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Proceedings of the International Conference on Computing in Civil and Building Engineering
W Tizani (Editor)

Predicting the desired thermal comfort conditions for shared offices

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Abstract

Ensuring thermal comfort is an important goal in the operation of any office building. Often these buildings are therefore controlled according to the predicted mean vote (PMV) model which is also adopted as the ISO 7730 norm. This model predicts the mean thermal preferences of an average group of people that would satisfy the thermal comfort needs of about 80% of the occupants. It is derived from a number of environmental and person-dependent variables that are either difficult to measure in practice or require the placement of many sensors which is very costly. Furthermore, this model produces precise results for well defined environmental conditions only. This paper presents two new case-based reasoning algorithms that predict the average comfort vote based on previously recorded votes. In order to determine how relevant the latter are to a new state a distance measure is defined that quantifies the similarity between two states. Based on that similarity the previous votes are weighted and the expected comfort vote for the new state is determined. The two algorithms differ in the definition of their distance function. One depends only on the temperature of the state and the other one depends on all the parameters of the PMV model. The paper concludes with an experimental evaluation using real field study data. The results reveal that the algorithm, which requires temperature sensors only, outperforms two existing PMV based approaches. It shows that the goals of increasing user comfort and reducing sensor costs can be achieved simultaneously when considering the comfort votes that occupants have previously provided. The experiments also show that for hot arid, wet equatorial, and temperature marine climate zones the measurement of the PMV value, rather than that of temperature alone, can lead to increased user comfort when considering previously recorded comfort votes.

Keywords: thermal comfort, case-based reasoning, decision support systems

1 Introduction

Several studies show that a comfortable working environment will lead to increased productivity and reduced sick leave days (Karjalainen and Koistinen 2007; Lorsch and Abdou 1994; Roelofsen 2002). Hence, ensuring, or even maximising, occupant comfort is an important goal in the operation of any office building. Some of these buildings therefore allow the individual control of room temperature that enable the occupants to create optimal comfort conditions for themselves (Wyon, 2000). There are also a number of approaches that control the rooms automatically according to the individual preferences of the occupants. Such preferences can be learned based on the comfort feedback (e.g. “I’m cold”) that the user provides explicitly by signalling his/her discomfort (Dalamagkidis et al., 2007), by verbally articulating his/her feedback (Baus et al., 2008), or by interacting with a simple user interface (Kolokotsa et al. 2009; Youngblood et al. 2005); or that he/she provides implicitly by adjusting the heater (Hagras et al. 2007; Liang and Du 2008).

However, these approaches assume that the user comfort feedback can be acted upon straight away and thus either that the office is occupied by a single user only or by several users with identical comfort preferences. Since it is very unlikely that a group of occupants have the same preferences, shared offices or meeting rooms are mostly controlled automatically according to well defined standards that cover the thermal comfort needs of about 80% of the occupants (ANSI/ASHRAE 55, 2004; ISO/DIS 7730, 2003). These standards are based on average criteria for population comfort under the guideline of the widely used Predicted Mean Vote (PMV) and Predicted Percentage of People Dissatisfied (PPD) indexes (Fanger, 1972). The PMV value is defined in terms of four environmental variables (indoor air temperature, mean radiant temperature, relative air velocity, and humidity), and two person-dependent variables (activity level and the value of clothing worn).

PMV based approaches have some drawbacks. Firstly, they intend to capture the comfort needs of average occupants rather than those of the specific users sharing a room. Secondly, they are not applicable to all environmental conditions (Humphreys and Nicol, 2002). Thirdly, they require a large amount of environmental data whose retrieval is very costly due to the many sensors needed. And, fourthly, getting the precise values for the required person-dependent data is often difficult.

This paper presents two approaches that tackle all these issues. They both take previously recorded individual comfort votes of occupants into account and thus address the first two weaknesses of PMV based approaches. The new average comfort vote is then predicted based on the relevance of these existing votes to the new state. The two algorithms distinguish themselves in the way they compute the degree of relevance of existing votes. One seeks to compute a vote prediction with high accuracy by taking all the parameters of the PMV model into account. The other one is only based on the temperature readings and thus, additionally, addresses the last two drawbacks of PMV based approaches. The paper concludes with an experimental evaluation of these approaches that demonstrate their benefits and suggest that for most conditions monetary savings can be made by resorting to temperature sensor readings only.

2 Thermal comfort and the predicted mean vote

Thermal comfort is often measured using the predicted mean vote (PMV) (Fanger 1972; ISO/DIS 7730, 2003) which is defined as the heat load that would be required to restore a state of 'comfort' for an average group of people. It depends on six variables: activity level and the value of clothing worn by the users, indoor air temperature, mean radiant temperature, relative air velocity, and humidity. For any state s for which these six variables are known the PMV value can be computed.

However, field studies on thermal comfort have shown that this model does not give correct predictions for all environments (Humphreys and Nicol, 2002). The work of (Kumar and Mahdavi, 1999) picks up this aspect and presents an approach that adjusts the PMV value depending on the climatic conditions. It computes the predicted comfort vote of a state by resorting to a database DB in which comfort votes of users in the same climate zone are recorded along with the PMV values of the states in which these votes were taken. Formally, each element of DB is of the form (q, s, v), where:

- q is the occupant,
- s is the state,
- v is the comfort vote on the seven point ASHRAE scale (ANSI/ASHRAE 55, 2004) that the occupant q provided in state s, e.g., $v = 3$ (resp. 2,1,0,-1,-2,-3) if his/her vote was "I'm hot." (resp. warm, slightly warm, comfortable, slightly cool, cool, cold).

This database is used in (Kumar and Mahdavi, 1999) to determine the difference between comfort votes and the corresponding PMV value in order to adjust future predicted votes accordingly.

3 Predicting the average thermal comfort vote for shared offices

This section presents an algorithm that predicts the thermal comfort votes of occupants, and hence their desired thermal conditions, more accurately than the existing PMV based approaches. The higher accuracy is achieved by additionally taking the comfort votes into account which the occupants have previously chosen to give. These votes are weighted with respect to their relevance to a new situation $\lambda = (s', Q)$, where Q is the set of users occupying the shared office O, and s' is the new state for which the average comfort vote for the occupants of O is to be predicted. This relevance is composed of two factors: the similarity between a formerly recorded state s and the new state s' and the identity of the occupant, i.e. whether the occupant q for which the vote in state s was recorded has his/her desk in office O or not. Naturally, the degree of relevance of a database entry $\delta = (q, s, v)$ to a situation $\lambda = (s', Q)$ is higher when q is similar to the elements in Q and s is similar to s'. For quantifying the similarity between two states we have defined two distinct distance functions:

$\Delta s_1 := | PMV(s) - PMV(s') |$ where $PMV(x)$ is the PMV value for state x as defined in (ISO/DIS 7730, 2003) and

$\Delta s_2 := | t - t' |$ where t (resp. t') is the temperature of state s (resp. s').

The former function Δs_1 takes all variables into account that have an impact on the thermal comfort of occupants while Δs_2 is based only on the temperature measurements. The motivation for considering two distinct distance measures is to determine whether there are some climate zones for which similarly accurate comfort predictions can be made without the need of measuring all the comfort dependant parameters. The degree of relevance of δ to λ for both distance functions $\Delta s \in \{\Delta s_1, \Delta s_2\}$ is then:

$$R((q,s,v),(Q,s')) := \begin{cases} (\Delta s + 1)^{-2} & \text{if } q \notin Q \text{ and } \Delta s \le c \\ k \cdot (\Delta s + 1)^{-2} & \text{if } q \in Q \text{ and } \Delta s \le c \\ 0 & \text{otherwise,} \end{cases}$$

where $c > 1$ and $k > 1$ are two constants. The former ensures that database records are ignored if their distance to the new state is too big. The other one ensures that previous votes of occupants in Q have more relevance than the ones of other occupants. The predicted average vote V is then obtained as the R-weighted average of the existing comfort votes:

$$V(Q, s', DB) := \frac{\sum_{(q,s,v) \in DB} R((q,s,v),(Q,s')) \cdot v}{\sum_{(q,s,v) \in DB} R((q,s,v),(Q,s'))}$$

4 Experimental evaluation

4.1 Used field studies

We have compared the new algorithms with the two existing ones introduced in Section 2 using real field studies (de Dear, 1998). Their collection contains 52 studies with over 20,000 individual comfort votes from different countries. However, for predicting the average vote for shared offices with 15 people no studies could be used that involved less than 15 occupants. Furthermore, some of the field studies contain votes that were collected for conditions with a PMV value beyond ± 3. Since the ASHRAE scale does not extend beyond these limits we removed the comfort votes taken in extreme conditions with $PMV(w) > 3$. This is in line with the analysis done in (Humphreys and Nicol, 2002) that did not consider such votes either.

After removing the studies and records as described above we were left with 36 field studies from 8 climate zones containing 15,782 comfort votes from 6,340 different users. Each of these votes is associated with the state in which it was taken that is also composed of the room temperature and the PMV value. Hence, these studies contain all the data that are needed as inputs for the four algorithms.

4.2 Experimental results

In order to test the performance of the presented algorithms we considered each field study individually and computed the predicted comfort vote for a situation $\lambda = (s', Q)$ based on all recorded comfort votes apart those that occupants Q have given in state s'. This method requires the identification of the occupants who have previously voted in state s' which was done by sorting the records of each field study according to their PMV (resp. temperature) value. The sorted records were then grouped in blocks of size n which ensures that records in the same block refer to a very similar state and hence can be used for predicting the average vote for offices shared by n occupants who are all exposed to very similar environmental conditions.

Experimental evaluations were conducted for the following algorithms: the two existing PMV based approaches *PMValg* (ISO/DIS 7730, 2003) and *PMVadj* (Kumar and Mahdavi, 1999) presented in Section 2 and the new case-based reasoning algorithms: *CBpmv* with the PMV based distance function Δs_1, and *CBtem* with the temperature based distance function Δs_2 (see Section 3). The two constants c and k of these algorithms were set to $k = 16$ for both approaches, and $c = 0.3$ for *CBpmv,* and $c = 0.8$ for *CBtem.* As we will show later the performance of the two approaches does not depend significantly on the specific settings of these constants.

For each field study all four algorithms were run to compute the predicted average comfort vote which was then compared to the vote which the occupants actually provided. The results of field studies within the same climate zone were then combined. Figure 1 illustrates for different office allocations what percent of their total comfort predictions were correct, i.e. predicted the discrete value of the seven point ASHRAE scale correctly. For instance, the results for the tropical savannah climate zone show that the existing algorithm *PMVadj* correctly computed the comfort vote for offices shared by 2 (resp. 3, 5, 9, 15) occupants in 50% (resp. 59%, 68%, 77%, 87%) of cases and that the other existing algorithm *PMValg* performed even worse. In contrast, when using algorithm *CBtem* 54% (resp. 64%, 73%, 86%, 96%) of the predictions were correct.

The experimental results shown in Figure 1 lead to the following observations: Firstly, the consideration of individual comfort votes always leads to increased prediction accuracy. Secondly, the computation of the PMV value and the gathering of all its dependent variables does not pay off in general. Although there are some instances in hot arid, wet equatorial, and temperature marine climate zones for which *CBpmv* performs better than *CBtem* these improvements are not significant. Thirdly, the figure shows that the prediction accuracy increases with an increase of occupancy. This might seem surprising since the number of relevant data records depends only on the state and not on the number of occupants (see definition of R). The reason for this increase lies in the unreliability of occupants who sometimes provide comfort votes that differ substantially from the votes which they have previously given in a similar state. The more occupants share an office, the better these discrepancies of individual votes can be compensated for, and even nullified. The latter holds, for instance, if one occupant gives a warmer vote than usual while another one gives a colder vote than usual.

Although Figure 1 clearly shows the supremacy of our approaches it still needs to be analysed whether the obtained improvements depend on optimally chosen values for the constants c and k. If that were the case then it would be necessary to first determine these values separately for each field study before the approaches could be used. Fortunately this is not required as Figure 2 shows. The left (resp. right) graph of that figure illustrates the average percentages of correct comfort vote predictions over all climate zones using different c and k values for algorithm *CBpmv* (resp. *CBtem*) and an occupancy of five people. The results reveal that for parameter ranges of $0.2 \le c \le 1$ and $1 \le k \le 30$

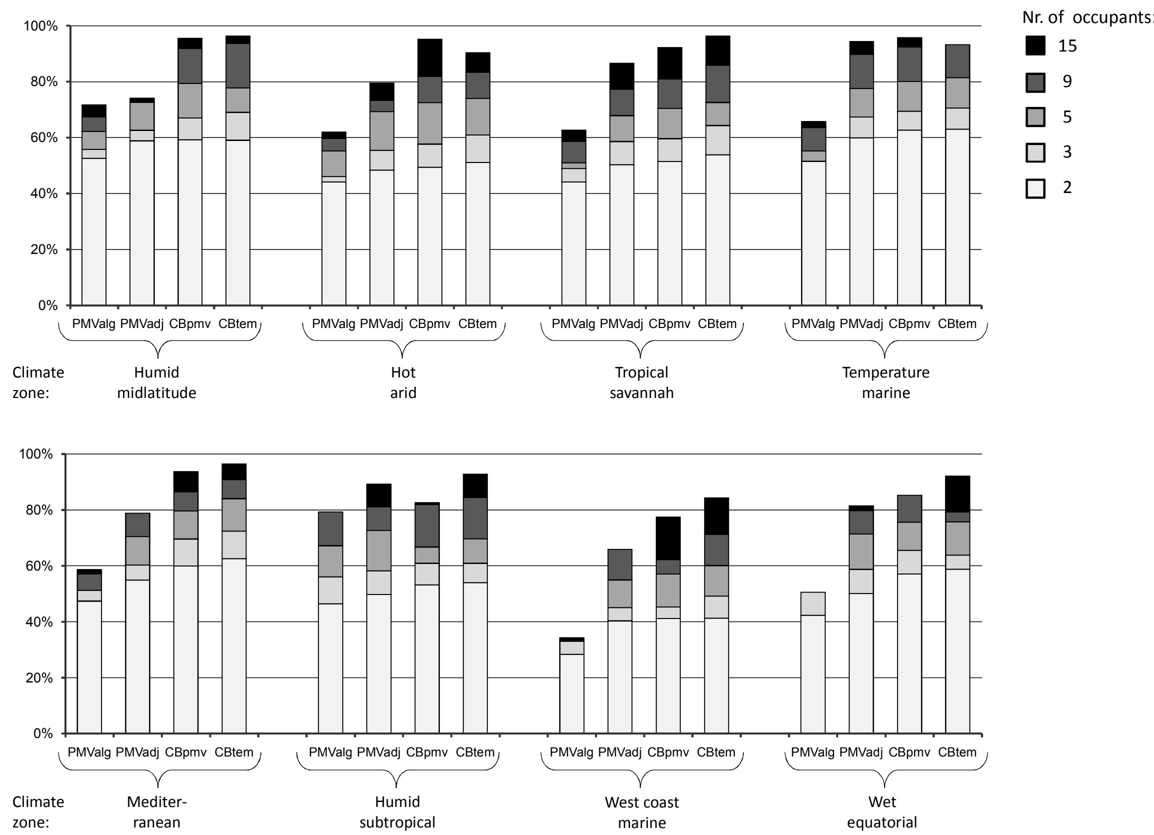

Figure 1, Percentage of correct comfort vote predictions for offices shared by 2,3,5,9, and 15 people

Algorithm *CBpmv* predicts between 70.2% and 73.9% of votes correctly and thus always performs better than *PMVadj* (resp. *PMValg*) that predicts 69.6% (resp. 52.3%) of votes correctly. For algorithm *CBtem* and parameter ranges of $0.2 \leq c \leq 2$ and $1 \leq k \leq 30$ the amount of correct predictions is even higher and ranges from 73.6% to 76.2%. Note, if the c value is too tight, i.e. $c < 0.2$ then there are too few relevant data which worsens the results. On the other hand, if the c value is too high than the states can no longer be considered similar. Here, the upper bound for predictions is even higher and ranges from 73.6% to 76.2%. Note, if the c value is too tight, i.e. $c < 0.2$ then there are too few relevant data which worsens the results. On the other hand, if the c value is too high than the states can no longer be considered similar. Here, the upper bound for algorithm *CBpmv* is lower than that of *CBtem* since states that differ by a PMV value of 1 are less similar than those that differ by 1 degree of temperature. Hence, Figure 2 shows that for any reasonably chosen values for constants c and k our two algorithms outperform the existing ones and can thus be used for arbitrary field studies.

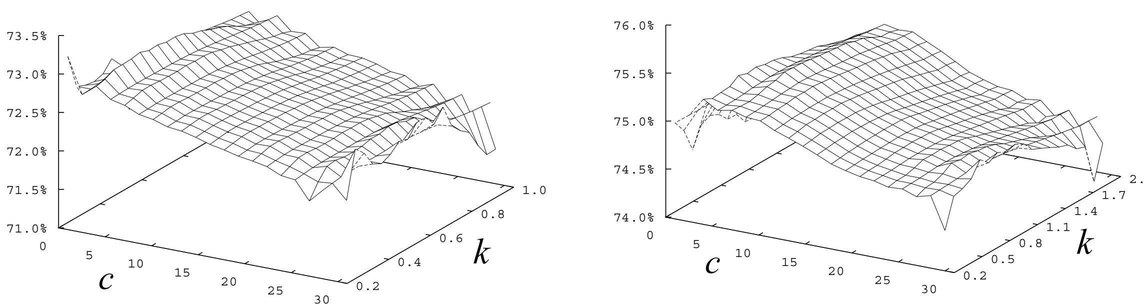

Figure 2. Average percentage of correct comfort vote predictions for offices shared by 5 people.

5 Conclusions

We have presented new algorithms for predicting the average comfort vote in shared offices and have evaluated them using real field studies containing over 15,000 occupant votes. The experiments have shown that the consideration of individual votes always leads to increased accuracy of the predicted average vote. This allows the control of shared offices according to the thermal comfort preferences of its occupants. More importantly, our evaluation revealed that in most cases these results can be achieved by taking only the temperature readings into account rather than the PMV value which would require the gathering of much more sensor data. The latter suggests that the deployment of our temperature based approach in practice could lead to big savings compared to the use of existing PMV based approaches. This results also from the fact that the data that is additionally required by our algorithm, the comfort votes of occupants, can be cheaply gathered using available equipment like desktop computers or mobile phones.

Acknowledgements

This material is based upon works supported by the Science Foundation Ireland within the SRC project ITOBO. We also thank those whose field studies were included in the database, and also of those who compiled it and made it freely available: Richard de Dear, Gail Brager, Donna Cooper.

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