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Thermal adaptation in occupant-driven HVAC control

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Abstract. Personal Comfort Models (PCM) build on state-of-the-art methods to predict individuals' thermal comfort responses based on occupant input and indoor environment measurements. Such models use machine learning and internet of things (IoT) to learn personal comfort requirements and integrate them into control systems for indoor environments. However, it is a challenging task to have consistent feedback from individuals, which is normally obtained from thermal comfort surveys. In this study, a PCM approach was tested, where the effects of thermal adaptation on occupants' thermal responses were analysed. Nine occupants participated during a three-week field study. Thermal preferences were learned by a framework grounded on fuzzy logic used to calculate a set point implemented in the HVAC control system of an open-plan office. The results show that only 29% of the occupants' thermal comfort improved and decreased on 71% of them, when implementing the user-driven control strategy. The performance of the demand-driven control strategy was mainly influenced by insufficient and poorly distributed data, as well as the effect of thermal expectations on occupants' thermal responses. These were affected by the better opportunities of behavioural adjustment offered by the participatory sensing approach as well as of their experience with the prevailing outdoor environment. The findings indicate that implementing demand-driven control grounded on user feedback should consider constant data renovation, accurate measurements of local indoor climate and occupants' thermal expectation.

Keywords: personal thermal comfort, adaptive thermal model, HVAC control, thermal comfort, participatory sensing, smart buildings

1 Introduction

HVAC (Heating, Ventilation, and Air Conditioning) systems focus on providing adequate thermal comfort and air quality. They also account for around 50% of the primary energy consumption in buildings [1]. There are two widespread thermal comfort models that define the criteria for HVAC system design and operation: the Predicted Mean Vote (PMV) and the Adaptive Model of thermal comfort. The PMV was

developed by P.O. Fanger based on a body heat balance and comprehensive studies under controlled conditions in climate chambers [2]. This model predicts the overall thermal sensation of a group of people, i.e., how people perceive their thermal environment, based on personal (clothing insulation, metabolic rate) and environmental (air velocity, mean radiant temperature, air temperature and air humidity) parameters. This model assumes that humans are passive recipients of thermal stimuli. On the other hand, the adaptive thermal comfort approach is based on the statement that people actively react in ways, which tend to restore their thermal comfort [5,6]. Adaptation occurs when there is a gradual diminution of humans' thermal responses due to repeated environmental stimulation. According to Fanger and Toftum [7], the expectation of the occupants depends on the duration of their thermal stimulation. When occupants are exposed to a warm environment for a long period, their neutrality differs from occupants who are used to a tight temperature control in an air conditioned building, which is caused by an adaptation process. There are two adaptive models included in thermal comfort standards: the EN 15251 adaptive model by Nicol and Humphreys [5] and the ASHRAE 55 model by de Dear and Brager [6]. Resulting from a number of field studies performed in different climate zones, these models provide a linear regression of acceptable indoor operative temperatures as a function of outdoor temperatures. The adaptive models are able to predict occupants' thermal sensations in naturally ventilated buildings, where occupants can adjust their clothing level and operate windows.

The PMV and the adaptive models show rather poor performance when predicting individuals' comfort responses [8]; they are not able to re-learn from new data, since they are based on fixed datasets; and the PMV model uses parameters that are difficult to determine in real applications (e.g., clothing insulation, activity level) [9]. New approaches to model thermal comfort have gained attention during the last decades, taking advantage of modern data-driven technologies such as machine learning and Internet of Things (IoT). The so-called Personal Comfort Models (PCM) is a data-driven approach to develop models that predict individuals' personal comfort responses [9-22]. Such models are developed as a combination of feedback from occupants (e.g., thermal sensation, thermal preference votes) and measured data (e.g., physiological parameters, indoor environment parameters, HVAC equipment measurements). By using algorithms based on machine learning, PCM are able to adjust when new input data is introduced and different learning methods to process the data can be tested. This flexibility offers the possibility to develop a new model when the working conditions of occupants change or their behavior varies. However, the performance of PCM depends on the quality and quantity of data provided by occupants. Low survey participation limits the number of input data provided to the learning algorithms, reducing their ability to make accurate predictions [9,10]. Understanding factors that influence occupants' feedback in PCM is crucial for optimizing their performance. In particular, no studies have analyzed the impacts of thermal adaptation in participatory sensing assessments used for PCM. This study evaluates the effects of thermal adaptation on occupant feedback when this was used as input to control HVAC systems. Thermal preferences obtained from an internet-based survey and indoor air temperature measurements were used to calculate a set point, which was

tested in an open-plan office. The aims of the assessment were the following: learn occupants' thermal preferences using machine learning, create a descriptive representation of personal thermal discomfort, calculate a demand-driven set point to control a HVAC system, and determine the influence of thermal adaptation on occupants' thermal responses obtained through participatory sensing.

2 Related work

Some of the first applications of thermal comfort in optimization algorithms employed the PMV index [11-13]. Those studies used a multi-valued fuzzy logic to classify thermal sensation or thermal preference votes into categories given by the PMV model. Stauffer et al. [14] developed a Model Predictive Control (MPC) method based on the PMV model, indoor climate measurements and weather forecast. Their system reduced the energy costs by around 20% while maintaining indoor air temperatures within comfortable values. However, the approach relied on the PMV input parameters, some of which are often difficult to estimate in real applications. Other studies focused on implementing machine learning to predict individual thermal responses. The degree to which the result of an approach is correct when predicting personal thermal responses is described as the predicting accuracy. Bayesian Networks (BN) were used by Ghahramani et al. to predict thermal preferences [15]. A 70% accuracy was obtained when applying that approach in a field study. Auffenberg et al. [16] also used BN to predict thermal sensation and found a 17.5% to 23.5% higher accuracy than the PMV and Adaptive models. Liu et al. [17] predicted thermal sensation votes using Artificial Neural Networks (ANN). This framework resulted in 80% accuracy when applied in a field study.

Data acquisition through surveys is crucial in terms of providing sufficient information to nourish learning algorithms. To bypass the hassle of repeated surveys, several studies aimed to find correlations between occupants' behaviour and thermal comfort. Kim et al. [10] used control behaviour based on Personal Comfort Systems (PCS) as input to several machine learning techniques. On average, their results showed 73% accuracy compared to the 51% accuracy obtained from the PMV and Adaptive models, when predicting personal thermal preferences. Luo et al. [18] tested the efficacy of PCS when providing personal thermal comfort conditions in climate chambers. They found that 80% of the occupants accepted the environment conditions provided by PCS.

Some studies attempted to predict personal thermal comfort by using data from physiological measurements to avoid obtaining behavioural responses from occupants. Choi et al. [19] researched the potential use of skin temperature to predict thermal sensation. The data were recorded from wearable devices tested in climate chambers and their results revealed 94% prediction accuracy. Liu et al. [20] used different physiological signals such as heart rate and skin temperature to predict personal thermal preferences. Their method used a decision tree algorithm, which achieved a mean accuracy of 75% in a field study.

Some studies have attempted to implement PCM to control HVAC systems in field research. Daum et al. [21] developed personalized comfort profiles using logistic regression techniques applied to thermal

feedback from occupants. This approach was used to complement the control system of shading devices in a field study. Two related studies [22,23] used fuzzy logic to calculate demand-driven set points based on personal thermal preferences. Their framework was integrated into the HVAC control loop of single and shared offices. In the first study, thermal comfort improved for 80% of the occupants and the daily average airflow required in the ventilation system was reduced by 39% [22]. In the second study, an additional 12% reduction in the daily average airflow was achieved, compared to the previous study, maintaining thermal comfort levels [23]. However, the sparsity of studies indicate that the application of PCM in HVAC control loops is still a developing field.

3 Methodology

The framework presented in this paper was based on the findings of Ghahramani et al. [23], who developed a PCM method and executed field experiments to test its performance. Their approach focused on machine learning to combine thermal preference votes with indoor air temperature measurements (T_a) to determine a demand-driven set point for HVAC control. Their method was able to adjust continuously the set point fed into a Building Management System (BMS), based on occupants' thermal preferences and airflow measured in the ventilation system.

This paper presents a different framework focused only on thermal comfort, where a single demand-driven set point was implemented in an open-plan office. During the first two weeks of assessment, occupants' thermal preferences and T_a measurements were employed to calculate a demand-driven set point. Then, the calculated set point was tested in the third week of the experiment. The outcome of the framework was evaluated based on the variation of the thermal preference responses along the assessment period.

3.1. Participatory sensing assessment

Occupants' feedback was obtained through an individual survey composed of a simple and precise question: "How would you prefer the temperature in the room?" People who participated in the survey were asked to state the answer of that question on a snapping scale (Fig.1-a), which was developed based on the findings from Jazizadeh et al. [24]. The numerical outcome of the survey was named Thermal Preference Value (TPV), which could take integer values between 0 and 18. Occupants were able to answer: "much colder" (TPV=0), Much warmer (TPV=18), No change (TPV=9) or any integer value in between. Once a vote was submitted, a participant was presented to a pie-chart with the distribution of that day's votes in the office (Fig. 1-b). The simplicity of the survey intended to maintain occupants' participation throughout the evaluation period. The participants were requested to vote as many times as possible per day, without providing more than one vote within a time-span of 15 minutes. This requirement aimed to avoid persistent participants expecting to get a rapid change of their thermal environment. However, all votes were considered in the final assessment, regardless the period between them.

Figure 1. Survey implemented in the field experiment.

3.2. User-driven HVAC control

User-driven HVAC control (UD-HVAC) is a framework that calculates an air temperature set point based on occupants' thermal preferences. The method focuses on thermal comfort optimization grounded on a fuzzy predictive model. Thermal preferences were used to create individual representations of thermal discomfort, which were then applied to calculate a single set point for the entire office. The process to obtain the set point is shown in Fig. 2.

Figure 2. Procedure to calculate the demand-driven set point.

In (Fig. 2-I), TPV and T_a measurements were recorded for two weeks. Both parameters were combined in (Fig. 2-II) to create thermal preference profiles (TP-profile) for each participant (Fig. 3-a). Fuzzy logic was used in (Fig. 2-III) to categorize occupants' thermal preferences, based on the Wang-Mendel method [25]. Each data point i , defined as $(TPV_i, T_{a,i})$, was classified into thermal preference categories, corresponding to fuzzy sets F_p , where $p=1, \dots, 7$. The categories considered were MW=much warmer; W=warmer; SW=slightly warmer; NC=no change; SC=slightly colder; C=colder; and MC=much colder. The more a data point belonged to a category, the higher its membership degree. The mapping curve that defined the membership degree of a data set corresponded to a membership function. Triangular membership functions with the form $\mu(TPV_i)$ were taken into account. Such membership functions show how much a TPV belongs to a specific thermal preference category or fuzzy set. Fig. 3-a, shows an example of a TP-profile where each TPV is classified into triangular fuzzy sets, represented in Fig. 3-b. For instance, a TPV of 9 has a membership degree of $\mu_4(TPV=9)=1$ in the NC fuzzy set. Accordingly, a TPV of 4 belongs to the fuzzy sets C and SC, with the corresponding membership degrees of $\mu_2(TPV=4)=0.3$ and $\mu_3(TPV=4)=0.7$.

Figure 3. Use of a thermal preference profile (a) to generate fuzzy sets based on TPV (b). MW=much warmer; W=warmer; SW=slightly warmer; NC=no change; SC=slightly colder; C=colder; and MC=much colder.

Each data point $(TPV_i, T_{a,i})$ was used to generate a logical rule. The membership degree of a data point in a fuzzy set F_p was defined as $\mu_{F_p}(TPV_i)$. The maximum degree of membership a data point could have in a fuzzy set was $\mu_{F_p^*}(TPV_i) \geq \mu_{F_p}(TPV_i)$ for all seven categories. An IF-THEN rule was created for all q data points and grouped in p clusters sharing the same IF part, as follows:

$$\text{If } TPV_i \text{ is in } F_p^*, \text{ then } T_a \text{ is centred at } T_{a,i} \quad (1)$$

The importance of a rule was given by a weight factor w , which corresponded to the maximum membership degree in the TPV fuzzy set, previously set as $\mu_{F_p^*}(TPV_i)$. To create temperature fuzzy sets T_p , the rules that share the same IF part were combined based on the following:

$$\text{If } TPV_i \text{ is in } F_p, \text{ then } T_a \text{ is in } T_p \quad (2)$$

Finally, the centre of each temperature fuzzy set $T_{p,av}$ was calculated according to Eq.3.

$$T_{p,av} = \frac{\sum_{i=1}^q T_{a,i} \cdot w_i}{\sum_{i=1}^q w_i} \quad (3)$$

where $T_{p,av}$ is the weighted average temperature in each fuzzy set, w_i represents the weight of a rule, $T_{a,i}$ is the temperature at each data point and i is the total number of rules generated, corresponding to the total number of data points. The final temperature fuzzy sets T_p are shown in Fig. 4-a.

In step (Fig. 2-IV), the aim was to develop a two-dimensional representation of thermal preference as a function of T_a , a so called thermal discomfort profile (TD-profile). The preferred temperature corresponded to the T_a with the highest membership degree in the NC temperature fuzzy set (e.g., 25.2°C in Fig. 3-b). In other words, an occupant would have the minimum preference to changes in temperature when exposed to that air temperature level. Thus, the preferred temperature was the temperature that minimized the thermal discomfort from an individual. Thermal discomfort was assumed to vary between 0 and 3, taking as a reference the thermal preference, described in ISO 10551 [26]. All fuzzy sets were assigned an integer coefficient between 0 and 3 depending on how separate they were from the preferred temperature. As shown in Fig. 3-a and Fig. 3-b, a point in the TD-profile was calculated from the multiplication between the coefficients 3, 2, 1 or 0 with the membership degrees of the corresponding fuzzy sets from the furthest to the closest to the preferred temperature. For instance, a T_a of 21°C in Fig. 3-a, belongs to two fuzzy sets: W and MW. The corresponding thermal discomfort value was then calculated as: $TD(T_a=21) = 0.7 \cdot 2 + 0.3 \cdot 3 = 2.3$ (dashed lines in Fig. 4). The same procedure was applied to determine the remaining points in a TD-profile.

Figure 4. Fuzzy sets based on T_a (a) and the corresponding thermal discomfort profile (b). MW=much warmer; W=warmer; SW=slightly warmer; NC=no change; SC=slightly colder; C=colder; and MC=much colder.

In step (Fig. 2-V) the individual TD-profiles from all participants in an office were combined into a single graph. Then, the demand-driven set point was calculated as the temperature that minimized the thermal

discomfort of the group of participants. In order not to have substantially low or high temperatures as set points, it was defined that the set point must be between 20 and 26°C. Such interval corresponds to the design indoor temperatures for winter and summer recommended for Category II in EN15251 [27]. The set point was then calculated as the T_a that fulfilled the following optimization:

$$\min(TD) \quad \sum_{j=1}^n \frac{TD_k(T_a)}{n} \quad (4)$$

Subject to $26 \geq T_a \geq 20$, for $k=1, \dots, n$

where TD_k is the thermal discomfort level of occupant k , as a function of the air temperature T_a and n corresponds to the number of occupants considered in the optimization.

3.2. Experiment

The field study was performed in an open-plan office located in Copenhagen, Denmark, during a period of three weeks, between the 9th of March and the 6th of April 2018. The office was placed on the 6th floor of a corporate building (consulting engineering company), with two facades with windows facing northeast and southwest (Fig. 5). The total number of occupants in the office was 45 workers from different nationalities, but only 16 participated in the survey. The occupancy level was not registered in the assessment. The entire office was divided into four zones: southwest (SW), northwest (NW), southeast (SE) and northeast (NE), without any partitioning. All HVAC equipment was controlled centrally by a Loytec BMS (Fig. 6), which

was able to measure indoor environmental parameters (T_a , CO_2 concentration and air pressure) in each zone through four sensors placed on opposite walls of the office (BMSM in Fig. 5). The BMS had sensors to measure T_a

Figure 5. Floor plan of the open-plan office considered in the field study with a representation of the devices for continuous measurements or CM (squares), participants (triangles) and the BMS indoor climate sensors BMSM (rhomboids). Floor area: 324 [m²]. Length/Width/Height: 22.8/14.2/2.8 [m].

every minute with an accuracy of $\pm 1^\circ\text{C}$, within a range of -50°C to 50°C . The ventilation system was demand-controlled based on both CO₂ concentrations and indoor air temperatures. The space was heated by 36 water-borne radiators placed under the windows in the open-plan office, and ventilation and cooling was provided through the ventilation system. The supply air temperature for summer and winter were 17°C and 19°C , respectively. The ventilation system compensated window openings by adjusting the damper position in the main ventilation duct of the office to keep the relative pressure at 35 Pa. However, windows were rarely opened during the assessment period since the mean daytime outdoor temperature was below 7°C [28]. According to Andersen et al. [29], the window opening behaviour is strongly related to outdoor temperature levels. The opening of the diffusers in each zone was adjusted to provide different ventilation rates to reach the desired temperature set point in each zone.

Figure 6. Screenshot of the BMS interface, targeting the studied open-plan office.

The study was divided into three distinct periods: one for observation, one for provocation and one for optimisation. In the first period, a single business-as-usual temperature set point was implemented in the office. The default method to determine the room air temperature set point was based on occupants' complaints to the facility manager. In the second period, the temperature set point was modified to promote variation in personal thermal comfort responses. Finally, a demand-driven set point was implemented in the third period of assessment, based on the information captured in the first two periods. During the three-week evaluation, T_a was measured and recorded every 5 min in five different locations of the office, using Hobo-

loggers (CM in Fig. 5). These loggers measure air temperature from -20°C to 70°C with an accuracy of $\pm 0.4^{\circ}\text{C}$.

4 Results

4.1 Measured temperatures

The statistics of the temperature measurements listed in Table 1 describe the differences in the variability of the indoor air temperature measured in the office. The measurements show that the mean indoor air temperature in the office was increasing throughout the evaluation period. The results also indicate that the third week of assessment had the largest variability of outdoor air temperature.

Table 1. Descriptive statistics of the indoor air temperature measured by the Hobo-loggers I, II, III, IV and V and outdoor air temperature $T_{a,out}$ during the three weeks of assessment. The format is: Mean / Minimum / Maximum / Standard deviation.

	Week 1	Week 2	Week 3
I	23.2 / 22.6 / 23.7 / 0.2	23.3 / 21.2 / 24.8 / 0.8	24.6 / 24.1 / 25.1 / 0.2
II	24.3 / 23.5 / 24.7 / 0.2	24.5 / 22.4 / 25.8 / 0.7	25 / 24 / 25.4 / 0.3
III	23.6 / 17.5 / 24.7 / 0.7	24.5 / 21.7 / 26.2 / 1	26 / 25 / 26.8 / 0.4
IV	22.3 / 21.5 / 23 / 0.3	22.5 / 20.2 / 24.2 / 0.9	24.5 / 23.7 / 24.9 / 0.3
V	22.5 / 21.7 / 23.4 / 0.3	23.7 / 20.9 / 26 / 1.3	24.9 / 24 / 25.6 / 0.4
$T_{a,out}$	1.2 / -3.0 / 5.2 / 2.1	2.4 / 0.1 / 5.9 / 1.2	9 / 2.6 / 14.3 / 3.1

4.2 Personal thermal preferences

Fig. 7 shows that there was a considerable difference between the numbers of votes provided by the participants. Only nine out of sixteen participants in the survey delivered more than 40 votes along the whole assessment period.

Figure 7. Number of votes per participant along the surveyed period.

The medians of the preferred temperatures of the participants differed between 22.5°C and 25.4°C as shown in Fig. 8. The figure also shows that the minimum and maximum differences between the preferred temperatures from a single occupant were 0.3°C (occupant 16) and 3.7°C (occupant 11) indicating that some

occupants were consistent in their preference and others preferred a rather wide range of temperatures. The participant that provided most votes (occupant 6) preferred temperatures within an interval of 1°C. There was no correlation between the number of votes provided and the variability of the preferred temperatures.

Figure 8. Occupants' preferred air temperatures.

The preferred air temperatures, considered as the indoor air temperatures by which occupants voted TPV=9, were plotted against the outdoor air temperatures in the instant each of such votes was made. A linear fit was applied between the preferred air temperatures and outdoor air temperatures for occupants' votes expressed during the morning (before 13:00) and during the afternoon (after 13:00), presented in Fig. 9. The correlation between outdoor air temperatures and preferred air temperatures was statistically significant during both morning and afternoon votes ($F=28.2$; $p<0.0000001$; $R^2=0.11$). The slopes of the curves in Fig. 9a and Fig. 9b were not significantly different ($p>0.05$), indicating that the change in occupant thermal preference following a change in outdoor air temperature was the same in the morning and in the afternoon. The correlation shows that the preferred temperature increased approximately 1°C for every 10°C the outdoor air temperature increased. However, the afternoon regression line showed a significant shift upwards as compared with the morning votes (y-axis intercepts of 24.2°C and 23.9°C respectively) ($p<0.03$). Hence, individuals' thermal preferences were significantly lower in the morning than in the afternoon. The results show a correlation between outdoor air temperatures and preferred air temperatures during three weeks within the heating season, which, however, is likely to differ between seasons.

Figure 9. Occupants' preferred air temperatures as a function of the air temperature outdoors for morning votes (before 13:00 hrs) (a) and afternoon votes (after 13:00 hrs) (b).

4.3 User-driven set point

The method described in Fig. 2 was applied to the seven most active of the sixteen participating occupants. It was not possible to define the TD-profiles for the rest of the participants due to a lack of sufficient feedback (Fig. 7) or a large variability on their preferred temperatures (Fig. 8). The last reason impeded the construction of fuzzy sets with well-defined boundaries. Fig. 10 shows the resulting aggregation of the TD-profiles for the seven participants. The minimization of thermal discomfort led to a demand-driven set point of 24.5°C. The figure also shows that the TD-profiles of occupants 7, 10 and 18 did not reach the lowest possible discomfort level of zero. This was caused by a lack of variability and/or number of votes provided by those occupants.

Figure 10. Aggregation of the thermal discomfort profiles to determine the demand-driven set point based on occupants' input (dashed line).

4.4 Set point implementation into the BMS system

The set point of the BMS was modified along the three-week evaluation period, as presented in Fig. 11. In the first period, from day 1 to 7, the business-as-usual set point corresponded to 23°C. Afterwards, from the 8th day until the first half of the 11th day, the set point was modified to stimulate different thermal responses from the occupants. From the second half of the 11th day until the 15th day, the demand-driven set point of 24.5°C was applied. However, on the last three days of assessment the set point started to oscillate disorderly, as shown in Fig. 11. Probably, there was an unexpected control error in the BMS that did not accept the demand-driven set point or there was an unexpected error in the system during that period.

Figure 11. Air temperature set points applied in the BMS during the working hours.

Figure 12 shows that the air temperatures measured by the BMS were different from the values obtained by the Hobo-loggers placed around the office (Fig. 13). The discrepancy between the T_a measured by the

Hobo-loggers in different areas of the office reached up to 2.6°C, on the 11th day of assessment, whereas the largest difference measured by the BMS sensors was only 0.7°C. According to the results, the maximum and minimum T_a measured locally by the Hobo-loggers were 26.7°C and 20.2°C, respectively, while the values measured by the BMS were 25.1°C and 21°C. The set point implemented in the BMS, shown in Fig. 11, did thus not account for local variation of the temperature around the office. Fig. 13 shows that occupants were exposed to temperatures up to 1.6°C higher and down to 0.8°C lower than the maximum and minimum air temperature set points defined in the BMS. This implies that occupants experienced air temperatures far outside the range that the BMS was able to detect. Thus, occupants' thermal comfort may have been compromised as a result of the limitations of the BMS temperature measurements.

Figure 12. T_a measured by the BMS on four internal walls placed in different orientations: northeast (NE), northwest (NW), southeast (SE) and southwest (SW).

Figure 13. T_a measured by five Hobo-loggers placed around the office.

4.5 Thermal comfort results

The average individual *TPV* during each assessment week was analyzed and is presented in Fig. 14. The first week corresponded to the first seven evaluation days, the second week were the following 4.5 days and the demand-driven set point was applied during the third week. It was considered that the closer occupants' thermal preferences were to a *TPV* of 9 (red line in Fig. 14), the better their thermal comfort. The figure shows that only two (28.6%) of the occupants who provided information to calculate the demand-driven set point improved their thermal comfort in the third week (occupants 5 and 10).

Figure 14. Average thermal preferences along the three weeks of assessment.

5 Discussion

The results obtained from the UD-HVAC control approach tested in an open-plan office showed some of the difficulties of demand-driven thermal environment control. The low thermal performance of the approach was affected by several factors: a low level of participation among the occupants, differences between the T_a values measured by the BMS with the actual temperatures in the office, and technical difficulties to implement the demand-driven set point in the HVAC control system. The results were not in accordance with the findings of [22,23], which calculated a demand-driven set point grounded on fuzzy logic and thermal preference, improving thermal comfort for approximately 80% of the occupants. However, their results were not statistically significant due to the small sample of participants considered. Moreover, the experiment from [22,23] considered small single or double offices, whereas the field experiment presented in this paper took place in a large open-plan office. Hence, the results were influenced to a larger extent by a BMS that was not able to measure the temperatures along the entire office. Additionally, the occupants in the single and double offices probably had more control over thermostat settings and window or door opening, compared to the limited individual control possibilities in open-plan offices, where the approach obviously could increase occupant influence.

The methodology presented in this paper offers the possibility to improve thermal comfort with two strategies: first, it creates a model of thermal comfort at a personal level, combining the requirements of individuals to provide an adequate thermal environment; secondly, the participatory sensing approach

improves occupants' perception of having some degree of control over their environment. Occupants' perception of control over their indoor environment has concrete implications on their thermal comfort responses [30,31]. Moreover, the methodology presented allows assessing directly the thermal comfort implications of an HVAC control strategy. There is no need to distribute questionnaires periodically among the participants to evaluate thermal comfort, as they permanently state their thermal comfort preferences through a web-based survey. However, the performance of the method relies on occupants' constant participation and the variability of their preferences. Occupants providing only a few thermal preference votes or votes with substantially high or low variability did not allow constructing well-defined TD-profiles. The first consequence of this was that some of the occupants were not considered in the demand-driven control approach. The second aftereffect was that there were TD-profiles that did not model well enough the actual personal thermal preferences. Finally, the demand-driven set point failed to improve occupants' thermal comfort, as presented in Fig. 14.

The performance of the method was also affected by a time-dependant variability of personal thermal preferences. A study carried out by Fanger [32] suggested that over a period of time, 95% of the preferred temperatures from a single person will vary within $\pm 1.2^{\circ}\text{C}$. However, a larger variation in preferred temperatures was observed among the participating occupants. The study made by Fanger was performed in climate chambers, which may explain the lower variability in the preferred temperatures that he observed. His study emphasizes the need of renewing constantly the data obtained from occupants' feedback and account for factors that may influence time-dependent variations of thermal responses.

The Adaptive Model of Thermoregulation suggested by Auliciems and de Dear [33] proposes that behavioural responses are expressions of thermal satisfaction through thermal preference. They are influenced by thermal expectation and physiological thermoregulation concerning current and previous experiences with thermal environments. The regression lines presented in Fig. 9 were significantly different between thermal preferences stated in the morning and in the afternoon. Occupants preferred lower air temperatures during the morning. This suggests that they were influenced by thermal expectations resulting from earlier experiences with outdoor environments. Occupants may have experienced a cold thermal sensation during their commuting time early in the morning, which changed along the day. This result is in agreement with the study of Bourdakos et al. [34], which showed that the preferred temperatures of occupants were lower after commuting to work due to higher metabolic activity levels. This suggests that there is a short-term physiological adaptation process when people arrive at their work place in the morning that should be taken into account in thermal comfort assessments. The study by de Dear and Brager [6] presented a regression line between preferred indoor operative temperatures and mean outdoor effective temperatures, with a slope of 0.11. This value is similar to the results presented in this paper (0.10 and 0.07 for morning and afternoon thermal preferences). As suggested by Fanger and Toftum [7], occupants' expectations are reduced as a result of repeated thermal stimuli. Accordingly, preferred air temperatures increase with increasing outdoor temperatures. The outdoor air temperatures shown in Fig. 9 represent individual

measurements taken at the same time each thermal preference vote was stated, whereas the results from de Dear and Brager considered mean outdoor effective temperatures (defined as the arithmetic mean between outdoor effective temperatures at 6am and 3pm). Hence, the results presented in this paper provide a better representation of the daily variations of thermal preferences and the short term influences of expectation into individuals' thermal comfort.

The PMV approach presented in ASHRAE 55 and EN15251 estimates thermal comfort responses based on indoor environment parameters and human characteristics. However, the results presented in Fig. 9 evidence that thermal expectation should also be considered to predict thermal responses.

Fig. 15 shows two logit regression models applied to the occupants showing preferences towards warmer than neutral (TPI>9) and colder than neutral (TPI<9). The intercept between both regression models is assumed as the preferred temperature ($T_{pref}=24.1^{\circ}\text{C}$). This temperature represents a condition in which the probabilities of occupants preferring a change in the indoor environment, either colder or warmer, is equal [35]. The preferred air temperature obtained with the logit model and the demand-driven set point presented in Section 4.4 differed only by 0.4°C . The fuzzy logic approach showed in this study not only estimates accurately the preferable thermal condition of a group of people, but also allows to have a more detailed representation of the thermal comfort profile of a single individual.

Figure 15. Logit regression models fitted to thermal preference votes.

Clark et al. [36] stated that adaptation to cold environments is mainly behavioural. Moreover, Chatonnet and Cabanac [37] defined that behavioural thermoregulation in humans is well developed and is likely to outpace other forms of thermoregulation. The large variation of the preferred temperatures and the correlation between thermal preference and outdoor temperature suggest that occupants' thermal preferences were not only influenced by physiological thermoregulation, but also by psychological adaptation and behavioural adjustment. Wohlwill [38] described three types of behavioural adjustment: personal adjustment (e.g., clothing, activity, eating or drinking), technological adjustment (e.g., opening or closing windows, operating personal heating/cooling devices) and cultural adjustment (e.g., changing schedules, siestas). The implementation of a personal thermal preference survey increased the possibility that occupants became

adapted through technological adjustment, which altered their thermal expectation. Adaptation through clothing changes might have occurred throughout a day, during the evaluation period. However, a study by Humphreys [39] proposed that the half-life (the time to reach half way of a steady-state value) for daytime clothing regulation was approximately 20 hours. He stated that people adapt better to seasonal temperature variations rather than daily changes because of adaptive time lags. Thus, adaptation through clothing adjustment should be particularly considered when executing a participatory sensing assessment along different seasons. Thermal adaptation processes should be analysed further when obtaining human feedback to control HVAC systems, focusing on data renovation and surveying methods.

6 Limitations and outlook

The UD-HVAC approach only focused on thermal comfort optimization. Including energy use variables to define demand-driven set points is among the research directions of the authors. On the other hand, the evaluation period was too short to analyze long-term variations of thermal comfort responses. Following publications will consider a PCM-based controller connected to a BMS, adjusting the room temperature set point continuously. Future assessments will also consider the occupancy level and the minimum number of thermal responses to have a suitable representation of individual thermal preferences. This will allow knowing the threshold by which an occupant can be included or not in the optimization to calculate a demand-driven set point. Finally, a BMS control system could be improved by using IoT devices to provide local temperature measurements, which can be achieved by means of low-cost wireless indoor environmental sensors [39]. The system could benefit from having a better representation of the air temperatures in the room, which could be used as input to a PCM-based framework.

The use of the operative temperature or the standard effective temperature SET in the methodology, would have given a more precise representation of the indoor thermal environment. However, given the restrictions of the office used in the study with regards to space use and visual impact, it was not possible to measure the mean radiant temperature during the assessment period.

7 Conclusions

This study tested the use of artificial intelligence to define heating set points based on occupants' temperature preferences. Personal thermal preferences were used to calculate a temperature set point which could only improve thermal comfort of 29% of the occupants. Accordingly, 71% of the occupants experienced a deterioration of their thermal comfort as a result of the demand-driven control approach. It was observed that thermal adaptation influenced individuals' thermal responses. The results were also influenced by a lack of occupant feedback and inaccurate BMS indoor air temperature measurements. Short-term

experience with outdoor environments leveraged occupants' daily preferred temperatures. Moreover, the survey applied influenced the level of thermal expectation, driven by a higher possibility of behavioural adjustments. These factors should be considered in future endeavours that use occupants' thermal responses to control indoor environments.

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Highlights

- A model to describe and predict personal thermal responses was created.
- Indoor air temperatures and thermal preferences were used to construct the model.
- A set point for heating and cooling was calculated and tested in a field study.
- Only 29% of occupants' thermal comfort improved with the user-driven set point.
- Thermal expectation influenced the daily variation of personal thermal responses.