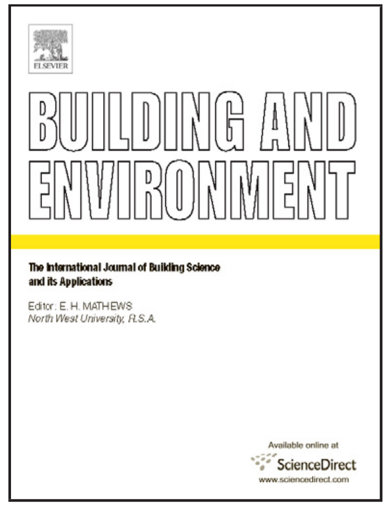

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On the behaviour and adaptation of office occupants

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On the behaviour and adaptation of office occupants

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January 11, 2008

Abstract

During the warm summer of 2006 a comprehensive longitudinal field survey of the adaptive actions of occupants, their thermal satisfaction and the coincident environmental conditions was conducted in eight Swiss office buildings. We have applied logistic regression techniques to these results to predict the probability of occupants' actions to adapt both personal (clothing, activity and drinking) and environmental (windows, doors, fans and blinds) characteristics. We have also identified, for each type of control action, the increases in temperature at which comfort votes are reported. These *"empirical adaptive increments"* have also been defined for combinations of control action. In this paper we present the field survey methodology as well as the results relating to the above, which we discuss along with scope for further related work.

Keywords: Thermal comfort, building controls, behavioural modelling, adaptation, building simulation.

1 Introduction

The deterministic features of building simulation programs are now relatively mature. Having performed well in controlled validation studies and now sporting easy-to-use interfaces, they are increasingly used by practitioners to inform building design. But their ability to emulate reality is undermined by a poor representation of stochastic variables, for example relating to climate and to human interactions with environmental controls; to the extent that predictions of like buildings may, in Baker's estimation, vary by a factor of two [5]. Environmental as well as personal interactions also influence human comfort, which in turn may influence subsequent control actions. Consequently there has been a considerable increase in the attention devoted to the modelling (both probabilistic and properly stochastic, e.g. based on Poisson or Markov processes) of human behaviour within the building simulation community in recent years.

In this paper we restrict ourselves to the probabilistic modelling of human actions to adapt their personal (clothing, activity and drinking) and environmental (windows, doors, fans and blinds) characteristics. In this we have been heavily influenced by the work of Nicol et al [9], who proposed a probabilistic approach for the prediction of the use of windows, lights, blinds, heating systems and fans. Their work was guided by the observation that, in the case of windows, *"there is not a precise temperature at which everyone opens a window, but as the temperature rises there is an increased probability that they will have done so"*. Following from this rationale, the probability for actions on controls was related to *outdoor* temperature using logit functions. *Indoor* temperature was rejected as a parameter, as it did not offer better correlations and is less appropriate as it is an output from simulation programs, while outdoor conditions are given inputs. **However, Nicol and Humphreys later reported [12] that indoor temperature was a more consistent predictor than outdoor temperature for the use of windows. This approach seems more sensible. As Robinson [13] points out, the use of outdoor temperature** may lead to the absurd result that occupants of adjacently located buildings based on fundamentally different designs (e.g. unglazed as opposed to fully glazed) would interact with controls with similar probability.

Rijal et al [17] have subsequently published an interesting refinement to Nicol's probabilistic model for the opening of windows, considering both indoor and outdoor temperature, using multiple logistic regression, for application within the dynamic simulation program ESP-r.

Also based on logistic regression analysis, Yun and Steemers [19] recently published a model of window-opening behaviour. A useful extension, compared to previous work (and in common with three types of model of light switching in Lightswitch-2002 [11]) is the use of separate probabilistic sub-models for window opening on arrival, departure and during occupancy. Furthermore, this model predicts changes in window state from open to closed and from closed to open using indoor temperature and previous window state as predictors. The influence of outdoor temperature were also tested but it was found that this offers no improvement in the quality of predictions.

In this paper we test the ability of both internal and external temperature to describe the probability of occupant interactions with a range of personal and environmental characteristics. We go on to discuss the relevance of other stimuli for such interactions and from this we introduce an approach by which a comprehensive model might be developed for the case of window opening and closing. We also discuss the effects of control actions on occupants' reported thermal sensation and in this we define a set of adaptive increments (the increase in temperature at which occupants report the same sensation vote compared to those that have not) for both individual and conjugate adaptive actions.

It should be noted that this work is in fact a byproduct of a field survey which was conceived to develop a new model of overheating risk [18], which is why non-thermal variables are not studied here.

2 Field survey methodology

During the summer of 2006 a field survey was conducted in several non air-conditioned office buildings, each located in Switzerland. The purpose of this survey was to identify the reasons and associated physical conditions for a space to overheat, in order to support the development of a new predictive model.

The buildings were selected based on a desire to have a reasonable diversity in terms of their design concept and the adaptive opportunities available to occupants. For reasons of practicality, they were all located within a 50 kilometer radius of Lausanne (latitude 46.5°N, longitude 6.7°E).

As part of this field survey, volunteers from each building were asked to complete a short electronic questionnaire which was installed on their personal computer. This longitudinal questionnaire (Figure 1), which appeared at regular participant-defined intervals throughout the three months of this study, asked for evaluations of their:

- Clothing and activity level,
- Thermal sensation and preference,
- Adaptive opportunities exercised.

With respect to adaptive opportunities, participants were asked whether they opened a *window*, lowered a *blind*, switched-on a *fan*, opened their office's *door* or had a *cold drink* during the preceding hour. Occupants' responses to the questionnaire were appended to a local data file, generally on a two-hourly basis, i.e. most participants completed the questionnaires three or four times per day.

In parallel, measurements were recorded at 45 minutes intervals from calibrated solar-shielded (using polished aluminium tubing) temperature sensors installed in close proximity to each participant's workstation. Furthermore, at the end of the study, local simultaneous climate data was obtained from the Swiss Federal Office of the Environment. **The answers to the electronic questionnaire were then linked to the previous record of thermal conditions.**

In total, a dataset of some 5908 entries from 60 participants with each including internal and external thermal conditions, personal characteristics, thermal comfort votes and adaptive actions taken has been produced, for the period 13 June to 27 September 2006. **Histograms of observed indoor and outdoor temperature during the period are given in Figure 2.**

3 Occupants' adaptive actions

We suppose that people adapt their personal and/or environmental characteristics to suppress or diminish discomforting stimuli. This follows from the *adaptive principle* **stated in [7]** that: *"If a change in the thermal environment occurs, such as to produce discomfort, people react in ways which tend to restore their comfort"*.

In particular we focus on the influence of thermal stimuli (indoor and outdoor temperature) on occupants' interactions with windows, blinds, fans and doors, and their consumption of cold drinks. We also consider adaptations to clothing and activity level. In each case our database is filtered so that we consider only those occupants for whom a given adaptive action under investigation was personally available.

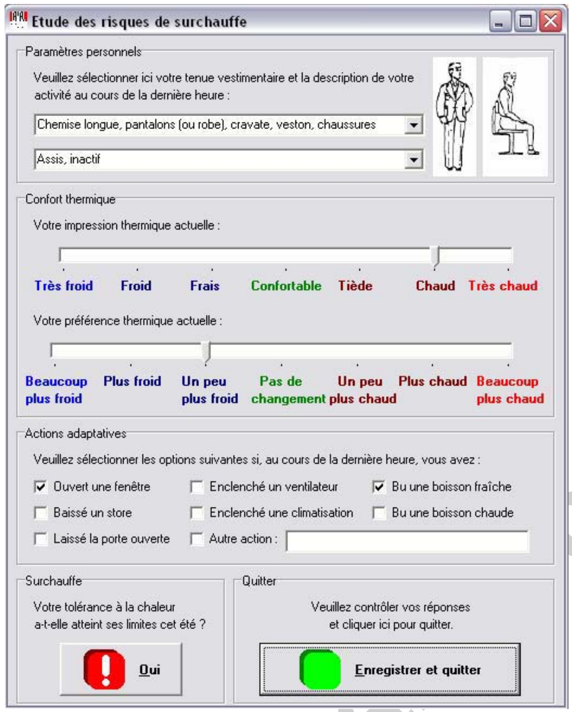

Figure 1: Longitudinal questionnaire window

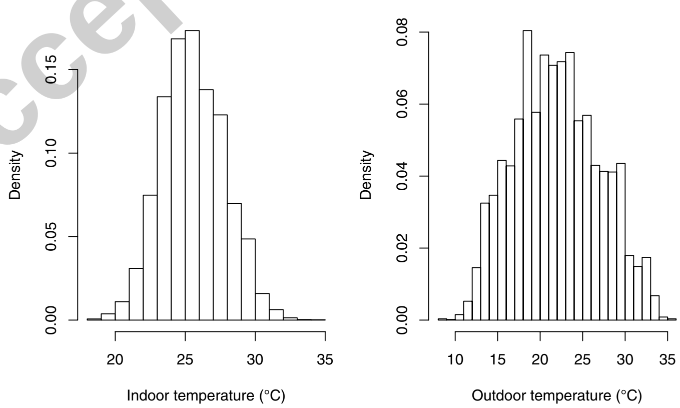

Figure 2: Distribution of temperature measurements in the database

In order to infer a probability distribution for the whole range of temperatures (both indoor and outdoor), a theoretically justified statistical method already used for such purposes by Nicol et al [9] and Rijal et al [17] is the logistic regression. The proposed probability distribution $p(\theta)$ follows the relationship

$$\log\left(\frac{p(\theta)}{1-p(\theta)}\right) = a\theta + b, \tag{1}$$

so that the actual probability distribution is given by the logit function

$$p(\theta) = \frac{\exp(a\theta + b)}{1 + \exp(a\theta + b)}. \tag{2}$$

Parameters a and b are then obtained through regression using the binomial family of generalised linear models, specifying the logit as the link function (see [10] for an introduction to these statistical methods). In Figures 3 to 7 and 10 **we present the fitted curves along with their standard error bands (probabilities for 1°C bins are for illustrative purposes).**

The logit distribution has several noticeable properties. It can be easily checked that $p(\theta)$ reaches 0.5 for a certain temperature $\theta_{50} = -b/a$. Moreover, the tangent of $p(\theta)$ at θ_{50} is $a/4$. Thus, the obtained slope a is linked with the sharpness of the variation of $p(\theta)$ near $\theta = -b/a$.

The former property allows us to interpret θ_{50} as the characteristic temperature at which half of the occupants will have used a given control, if available. The parameter a measures indirectly the sensitivity of occupants to temperature changes around this value. In particular if a is zero the distribution becomes independent of θ, and for very large a, $p(\theta)$ tends to a step function. We can therefore interpret low values of a, together with the associated p-value, as a sign that θ is irrelevant to the explanation of a given action. Conversely, large values of a increase the deterministic degree of predictions.

3.1 Results summary

We show here the results obtained by logistic regression for the different adaptive actions studied. A summary of the regression parameters obtained is given in Table 1 for fits with indoor and outdoor temperature. Specific results for each type of adaptive action studied are discussed below.

We base our conclusions regarding the validity of an inferred model on the value obtained for its associated *deviance* $D = -2\log(\lambda/\lambda_S)$, where λ is the likelihood of the considered model and λ_S the likelihood resulting from a saturated model. We can then define then the *G-statistic* as $G = D_{\text{null}} - D = -2\log(\lambda_{\text{null}}/\lambda)$, with the index "null" referring to a model with no variable. If the model has k free parameters, the G-statistic has a χ^2 sampling distribution with k degrees of freedom, from which p-values can be computed [3]. Unless otherwise stated, we shall not present these p-values, as they are generally highly significant ($p < 0.001$). This procedure is analogous to the analysis of variance used with linear models, where high values for G, in relation to the number of predictors used, denote significant effects.

Another valuable statistical parameter is the *Bayesian Information Criterion* (BIC). This is **defined by** $-2\log(\lambda/\lambda_S) + k\log N$, where N is the sample size (see the second column of Table 1). With this definition, the BIC measures the balance between the information brought by the model and the complexity induced by the number of predictors. Alternative fitted models can then be compared with lower BIC values indicating the models with the best balance between complexity and information. The BIC obtained are however limited here to the comparison between models for the same control, as the database sizes are different between controls.

Together with the above tests, we also wish to select models that provide good values for slope a, as they allow better (more deterministic) predictions in the context of building simulation. Another statistic of interest is an adapted version of R^2 proposed by Nagelkerke [4], which describes proportion of deviance explained by these logistic regression models, and is defined as

$$R^2 = \frac{1 - \exp((D - D_{\text{null}})/N)}{1 - \exp(-D_{\text{null}})/N)}. \tag{3}$$

We do not expect to obtain very high values for Nagelkerke's R^2, as thermal stimuli cannot explain alone the variations of probabilities.

Control	Nb. occ. & entries	Thermal stimulus	a	b	θ_{50}	G-statistic	Residual deviance	BIC	R^2
Windows	40	Indoor	0.220 ± 0.015	-5.64 ± 0.38	25.6	238.1	5209.9	5227.3	0.08
	3931	Outdoor	0.049 ± 0.006	-1.12 ± 0.15	22.9	57.4	5390.5	5407.9	0.02
Blinds	31	Indoor	0.425 ± 0.021	-11.37 ± 0.54	26.8	535.1	3438.0	3455.4	0.22
	2957	Outdoor	0.139 ± 0.008	-3.54 ± 0.19	25.5	313.1	3660.0	3677.4	0.14
Fans	37	Indoor	0.696 ± 0.026	-19.32 ± 0.70	27.8	1110.1	3081.3	3098.7	0.39
	3538	Outdoor	0.311 ± 0.011	-8.18 ± 0.28	26.3	1132.5	3058.9	3076.3	0.39
Doors	26	Indoor	0.331 ± 0.022	-8.14 ± 0.55	24.6	273.7	2817.5	2834.9	0.15
	2250	Outdoor	0.026 ± 0.009	-0.35 ± 0.19	13.5	9.4	3081.8	3099.1	0.01
Drinks	60	Indoor	0.243 ± 0.013	-6.94 ± 0.34	28.6	366.3	7181.8	7199.1	0.08
	5907	Outdoor	0.108 ± 0.006	-3.10 ± 0.14	28.7	366.7	7181.3	7198.7	0.08
Clothing	60	Indoor	0.248 ± 0.013	-6.11 ± 0.33	24.6	407.8	7723.4	7740.8	0.09
	5907	Outdoor	0.162 ± 0.006	-3.33 ± 0.14	20.6	817.7	7313.5	7330.9	0.17

Table 1: Regression results and statistical tests for fits with indoor and outdoor temperature

3.2 Windows

Logistic regression on our data gives interesting results concerning actions on windows – the most widely employed adaptive action during our study (Figure 3). Predictions of the probability of opening windows as a function of indoor temperature are significant ($G = 238.1$), although the **deviance difference** is smaller than for other controls. The distribution of window openings has a rather low θ_{50} value, which implies that actions on windows are widely used by occupants for moderate indoor temperatures. However, the slope is rather low ($a = 0.220$), **as is** R^2**,** suggesting that other parameters need to be accounted for. There is nevertheless a clearly significant influence of indoor temperature, in agreement with previous published work [19].

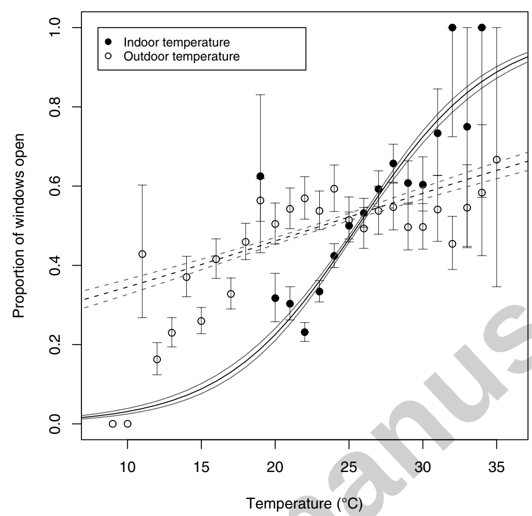

Figure 3: Window opening probability as a function of indoor and outdoor temperature

The link with outdoor temperature on the other hand is rather less convincing, with one of the lowest G-statistic and R^2 observed in this study ($G = 57.4$, $R^2 = 0.02$). The value of the slope is also very low at $a = 0.049$. Assuming that the use of logistic regression is appropriate, outdoor temperature could be discarded as a driving stimulus for opening windows, which is in contradiction to [9] and supports [13].

However, we are not able to reject outdoor temperature as a valid parameter influencing the opening / closing of windows to avoid draughts, excess heat gains or to promote free cooling. Possible approaches for a comprehensive treatment of window opening and closing, which account for these stimuli, are discussed in Section 5.

3.3 Blinds

Logistic regression with indoor temperature gives clear results ($G = 535.1$, $R^2 = 0.22$). The value of θ_{50} is higher than for windows with $\theta_{50} = 26.8$°C, which shows that blinds are less likely to be used than windows under moderate indoor conditions. Nevertheless, the high value of the slope ($a = 0.425$) indicates a rather sharp sensitivity to indoor temperature around this value (Figure 4). This shows that thermal stimuli play an important role for the prediction of actions on blinds.

G-statistic from outdoor temperature is acceptable ($G = 313.1$), although much lower than from indoor temperature, as are the slope and R^2 ($a = 0.139$, $R^2 = 0.14$). Nevertheless outdoor temperature could be retained as a driving stimulus, which was not the case for windows. Values of BIC suggest in contrast that indoor temperature has slightly higher predictive power.

3.4 Fans

Although the use of fans has a somewhat negligible impact upon a room's energy balance, the influence on the human heat balance and thereby human thermal comfort is non-negligible, with possible consequences

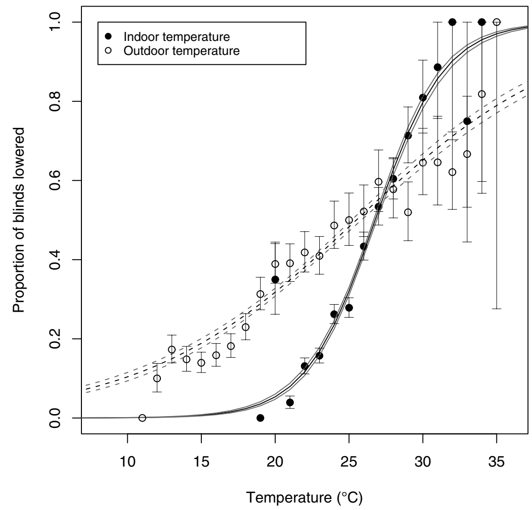

Figure 4: Blind closing probability as a function of indoor and outdoor temperature

for subsequent actions on other controls. It is thus sensible to consider fan use here.

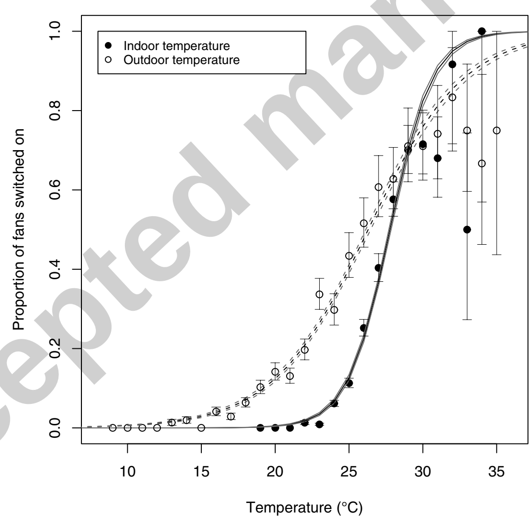

Figure 5: Fan switch-on probability as a function of indoor and outdoor temperature

Logistic regression with indoor temperature is highly significant ($G = 1110.1$, $R^2 = 0.39$) with a high characteristic temperature for action ($\theta_{50} = 27.8$°C). The slope is the highest of all the studied controls ($a = 0.696$), which shows a strong sensitivity to indoor temperature around θ_{50} (see Figure 5). Actions on fans are expected to be well described by indoor temperature, as they seem to be driven mostly by local thermal stimuli, which is not necessarily the case for the other controls, such as windows and blinds which regulate energy exchanges with the outdoor microclimate.

Nevertheless relevant results are also obtained with outdoor temperature, with G-statistic, R^2 and BIC being very similar to that found for indoor temperature, but once again with a less sharp slope ($a = 0.311$). This difference tends once again to advocate the use of indoor as opposed to outdoor temperature as a basis for prediction, as sharper slopes indicate more deterministic relationships.

3.5 Doors

Logistic regression applied to our data (Figure 6) shows acceptable results with respect to indoor temperature ($G = 273.7$, $R^2 = 0.08$), as the case for windows. The characteristic temperature ($\theta_{50} = 24.6°C$) is the lowest observed, and the slope is shallow ($a = 0.331$).

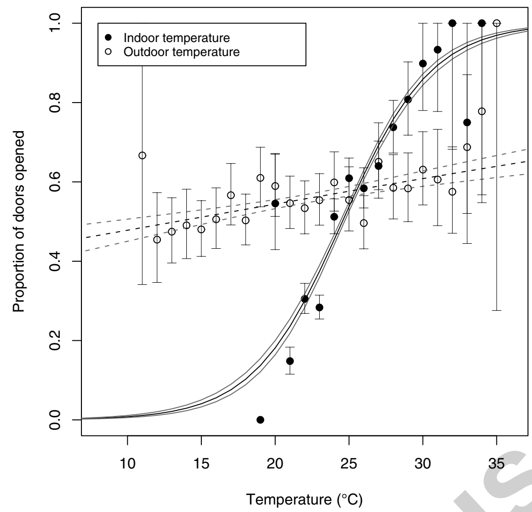

Figure 6: Door opening probability as a function of indoor and outdoor temperature

A clear relationship between door opening and outdoor temperature would not really be expected (as doors unlike windows are not interfaces between indoor and outdoor conditions). Results with logistic regression are especially unconvincing ($G = 9.4$, $R^2 = 0.01$) and the slope is extremely low ($a = 0.026$). Furthermore, this is the only instance for which the intercept ($b = -0.35$) is not statistically significant ($p > 0.05$). According to our results, door openings may thus be considered as essentially independent of outdoor temperature.

3.6 Cold drinks

As with the use of desk fans, the consumption of cold drinks influences human thermal regulation. Therefore, whilst not *directly relevant* to dynamic simulation programs, this does influence occupant satisfaction and may increase tolerance to higher indoor temperatures with possible implications for other control actions, so that there is an *indirect relevance*. Note that we have assumed that each participant had access to cold drinks.

Regression with indoor temperature (Figure 7) shows good significance ($G = 366.3$, $R^2 = 0.08$), the characteristic temperature is the highest in this study ($\theta_{50} = 28.6°C$) and the slope is similar to that observed for windows ($a = 0.243$).

The relationship with outdoor temperature is of better quality than was observed for other controls ($G = 366.7$, $R^2 = 0.08$), with practically identical G-statistic, R^2 and BIC as with indoor temperature. The intermediate value for the slope ($a = 0.108$) suggests however, as was the case with fans, that cold drink consumption is better explained by indoor than outdoor temperature.

Finally, it is noteworthy that there are no significant bins producing probabilities above 0.7, suggesting perhaps that a certain proportion of the population simply does not exercise this adaptive opportunity.

3.7 Activity and Clothing

As noted earlier occupants may, in principle, also adapt their clothing and activity levels in response to environmental stimuli. In contrast with residences in which occupants have the freedom to adapt their activities according to their personal preferences (which may or may not be decided in response to environmental stimuli), in workplaces our activities tend to be dictated by the tasks in hand. Metabolic

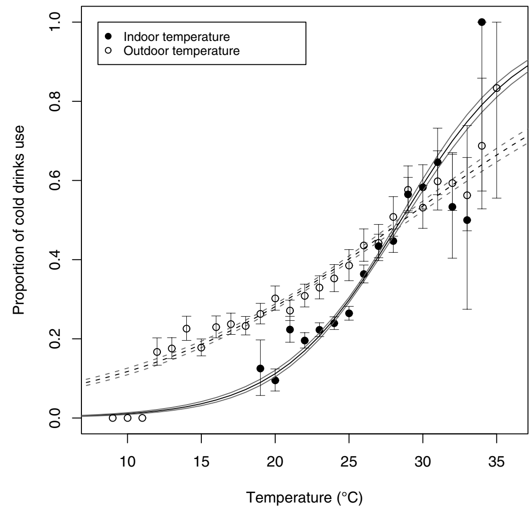

Figure 7: Cold drink consumption probability as a function of indoor and outdoor temperature

activity in offices may be particularly constrained, being essentially sedentary (desk-based) in nature. It is, we suggest, due to this constrained potential that we observe no discernible statistical correlation between the adaptation of activity and thermal stimuli (whether indoor or outdoor temperature). Indeed of our dataset of almost 6000 entries, less than 400 changes in activity were reported and the probability of such a change does not exceed 0.09 for any temperature bin. Furthermore, within the range $0.01 < p(\theta) \leq 0.09$ we observe no clear tendency to reduce activity level with temperature. **It is however possible that, under extreme thermal conditions, occupants have varied the intensity of their desk-based activity for a particular (constrained) type of activity, but our experiment was not designed to address this question.**

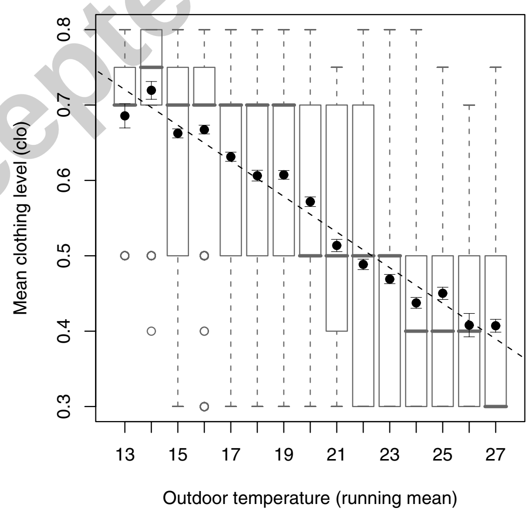

Figure 8: Mean clothing level as a function of running mean outdoor temperature (with medians and quartiles in gray and means in black)

In certain office environments, particularly those in which formal attire is favoured, occupants may also be constrained from adjusting their clothing level. Occupants of our relatively informal case study buildings however were able to adjust their clothing level in a rather unconstrained way. We should distinguish here between adaptation of clothing level between days and the occurrence of such adaptations during the day. By this we mean that occupants may choose their attire at the beginning of the day as a predictive strategy, based on historic experience (e.g. *it was warm yesterday and I expect it to be warmer still today, therefore I will reduce my clothing level today*) and/or they may wear several layers of clothing and remove these layers as a function of their thermal sensation (e.g. *it is cool at the moment, but I expect it to be warm this afternoon, therefore I will provide myself with the possibility to reduce my clothing level during the day*). As with activity, our results indicate that this latter opportunity is seldom exercised. Only around 200 changes in clothing level during the day were recorded, so that the probability of such a change does not exceed 0.07 for any temperature bin. However, within the range $0.01 < p(\theta) \leq 0.07$ we do observe a marginal tendency to reduce clothing level with temperature. Nevertheless, given the relative insignificance of the probability of such a change from occurring (the total cumulative probability is 0.033) we do not attempt to chart this relationship (likewise with activity level changes).

Our results do however indicate that the former type of adaptation is exercised; **based on the *exponentially weighted running mean outdoor temperature* [15]:**

$$\begin{aligned}\theta_{\mathrm{out,rm}} &= (1-\alpha)\cdot(\theta_{\mathrm{d}-1}+\alpha\cdot\theta_{\mathrm{d}-2}+\alpha^2\cdot\theta_{\mathrm{d}-3}+...)\\ &\cong (\theta_{\mathrm{d}-1}+0.8\cdot\theta_{\mathrm{d}-2}+0.6\cdot\theta_{\mathrm{d}-3}+0.5\cdot\theta_{\mathrm{d}-4}+0.4\cdot\theta_{\mathrm{d}-5}+0.3\cdot\theta_{\mathrm{d}-6}+0.2\cdot\theta_{\mathrm{d}-7})/3.8,\end{aligned}$$

with $\alpha = 0.8$ **and** $\theta_{\mathrm{d-i}}$ **being the daily mean outdoor temperature i days before**. In particular, we observe a rather clearer relationship between $\theta_{\mathrm{out,rm}}$ and the level of clothing insulation during that day (see Figure 8), as was also observed in [8]. Indeed we obtain from a linear regression on temperature bins that clo $= -0.0236 \cdot \theta_{\mathrm{out,rm}} + 1.0276$, with good agreement ($R^2 = 0.97$ on bins, $R^2 = 0.26$ **on raw data**).

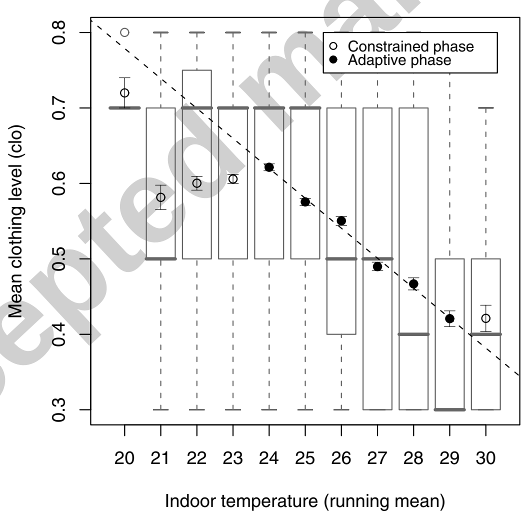

Figure 9: Mean clothing level as a function of running mean indoor temperature (with medians and quartiles in gray and means in black)

Regressions with indoor temperature give less straightforward results, particularly with respect to running mean indoor temperature (Figure 9). For 24°C $\leq \theta_{\mathrm{in,rm}} \leq$ 29°C, occupants clearly behave adaptively, and this may be described by a linear relationship clo $= -0.0397 \cdot \theta_{\mathrm{in,rm}} + 1.5730$, ($R^2 = 0.99$ on bins, $R^2 = 0.14$ **on raw data**). For $\theta_{\mathrm{in,rm}} >$ 29°C the clothing level remains constant, because it is not possible for occupants to be more lightly attired (there is a certain minimal acceptable clothing level). The plateau of clothing level in the range 20°C $\leq \theta_{\mathrm{in,rm}} <$ 24°C may be due to a compromise between moderate internal and warmer external conditions, or to a general seasonal adaptation, or perhaps even due to errors in judgement (occupants may have adapted to a cooler than predicted temperature, so that they have erroneously under-clothed themselves). We would expect our adaptive trend to continue as we approach the heating season so that clothing plateaus at a winter attire maxima.

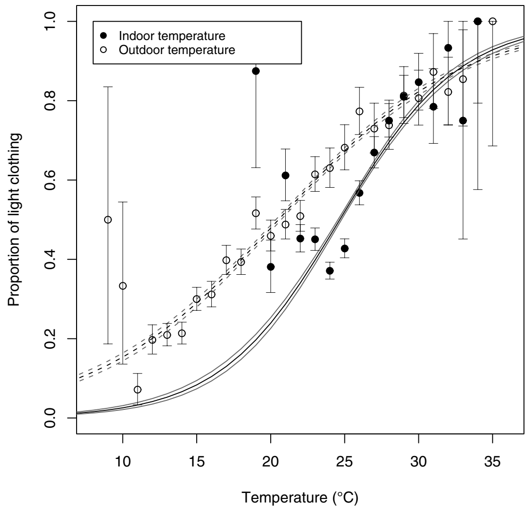

Figure 10: Light clothing probability as a function of indoor and outdoor temperature

Logistic regression can also be applied to this case. For this we simply reduce occupants' clothing levels to two categories – **lower or equal to 0.5 (clo) or higher or equal to 0.7 (clo), which cover all proposed options for clothing**, see Figure 10. In this way the choice to wear light clothing can be considered as an adaptive action of the same type (eg binary) as the ones studied above. The slope obtained is again higher for indoor temperature ($a = 0.248$) than for outdoor temperature ($a = 0.162$), but the G-statistic and R^2 from indoor temperature are around half ($G = 407.8$, $R^2 = 0.09$) that for outdoor temperature ($G = 817.7$, $R^2 = 0.17$). In other words, outdoor temperature is twice as effective at explaining the variation in clothing level. For this reason, outdoor temperature is a better choice as a driving predictor of clothing level. Logistic regression with running mean outdoor temperature gives even better results, with $G = 1135.6$ and a higher slope ($a = 0.287$).

In conclusion, clothing adaptation tends to be more a predictive strategy – the level being set at the beginning of the day, based on prior experience of thermal (especially outdoor) conditions, with opportunities for adaptation during the day being rarely exercised. However, such adaptations may be more frequently exercised during variable (eg inter-seasonal) weather. Unfortunately our dataset does not cover such periods.

Finally, and by way of summary, we present in Figure 11 the probability distributions derived from logistic regression on all of the above types of adaptive action, in relation to indoor air temperature. From this it is again clear that, whilst indoor temperature is better correlated with window openings than outdoor temperature, this variable alone is insufficient. Conversely, in the case of fans it appears that indoor temperature may be used as the sole stimulus with a good degree of confidence.

3.8 Simultaneous consideration of indoor and outdoor conditions

Based on Rijal's conclusions in [17], we have applied multiple logistic regression on our data in order to obtain probability distributions depending jointly on indoor and outdoor temperature. The aim here is to obtain constants a_{in}, a_{out} and b for use in the multiple logit function

$$p(\theta_{\text{in}}, \theta_{\text{out}}) = \frac{\exp(a_{\text{in}}\theta_{\text{in}} + a_{\text{out}}\theta_{\text{out}} + b)}{1 + \exp(a_{\text{in}}\theta_{\text{in}} + a_{\text{out}}\theta_{\text{out}} + b)}. \tag{4}$$

Couples of values $(\theta_{\text{in}}, \theta_{\text{out}})$ may be evaluated for the median thermal conditions of use of controls, following the relationship $a_{\text{in}}\theta_{\text{in}} + a_{\text{out}}\theta_{\text{out}} + b = 0$. Results from this multiple logistic regression analysis are displayed in Table 2.

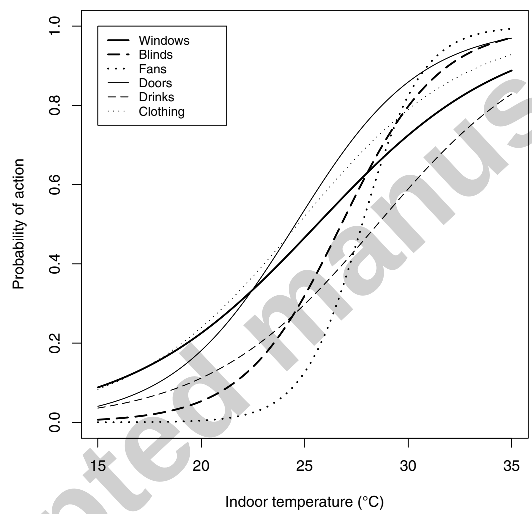

Figure 11: Probability distributions for all types of adaptive actions

Control	a_{in}	a_{out}	b	Total G-statistic	Residual deviance	Added G-statistic	BIC	R^2
Windows	0.301 ± 0.022	-0.050 ± 0.010	-6.58 ± 0.42	265.8	5182.1	27.7	5208.1	0.09
Blinds	0.407 ± 0.029	0.010 ± 0.012	-11.15 ± 0.59	535.9	3437.2	0.8	3463.3	0.22
Fans	0.396 ± 0.033	0.187 ± 0.016	-15.75 ± 0.73	1286.1	2905.3	153.6	2931.4	0.44
Doors	0.594 ± 0.033	-0.162 ± 0.014	-11.20 ± 0.65	420.7	2670.4	147.0	2696.5	0.23
Drinks	0.140 ± 0.019	0.062 ± 0.008	-5.67 ± 0.38	421.1	7126.9	54.4	7153.0	0.10
Clothing	-0.020 ± 0.019	0.169 ± 0.009	-2.97 ± 0.37	818.8	7312.4	1.1	7338.4	0.17

Table 2: Regression parameters for multiple logistic regression

We observe in all cases that the obtained values of a_{out} are extremely small (with $p > 0.05$ for blinds) and thus do not offer any reliable predictive properties. Furthermore, in the case of blinds, fans and drinks, we find that the values of a_{in} from multiple logistic regression are smaller than those from single regressions on indoor temperature, indicating that the main (internal) stimulus is being dampened by the other (external). For windows and doors a_{out} is negative, indicating a decrease in the use of controls for higher outdoor temperatures, which is somewhat suspicious, knowing that regression with outdoor temperature alone was itself not convincing in these cases.

We notice, too, that the difference in Nagelkerke's R^2 is negligible for most controls, except in the case of fans and doors, for which there is a small increase. Furthermore, some parameters are not significant for blinds and clothing ($p > 0.05$).

Finally, the correlation between θ_{in} and θ_{out} in our data is 0.74, so that the presence of (albeit weak) correlations with external temperature are (in some cases) due to the partial dependence of internal temperature on this variable (particularly in naturally ventilated buildings). It is not recommended to use two strongly correlated predictors in the application of generalised linear models, **as an increase in one leads to an increase in the other, which makes interpretation of regression coefficients difficult. However, for periods when the buildings are not free-running, this approach could be applied rigorously, but this would be of little interest in the present context.**

Considering the observations above it appears clearly that multiple logistic regression does not offer improvements in predictive accuracy, and may furthermore induce erroneous trends caused by high correlation between driving variables. We present in Section 5 a more appropriate approach for dealing simultaneously with several variables in the prediction of control actions.

4 Effects of adaptive actions on thermal sensation: empirical adaptive increments

Control in use	**Without action (°C)**	**With action (°C)**	**Offset (°C)**	**Confidence interval**	**N (no action)**	**N (action)**
Windows	24.22 ± 0.04	25.10 ± 0.06	0.88 ± 0.06	[0.77,1.00]	1562	1499
Blinds	24.45 ± 0.03	25.50 ± 0.08	1.05 ± 0.08	[0.89,1.21]	2486	575
Fans	24.55 ± 0.03	26.49 ± 0.13	1.94 ± 0.13	[1.71,2.17]	2897	164
Doors	24.43 ± 0.04	24.92 ± 0.06	0.49 ± 0.06	[0.37,0.61]	1731	1327
Drinks	24.57 ± 0.04	24.88 ± 0.07	0.31 ± 0.07	[0.17,0.44]	2269	792
Clothing	24.49 ± 0.04	24.82 ± 0.06	0.33 ± 0.06	[0.21,0.45]	1612	1449

Table 3: Reported comfort temperatures depending on the non-exclusive use of controls, with observed offsets, 95 % confidence intervals for offsets and dataset sizes

Having at our disposal simultaneous data for occupants' actions on controls and instantaneous thermal comfort votes, it is of special interest to determine whether the use of the studied controls plays a role in the reported thermal sensation of occupants, using the usual seven point thermal sensation scale [1]. For this purpose, we use the full dataset. That is we also include occupants that do not benefit from a particular adaptive control opportunity, as we focus particularly on the value added from having and exercising this possibility. To ascertain this value added from adaptive actions we determine the difference in mean temperature for "neutral" thermal sensation votes *with* and *without* having exercised a given adaptive action. This is equivalent to the notion of *adaptive increments* proposed by Baker and Standeven [6], and later reformulated by Oseland et al [7], albeit based on assumed boundary condition changes to the steady state Fanger model [1].

We have two sets of results for these empirical adaptive increments: (i) those generated for cases when the control action in question has or has not been exercised, but others may have been; and (ii) those in which this is exclusively the case (i.e. the data has been filtered to cases of no control action and *exclusively* the control action in question).

Although the latter case relates to a more rigorous definition of our adaptive increments, as possible bias due to the presence of other actions are then eliminated, we retain the former for interest; because the statistical significance of the associated results is higher.

4.1 Increments based on non-exclusive control actions

Figure 12 shows the distribution of indoor temperature with respect to reported thermal sensation, distinguishing whether a given control is exercised (either alone or possibly in conjugation with others). In general we observe increases or offsets in the mean temperature at which a given thermal sensation vote is reported, **which are all significant according to two sample t-test ($p < 0.001$)**. In other words for the same vote occupants tolerate higher temperatures when they have exercised some form of adaptive control action. The corresponding increments vary from 0.3°C for cold drinks to 1.9°C for fans (see Table 3).

It is also interesting to estimate the simultaneous influence of different controls. For example, in Figure 13 we show results for conjugated actions including windows and blinds (upper chart), and windows and doors (lower chart), in both cases possibly associated with other adaptive actions. We observe in the former case that the use of doors without windows does not imply a clear offset, but the joint use of these controls does lead to an *extra increase* in adaptive increment. In the latter case, each control exercised alone yields a clear increment, and their joint effect is *approximately additive*. However, for some other conjugations of controls, which we will not chart here, interactions are not constructive (their combined increment is lower than their component parts).

4.2 Increments based on exclusive control actions

When considering increments based on exclusive control actions, we use a linear model for the *comfort temperature* $\hat{\theta}$, which can be written $\hat{\theta}_{ij} = \mu + \alpha_i + \varepsilon_{ij}$, where $i = 1, \ldots, I$ and $j = 1, \ldots, J_i$. The values obtained for α_i are the effects on the comfort temperature produced by a given combination of adaptive actions, with ε_{ij} being the residuals. For conjugations of our exclusive actions on five controls, α has $I = \sum_{k=0}^{5} \binom{5}{k} = 32$ levels. The values for J_i, which are the numbers of data available for each level, are referred to in the "Occurrences" column of Table 4.

It is sensible to set $\alpha_1 = 0$, a choice corresponding to treatment contrasts, where the level $i = 1$ represents the reference group where no action is taken. The values obtained for $\alpha_i (i > 1)$ can then be directly interpreted as the empirical adaptive increments in comfort temperature produced by the associated control combination. Furthermore, the latter choice $\alpha_1 = 0$ enables direct interpretation of related statistical significance tests.

Our results for exclusive control actions are summarised in Figure 14 with box plots of increments for all observed combinations of controls where sufficient data is available, and in Table 4 with the associated increments. It can be observed in Figure 14 that our data do not show any sign of skewness or unequal variance between groups, and produce a reasonable amount of outliers. Moreover normal quantile and residuals plots, which are not displayed here, do not show any evidence to limit the scope of application of linear models.

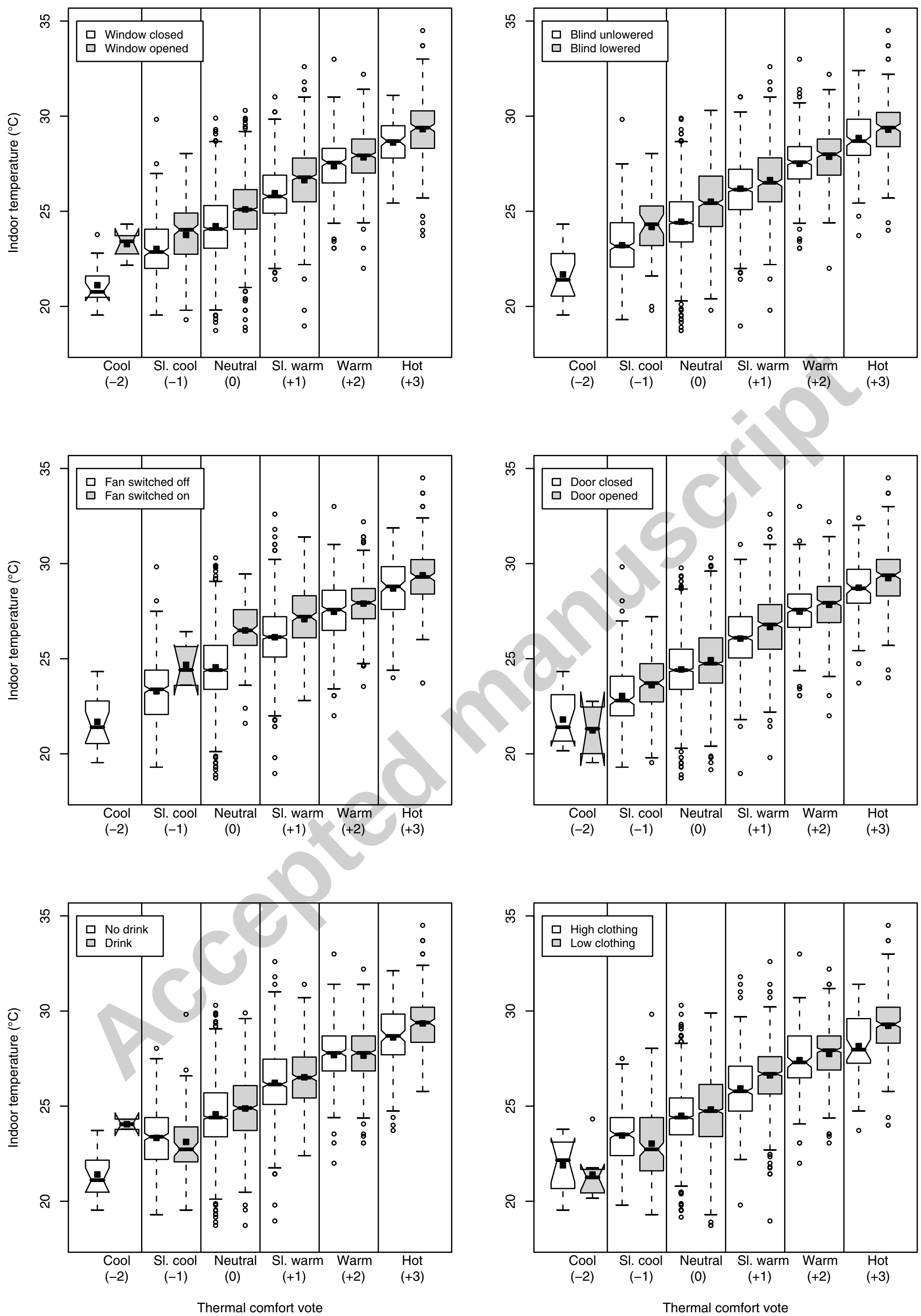

Figure 12: Controls' use influence on indoor temperature distribution for given thermal comfort votes

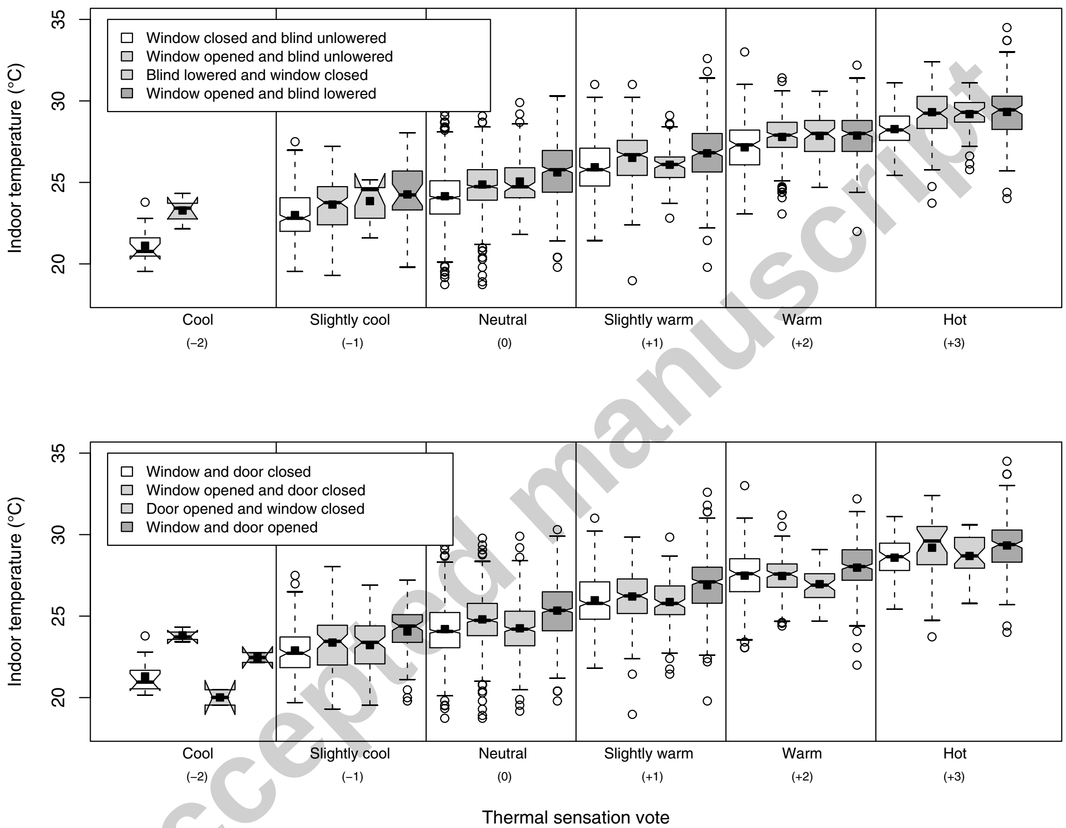

Figure 13: Joint influence of two types of conjugated adaptive actions on indoor temperature distribution for given thermal sensation votes

Our observed empirical adaptive increments are particularly evident in the case of windows, fans and drinks (Table 4), although the limited amount of data for exclusive use of controls does not enable us to draw precise conclusions in all cases. In particular, for the cases of isolated use of blinds or doors, we note that the p-value is superior to the usual 0.05 threshold of statistical significance. However, the clear result obtained for non-exclusive actions on blinds suggests that there is an impact on neutral temperature (and thereby adaptive increments). Given the large amount of data available for exclusive actions on doors on the other hand, it is clear that there is no statistical impact on adaptive increment.

No events were recorded for the combinations WBF and BFDd, and their increments couldn't be computed. It is important to note that adaptive increments presented here do not distinguish between high and low clothing levels and as such are not strictly speaking fully exclusive. To do so we would need to add another sub-category to each of our conjugations; for whom many are already lacking data, so that error bounds in the increments are rather high, likewise the p-values. Furthermore, the coefficient of determination R^2, defined as

$$R^2 = 1 - \frac{\sum(\hat{\theta}_{\text{fitted},i} - \hat{\theta}_i)^2}{\sum(\hat{\theta}_i - \hat{\theta}_{\text{mean}})^2}, \tag{5}$$

grows from 0.163 for the current model to 0.185 for the model with 64 levels including clothing. However, BIC increases then from 11597 to 11604. This suggests that a model with clothing would be saturated using our data. We will therefore not list here the increments obtained with respect to clothing levels, but mention in Table 4 the proportion of occupants lightly dressed for each combination of adaptive actions. A clear trend towards a higher proportion being lightly clothed for combinations of three and four controls can be observed (as expected because both are favoured by high temperatures) so that the associated increments are only modestly influenced by clothing. A full list of exclusive adaptive increments with respect to clothing could be computed using a larger dataset, which would allow us to assess rigorously the interactions between this latter and other adaptive actions.

Controls in use	Comfort temperature	Occur-rences	Adaptive increment	t value	p-value	Interaction constant	Proportion lightly dressed
None	23.98	777	0.00 ± 0.06	430.60	< 0.001		0.50 ± 0.03
W	24.56	348	0.58 ± 0.10	5.82	< 0.001		0.44 ± 0.04
B	24.44	28	0.46 ± 0.30	1.55	**0.12**		0.37 ± 0.12
F	25.37	16	1.39 ± 0.39	3.55	< 0.001		0.44 ± 0.17
D	24.13	339	0.15 ± 0.10	1.51	**0.13**		0.39 ± 0.03
d	24.67	204	0.69 ± 0.12	5.65	< 0.001		0.36 ± 0.04
WB	25.78	83	1.80 ± 0.18	10.05	< 0.001	1.72 ± 0.83	0.40 ± 0.07
WF	26.80	10	2.82 ± 0.49	5.71	< 0.001	1.43 ± 0.61	0.50 ± 0.22
WD	24.89	301	0.92 ± 0.11	8.69	< 0.001	1.25 ± 0.48	0.38 ± 0.04
Wd	24.77	189	0.79 ± 0.13	6.31	< 0.001	0.62 ± 0.21	0.35 ± 0.04
BF	25.27	14	1.30 ± 0.42	3.10	1.99E-03	0.70 ± 0.49	0.14 ± 0.10
BD	24.95	49	0.97 ± 0.23	4.25	< 0.001	1.58 ± 1.40	0.61 ± 0.11
Bd	25.84	10	1.86 ± 0.49	3.76	< 0.001	1.61 ± 1.02	0.50 ± 0.22
FD	25.43	**1**	1.45 ± 1.55	0.93	**0.35**	0.94 ± 1.31	0.00
Fd	27.31	4	3.33 ± 0.78	4.28	< 0.001	1.60 ± 0.77	0.25 ± 0.25
Dd	24.09	103	0.11 ± 0.16	0.65	**0.51**	0.13 ± 0.23	0.65 ± 0.08
WBD	25.36	219	1.38 ± 0.12	11.65	< 0.001	1.16 ± 0.58	0.54 ± 0.05
WBd	24.64	45	0.66 ± 0.24	2.78	5.51E-03	0.38 ± 0.25	0.82 ± 0.14
WFD	26.55	25	2.57 ± 0.32	8.14	< 0.001	1.21 ± 0.49	0.46 ± 0.14
WFd	25.43	**1**	1.45 ± 1.55	0.93	**0.35**	0.54 ± 0.71	0.00
WDd	25.09	153	1.11 ± 0.14	8.06	< 0.001	0.78 ± 0.27	0.50 ± 0.06
BFD	26.14	**1**	2.16 ± 1.55	1.39	**0.16**	1.08 ± 1.20	1.00
BFd	26.58	4	2.60 ± 0.78	3.34	< 0.001	1.02 ± 0.63	0.25 ± 0.25
BDd	25.59	8	1.61 ± 0.55	2.92	3.54E-03	1.23 ± 0.92	0.38 ± 0.22
FDd	26.67	4	2.69 ± 0.78	3.46	< 0.001	1.20 ± 0.68	1.00 ± 0.50
WBFD	26.79	58	2.81 ± 0.21	13.29	< 0.001	1.08 ± 0.46	0.86 ± 0.12
WBFd	26.14	**1**	2.16 ± 1.55	1.39	**0.16**	0.69 ± 0.70	0.00
WBDd	25.61	41	1.63 ± 0.25	6.57	< 0.001	0.87 ± 0.42	0.68 ± 0.13
WFDd	27.09	11	3.11 ± 0.47	6.60	< 0.001	1.10 ± 0.45	0.64 ± 0.24
WBFDd	26.83	14	2.85 ± 0.42	6.82	< 0.001	0.87 ± 0.40	0.71 ± 0.23

Table 4: Increments in comfort temperatures for the simultaneous use of several controls (W: windows, B: blinds, F: fans, D: doors, d: drinks)

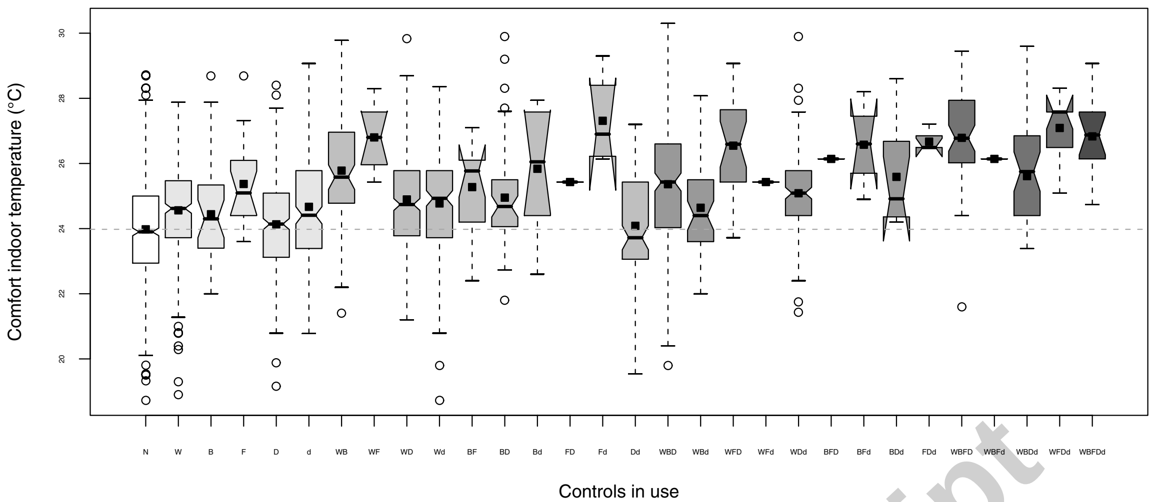

Figure 14: Joint influence of all controls on comfort temperature, with notches along the median denoting its statistical uncertainty, and solid squares for means (see Table 4 for explanation of notation on x-axis)

As previously observed in Figure 13, for some controls, when used simultaneously, offsets in comfort temperature tend to be accentuated while for other conjugations they tend to be dampened. In other words conjugations of controls do not yield simply (linearly) additive adaptive increments.

To examine this issue, let us define the joint increment D_{ij} of two controls providing individually the increments D_i and D_j. We can set $D_{ij} = \alpha_{ij}(D_i+D_j)$, where α_{ij} is an *interaction term*. When $\alpha_{ij} > 1$, an extra increment appears due to constructive interactions between controls, while when $\alpha_{ij} < 1$, controls do not fully interact constructively. Extending this definition, it is also possible to evaluate three-term and four-term interaction terms. Table 4 gives $\alpha_{ij(kl)}$ values for control conjugations where sufficient data are available.

Note however that the precision of many of these constants is dampened by statistical uncertainties in the increments. It is nevertheless of particular interest to note the statistically significant constructive interaction of windows and doors, the latter obviously playing a role in ventilation, but only in conjugation with another control of similar purpose. Conversely, we remark that our data show clearly that interactions of windows or doors with drinks are not constructive.

Finally it is of interest to compare these empirical adaptive increments with those of Oseland et al [7], who predicted increments of 1.1°C for windows, 0.9°C for cold drinks and 2.2°C to 2.8°C for fans. These proposed increments are all larger than we have observed.

5 Discussion

In the regression analysis used here, the parameter a describes occupants' sensitivity to indoor and outdoor temperature regarding the exercising of adaptive actions. In order of decreasing sensitivity we find that fans, blinds, doors, clothing, consumption of cold drinks and windows are well described by internal temperature, and in all cases better so than with outdoor temperature, as we always observe that $a_{\text{in}} > a_{\text{out}}$. But we do nevertheless find that actions on fans and blinds, the consumption of cold drinks and adopting low clothing levels may be acceptably modeled by outdoor temperature.

In order to better qualitatively understand their relative relevance, we compute a simple ratio $a_{\text{in}}/a_{\text{out}}$ (that is the ratio of the slope calculated for indoor and outdoor temperatures respectively), displayed in Table 5 along with G-statistic differences between fits with indoor and outdoor temperature and the ratio $R^2_{\text{in}}/R^2_{\text{out}}$. In support of the previous statement we observe that, in all cases, sensitivity to outdoor temperature in the use of these controls is overwhelmed by that to indoor temperature. Adjustment quality with indoor temperature is much superior for windows, blinds and doors, and practically equivalent for drinks and fans. However, the G-statistic and R^2 for outdoor temperature are double that for indoor temperature in the case of clothing, with a low slope ratio. As previously concluded, this shows that clothing level could be more reliably modeled by outdoor conditions, using for example logistic regression on running mean outdoor temperature.

Control	$\mathbf{a_{in}/a_{out}}$	$\mathbf{D_{in} - D_{out}}$	$\mathbf{R^2_{in}/R^2_{out}}$
Clothing	1.53	-409.9	0.52
Fans	2.24	-22.4	0.98
Drinks	2.25	-0.4	1.00
Blinds	3.06	222.0	1.65
Windows	4.49	180.7	4.05
Doors	12.73	264.3	27.55

Table 5: Slope ratios

However, our results do not allow us to totally discard outdoor temperature influences on other controls. For example, although actions on windows seem mainly to be governed by indoor temperature, outdoor temperature may play a role for low values (e.g. as a resistance to opening or as a stimulus for closing), but the data from our summer field survey are insufficient to examine this issue. Cold drink consumption is also reliably modeled by outdoor temperature, perhaps suggesting the presence of some form of *seasonal adaptation*, rather than a full influence of internal conditions.

There is also the question as to whether temperature may be regarded as the sole or predominant driving stimulus for adaptive actions. This may be plausible for personal characteristics and possibly also with respect to the use of fans and doors (though in the latter case organisational socio-cultural factors may play an important role, though these are difficult to quantify, especially at the design stage). Windows and blinds on the other hand, which directly moderate interactions with the external environment, are somewhat more complex.

Opening windows for example allows occupants to align indoor temperature with the current outside temperature, to dilute internally generated pollutants and to increase local air velocity; this latter assisting with occupants' physiological cooling. For these internal (or possibly external) temperature and internal pollutant concentration are likely to be the key stimuli for opening windows. However, external stimuli may act to reduce the probability with which windows are opened, or the duration for which they are left open. Examples include temperature, wind speed, rainfall and noise.

Rijal et al [17] attempt to consider both internal and external temperature in their recent probabilistic model of window opening (not closing) behaviour, with internal and external temperature being similarly treated. However, this approach does not address the influence of cold outdoor temperature on the duration of opening windows (to minimise draughts). Furthermore, since in free running buildings we expect indoor and outdoor temperature to be correlated it is not clear whether there is a real "direct" influence of outdoor temperature on window opening probability or whether this is "indirect" due to the intrinsic correlation between indoor and outdoor temperature. In the latter case this may actually reduce the quality of the model due to a dampening of the contribution of indoor temperature, as verified in Section 3.

We suggest that a more robust and general approach would be to address each of the factors influencing window opening and closing behaviour in an explicit way; to identify to which our behaviour is most sensitive and to model these influences as a logical sequence. For example, we may record an internal temperature and/or pollution concentration stimulus to open windows. This may or may not be followed by a corresponding negative stimulus based on outdoor temperature, noise, wind speed or precipitation. We may later record an internal temperature stimulus to close windows, likewise if we are about to leave for the evening (alternatively we may leave them open, if we predict the following day to be warm). Figure 15 suggests a general scheme for this approach.

Following from the above rationale, the lowering of blinds allows occupants to reduce solar heat gains (and thus dampen the rate of indoor temperature increase), to avoid glare and to regulate internal illuminance - so that **radiance/luminance distribution (see [16]) and temperature** are the key stimuli. Again, a similar logic sequence could be employed given appropriate probabilistic responses to visual stimuli.

Even with respect to thermal stimuli alone, our results are somewhat limited, as they relate only to a temperate climate. To generalise modelling of responses to temperature it would be desirable to obtain data from non-temperate (e.g. tropical) climates so that results for larger ranges of relative humidity, which may play a role on adaptive actions and/or increments for some controls, may be gathered. Concerning this latter point we should also note that, for some configurations, the suggested adaptive increments suffer from relatively high uncertainties due to the limited amount of available data. Additional measurements would strengthen these results.

Furthermore, we have yet to investigate the relative prioritisation of different control actions. In other words we have not yet studied in what sequence occupants exercise the adaptive opportunities available to them (at the moment we may find that, at a given simulation time step, an occupant exercises all adaptive opportunities, whereas we would intuitively expect this to be a progressive process) and the extent to which one action influences the timing of another. However the characteristic temperature θ_{50} at which adaptive actions are taken (see Table 1) suggests the following sequence: clothing, doors, windows, blinds, fans and drinks.

Finally, research is still at an embryonic stage regarding the inertia of control actions due to different stimuli, be these thermal, visual, olfactory or acoustic. For instance, visual stimuli, like glare, provoke a more immediate action from occupants than usual thermal or olfactory stimuli. Little is known, too,

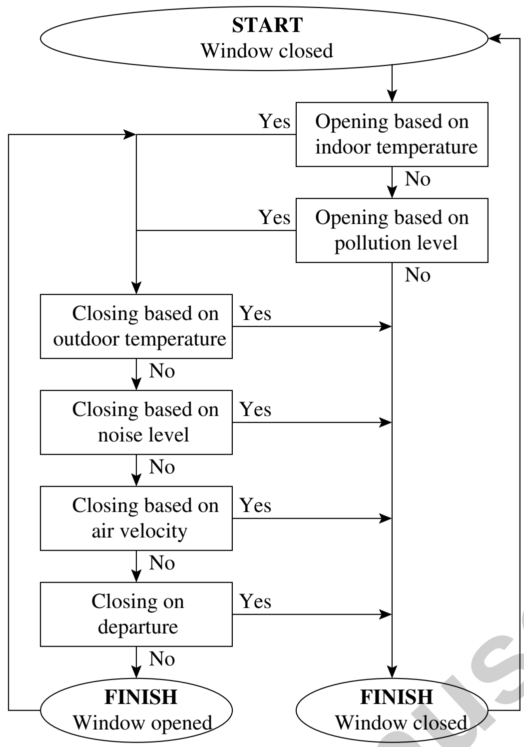

Figure 15: Scheme for the treatment of actions on windows

regarding the influence of group dynamics on the use of controls in multi-occupied offices. See Robinson [13] for further discussion.

6 Conclusion

During the warm summer of 2006 a comprehensive longitudinal field survey of the adaptive actions of occupants, their thermal satisfaction and the coincident environmental conditions was conducted in eight Swiss offices. Based on analysis of these results we have:

- applied logistic regression techniques to predict the probability of occupants' actions to adapt both personal (clothing, activity and drinks) and environmental (windows, doors, fans and blinds) characteristics as a function of both internal and external temperature;

- identified, for each type of control action, the increases in temperature at which thermal sensation votes are reported. These *empirical adaptive increments* have also been defined for conjugations of control action.

We find that in general the probability of occupants' interacting with their personal/environmental characteristics is considerably better described by internal than by external temperature. However, in the case of environmental characteristics these thermal stimuli alone are insufficient to describe the set of circumstances under which such actions take place. Furthermore, only the opening of windows, lowering of blinds and switching on of fans is considered (closing, raising and switching off are ignored). A promising route to address this would be by means of multi-nested control logic, with each decision possibly being based on a probabilistic approach. This requires further work to develop the outstanding probabilistic models but also to understand relative priorities between control actions and how individual differs from group-based control. When complete this would then provide a comprehensive basis for integrating occupant interactions with controls in building simulation programs and also an improved basis for predicting occupant environmental satisfaction.

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