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Personalised Building Controls Based on Individual Thermal Preferences for Energy Efficiency and Thermal Comfort

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Abstract. It is a challenge for traditional building control systems to meet occupants' needs in shared spaces due to the lack of understanding of individual occupant thermal preferences. This is a barrier to balancing energy efficiency and indoor environmental quality (IEQ). Advanced statistical learning methods offer new solutions towards more energy-efficient and user-centric control logics. In this work, a control logic is proposed to optimise the heating, ventilation and air conditioning (HVAC) operation based on thermal comfort archetype preferences, leveraging the ASHRAE Global Thermal Comfort Database II in conjunction with energy simulations. First, we apply the k-means clustering algorithm to categorize occupants into different archetypes regarding their common feedback on the thermal environment. Then, we fit a Bayesian logistic regression model to predict the thermal comfort preferences of different archetypes based on IEQ data. Finally, we identify two occupant-centric control logics to optimize HVAC operation to meet occupants' requirements: (i) considering a unified response of thermal comfort in the space, and (ii) ensuring the dynamic optimal setpoint when conflicting occupant archetypes are present. Having compared this control logic with a common rule-based logic, our results demonstrate the potential of occupant-centric controls and the importance of multi-objective metrics in accounting for energy efficiency.

Keywords: Thermal Comfort · Occupant Archetypes · Optimization · Building Controls · Building Energy Performance

1 Introduction

In recent years, Building Automation and Control Systems (BACS) have been recognized as valuable tools for reducing energy consumption in buildings [1]. While several categories, such as heating, cooling, lighting, and blind control, are traditionally considered in BACS energy performance, occupant behaviour impacts are not sufficiently described [1]. A few papers have shown that occupant behaviour has an impact on building energy consumption, thus to achieve energy efficiency is key to consider occupant behaviour when designing building controls [2].

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Occupant-centric controls offer a promising approach to address this gap by placing occupants' needs for indoor environments at the center of understanding how energy performance, indoor environmental quality (IEQ), and comfort are interrelated [3]. Along with it, personal comfort models have shown promise to improve comfort and energy efficiency in building controls, leveraging predictive power on subjective comfort preferences over other generalist comfort models, such as Predictive Mean Vote (PMV) [4]. However, BACS based on personal comfort models face two main challenges in shared spaces: (i) inferring the personal preferences in a realistic manner from the IEQ conditions and integrating them with the control logic [4], because of the limited capacity of actual building controls to consider comfort in a personal and subjective manner, and (ii) negotiating between competing occupant preferences in the same space [4].

To address the first challenge, previous work has tried to include thermal preference responses. However, those models include thermal preferences in a deterministic manner as votes or requests to the control logic [5, 6], overlooking the dynamic and probabilistic impact of the IEQ on the thermal preference of the occupant. Models that capture uncertainty, such as Bayesian models, are conceptually closer to the reality of human comfort perception, therefore allowing better inference of thermal preferences [7–9]. On the other hand, numerous existing operational strategies have failed to accommodate occupants' dynamic needs, due to the lack of optimization algorithms that are able to address competing thermal preferences among occupants in a shared space [10].

In this work, we focus on assessing the potential of personalized comfort models in dynamic building controls. Specifically, we discuss the use of Bayesian models for thermal comfort models based on historical data. Also, optimization tools are used to find suitable IEQ when competing occupant archetypes are present in shared spaces. In addition, the impact on the building energy consumption is assessed.

2 Methodology

Firstly, occupant archetypes based on thermal preferences are developed by clustering thermal preference responses. Secondly, each of these archetypes is associated with a Bayesian thermal comfort model that predicts the preferred indoor temperature based on subjective occupant feedback and indoor thermal data. Then, the Bayesian models are utilized to inform HVAC setpoint control logic, according to two scenarios: (i) tailoring all thermal preference responses as a constant unified response of thermal comfort in the space, and (ii) dynamically responding to the presence of different occupant archetypes' following a random occupancy schedule. These two scenarios are then evaluated and compared in terms of overall user comfort and energy consumption against a rule-based scenario that is only programmed to optimise energy efficiency, maintaining setpoints at 19 °C in winter and 24 °C in summer.

2.1 Occupant Archetypes and Bayesian Thermal Comfort Model

We used the ASHRAE Global Thermal Comfort Database II [11] to create the occupant archetypes, and to train a Bayesian thermal comfort model based on thermal data and subjective occupant data reported. A sub-dataset with 4,065 measurements was selected for this study [12], based on the following criteria: office building type located in Europe; temperate oceanic climate; indoor environmental quality measurements; occupant behaviour and subjective thermal preference responses (-1: "prefer cooler", 0: "prefer no change" or $+1$: "prefer warmer").

To create occupant archetypes, only information from respondents ("subject ID") with more than three thermal preference responses during the experiment was considered. We created different occupant archetypes using the K-means algorithm [14] based on the mean of their thermal preference responses and the season of the experiment. The efficacy of the clustering methodology was assessed by evaluating the Silhouette scores to determine the optimal number of clusters (k). A Silhouette score exceeding 0.5 indicated strong clustering performance. The Kruskal-Wallis test, a non-parametric test for comparing more than two clusters, was conducted to examine differences between clusters.

In order to infer occupant thermal preferences during the simulation, we developed a Bayesian thermal comfort model for every occupant archetype. A probabilistic model is learned based on Bayesian Multinomial Logistic Regression that uses the SoftMax function [9, 13]. This function describes the probability of belonging to one of three classes, K: "prefer cooler," "prefer no change," or "prefer warmer", based on input features, x, i.e., the indoor air temperature (iat), indoor relative humidity (rh), clothing level (clo), metabolic rate (met), and season (winter/summer). In this model, w is a vector of weights, b represents the intercept value, i is a training example, L is the observation, and M is the number of features:

$$P(y = k|z^{(i)}) = \frac{e^{Z^{(i)}}}{\sum_{k=0}^{K} e^{Z_K^{(i)}}}, z = b + \sum\nolimits_{L=0}^{M} w_L x_L \tag{1}$$

We trained the model using the PyMC library in Python [14], a probabilistic programming library to build Bayesian models. A distinct Bayesian model was fitted on the 70% of the chosen ASHRAE database for each archetype. The training generated 2,000 samples with a 0.95 acceptance rate and estimated the posterior distributions through 2,000 Markov chain Monte Carlo (MCMC) iterations. Subsequently, we analysed the highest density intervals (HDI) to identify the best predictors for thermal preferences. The remaining 30% of the dataset was used for model testing, with the Area Under the Curve (AUC) and accuracy metrics computed to assess model performance.

2.2 Occupant-Centric Control Logic

We use EnergyPlus version 22.2.0 to model a single-zone office of 48 m^2 in Amsterdam (The Netherlands), using a typical meteorological year (TMY) weather data. We run the simulations during winter (December, January, and February) and summer (June to August), with four timesteps per hour. The heating and cooling systems were modelled as an Ideal Loads Air System. For the simulations, a fixed occupancy schedule is considered from 8:00 to 18:00 with a distribution of three occupants, whereas the rest of the time, the building is unoccupied. To emulate the realistic thermal comfort pattern of an office building, we randomly assigned occupants their respective occupant archetypes. We applied an advanced occupant-centric control logic throughout the Energy Management System (EMS) module with the EnergyPlus Python API.

During the simulation, we inferred the thermal preference of the occupant archetypes by using the related Bayesian thermal comfort model at each timestep. For the inference, indoor air temperature and relative humidity are retrieved from the EnergyPlus simulation outputs, while keeping the other features constant with the mean values of the dataset, i.e., metabolic rate of 1.25, clothing of 0.93 for winter and 0.62 for summer; and season value of 0 for winter, and 1 for summer. With the Bayesian model, thermal comfort is defined by the probability of the "no change" class for every occupant archetype due to the specific features set. Therefore, the maximum probability of thermal comfort can be achieved by changing the indoor temperature to increase the probability of the "no change" class. The comfort reward (2), for the occupant-centric control logic, represents the normalized probability of thermal comfort, expressed as a percentage of the maximum thermal comfort achievable by adjusting indoor air temperature.

$$R_{comfort}(z^{(i)}) = \left(1 - \frac{maxP(y = \text{"}no\ change'') - P\left(y = \text{"}no\ change''\middle|z^{(i)}\right)}{maxP(y = \text{"}no\ change'')}\right) * 100 \tag{2}$$

The occupant-centric control logic (Fig. 1) dynamically adjusts the HVAC setpoint during the simulation with a proportional controller based on the optimal air temperature. A gradient-based optimization algorithm (L-BFGS) is used due to its flexibility and convergence speed [15]. The algorithm optimization decision is based on the indoor air temperature, and the other predictors (rh, clo, met, and season) are considered constraints. For the unified response, the algorithm optimizes Eq. (2) for the overall thermal comfort, without considering occupancy patterns, to identify the peak of the "no change" class on the three occupants' unified Bayesian thermal comfort models. And, for the dynamic response, the algorithm optimizes Eq. (2) for every archetype, determining the optimal air temperature when different competing occupant archetypes are present in the space. However, if desired, we could give preference to a particular occupant archetype to shift the optimal air temperature.

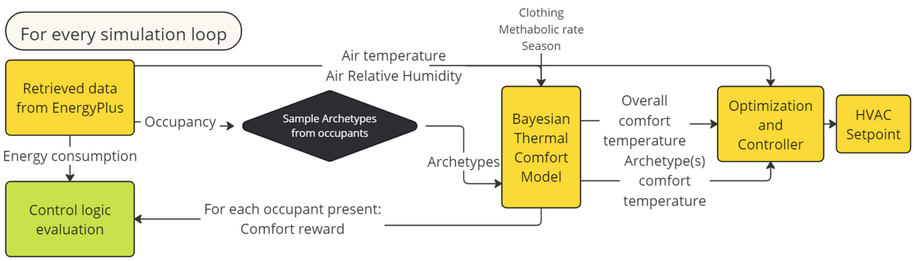

Fig. 1. Flow diagram for occupant-centric control logic.

3 Results

3.1 Occupant Archetypes Based on Individual Thermal Preferences

Analyzing 230 occupants in several possible clusters, we obtain the following best Silhouette scores: 0.58 in three clusters, among 10 possible clusters tested. We, therefore, continue the analysis with three clusters (archetypes), with 4,065 thermal preference responses: *Frost Followers* (mean = −0.50, n = 1,016), *Neutrals* (mean = +0.01 n = 2,184), and *Heat Huggers* (mean = +0.46, n = 865) after analysing the descriptive, and statistical ($p < .001$) differences. For every occupant archetype (Fig. 2), we fit a Bayesian multinomial logistic regression model. The HDI results find air temperature to be the most significant predictor for all occupant archetypes, in contrast to the metabolic rate and season (summer or winter). The prediction accuracy and AUC results were 0.65 and 0.7, respectively.

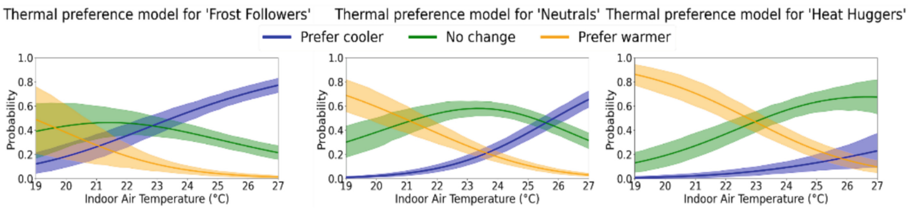

Fig. 2. Thermal preference posteriors for **a**. *Frost Followers* **b.** *Neutrals.* **c.** *Heat Huggers.* In relation to indoor air temperature, with other features considered at mean values. Blue, green, and orange areas represent the mean and standard deviation of the probability of being in one of those three classes, preferring cooler, no change, or warmer, respectively.

3.2 Thermal Comfort and Energy Performance of Occupant-Centric Controls

When operating with a unified response (Fig. 3), the occupant-centric control logic does not respond to the occupancy patterns of the three occupants. However, it is able to provide a mean comfort reward of 76% because it considers the occupants' unified thermal responses. Only when the *Frost Followers* are present do we achieve a comfort reward of almost 100%, meaning that the overall thermal comfort responses are closer to that occupant archetype. On the other hand, the dynamic response (Fig. 4) offers a higher mean comfort reward (82%) and better responds to single occupancies by getting a comfort reward of 100% when only one occupant archetype is present. We see how the dynamic response logic seeks an optimal setpoint when several occupant archetypes are present in the space, therefore, obtaining a higher comfort reward than the unified response one.

We obtained occupancy patterns for the three occupant archetypes between 43% and 47% of the occupied time in every simulation. For winter (Table 1), the occupant-centric control logic provided 7% more thermal comfort time when optimizing for dynamic response compared to the unified one. However, it consumed 5% more energy because

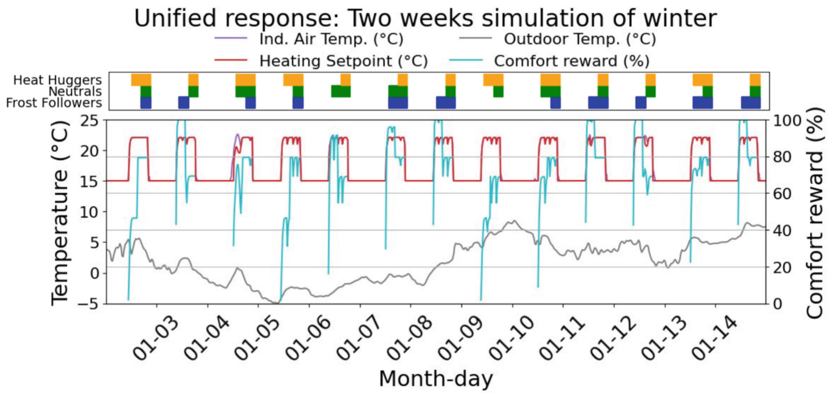

Fig. 3. Two-week simulation for occupant-centric control logic: Unified response. The plot presents how the heating setpoint changes air temperature, and the comfort reward shows the (miss)alignment between the occupant archetype (top figure, blanks mean unoccupied) thermal preference and the air temperature. The climb of the comfort reward at the beginning of the occupied time is due to the delay in heating the space from 15 °C.

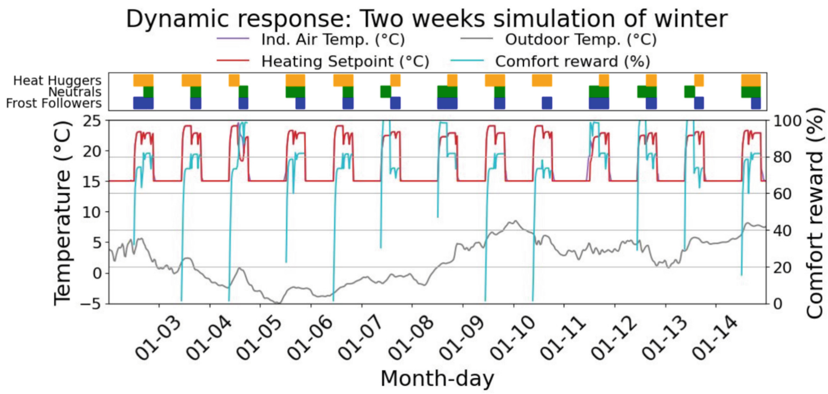

Fig. 4. Two-week simulation for occupant-centric control logic: Dynamic response. The caption can be explained with the previous figure (Fig. 3).

the overall setpoint required was 0.5 °C lower in unified response. The energy-efficient scenario of 19 °C offered 34% less energy consumption, compromising comfort 45% of the time, compared to optimizing for dynamic response. For summer (Table 1), the occupant-centric control logic provided more comfort and energy efficiency when optimizing for dynamic response than unified control. The scenario of 24 °C was 4% of the time behind in terms of thermal comfort, and 13% more energy-efficient compared to the occupant-centric control logic for dynamic response. Overall, when optimizing for dynamic response in comparison to a unified one, we obtained 7% more thermal comfort and 2% more energy consumption.

Table 1. The results of the occupant-centric control logic compared to the baseline.

	Winter			Summer		
	Fix Setpoint 19 °C	Occupant-centric control logic		Fix Setpoint 24 °C	Occupant-centric control logic	
		Unified response	Dynamic response		Unified response	Dynamic response
Mean comfort reward (%)	45	76	82	78	76	82
*Energy consumption (kWh)**	1.01	1.46	1.53	0.42	0.51	0.48

* mean energy consumption per occupied hour

4 Conclusions

In this study, we proposed an occupant-centric control logic in a simulated environment with three occupants. We aligned those occupants with their respective occupant archetypes obtained from clustering thermal preference responses from the ASHRAE dataset. The proposed Bayesian thermal comfort model effectively considers feedback responses from users. Although this model can capture the uncertainty of thermal comfort, the accuracy results should be improved by including other predictors. Future work should explore dynamic Bayesian models to update the comfort model in real-time based on temporal feedback on thermal preferences. When applying this approach in a real building, it is important to analyze the relevance of developing occupant archetypes that aggregate a shared group of individuals versus personal comfort models.

The occupant-centric control logic shows the potential of using personal comfort models in building controls to improve overall thermal comfort in shared spaces. By tailoring the setpoints to occupants, thermal comfort significantly improves while maintaining nearly the same level of energy consumption. To effectively implement personal comfort models in building controls, it is crucial to learn and predict occupants' preferences. Further research should explore more advanced optimization algorithms to better address the trade-off of comfort and energy consumption when considering personal comfort models. Multi-objective optimization algorithms have proven their capability to do so. Nonetheless, this framework proposes a valuable baseline for the realistic inclusion of individual thermal preferences in shared spaces on dynamic building controls.

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