

A Machine Learning Approach for Predicting Thermal Comfort in a Bangkok Academic Library: Integrating Logit and Random Forest Models

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Abstract

A study of thermal comfort was conducted in a 4-story academic library located in Bangkok, Thailand. Since limited thermal comfort studies have been conducted for academic libraries located in a tropical climate. The field measurements by a set of sensors and questionnaire surveys were conducted among 234 library occupants. The measurements led to the average air temperature, relative humidity, and air velocity of about 24.39°C, 55.39%, and 0.073 m/s, respectively. Hence, the thermal comfort was evaluated using the Predicted Mean Vote (PMV) and the Predicted Percentage of Dissatisfied (PPD) based on the ASHRAE 55 standard, and the Actual Mean Vote (AMV) from the occupants' perception. PMV and AMV were found to be -0.74 and -0.12, implying that the library environment was slightly cooled. Although the conventional standard PMV was widely used, it might not accurately represent real-time thermal preferences and cannot be practically integrated into the Heating, Ventilation, and Air-Conditioning (HVAC) control. In addition to the conventional method, two Machine Learning (ML) models, Random Forest (RF) and Support Vector Machine (SVM), were investigated for their predictive performance. For the ML model development, five environmental variables (T_a , T_{mrt} , V_a , RH, and CLO) were used. It was found that the RF model performed well with an R-squared of about 0.9876, while SVM achieved only 0.8067. Therefore, the key findings support the application of the ML approach, especially RF, to enhance HVAC control for energy management strategies while maintaining the thermal comfort of library occupants in academic buildings located in tropical climates.

Keywords: Academic library, Energy conservation, Logit regression, Random forest, Thermal comfort

INTRODUCTION

Thailand is located in a tropical zone with hot and humid climatic conditions. Thus, most of Thailand's academic library buildings were air-conditioned. The optimal indoor temperature and humidity should be maintained, corresponding with the ASHRAE standard and energy management measures [1], [2], [3]. Both undergraduate and graduate students normally spend several hours on self-study, doing homework and exercises, which require concentration to process complex information. Thermal comfort and discomfort could significantly affect their learning performance.

According to the ASHRAE Standard 55 [3], thermal comfort means the mental condition of the space occupants to express their satisfaction with the environment. Based on the heat balance model, to determine the thermal comfort indicators, Predicted Mean Vote (PMV) and Predicted Percentage of Dissatisfied (PPD), 6 factors are required for calculation: air temperature (T_a), relative humidity (RH), air velocity (V_a), mean radiant temperature (T_{mrt}), metabolic rate (MET), and clothing insulation (CLO) [4]. These inputs were obtained from spot measurements using a static set of sensors. The PMV and PPD were calculated manually; however, the static mathematical model was not practical to capture the dynamic thermal comfort perception of occupants. Through digital transformation from the static evaluation of PMV and PPD, the IoT-based monitoring system could enhance the understanding of the dynamics of the local occupant thermal perception, and also facilitate energy saving in smart buildings. The Machine Learning (ML) approaches, especially Random Forest (RF) and Support Vector Machines (SVM), were ready to be applied to reflect the occupant responses faster.

Based on the literature reviews, ML models were applied for the prediction of thermal comfort in public transportation and smart classrooms, with high accuracy [5], [6]. However, the international ASHRAE 55 standard may underestimate local thermal preferences within library environments in tropical climates. Therefore, it is necessary to develop region-specific predictive models [7]. This leads to the objective of this study to investigate thermal comfort in a university library located in central Bangkok, Thailand, and to examine whether ML models can improve the prediction of occupant thermal response under tropical conditions.

LITERATURE REVIEW

1. Theoretical Foundations of Thermal Comfort

The thermal comfort assessment has relied on the heat balance model [4]. This model uses both physical and physiological variables to determine the PMV and PPD. It has been adopted in accordance with ASHRAE 55 [3] and ISO 7730 [8]. The theoretical basis of the model is based on the principle of human thermal equilibrium. Thermal comfort would be achieved if the heat produced by the human body is balanced with the heat exchanged with the surrounding environment. The PMV was calculated by equation (1) as proposed in ASHRAE Standard 55.

$$PMV = (0.303(e^{-0.036M}) + 0.028)L \quad (1)$$

Where M is the metabolic rate in W/m^2 and L is the thermal load on the human body in W/m^2 . According to the heat balance, the thermal load (L) is the difference between the body's internal heat production and the heat loss that the body experiences to maintain thermal equilibrium, computed by equation (2).

$$L = (M - W) - (3.05 \times 10^{-3})[5733 - 6.99(M - W) - P_a] - 0.42[(M - W) - 58.15] \quad (2)$$

$$-(1.7 \times 10^{-5})M(5867 - P_a) - 0.0014M(34 - T_a)$$

$$-(3.96 \times 10^{-8})f_{cl}[(T_{cl} + 273.15)^4 - (T_{mrt} + 273.15)^4] - f_{cl}h_c(T_{cl} - T_a)$$

Where:

M is metabolic rate (W/m^2), W is external work (W/m^2) that in this case is 0, P_a is water vapor partial pressure (Pa), T_a is air temperature ($^{\circ}C$), T_{mrt} is mean radiant temperature ($^{\circ}C$), T_{cl} is clothing surface temperature ($^{\circ}C$), f_{cl} is the clothing area factor, h_c is the convective heat transfer coefficient ($W/m^2 \cdot ^{\circ}C$)

However, the static models, as in equations (1) and (2), cannot account for the “adaptive” nature of occupants in tropical climates. In addition, the higher thermal tolerance due to acclimatization and psychological factors leads to a difference between the PMV and the Actual Mean Vote (AMV) [9].

2. Thermal Comfort in Educational and Library Environments

Educational buildings have challenges for Heating, Ventilation, and Air-Conditioning (HVAC) management due to fluctuating occupancy density and diverse activity levels. The thermal satisfaction in academic libraries directly correlates with student productivity and cognitive performance. However, conventional HVAC control systems regularly maintain a constant temperature setpoint. This leads to both energy waste and discomfort, i.e., over-cooling. Identification of region-specific comfort zones in a recent evaluation of Southeast Asian university buildings suggested the optimization of occupant well-being and energy efficiency [7], which challenges the employment of the ML approach.

3. Machine Learning Applications in Thermal Prediction

Since the traditional model was static and not able to handle non-linear human feedback, ML algorithms can process large datasets from IoT sensors to identify occupant preference patterns. The ML-driven predictive models enable HVAC adjustments. The transformation to smart environments would respond dynamically to occupant needs [10]. The effectiveness of SVM and RF algorithms is highlighted. SVMs could handle high-dimensional spaces, possibly used for the classification of thermal sensations with high precision [5]. RF, an ensemble learning method, has robustness against noise and can rank the importance of environmental features [5], [6]. In comparison, SVMs provide a solid baseline when dealing with heterogeneous data from field surveys, while RF achieves higher stability [5].

METHODS

The research methodology consists of 7 stages: field measurements to obtain five environmental variables (T_a , T_{mrt} , V_a , RH, and CLO), occupant surveys for subjective thermal sensation votes, PMV & PPD calculation based on the conventional standard, comparison of PMV and AMV, probability analysis of thermal acceptability by Logit regression analysis, ML model (RF and SVM) development from the dataset, and finally performance comparison of SVM and RF models for HVAC application suitability.

1. Site Description and System Configuration

The experimental site was a 4-story academic library, located in central Bangkok, with split-type air conditioners (AC) having 10 air-handling units (AHUs) to supply cold air to each floor [11]. The AC system was operated for 13 hours from 8:00 a.m. to 9:00 p.m. The air duct network from the AHUs supplied cold air to the conditioned space via the distributed air grille diffusers. Figure 1 shows the number of diffusers and volume flow rate in cfm (cubic feet per minute). The circulated air was discharged toward the walls and bookshelves instead of directly to the occupants' desks.

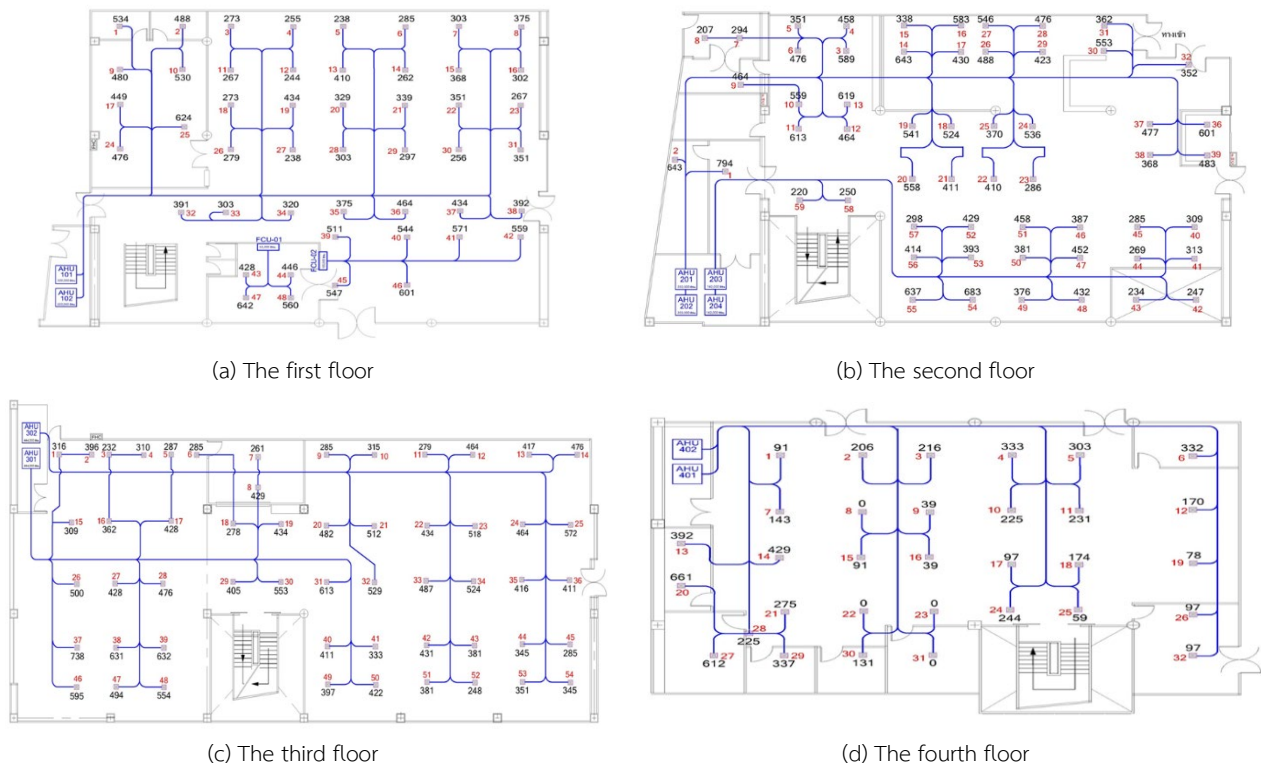


Figure 1: Air duct system of the library showing the number of air grille diffusers and volume flow rate in cfm

2. Instrumentation and Measurements

The indoor data were measured by a set of field instrumentation (Figure 2) placed on the table near the occupants' seats (Figure 3), while a field survey was conducted using a one-page questionnaire to collect data required by the static model. The measuring devices were composed of (1) a Benetech GM8903 hot-wire anemometer for air velocity measurement (accuracy $\pm 3\%$), (2) a UNI-T UT333 thermo-hygrometer for air temperature and relative humidity (accuracy $\pm 2^\circ\text{C}$ and $\pm 5\%$ RH), and (3) a Lutron WBGT-2010SD for globe temperature measurement, which would be used to compute the Mean Radiant Temperature (accuracy $\pm 0.6^\circ\text{C}$)



Figure 2: Setup of the measuring equipment

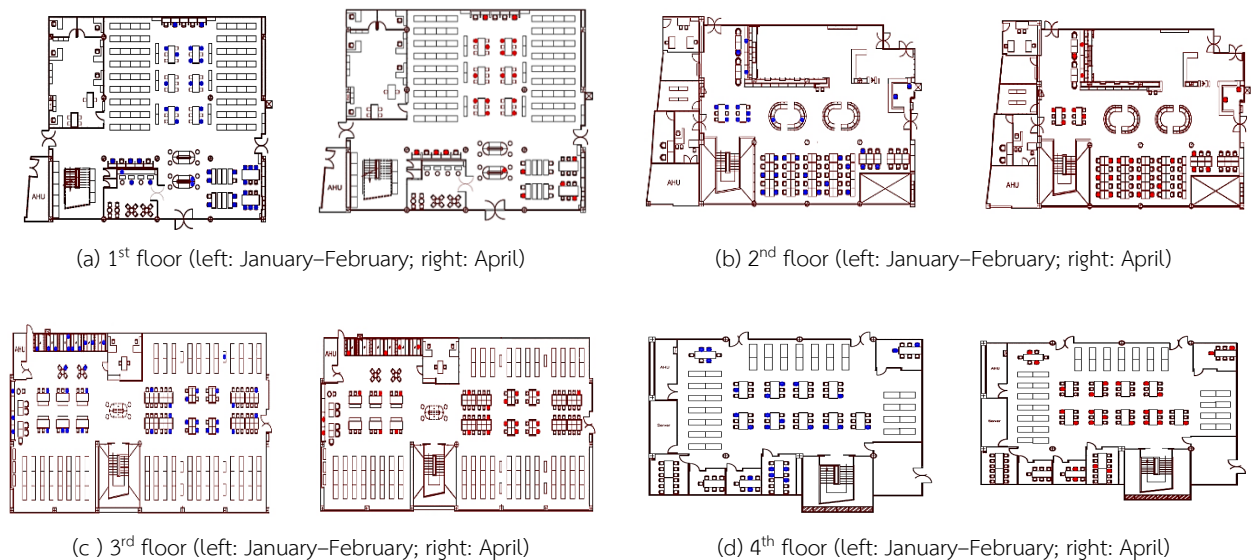


Figure 3: Location of the questionnaire's respondent seats (a) floor 1, (b) floor 2, (c) floor 3, and (d) floor 4 (left: January–February, right: April)

3. Subjective Survey and Data Collection

The questionnaire survey was conducted during two periods: the cool and dry season (January–February 2019), and the hot and humid season (April 2019). The questionnaire was designed based on the ASHRAE Standard 55 using a 7-point integer scale from -3 (cold) to +3 (hot). The occupants spent approximately 10 to 15 minutes answering the questionnaire to ensure their thoughtfulness. The CLO of occupants was obtained from the questionnaire survey, including a checklist of clothing items commonly worn by Thai university students, where

their responses were converted into clothing insulation values based on the ASHRAE 55 standard table. The 234 occupants' locations from all four floors of the library were depicted in Figure 3. In addition, a constant metabolic rate of 1.0 MET was assumed for all occupants because the activity of undergraduate and graduate students in the library was normally reading, studying, using computers, and doing assignments that are consistent with the activity level of seated and quiet office-type work in the standard. Therefore, the fixed 1.0 MET was reasonable and not included in the descriptive statistics or in Table 1.

Table 1: Descriptive statistics of ML input features

Inputs	T_a	T_{mrt}	V_a	RH	CLO
Count	234	234	234	234	234
Mean	24.39	24.31	0.07	55.69	0.48
Standard Deviation	0.94	0.97	0.14	5.75	0.10
Minimum	22.50	21.87	0.00	45.00	0.25
25%	23.70	23.78	0.00	51.30	0.43
50%	24.30	24.20	0.01	56.35	0.45
75%	25.10	24.94	0.08	60.50	0.52
Maximum	27.20	29.31	0.97	68.00	1.04

4. Predictive Modeling Framework

The predictive ML model used data from field measurements and surveys to predict the thermal comfort indices. Five input data (T_a , T_{mrt} , V_a , RH, CLO) were used for pre-processing, training, testing, and validation of two ML models: RF and SVM. Consequently, the PMV and PPD predicted by these two ML techniques were compared statistically against the traditional values. In addition, the Actual Mean Vote collected from the occupants was used to support the model training phase. The pseudocode of the thermal comfort prediction framework is as follows:

- Input: Environmental variables (T_a , T_{mrt} , V_a , RH), Personal variable (CLO), Target variable (PMV)
- Output: Predicted PMV, Model performance metrics (R-squared, MSE, MAE, RMSE, MBE)
- Step 1: Do physical measurements and collect questionnaire responses.
- Step 2: Calculate PMV and PPD according to ASHRAE Standard 55.
- Step 3: Construct the dataset consisting of: $X = [T_a, T_{mrt}, V_a, RH, CLO]$ and $y = PMV$
- Step 4: Preprocess the dataset by removing incomplete records, normalizing variables for SVM, and splitting the data randomly into training and testing datasets.
- Step 5: Train the Random Forest (RF) model using the training dataset.
- Step 6: Train the Support Vector Machine (SVM) model using the training dataset.
- Step 7: Predict PMV values using both trained (RF and SVM) models.
- Step 8: Compare predicted PMV with actual PMV from the static model.
- Step 9: Evaluate ML model performance using R-squared, MSE, MAE, RMSE, and MBE.
- Step 10: Report and select the model with the best predictive performance.

4.1 Random Forest (RF): Random Forest is constructed from independent decision trees during the training phase and calculates the mean prediction of all trees to generate output [12]. Its advantage is the reduction of overfitting by using bootstrapping and selecting random features. For thermal comfort applications, RF could capture complex input features and provide stability in PMV prediction, which contains measurement noise.

4.2 Support Vector Machines (SVM): Support Vector Machines can do regression with high precision due to their robust class of supervised learning models [13]. It identifies an optimal hyperplane that approximates the five-input relationship and the PMV. Moreover, the SVMs used non-linear kernel functions called the Radial Basis Function (RBF) that effectively map the non-linear characteristics of the library occupants' perception.

4.3 Comparative Handling of the 5-Input Dataset: Machine learning has to handle the input dataset before the training process. In this research, both RF and SVM required pre-processing of the five-input dataset (T_a , T_{mrt} , V_a , RH, and CLO). In comparison, RF resulted in robustness and stability, while SVM provided sophisticated mathematical solutions. RF could identify non-linear interactions among input variables effectively without extensive data scaling. It prioritized the most important inputs: T_a , V_a , and T_{mrt} . On the other hand, the SVM used kernel tricks to capture the complexity and dynamics of the input; however, it was sensitive to the input scale. Therefore, the small range of V_a must be normalized alongside those of T_a and T_{mrt} .

RESULTS AND DISCUSSION

1. Dataset Characteristics and Descriptive Statistics

The undergraduate and graduate students or respondents were mainly 20–25 years old, with the ratio of females to males about 72.8–27.2%. Table 1 shows the descriptive statistics of the five input features: air temperature (T_a), mean radiant temperature (T_{mrt}), air velocity (V_a), relative humidity (RH), and clothing insulation (CLO). The average values of air temperature and mean radiant temperature are 24.39°C ($\pm 0.94^\circ\text{C}$) and 24.31°C ($\pm 0.97^\circ\text{C}$), respectively.

The average globe temperatures (T_g) was 24.29°C ($\pm 0.91^\circ\text{C}$). Air velocity (V_a) was low, averaging 0.073 m/s ± 0.14 m/s. This reflects the stagnant air conditions regularly found in library settings. The calculated PMV averaged -0.74 ± 0.53 , illustrating that the general thermal state was slightly cool in the region of the ASHRAE scale.

The mean radiant temperature (T_{mrt}) was calculated using the T_a , the T_g , and the V_a . The formula is presented in equation (3) below:

$$T_{mrt} = \left((T_g + 273.15)^4 + \frac{1.1 \times 10^8 \times V_a^{0.6}}{0.95 \times 100^{0.4}} (T_g - T_a) \right)^{0.25} - 273.15 \quad (3)$$

T_{mrt} typically exceeds T_a , however, the average T_{mrt} from this research was slightly lower than the average T_a . T_{mrt} exceeded T_a only 56% of the observations, resulting in a Mean Bias Error (MBE) of -0.186°C . This phenomenon could be attributed to the specific HVAC configuration described in the methodology. The cool air from the diffusers is directed toward the library walls or bookshelves before mixing with the ambient air. It therefore effectively lowers the surface temperatures of the building envelope.

The operative temperature represents the uniform temperature of an enclosure, where an occupant exchanges a similar amount of heat as the actual non-uniform environment. Consequently, based on linear regression, the relationship between air temperature (T_a) and operative temperature (T_o) was as follows in equation (4):

$$T_o = 1.009(T_a) - 0.0116 \quad (4)$$

2. Comparative Analysis of PMV and AMV

The thermal comfort assessment according to ASHRAE Standard 55 provided an average PMV of -0.18. This indicates a slightly cool sensation among occupants. Consistently, the PPD averaged 9.20%. This value is lower than 10%; therefore, classified as category A of the ASHRAE standard, which implies a high level of occupant satisfaction. The real occupant thermal perception is called the Actual Mean Vote (AMV). The average AMV obtained from questionnaires was -0.12, with a standard deviation of about 1.02. It was noted that the calculated PMV was -0.18, which is close to the respondent's average AMV. Using linear regression, the AMV and PMV are functions of the operative temperature (T_o), as illustrated in Figure 4 and Equations (5) and (6), which are functions of the ambient and mean radiant temperatures.

$$AMV = 0.2085(T_o) - 5.186 \quad (5)$$

$$PMV = 0.3706(T_o) - 9.2982 \quad (6)$$

Based on equations (5) and (6), the interception of AMV and PMV to the temperature axis gave the neutral operative temperature about 24.85°C and 25.10°C; therefore, PMV provided a slight overestimation. In comparison between PMV and AMV values, the Mean Bias Error (MBE) and Mean Absolute Error (MAE) were -0.186 and 0.342, respectively. This implied that PMV was normally lower than AMV, especially when T_o was lower than 25.2°C.

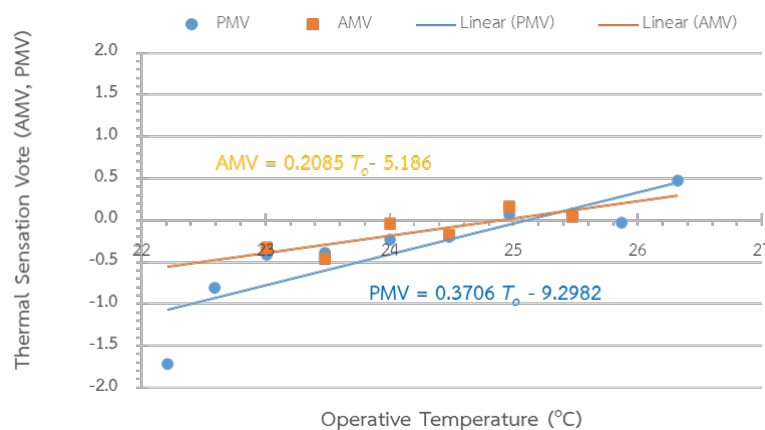


Figure 4: Relation between AMV and PMV with the operative temperature

3. Probabilistic Analysis of Thermal Acceptability

A binary logit regression was used to determine the operative temperature from the intersection of the fitted thermal preference probability curves. In Figure 5, the probability was the dependent variable, while the operative

temperature was the independent variable, creating two curves of thermal preference category. The neutral operative temperature was then identified statistically using logit regression [14] based on the intersection of two curves, the “cooler than neutral” and “warmer than neutral”.

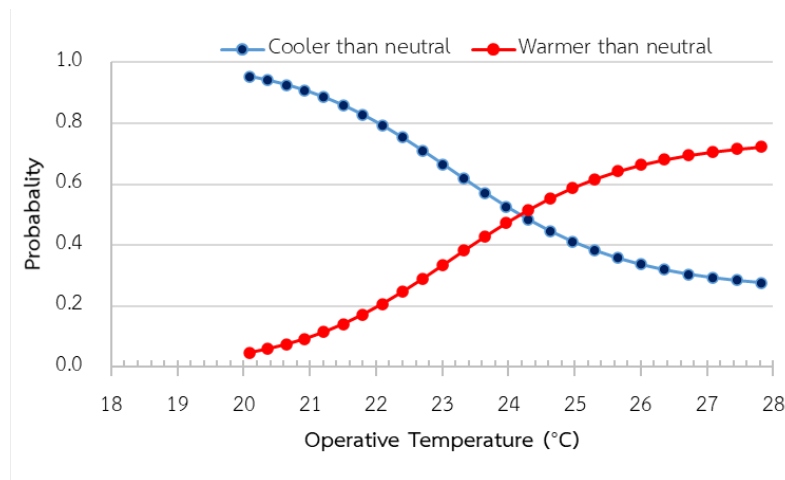


Figure 5: Probability of thermal acceptability based on the logit regression model of Actual Mean Vote (AMV).

At lower operative temperatures, there is a high probability that occupants will feel cooler than their comfort state. Between 21–26°C, the probability of “cooler than neutral” declines sharply. At temperatures above 26.8°C, the probability drops to below 0.3 but does not converge to zero. The reason is the limited density of AMV data points at higher thermal extremes. In contrast, the probability of occupants feeling “warmer than neutral” is low at lower operative temperatures. However, between 22–25°C, it increases significantly. Finally, this probability exceeds 0.7 at temperatures above 27°C.

The optimal thermal comfort temperature from Figure 5 was 24.29°C, at which the response rate was 0.5 (50%). It is found that this logit-derived optimal temperature is slightly lower than the 24.85°C from linear regression depicted in Figure 4. Therefore, it implies that library occupants in a tropical climate would prefer a cooler-than-neutral state during cognitive activities.

4. Machine Learning Performance and Feature Correlation

A correlation matrix was developed before training the ML, as illustrated in Figure 6. Air temperature (T_a) showed a moderate positive correlation with PMV (0.56). On the contrary, air velocity (V_a) showed a significant negative correlation with PMV (-0.68). It would confirm that the air temperature and air velocity are strong predictors of thermal sensation within the library environment. The ambient temperature was more important than the mean radiant temperature, influenced by direct cooling of the surrounding wall by cold air from diffusers. It is expected that the RF algorithm could quantify the importance of inputs, especially those that mostly influence the occupant’s thermal comfort.

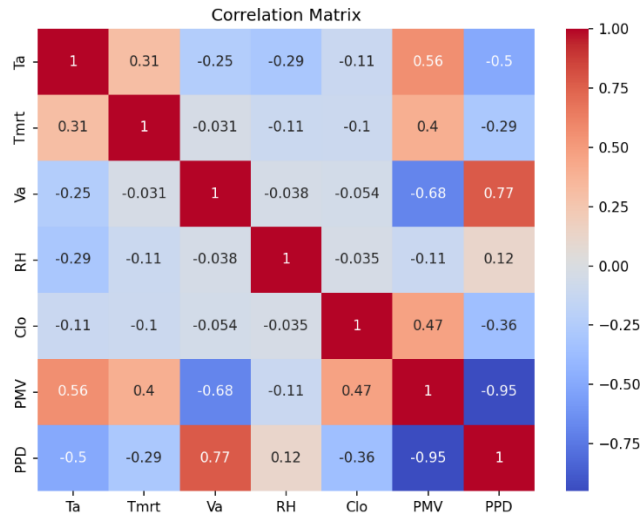
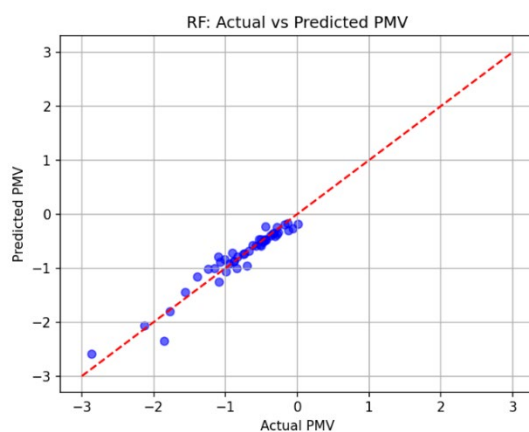


Figure 6: Correlation matrix

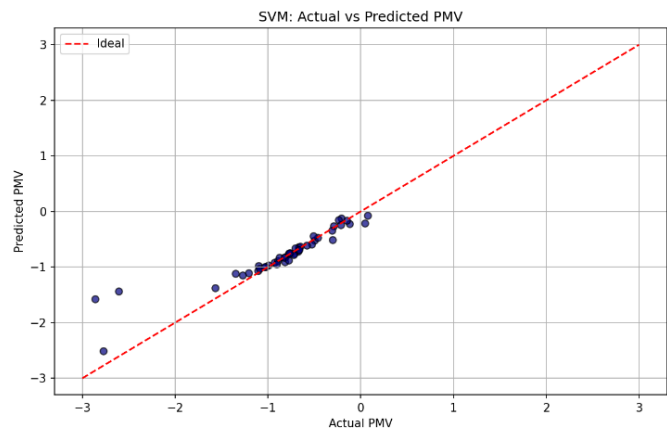
5. Machine Learning Model Performance and Comparison

For thermal comfort forecasting by ML, the input dataset is composed of five inputs: T_a , RH, V_a , T_{mrt} , and CLO, and one target output as PMV. It was used for training and validating both RF and SVM models. However, the metabolic rate can be assumed to be constant at 1.0 MET for practical implementation, given the typical, similar sedentary activities of the academic library occupants.

5.1 Actual vs. Predicted Performance and Comparison of RF and SVM: To evaluate the training algorithms, two scatter plots between the actual and predicted PMV using RF and SVM models were illustrated in Figure 7. RF provided good alignment with an R-square of about 0.9334, while SVM gave a lower R-square of about 0.8076 and performed well in the region of -1 to 0. To compare the performance of RF and SVM, five statistical indices were compared in Table 2. They are Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Bias Error (MBE), and Coefficient of Determination or R-squared. It was found that all MSE, MAE, and RMSE of SVM were higher than those of RF. The minimum prediction error was MBE from RF, which was only -0.0017.



(a) Random Forest (RF)



(b) Support Vector Machine (SVM)

Figure 7: Scatter plots of actual and predicted PMV (a) Random Forest, (b) Support Vector Machine

Table 2: Performance comparison of SVM and RF models

Type	Random Forest (RF) Model	Support Vector Machine (SVM) Model
Mean Squared Error (MSE)	0.0212	0.0731
Mean Absolute Error (MAE)	0.1042	0.1181
Root Mean Squared Error (RMSE)	0.1457	0.2704
Mean Bias Error (MBE)	-0.0017	0.0616
R-squared (R^2)	0.9334	0.8067

5.2 Model Suitability: The RF is more suitable for the PMV prediction since it handles non-linear relationships with reliability and adaptability. It was easier to integrate into the dynamic control strategy of the modernized HVAC. Using an ML-driven approach, the building manager will be able to personalize the HVAC system to comply with occupant feedback on comfort expectations. To simplify the HVAC control, while MET can be assumed constant, CLO might be calculated using an empirical function between CLO and the indoor temperature (T_a) and relative humidity (RH) derived from the historical questionnaire data; therefore, direct input of CLO into the ML model would not be needed. In addition, real-time adjustments could be done by adding an RF model to the IoT controller.

6. PPD Prediction

The PPD was calculated by the PMV using the non-linear function from the standard ISO 7730 [8], [15], [16] as in equation (7). The RF model gave good agreement between the actual PPD and the predicted PPD, with an R-squared of about 0.9876, while that of SVM was 0.6882. This strengthens the ability of RF over SVM in handling the non-linear term PMV^4 , the tipping point of thermal dissatisfaction.

$$PPD = 100 - 95 \times \exp(-0.03353 \times PMV^4 - 0.2197 \times PMV^2) \quad (7)$$

In addition, the SVM depends on a geometric hyperplane that might struggle with this PMV^4 term; therefore, it has less resilience to this nonlinear term. This study focused on PMV prediction by an ML approach; however, PPD can be reported along with PMV to ensure whether the HVAC control can maintain the percentage of dissatisfied occupants below 10%.

7. Energy Strategies

The thermal comfort and energy strategy should be balanced. The findings for the case study academic library recommended the indoor temperature to be maintained within the narrow range 24.29–24.85°C. However, the cooling load caused by radiant surfaces could be reduced by simply adding solar films to the glass windows, since the peak T_{mrt} of about 29.31°C was addressed. The air velocity should be increased to enhance air circulation. This has the advantage of allowing a higher temperature setpoint with trade-off air velocity.

The ML algorithm could identify the discomfort thresholds before they occur [17], [18]. By introducing the RF model to the IoT controller of the HVAC system, the existing 10 AHUs could be managed in real time to enhance airflow modulation and minimize waste energy in those unoccupied zones.

8. Practical Implications and Limitations

The resulting RF model can be used to support thermal comfort prediction in academic libraries. The model could be practically integrated with an IoT-based HVAC control system having real-time measurement of T_a , RH, and V_a , while using constant MET due to the assumed sedentary activities of library occupants. However, CLO would be estimated using an empirical model from historical survey data.

This study has several limitations; the dataset was obtained from a single academic library in Bangkok that might not represent other building types or climates, and CLO values were obtained from questionnaires rather than automatic measurements. Therefore, future studies should include data collection from multiple buildings and estimate CLO using a practical method for real-time applications.

CONCLUSION

The research on machine learning model prediction for thermal comfort was conducted in a four-story academic library, gathering a dataset by field measurements and occupants' surveys by questionnaire. The PMV and PPD complied with the ASHRAE comfort criteria, although occupants felt slightly cooler than neutral. In comparison between two Machine Learning (ML) models trained by local data, Random Forrest (RF) and Support Vector Machine (SVM), the RF provided more accurate results for PMV and the corresponding PPD values. The research findings suggest that ML models developed by local data can complement the traditional PMV and enhance the modernized HVAC control strategy. Future work should explore the application of the proposed approach in other building types and climatic conditions.

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