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Personalised Thermal Comfort Model for Automatic Control of a Newly Developed Personalised Environmental Control System (PECS)

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Abstract. Personalised Environmental Control Systems (PECS) are devices that cater to the individual needs by providing micro-climate heating, cooling, and ventilation. However, to ensure comfort, energy savings, and productivity, a comfort model based automatic control is required. For its development, thermal preference, physiological information, and data on the surrounding indoor climate were gathered from 24 subjects when using a newly developed PECS with heating, cooling, and ventilation functions. Since PECS should ensure a high level of comfort while providing energy savings through background temperature relaxation, multiple steady-state ambient temperature settings ranging from 18 to 28 °C were tested. The data were clustered according to the subject's self-assessed general thermal preference, namely neutral, warmer, and colder. Machine learning was used to generate a cluster-based personalised comfort model using environmental, physiological, and behavioural indicators. The prediction performance of the models was 11 to 18 percent points higher than that of current group comfort models, predicted mean vote (PMV), which is independent of occupant similarities. The advantage of the personalised approach was the increased performance of the thermal comfort prediction at no expense of occupant sensitive information. Although reliant on estimates of physiological indicators, the models' performance may be increased using real-time data acquisition.

Keywords. Experiment, Automatic control, Personalised comfort model, Machine learning, Personal environmental control system.

1 Introduction

Personalised Environmental Control Systems (PECS) are devices that cater to the individual needs by providing heating, cooling, and ventilation to the micro-climate, i.e. the space near the occupant. Compared to total volume heating, ventilation, and air-conditioning systems, PECS can enhance comfort at low energy expense while being able to address interpersonal differences [1]–[3].

PECS implementation is - among others, e.g. lack of design criteria and operation guidelines [3] - challenged by the need of an automatic control to able to reduce the need for human interaction. As people are known to lose interest and have a delayed reaction to change in comfort [4], an automatic control is required to ensure comfort but also an operation that promotes energy savings, i.e. without a conflicting operation between PECS and the total-volume system. Moreover, in order to alleviate the need for occupant interaction, thus minimizing distraction and enhancing productivity, a comfort model is required to accurately predict thermal preference when PECS are installed.

High performing individual comfort models have already been analysed, however reliant on a period of data acquisition of physiological indicators before predictions can be made. Katić et al. [5] used support vector machine (SVM) and ensemble algorithms to predict individuals' thermal preference using the PECS's operation, skin temperatures, time, and environmental data reaching a median accuracy of 84%. By making use of random forest (RF), K-nearest Neighbors (KNN), and SVM algorithms, Aryal et al. [6] reached accuracies up to 90% for predicting thermal sensation with environmental, physiological, and PECS operation. Yu et al. [7] reached individual thermal sensation prediction accuracies of 75% to 84% with the KNN algorithm using environmental, physiological and occupant characteristics when the PECS was in use. Due to the on-site data acquisition dependency though, practical implementation of individual comfort models is yet to be performed [5]. Therefore, the objective of the study was to develop personalized comfort models

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using data from occupants with similar preferences, also known as Cohort Comfort Model (CCM) [8], thus eliminating the need for a training period before accurate predictions can be made.

2 Methods

In order to develop the comfort model for PECS automatic control, human subject experiments were conducted in a climate chamber to observe and analyse their interaction with a PECS. The experiments exposed human subjects to different steady-state indoor thermal conditions while recording their thermal response and environmental, physiological, and behavioural indicators. Two scenarios were investigated, one with and one without PECS, the latter allowing the subjects to make use of a desk-based PECS to adjust their local environment to their preference.

Since the goal was simplicity, data gathered from the subjects was clustered according to their self-assessed general thermal preference. During implementation, the same indicator would be used to assign the personalized comfort model to the occupant. In this way, no sensitive information would be required from the occupant during implementation. Since practicality was an additional requirement, the physiological indicators were acquired with consumer-grade sensors.

2.1 Personal environmental control system

The desk based PECS used was a multi-component unit comprised of a desktop and an under-desk unit [9]. The desktop unit had an air terminal device (ATD) intended to supply fresh air to the occupant's breathing zone.

The recirculated air could also be cooled, though having a limited cooling power. Two flexible heating panels arched around the lower body, i.e. oriented towards the shins and thighs, were attached to the under-desk unit.

2.2 Experimental campaign

Since the goal of PECS implementation is to ensure a high level of comfort while providing energy savings through background temperature relaxation, five steady-state room temperature conditions were generated in a climatic chamber, namely 18 °C, 20 °C, 23 °C, 26 °C, and 28 °C, to which 24 university students (equal male and female distribution) were exposed. Relative humidity was measured but not controlled during the exposure. During each session, a group of four subjects, each assigned to a desk, performed light office work and were asked to fill in questionnaires in order to record their thermal preference. Moreover, each subject's general thermal preference, i.e. neutral, warmer, or colder was recorded before the experimental campaign. For each room temperature setting, two scenarios were conducted per subject, with and without PECS, each lasting three hours. In the scenario with PECS, the subjects had full control over the system's heating, ventilation, and cooling functions. Heating and ventilation could be adjusted in intensity on a scale from 0 to 10 while cooling from 0 to 5, all with an increment of 1 where 0 represented OFF and 10 or 5 the maximum, respectively.

Subject clothing was controlled and adjusted according to the temperature condition. For room temperatures higher than or equal to 26 °C the subjects wore underwear, socks, pants, and a T-shirt, equivalent to a clothing value of 0.5 clo. For a neutral expectation, 23 °C, a shirt was added increasing the clothing value to 0.75. For room temperatures lower than or equal to 18 °C, the subjects wore also a sweater leading to a clothing value of 1 clo. The values included the office chair which accounted for a clothing insulation of 0.1 clo.

Each subject's thermal preference was recorded every ten minutes during the first hour, while once every twenty minutes for the rest of the session, leading to a maximum of 130 observations per subject. The thermal preference vote (TPV) was recorded using a scale ranging from warmer to cooler based on the ASHRAE 55 standard [10] and adjusted from the works of Jazizadeh et al. [11], [12] and Aguilera et al. [13]. It was implemented using a snapping slider, which could take values between warmer (+8), no change (0) and cooler (-8) with an increment of one. Only the minimum, middle, and maximum values were annotated while the tick values were not visible to the subjects.

Environmental, physiological, and behavioural indicators were recorded with a sixty-second or higher resolution. A description of the indicators, sensor placement, and detailed information on the experimental campaign can be found in Shinoda et al. [14].

2.3 Dataset

In order to generate a personalized comfort model according to the subject's self-assessed general thermal preference, namely neutral, warmer, and colder, the data from each subject was clustered according to the aforementioned categories. Fourteen, seven, and three subjects were assigned to each cluster, respectively. Each dataset consisted of instantaneous values of environmental, physiological, and behavioural indicators recorded concurrently with the TPV from both sessions, i.e. with and without the PECS. A binary variable was used to distinguish between the two sessions. After excluding any missing TPV values, 1734, 883, and 374 observations were obtained in the neutral, warmer, and colder clusters, respectively.

The distribution of each variable as a function of the general thermal preference is shown in Fig. 1. The environmental indicators present in each dataset were the operative temperature (T_{op}) and the relative humidity (RH) measured in the close vicinity of the occupant. The physiological indicators included were the heart rate (HR), the forehead skin temperature ($T_{sk,fhead}$), the wrist skin temperature ($T_{sk,wrist}$), and the wrist skin relative humidity ($RH_{sk,wrist}$). Except for the HR measurements, which were obtained using a chest band but complemented by a smartwatch to obtain a full set of observations, the rest of the physiological indicators did not present any missing values. Behavioural indicators

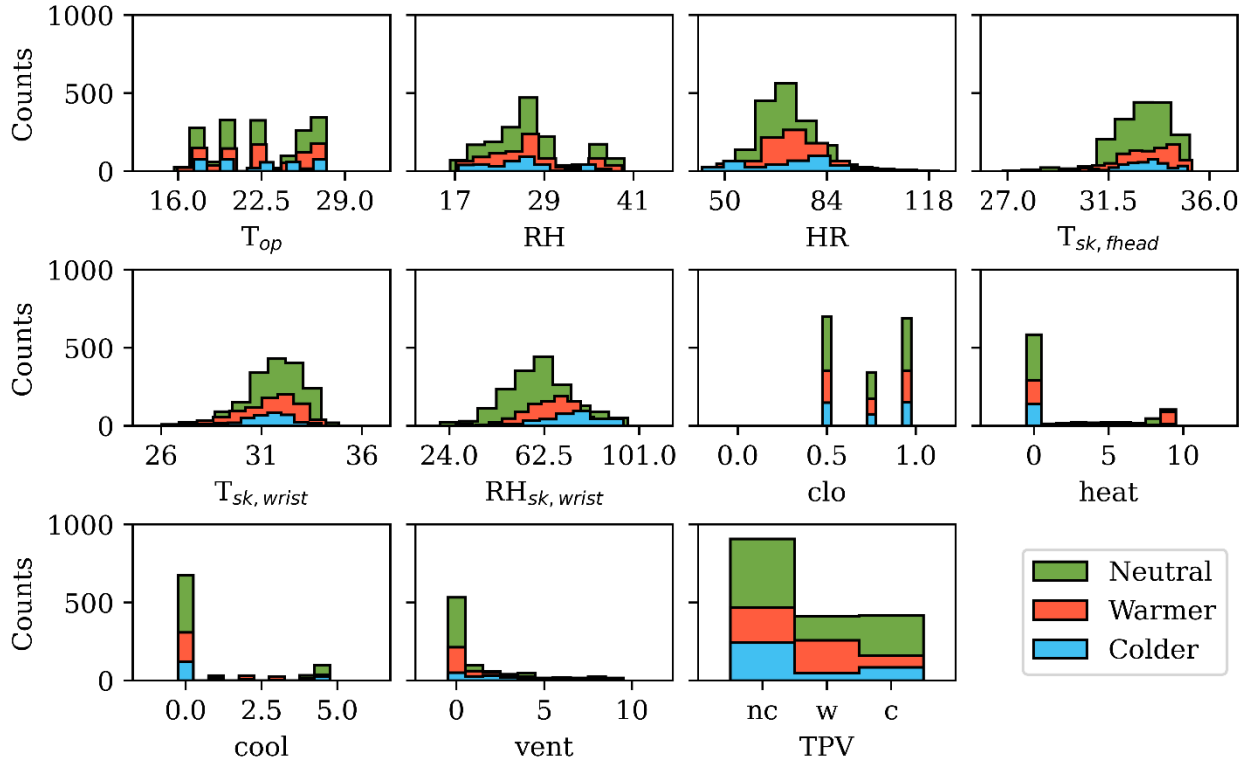

Fig. 1. Variable distribution across the three general thermal preference clusters, namely neutral, warmer, and colder. The input variables included in the dataset were the operative temperature (T_{op}), relative humidity (RH), heart rate (HR), forehead skin temperature ($T_{sk,fhead}$), wrist skin temperature ($T_{sk,wrist}$), wrist relative humidity (RH_{wrist}), clothing (clo), and the level of heating (heat), cooling (cool), and ventilation (vent) provided by the PECS. The distribution of the predicted variable, thermal preference vote (TPV), grouped into three categories, no change (nc), warmer (w), and colder (c) is also shown.

were comprised out of the clothing value (clo) and PECS operation, namely heating (heat), cooling (cool), or providing ventilation (vent). The predicted variable was the TPV, however distributed into three categories, i.e. no change (nc) for $|TPV| \leq 1$, warmer (w) for $TPV > 1$, and colder (c) for $TPV < -1$.

The variable distribution (Fig. 1) showed that more warmer than colder votes were obtained in the warmer cluster, while opposite for the colder cluster. The difference between the warmer and colder votes in the neutral cluster was however equal. The distribution of the environmental indicators showed that slight variations occurred in the micro-environment in terms of T_{op} and RH. The heating and cooling functions of the PECS were mostly set towards the highest setting when operating. However, the distribution of the ventilation signal was mostly oriented towards low speeds, i.e. in the lower half of the setting range. In terms of clothing behaviour, the total number of observations was equal for clo values of 0.5 and 1 but smaller for a clo value of 0.75 since the latter was only utilized for the 23 °C sessions. Physiological indicators such as the HR and $RH_{sk,wrist}$ were positively skewed, while the skin temperatures were negatively skewed. A pronounced difference in the distribution mode was visible for the HR and $RH_{sk,wrist}$ between the clusters.

2.4 Model training and testing

The objective was to predict thermal preference, i.e. warmer, no change, or colder, by using the environmental, physiological, and behavioural data. One model was developed for each self-assessed general thermal preference cluster, i.e. neutral, warmer, and colder.

The model training and testing was made on the entire dataset in Python version 3.8.5 using the scikit-learn module [15]. A nested K-fold cross validation (CV) was used where the training data of the outer CV was split in a train and test set for the inner CV. A K value equal to ten was used at each level. The data were shuffled before splitting it into the train and test sets. The percentage of samples for each class present in the dataset was preserved during the split at each level.

Five algorithms were selected, namely regularized Logistic Regression (rLogit), Naïve Bayes (NB), K-Nearest Neighbors (KNN), Random Forest (RF), and Support Vector Machine (SVM) [16], [17]. Each algorithm's hyper-parameters were optimized at the inner cross validation level, after selecting appropriate ranges through randomized grid searches. In the regularized Logit algorithm, an L2 (Euclidian) penalty was used while the regularization parameter, λ, was tuned. In the NB algorithm Laplace smoothing was included, with $\alpha > 0$. An L2 metric was selected in the KNN algorithm while the number of neighbors was optimized. For the RF, different number of decision tree estimators, tree depth, and maximum number of features were tested. In the SVM the radial basis function kernel was chosen as it can deal with non-linear relationships present between the thermal response and the

physiological indicators [18], while the regularization parameter, C, was optimized.

At both the inner and outer CV the F1-score was computed using the scikit-learn module in python [15]. The F1-score, used as the performance measure, represents the harmonic mean between recall and precision, providing an estimate of the model's ability at identifying each thermal preference while reducing the misclassification rate. The model with the lowest F1-score at the inner cross validation was selected. The macro-average value was used to assess model performance, as identifying each thermal preference was equally important.

At the outer level, the performance of the models was estimated by training and testing the optimized algorithm on the entire dataset. In order to take the randomness of the CV training sets into account and obtain generalizable estimates of the error, the outer CV was ran twice [16].

2.5 Comparison to other comfort models

The generated models were compared to the Predicted Mean Vote (PMV) and a baseline (Base). The Base predicted always the most frequent class in the training data at each fold [15]. The PMV was calculated using the pythermal library [19].

Although not a personalized thermal comfort model, the PMV was used for comparison since it represents a standardized comfort model currently used in the built environment [20]. This was done as a personalized comfort model should at least lead to a higher performance than a comfort model dedicated to estimate the mean thermal sensation of a group of people not necessarily sharing common characteristics. Since the PMV predicts thermal sensation, i.e. cold, neutral, warm, the output was adjusted to reflect preference. Thus, a $|PMV| \leq 0.5$ was considered as no change, $PMV < -0.5$ as warmer, and $PMV > 0.5$ as colder as described by Ghahramani et al. [21] and used by Kim et al. [22].

In order to assess and compare the generated models between themselves and to the PMV and Base models, a pairwise statistical t-test was used [16]. A significance level of 0.05 was chosen, but the results were adjusted by using the false discovery rate (FDR) with an α threshold of 0.05 [17].

3 Results

3.1 Model performance

Fig. 2 shows the results of the CV and the estimated performance of the models. No matter the general

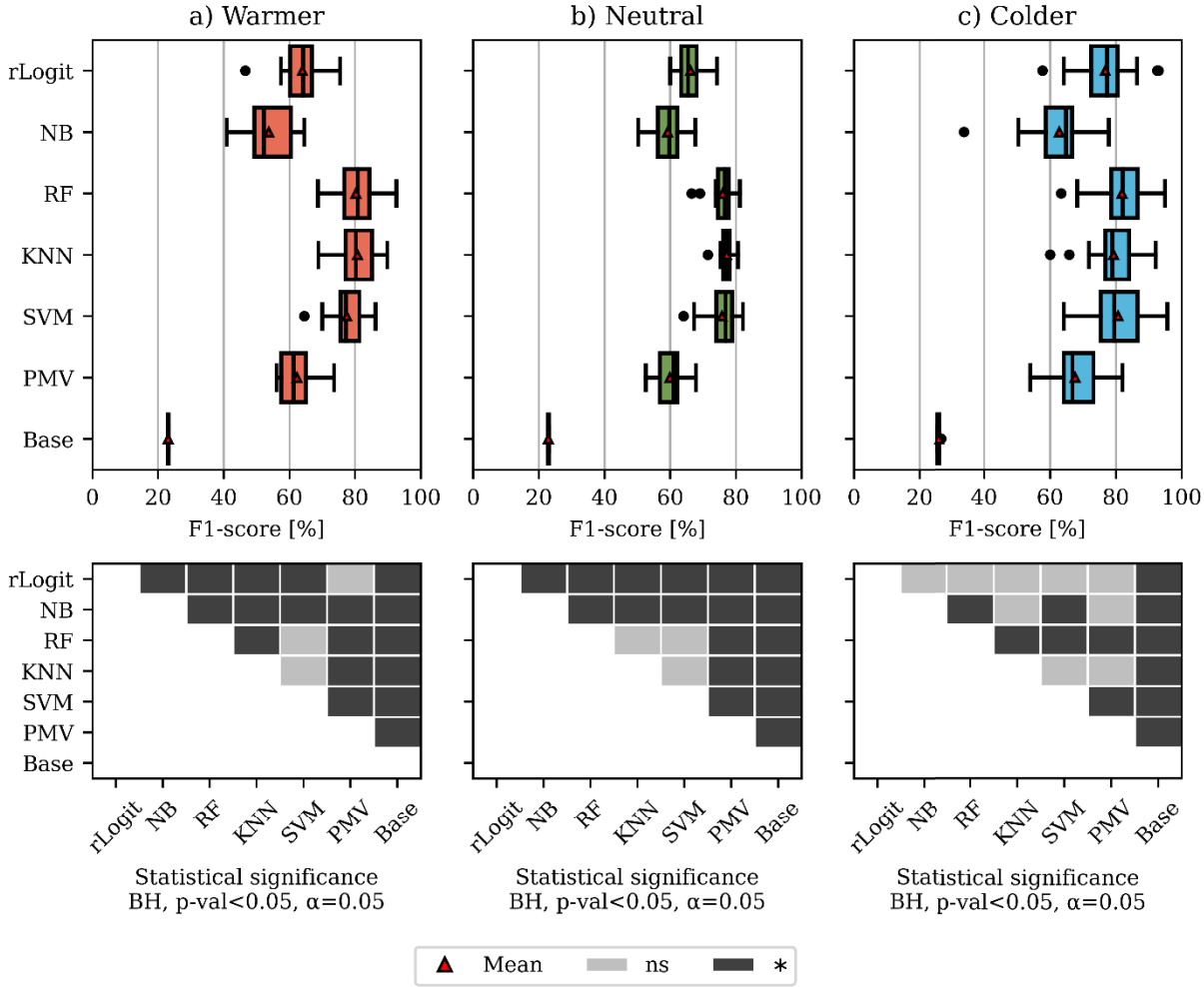

Fig. 2. Model performance and statistical significance resulting from the pairwise t-tests (p-val=0.05). A Benjamini-Hochberg (BH) p-value correction of α=0.05 was applied.

thermal preference cluster, i.e. warmer, neutral, or colder, all comfort models performed significantly better than the random guess (Base), reaching an F1-score up to 57 percent points higher.

For all clusters, the models developed with the RF, KNN, and SVM algorithms reached similar performance with F1-scores ranging between 76 and 83%. In the warmer and neutral clusters, these models showed a significantly higher performance than the ones using the rLogit and NB algorithms. No significant difference was observed between the rLogit based model and the rest of the models in the colder cluster. The worst overall performing model, based on the NB algorithm, performed however significantly worse than the RF and SVM based models even in the aforementioned cluster.

Compared to the PMV, the models using the RF, KNN, and SVM reached a performance 16 to 18 percent point higher for the warmer and neutral clusters. The difference reduced to only 11 to 16 percent point in the colder cluster. However, out of all the ML models, only the KNN and RF led to a significantly higher performance compared to the PMV independent of the cluster.

3.2 Feature importance (RF)

Fig. 3 shows the feature importance and the feature permutation importance for the RF based model. The former estimates the importance of each feature based on the mean decrease in impurity within each tree. The latter method is independent of the algorithm and measures the decrease in model performance if one feature value is randomly shuffled [15]. Aside from the environmental, physiological, and behavioural variables, two additional features are visible, PECS and REF, which represent the one-hot-encoded categorical feature indicating the two sessions.

Both the T_{op} and RH had similar importance across the clusters in the RF based model fit, shown by the feature importance graph. Although, affecting the model's performance as shown by the feature permutation importance, the two features impacted the model performance differently across clusters. The same effect was observed in the physiological features' case where permutation of skin temperatures had a higher effect on the performance in the neutral and warmer clusters and skin relative humidity had a higher effect on the colder cluster.

Clothing also presented a stronger effect in the warmer and neutral than colder clusters. The PECS's operation showed limited effect on the model's performance except for the cool function, which had an impact in the warmer and neutral clusters. Although not having a strong effect on the model fit, differentiating between the PECS and REF scenarios increased the prediction power.

4 Discussion

Machine learning was used to develop personalized comfort models as a possible control indicator for personalized environmental control systems (PECS). By making use of a non-sensitive indicator, namely the self-assessed general thermal preference, data obtained from a climate chamber experiment with 24 subjects was clustered in three categories, warmer, neutral, and colder, generating three personalized thermal comfort models. The approach was justified by the distribution of the thermal preference votes, which were skewed in the direction of the general thermal preference for each cluster. The subjective nature of people's self-assessment based on previous experience may lead to a

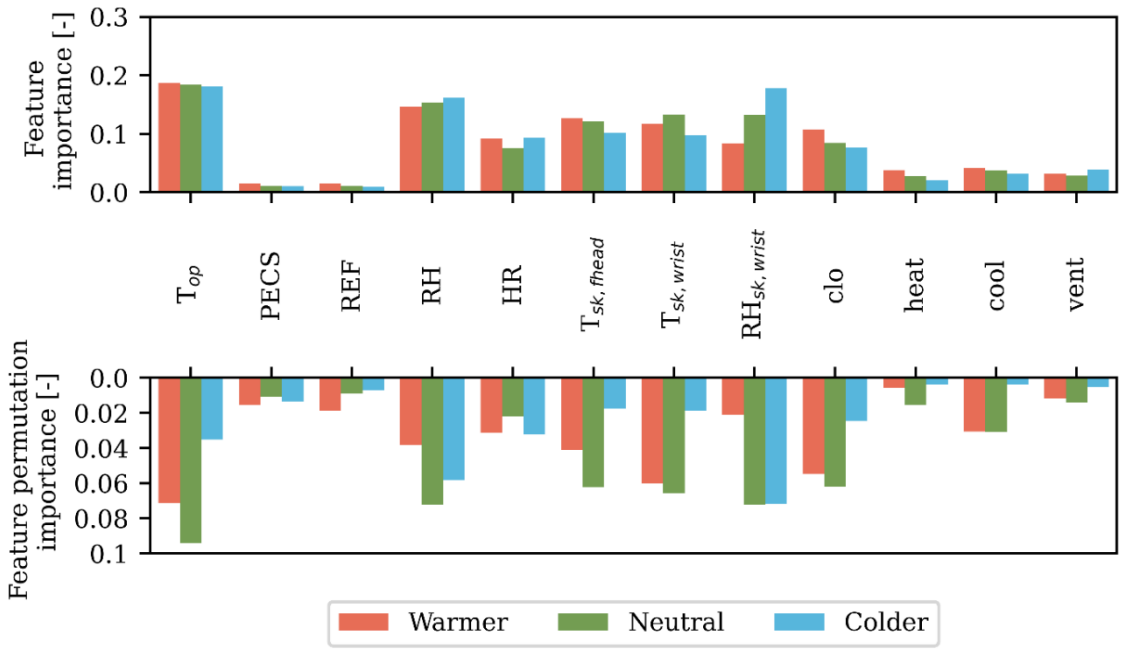

Fig. 3. Feature importance and feature permutation importance for the models generated with the Random Forest (RF) algorithm.

degree of uncertainty in the model development and cluster assignment. However, the availability of multiple models would allow the user to switch to a different general thermal preference if the initial setting is not satisfactory.

By comparing multiple ML algorithms it was determined that the Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) reached a similar performance but significantly higher than random guess and existing comfort models such as the PMV, however dependent on the general thermal preference. The three algorithms represented a better choice for modelling thermal comfort than regularized Logistic Regression (rLogit) and Naïve Bayes (NB) in accordance with the literature [22], [23]. As the rLogit represents a linear model while the NB assumes conditionally independent variables, properties not valid for thermal comfort prediction, the two algorithms were unable to accurately separate the three predicted classes [16], [17], [24], [25]. On the other hand the KNN algorithm attempts to find similarities in the data, which resembles people's reasoning when rating their thermal environment. SVM is robust to noise and able to handle high-dimensional data. The RF algorithm makes its prediction based on a collection of decision trees increasing the reliability of the overall estimate, though at a higher computational cost.

The differences in model performance between the ML models and the PMV are however, limited to the data available and the assumptions made. Although registering a lower performance, the PMV comfort model was developed on data gathered from a greater population. The limited population in the colder cluster and hence lower variability in thermal preference votes could have attributed to the smaller difference between the PMV and the ML models. Thus, additional data must be collected while obtaining an equal distribution across clusters. Although metabolic rate was assumed constant and equal to 1.2 met, clothing data were included in the PMV calculation increasing the model's prediction. The PMV conversion to TPV, i.e. using ±0.5 as the limit between warmer, no change, and colder categories as explained in chapter 2.5, benefitted the prediction. This limit led to a narrower range for the neutral or no change classes than limits used in other studies ±1 [7] or ±1.5 [8]. Thus, a finer distinction could be made between neutral and colder/warmer classes. As the TPV was not assessed in the experiments on which the PMV was generated [26], these limits require further assessment.

According to the literature [25], [27], [28] using the operation of the PECS as model features could improve prediction. However, the feature importance analysis on the RF algorithm results showed that the distinction between the two scenarios, PECS and REF, and the PECS operation (heat, cool, vent) were of little relevance to the personal comfort model. This may have been partly due to the limited cooling effect of the analysed PECS on thermal comfort as shown in previous studies [9], [14] and of the clothing profile which varied according to the indoor temperature. Environmental and physiological indicators were of higher importance to the model, with differences between clusters, which could be attributed to the presence of inter-personal differences. The relative importance of indicators such as Top, RH, $T_{sk,fhead}$, $T_{sk,wrist}$, and $RH_{sk,wrist}$ may however not be representative as the indicators are highly correlated.

Although further investigation on the input data and validation is required, the advantage of the personalized approach in the model development is the increased performance of the thermal comfort prediction at no expense of sensitive information from the occupant, such as occupant characteristics, or intrusive sensors for measuring physiological indicators. This type of model represents one possible baseline control for PECS, with its prediction power subject to available estimates of the physiological indicators. The performance may however be improved by integrating real-time measurements of subjective responses and physiological and behavioural indicators. Additional personalization according to other occupant characteristics such as age or body mass index (BMI) may further improve performance however at the expense of using sensitive information.

5 Conclusion

By integrating self-assessed general thermal preference, machine learning (ML) based personalized comfort models can be obtained, able to reach higher prediction performance than the PMV. Thus, it is envisioned that for a lower level performance, estimates of physiological and behavioural indicators would be used, while for an increased performance, future occupants would be required to wear sensors, e.g. smartwatches, for real-time data acquisition and model adjustment. This may enable the development of potent automatic control algorithms for PECS without the need of sensitive or real-time information.

A significantly higher performance was obtained with ML algorithms able to deal with non-linearity and dependent variables, i.e. RF, KNN, SVM. Environmental and physiological indicators had similar predictive power for the model fit. Although the PECS operation is relevant for thermal comfort prediction, clothing had a higher importance and its estimation may be especially relevant for improving comfort model performance.

Acknowledgements

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