in different conclusions [2, 6-8]. Outdoor weather can have psychological effect on thermal comfort in air-conditioned (HVAC) buildings, and direct effect on thermal comfort in naturally ventilated (NV) buildings. This paper investigates the importance of these three factors (age, gender and outdoor weather) on thermal comfort in building indoors.

In this paper, we have proposed a data-driven approach to predict individual thermal comfort in real time using several environmental and human factors including the six Fanger's factors and the three new proposed factors- age, gender and outdoor weather. Machine learning algorithms [9-13] have been used for this approach because they can deal with big data, and yet have high computational speed as compared to PMV model, which has a long and complex iterative computation process. HVAC and NV buildings are studied separately. The proposed model has been compared with Fanger's PMV model, as well as modified PMV models (ePMV, aPMV) that are based on the adaptive model [14, 15].

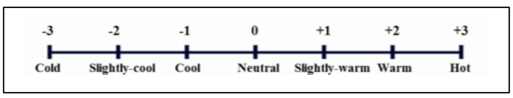

Figure 1. ASHRAE Thermal Comfort scale

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Several work [2, 13, 16] have been done to predict thermal comfort, but this study differs from them in the following ways: this is a data-driven approach unlike most of them; it is specific to equatorial climate and buildings of Singapore (different climatic regions have different building envelopes and properties suited to their climates); air-conditioned and naturally ventilated buildings are studied separately; three new features, namely age, gender, and outdoor weather have been introduced, and lastly, outdoor effective temperature has been used for outdoor weather data, because unlike air temperature, effective temperature is representative of the overall weather.

II. Proposed Prediction Model

We propose a data-driven approach to real time prediction of individual thermal comfort level. The thermal comfort reported by occupants on the ASHRAE scale (Fig. 1) is first classified into three levels: *Cool discomfort* [-3,-1), *Comfortable/neutral* [-1, 1], *Warm discomfort* (1, 3]. This level is taken as ground truth or actual thermal comfort level. Our approach is based on supervised machine learning algorithm wherein a classifier learns the pattern between the inputs and the outputs, and gains the ability to predict the output for unseen future input. The overview of the approach is presented in Fig. 2. 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 HVAC 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 (fans etc.). The inputs are called as features and a set of inputs is called a feature set. In this case, feature selection is not done as we consider all the mentioned inputs as important. Unlike several indoor thermal studies, we have not discarded mean radiant temperature as studies show that it is in fact one of the most important factors, especially in a wet equatorial region as Singapore [17] where solar radiation is high.

There are two types of thermal comfort models- static and adaptive. Fanger's PMV model is a static model, applicable to both HVAC and NV case, while the adaptive model is more suited for NV buildings. In this paper, HVAC and NV buildings have been studied separately because they have different thermal dynamics, not only in terms of control, but also the influencing factors. According to the adaptive model, in NV buildings, several other factors such as the occupant's adaptation abilities, psychological state, thermal preferences and control also play a role in the way thermal comfort is perceived [15]. The modified PMV models, namely the ePMV and aPMV models take into account these extraneous factors while predicting the comfort level [14, 15, 19]. These modified models have been discussed in later sections.

The rest of the paper is as follows: section III describes the methodology used: the dataset, its processing and the six machine learning algorithms studied, section IV presents the results and discussion for HVAC and NV buildings and the

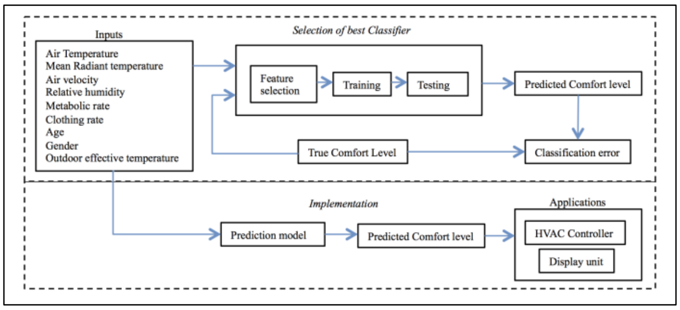

Figure 2. Overview of proposed approach

importance of proposed features- age, gender, and outdoor weather; lastly section V concludes the findings.

III. Methodology

A. Data Preprocessing

ASHRAE is one of the main organizations that set thermal comfort standards and guidelines. For this study, we have used the database of thermal comfort experiments performed in Singapore by de Dear et al., which is publicly available as part of the ASHRAE RP-884 project [18]. 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 (HVAC) 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 HVAC 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, 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 rate), 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 HVAC and NV buildings respectively.

B. Feature Set and Output

The following factors were included in the feature set:

- Fanger's parameters: The six Fanger's parameters are well established as definite influencers of thermal comfort: air temperature (T_a), mean radiant temperature (*MRT*), relative humidity (*RH*), air speed (V_a), clothing rate (*Clo*), and metabolic rate (*M*).
- Outdoor effective temperature (ET_{out}): The effective temperature indicates the combined effect of air temperature, relative humidity and air velocity [18]. Thus it better represents overall outdoor weather, as compared to using only outdoor air temperature.
- 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:

$f_{NV\_wo} = \{T_a, MRT, V_a, RH, M, Clo\}$, and

$f_{NV\_w} = \{T_a, MRT, V_a, RH, M, Clo, A, G, ET_{out}\}$.

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

$f_{HVAC\_wo} = \{T_a, MRT, V_a, RH, M, Clo\}$, and

$f_{HVAC\_w} = \{T_a, MRT, V_a, RH, M, Clo, G, ET_{out}\}$.

The ratio of gender proportion in HVAC 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 comfort experiments required the occupants to fill a questionnaire/survey wherein each occupant was supposed to express their thermal sensation on the ASHRAE thermal scale (Fig. 1). This reported sensation is called as the Actual Mean Vote (AMV) [2, 3].The AMVs were classified into 3 comfort levels: *Cool discomfort* [-3,-1), *Comfortable/neutral* [-1, 1], *Warm discomfort* (1, 3]. This thermal comfort level is considered the actual or ground truth for the classifiers.

C. Machine Learning Algorithms

This study is a case of supervised learning, as inputs and outputs are both provided. Our aim is to implement several classification algorithms and select the method with the best classification accuracy. 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 HVAC 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 (ANN), 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 HVAC case; and training (409), validation (87), and testing (87) for NV case.

We have tested six different machine learning classifiers on the datasets of each type of building. This is repeated for each of the two feature sets per building type, HVAC: (f_{HVAC_wo}, f_{HVAC_w}), and NV: (f_{NV_wo}, f_{NV_w}). The different classifiers studied are discussed briefly as follows:

1) Support Vector Machine (SVM): SVM is an extension of support vector classifier which is based on the concept of a hyperplane that separates different classes of training observations with a soft margin, using kernels [9, 10, 12]. In SVM, cost (C) is a non-negative tuning parameter that is used to control the bias-variance tradeoff. In this study, we have experimented with different types of kernels, and Radial basis Function (RBF) worked best among them. We found the best tuning parameters of cost and gamma (γ) using 10-fold cross-validation, the values of which are presented in Table I. We have used a C-type classification (C-SVC) with one-versus-one approach.

2) Artificial Neural Networks (ANN): ANN is based on the human biological neuron networks, wherein signals are passed between a defined numbers of neurons over weighted connection links, with each neuron using an activation function to determine the output signal [10, 11]. In our study, we have used a two-layer feed forward ANN, 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 (N) is mentioned in Table I.

3) 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 [9].

4) 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 [9].

5) K- Nearest Neighbours (KNN): The KNN classifier is one of the simplest yet powerful classifiers [9, 10]. 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.

6) Classification Trees (CT): CT classifier is a decision tree that is grown using recursive binary splitting [9, 10]. 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.

TABLE I. OPTIMAL TUNING PARAMETERS OF LEARNING ALGORITHMS

	HVAC		**NV**	
	f_{HVAC_wo}	f_{HVAC_w}	f_{NV_wo}	f_{NV_w}
SVM	C=1 γ=0.1	C=1 γ=0.1	C=1 γ=0.5	C=1 γ=0.1
ANN	N = 20	N = 20	N = 20	N = 20
KNN	K=1	K=1	K=1	K=1

IV. Results and Discussion

A. Performance Metrics

We have used Classification accuracy as the criterion for comparing performance of the algorithms. The classification accuracy is basically the percentage of the test samples whose thermal comfort level have been correctly predicted by the learning algorithm. Confusion matrix is a table that provides a visualization of a supervised algorithm's performance. Each row consists of the true labels of the comfort level, and columns represent the predicted comfort levels. Classification accuracy is the ratio of the sum of the diagonals in the confusion matrix to the total number of test samples.

B. Air conditioned buildings (HVAC)

Table II 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_{HVAC_wo} and f_{HVAC_w} respectively. The Fanger's PMV model reaches an accuracy of 65.5%. It is observed that all the classifiers studied outperforms the Fanger's method at predicting the actual comfort level, 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 Fanger's parameters results in improved accuracies for all the methods. This implies that gender and outdoor weather environment are important factors for thermal comfort in HVAC buildings.

C. Naturally ventilated buildings (NV)

Table III presents the results of the predictive performance of the six machine learning classifiers on the test dataset of naturally ventilated buildings. The first and second column presents the classification accuracies for feature sets f_{NV_wo} and f_{NV_w} respectively. The Fanger's PMV model reaches an accuracy of 41.68%. PMV model gives better results in air-conditioned buildings, which is consistent with previous studies that the PMV model is better suited to HVAC case compared to NV case [14, 15]. It is observed that all the classifiers studied outperforms the Fanger's 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.

TABLE II. PREDICTION ACCURACY (%)– HVAC BUILDINGS

	f_{HVAC_wo}	f_{HVAC_w}
SVM	79.70	81.20
ANN	79.40	85.30
LR	76.81	79.71
LDA	73.91	76.81
KNN	72.46	75.36
CT	72.46	75.36
Fanger's PMV	65.50	

TABLE III. PREDICTION ACCURACY (%)– NV BUILDINGS

	f_{NV_wo}	f_{NV_w}
SVM	71.43	73.14
ANN	70.10	72.40
LR	70.28	73.14
LDA	61.14	64.00
KNN	56.00	61.71
CT	62.86	64.57
Fanger's PMV	41.68	

The confusion matrices for SVM and LR are presented in Table IV. To decide which method performs better, we have calculated Positive Predictive Value (PPV) or Precision for each of the comfort levels. 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 (Table V) shows that SVM performs better at each comfort level, with almost same and balanced precision for each level unlike LR which is biased towards *comfort* level.

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. Besides thermal control, thermal preferences, expectations, and adaptation abilities (physiological, behavioral, psychological), can also influence thermal sensation. These factors are not taken into consideration by the Fanger's PMV model, which may explain its low prediction accuracy. In order to include these extraneous factors, modified PMV models were developed specifically for naturally ventilated buildings.

TABLE IV. CONFUSION MATRIX FOR SVM AND LR FOR NV CASE

		SVM				**LR**		
		Predicted Comfort Level						
		-1	**0**	**+1**		**-1**	**0**	**+1**
True Comfort Level	**-1**	8	15	0		8	2	0
	0	2	97	7		17	87	18
	+1	0	23	23		0	10	33

TABLE V. POSITIVE PREDICTIVE VALUE (PPV) / PRECISION

Comfort Level	**SVM**	**LR**
Cool discomfort (-1)	0.8	0.3
Comfortable (0)	0.7	0.9
Warm discomfort (1)	0.8	0.6

Fanger developed an extended PMV model which takes into account these extraneous factors, and predicts the actual thermal sensation as in (1), where '*e*' is called as the expectancy factor [14, 19].

$$ePMV = e * PMV \tag{1}$$

Another modified PMV model is the adaptive PMV model developed by Yao et al. [15, 19]. It uses an adaptive coefficient 'λ' to predict the actual thermal sensation as in (2).

$$aPMV = PMV / (1 + \lambda * PMV) \tag{2}$$

For this study, we have calculated '*e*' and 'λ' according to the method mentioned in [19], and their values are given in Table VI. A comparison of our method with the existing methods reveals that our method outperforms them at an accuracy of 73.14% (Table VII). It is also observed that the extended PMV model at 61.75% performs almost two times better than the adaptive PMV model at 35.51%.

TABLE VI. CALCULATED COEFFICIENTS OF MODIFIED PMV MODELS

ePMV	$e = 0.6$
aPMV	$\lambda = -0.3217$

TABLE VII. ACCURACY (%) OF PMV MODEL, MODIFIED MODELS, AND PROPOSED MODEL

Fanger's PMV	41.68
ePMV Model	61.75
aPMV Model	35.51
Proposed Approach	73.14

V. CONCLUSION

This paper presents a data-driven approach for real-time prediction of thermal comfort at individual level. The model takes in several environmental and human factors as input, and predicts the occupant's thermal comfort level ('*cool-discomfort*', '*comfort*', '*warm-discomfort'*), which can then be fed as signal to HVAC controller or used for manual control. Six different state of the art machine learning classifiers have been studied. Results show that our approach achieves prediction accuracies of 73.14-81.2%, outperforming the traditional Fanger's PMV model, which has accuracies of 41.68-65.5%. Age, gender, and outdoor effective temperature, which are not included in the PMV model, are found to be important factors for thermal comfort. The proposed approach also outperforms modified PMV models- the extended PMV model and the adaptive PMV model which attain accuracies of 61.75% and 35.51% respectively. The proposed approach can help to achieve an optimal balance between thermal comfort and energy consumption, which is a vital objective of smart building and smart cities. In future, we aim to study the scalability of this approach to other climatic regions, probably a cold climate, where a good deal of energy consumption is due to heating in buildings.

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