AN INTEGRATED ADAPTIVE MODEL FOR OVERHEATING RISK PREDICTION

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ABSTRACT

Based on results from a field survey campaign, this paper describes three new developments which have been integrated to provide a comprehensive basis for the evaluation of overheating risk in offices. Firstly, a set of logistic regression equations have been derived to predict the probability of office occupants' adaptation of personal and environmental characteristics. Secondly, empirical adaptive increments (offsets in comfort temperature) have been derived for each of these modes of adaptation. Thirdly, these adaptive increments are used to derive *adapted* degree-days of overheating stimuli for input to a new model to predict overheating risk. Based on analogy between the charging and discharging of humans' tolerance to overheating stimuli and that of charge in an electrical capacitor, this analytical model uses empirical coefficients to tune its (dis)charging time constants to a given population and situation. This paper introduces these developments and how they may be coupled to building simulation programs to predict the risk that proposed design solutions will overheat. Scope for further development, as well as possible alternatives to the presented approach, are also discussed

KEYWORDS

Thermal comfort, overheating risk, adaptive actions, empirical adaptive increments, integration, building simulation.

1 INTRODUCTION

Building design evolves in response to performance criteria, be these financially, aesthetically, environmentally or otherwise based. With increasing pressure to eliminate or reduce the intensity of use of mechanical cooling systems, overheating risk is becoming increasingly important as one of these design criteria. Traditionally spaces have been judged to have overheated based on some instantaneous heat stress: an instantaneous departure from some comfort zone (eg. ASHRAE (1996)). However, some more recent standards such as that due to van der Linden et al (2002) are based on some limiting accumulation of overheating stimuli. But there has not as yet been a definitive study to support application of either one of these approaches, nor for defining the limits used. The present paper describes the results of a research project that was conceived to resolve this lack of rigour in overheating definition and to formulate a model to predict overheating risk. A further related aim was to understand whether and to what extent occupants are more tolerant of overheating stimuli when they have exercised opportunities to adapt their personal and/or environmental characteristics. If adaptive actions do influence overheating risk then, for this work to be useful, some basis for predicting the probability that these actions will take place should be provided for; likewise the implications for overheating risk. Such an integrated model could then be coupled to a building simulation program which would in turn predict the corresponding physical responses of these adaptive actions. In this paper we present a first attempt to do just this.

In the next section the field survey methodology that was conceived to support the development of the proposed model of overheating risk prediction is briefly presented, along with results regarding causes of overheating. A new analytical model for predicting overheating risk, based on analogy with an electrical capacitor, is then described. Finally an approach to modelling human adaptations to reduce discomforting stimuli and their corresponding effects on thermal satisfaction is presented. This is based on empirical adjustments of neutral temperature (empirical adaptive increments), although alternative approaches based on steady state (Fanger) and dynamic thermal comfort models are also discussed.

The paper closes by discussing some weaknesses as well as possible improvements to the new model.

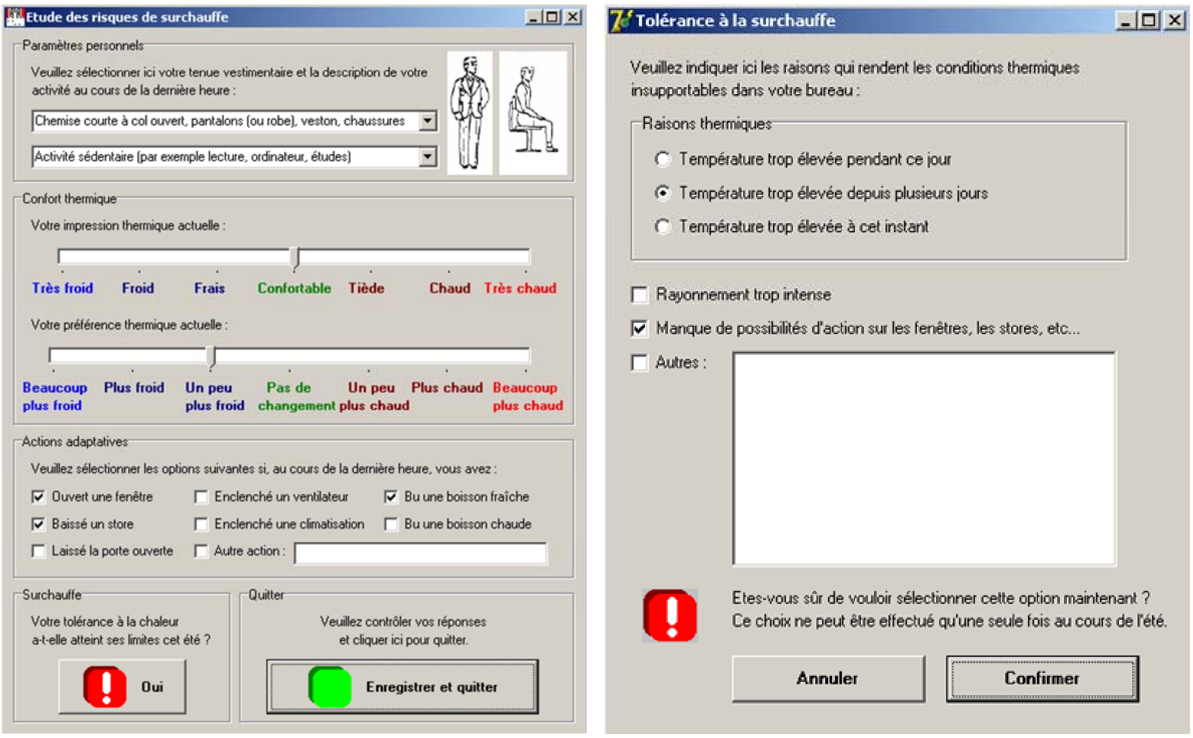
2 FIELD SURVEY METHODOLOGY

During the summer of 2006 a field survey was conducted in eight non air-conditioned office buildings, each located within a 50km radius of Lausanne (latitude 46.5°N, longitude 6.7°E), Switzerland. Their selection was based on a desire for reasonable diversity in terms of their design concept and the adaptive opportunities available to occupants.

For each building, volunteers were asked to complete a short electronic questionnaire which was installed on their PC. This questionnaire (Figure 1a), which appeared at regular participant-defined intervals, asked for evaluations of:

- Clothing and activity level.
- Thermal satisfaction and preference.
- Adaptive opportunities exercised.

The purpose of this dialogue box was to produce time-series data regarding participants' adaptive actions and their evolving perception of the parameter(s) under examination.


Etude des risques de surchauffe

Paramètres personnels

Veuillez sélectionner ici votre tenue vestimentaire et la description de votre activité au cours de la dernière heure :

Chemise courte à col ouvert, pantalons (ou robe), veston, chaussures

Activité sédentaire (par exemple lecture, ordinateur, études)

Confort thermique

Votre impression thermique actuelle : Confortable

Votre préférence thermique actuelle : Un peu plus froid

Actions adaptatives

Veuillez sélectionner les options suivantes si, au cours de la dernière heure, vous avez :

☑ Ouvert une fenêtre
☑ Baissé un store
☐ Laissé la porte ouverte
☐ Enclenché un ventilateur
☐ Enclenché une climatisation
☐ Autre action :
☑ Bu une boisson fraîche
☐ Bu une boisson chaude

Surchauffe

Votre tolérance à la chaleur a-t-elle atteint ses limites cet été ?

Quitter

Veuillez contrôler vos réponses et cliquer ici pour quitter.

Tolérance à la surchauffe

Veuillez indiquer ici les raisons qui rendent les conditions thermiques insupportables dans votre bureau :

Raisons thermiques

○ Température trop élevée pendant ce jour
● Température trop élevée depuis plusieurs jours
○ Température trop élevée à cet instant

☐ Rayonnement trop intense
☑ Manque de possibilités d'action sur les fenêtres, les stores, etc...
☐ Autres :

Etes-vous sûr de vouloir sélectionner cette option maintenant ? Ce choix ne peut être effectué qu'une seule fois au cours de l'été.

Figure 1 Longitudinal e-questionnaire (1a: left) and dialogue box for explaining causes of overheating (1b: right)

Participants were also asked to press an 'overheated' button once they felt that their thermal tolerance had been surpassed. To ensure that unambiguous information would be obtained participants were asked to select this option one time only. After confirming their choice, this prompted a further dialogue box (Figure 1b) which requested participants to describe the circumstances that led to this transition in tolerance (i.e. from the space having been thermally acceptable to now having overheated). More specifically whether this was caused by excessive temperatures during the moment in question, throughout the day in question or throughout several prior days. Participants were also asked to remark whether this overheating was influenced by excess solar gain, a lack of control options or to offer alternative explanations.

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 four times per day). In parallel, measurements were recorded at 45min intervals from calibrated solar-shielded temperature sensors, installed in close proximity to each participant's workstation. Finally, at the end of the study, local simultaneous climate data was obtained from the Swiss Federal Office of the Environment.

In total there were 60 participants in this study, who produced a total of 5 908 responses (i.e. each participant completed the questionnaire an average 98 times) for the period 13 June to 27 September 2006.

3 OVERHEATING RISK

Of the sixty participants only twenty two reported that their thermal tolerance had been exceeded. Of these only 18% (4 of 22) indicated that this was caused by excess temperature at the moment in question, whereas 27% (5 of 22) indicated that this was due to excess temperature during the day in question and 55% (12 of 22) that this was due to excess temperature during the past several days (Figure 2).

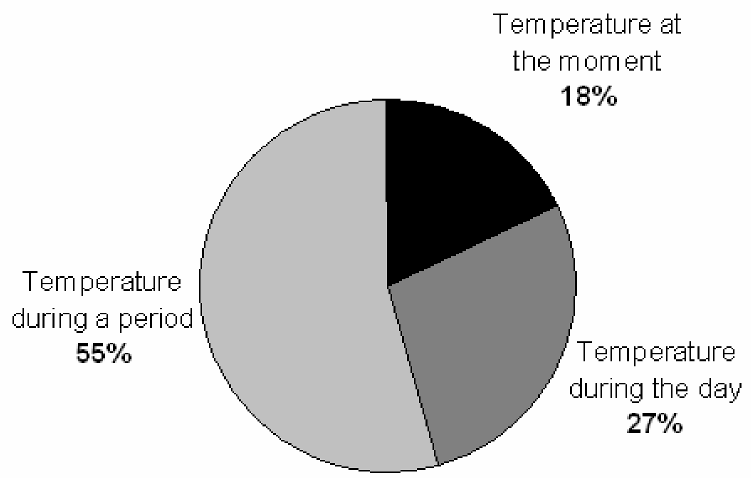


Figure 2 Distribution of time periods responsible for overheating

This result tends to confirm that occupants are tolerant of occasional departures from comfort; or more specifically that overheating is due to an accumulation of heat stress events rather than a single event (which may regarded a special case of an accumulation of heat stresses over a very short period of time).

Following from this rationale that it is an accumulation of stimuli that leads us to consider a space as having overheated, the principal hypothesis of the present model is that (the storage of) human tolerance to overheating stimuli can be considered as equivalent to the storage of electrical charge in a capacitor. By this it is meant that during a series of particularly warm days this overheating tolerance is **dis**charged. If this is followed by a cooler period then this tolerance is **re**charged. An extreme example of this is a recharging of tolerance during winter-time in readiness for discharging during the following summer (Figure 3). If tolerance $T \in [0,1]$ then the probability of overheating $P_{OH} = 1 - T$.

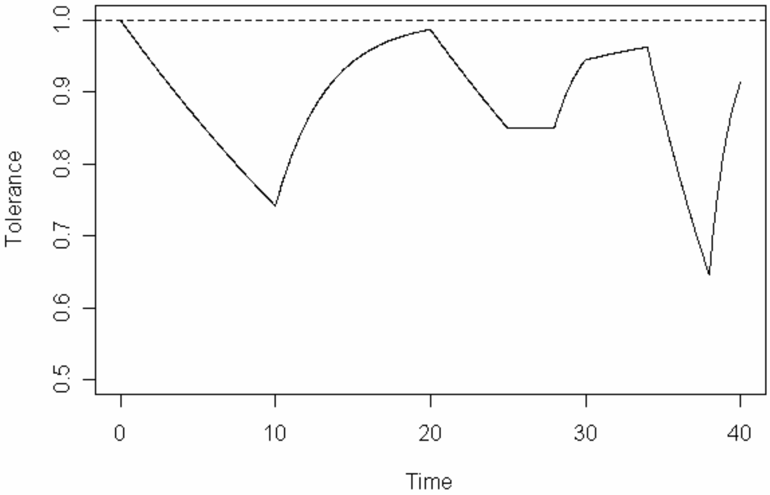


Figure 3 (Dis)charge of tolerance to overheating stimuli as analogue to overheating risk.

Now, it can be shown that, whilst discharging, the voltage U_C at the bounds of a capacitor at time t is $U_C(t) = U_{C_0} \exp(-t/RC)$, whereas whilst charging we have that: $U_C(t) = U_0(1 - \exp(-t/RC)) + U_{C_0} \exp(-t/RC)$. In these expressions the product RC is a (dis)charging time constant τ and $U_{C0} = U_C(t = 0)$ corresponds either to the initial voltage or to that at the transition from charging to discharging. In the context of overheating U_0 shall be set to 1, $U_C(t)$ shall be interpreted as the probability of having overheated $P_{OH}(t)$ due to an accumulation of heat stimuli and $U_R(t)$ as the tolerance to these stimuli, so that $U_R(t)+U_C(t)=1$ for any time t[1].

In this model it is assumed that the heat stimuli may be represented by the excess of some reference temperature θ^*, say 25°C. The reciprocal of our time constant $1/\tau$ is therefore replaced with the *time-varying* expression $\alpha(\theta(t)-\theta^*)$ in the charge expression, given a constant α, and with $\beta(\theta^*-\theta(t))$ in the discharge expression, with α,β being parameters to determine empirically. Furthermore, if heat stimuli are accumulated in the form of degree-hours (*DH*) above a reference temperature during the period t_i,t_j as $DH_{ti,tj}=(\theta(t_i)-\theta^*)\cdot(t_j-t_i)$ the following expression for charging during n consecutive periods $[t_0,t_0+\Delta t],\ldots,[t_n-\Delta t,t_n]$ is obtained (see Robinson and Haldi (2007) for a full derivation):

$$P_{OH}(t_n)=(1-P_{OH}(t_0))\cdot 1-\exp(-\alpha\sum_{i=1}^{n}DH_{t_0,t_i}) \qquad \text{...[1a]}$$

and for discharging during n periods we have:

$$P_{OH}(t_n)=P_{OH}(t_0)\cdot\exp(-\beta\sum_{i=1}^{n}DH^*{}_{t_0,t_i}) \qquad \text{...[1b]}$$

where $P_{OH}(t_0)$ is either zero at the start of a simulation or refers to the probability of overheating at the time of transition from charging to discharging (or vice versa) and $DH^*_{ti,tj}=(\theta^*-\theta(t_i))\cdot(t_j-t_i)$. In this way the temporal evolution of the probability of overheating within the limits [0,1] may be modelled, during an arbitrary time period. By way of example, shown left in Figure 4 is a hypothetical curve of step changes in temperature with time whilst on the right the resultant evolution of overheating probability is presented with respect to a reference temperature of 25°C, for both charging and discharging. This latter figure is also the inverse of the thermal tolerance chart that was presented for illustrative purposes in Figure 2 above.

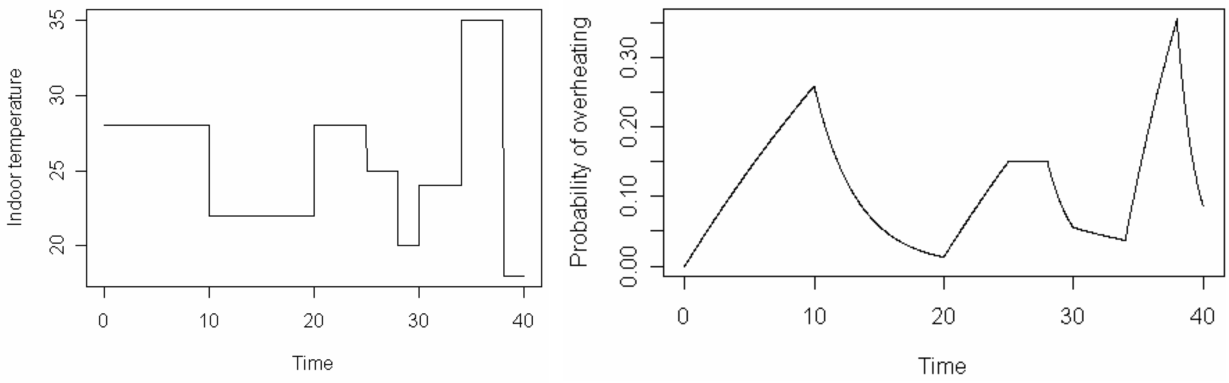


Figure 4 Step changes in indoor air temperature (left) and the overheating probability response curve (right)

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[1] The charge of an electrical capacitor as opposed to the temperature of a solid is taken to be a more coherent basis of analogy with this simple overheating model (though either may in principle be employed). Furthermore, it is not the intention of this model to equate overheating with a human heat balance model (of necessarily small time constant), but rather to the psychological tolerance to an accumulation of thermal stresses. Use of an electrical as opposed to thermal capacitance model helps to avoid this possible confusion.

Now, during the warmest period of the field survey campaign in which all overheating events were logged, no internal air temperature below 25°C was recorded during working hours. The period was thus a continuously charging period of overheating probability (or inversely a discharging of tolerance). Under such (continuously charging) circumstances Eq. 1a may be simplified somewhat, so that:

$$P_{OH}(t) = 1 - \exp\left(-\alpha' DH_{t0,t}\right) \qquad \text{...[2]}$$

where $\alpha' = \alpha\Delta t$. α' may then be determined using the regression equation $\log\left(1 - P_{OH}(t)\right) = -\alpha' DH_{t0,t}$ where P_{OH} is the observed cumulative probability of overheating (Figure 5). Performing this regression on our data gives a value of $\alpha' = 4.75(\pm 0.14)\cdot 10^{-4}$ [$K^{-1}h^{-1}$] with good agreement ($r^2 = 0.98$), albeit perhaps based on a limited range of 0 < (DH>25°C) < 1200. The corresponding predicted probability of overheating using this simplified form of the model (i.e. for continuous charging) is compared with the measurement results in Figure 6.

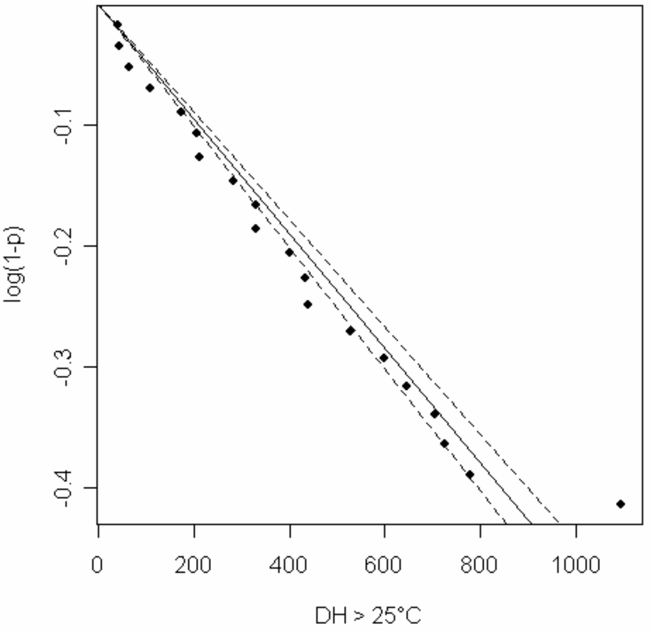

Figure 5Linear regression for derivation of empirical coefficient α′ with 95% confidence interval

Note that this new model predicts the *probability* that a population will perceive a given space to have overheated, but this may also be interpreted as the *proportion* of a given population that will perceive a space to have overheated.

Now, to test the proposed model thoroughly, data spanning the entire range P_{OH} [0,1] would ideally be available, but unfortunately the summer of 2006 was not sufficiently warm to provide these data. Nevertheless since building designers seek to ensure the comfort of the majority of a building population, so that current thermal comfort standards target a percentage of people dissatisfied (PPD) of ≤20%[2], this model may be considered valid

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[2] For example, ASHRAE-Standard 55 has traditionally defined an acceptable thermal environment as one in which there is 80% overall acceptability (Olesen and Brager, 2004).

[Figure 6] within the range of practical application [i.e. it compares well with measurements in the range $0 \leq P_{OH} \leq 0.2$ that is of interest to building designers[3]]. See Robinson and Haldi (2007) for further discussion.

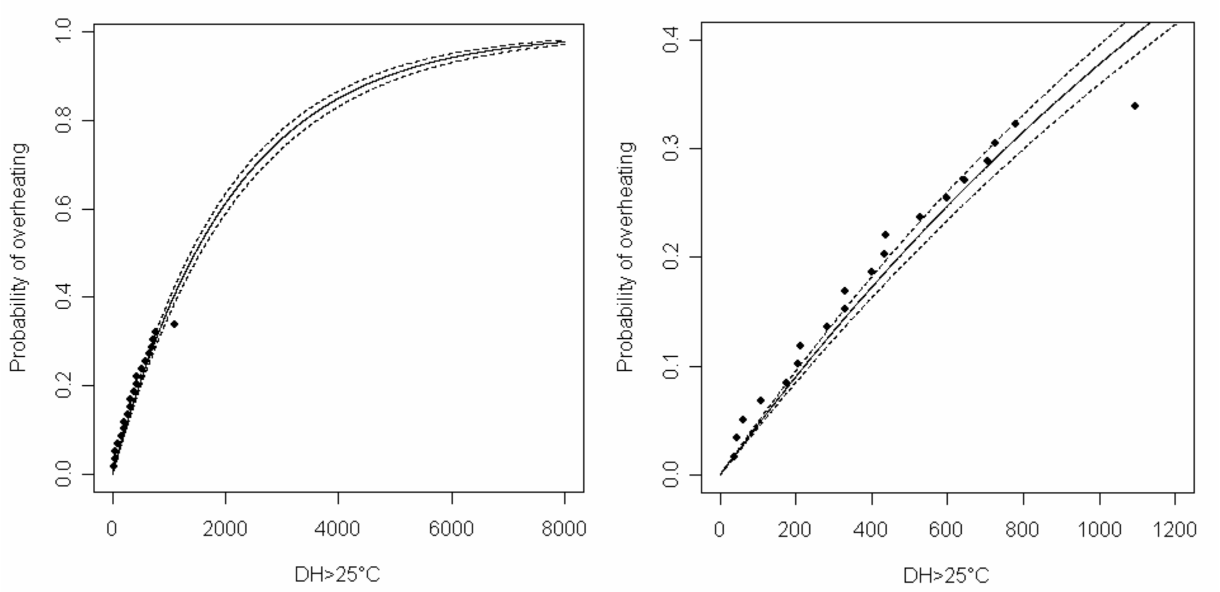

Figure 6Predicted (solid line) and measured (solid diamonds) overheating probability as a function of DH>25°C in the probability range [0,1] (left) and focussing on the range [0,0.4] (right), with 95% confidence intervals.

Although it has not been possible to obtain data with which to calibrate β (for this at least two warm periods interrupted by a cool period would be needed), it is plausible that $\beta \gg \alpha$ (perhaps of the order $\beta \approx 10\alpha'$). This, it is supposed, is because occupants are psychologically more sensitive to the thermal relief that they feel during a cool period which follows a warm period in which their tolerance has been gradually discharged.

4 INTEGRATION OF ADAPTIVE PROCESSES

As Oseland et al eloquently suggested in 1998, "if a change occurs such as to produce discomfort, people react in ways which tend to restore their comfort". Furthermore, when available adaptive opportunities are exercised, these tend not only to reduce discomforting stimuli (e.g. shading to reduce radiation absorption; window openings to increase convective cooling etc) but also to affect "cognitive tolerance" to these stimuli: so that when the cause of discomfort is understood (and indeed partially the occupant's responsibility) tolerance is increased (Baker and Standeven, 1996). These physiological and psychological adaptive processes are suggested to increase occupants' summertime neutral temperature (the temperature at which they feel neither warm nor cool), with consequent implications for overheating risk

This notion of adaptability is **implicit** in the coefficient α' of the above model, in the sense that it has been tuned to a set of buildings within which occupants have some degree of control over their environment. To take this into

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[3] Although *PPD* and P_{OH} are semantically different, the former referring to instantaneous satisfaction, the latter to satisfaction with accumulated overheating stimuli, the spirit is similar, in that we seek to satisfy at least 80% of the population.

account in an **explicit** way, and thereby produce a more general form of model, several options are available. One option would be to define different sets of coefficients *α, β* for buildings with different degrees of adaptability (provided of course that sufficient data exists). In this the model would be of direct use as a basis for judging the overheating risk of other buildings, provided that there was a good match between these other buildings and those used to define *α, β*.

An alternative and more robust approach would be firstly to remove the effects of adaptive processes (elevation of neutral temperature[4]) from our coefficients *α, β*. In the simplified case of continuous discharging of overheating tolerance, this would be achieved by reducing $DH_{t0,t}$ in the regression $\alpha' = -\log(1 - P_{OH}(t))/DH_{t0,t}$ by an amount equal to the set of offsets in neutral temperature arising from occupants' adaptive actions (or *adaptive increments* as Baker and Standeven (1996) christened them). Put more clearly the degree hours of overheating during the period t_i, t_j are then $DH_{ti,tj} = \left([\theta(t_i) - \Delta\theta(t_i)] - \theta^*\right) \cdot (t_j - t_i)$, where $\Delta\theta$ is the accumulation of adaptive increments arising from the probabilities of exercising all **measured** single and conjugate adaptive actions at time *t*, so that:

$$\Delta\theta(t) = \sum_j P_j\left(\theta_{in}(t)\right) \cdot D_j + \sum_{kl} P_{kl}\left(\theta_{in}(t)\right) \cdot D_{kl} + \ldots,$$

where D_j are the adaptive increments caused by the isolated use of one of *n* controls and D_{kl} by the conjugations of two controls ($j,k,l = 1,\ldots,n$). The corresponding regression for the case in which degree-days of overheating stimuli have been reduced according to probable adaptive increments is shown in Figure 7 (left). The corresponding coefficient $\alpha' = 7.79(\pm 0.34) \cdot 10^{-4}$ [$K^{-1}h^{-1}$] and the predicted overheating probability distributions are shown centre and right in Figure 7[5].

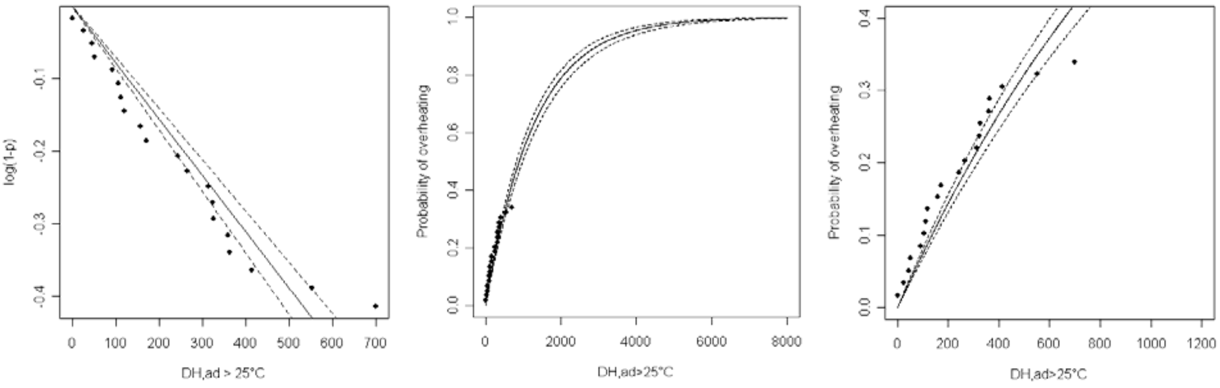

Figure 7: Linear regression for derivation of un-adapted α′(left) and the corresponding overheating probability curves for the range [0,1] (centre) and [0,0.4] (right). Predictions are represented by solid lines and 95% confidence intervals by dotted lines.

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[4] the difference in median temperature for "neutral" thermal sensation votes *with* and *without* having exercised a given adaptive action.

[5] Note that for consistency of presentation the solid diamonds in this case relate to predictions using $DH_{t0,t}$ adjusted according to the same probabilistic adaptive increments used in deriving the coefficient α'.

The resultant *non-adaptive* model then becomes an *adaptive* one when the *simulated* thermal input $DH_{t0,t}$ in [eq. 2] has been adjusted according to the adaptive increments $\Delta\theta$ arising from the various *simulated* single or conjugate adaptive actions taken (i.e. the model is now in principle generalised, so that overheating risk may be predicted for any proposed building, given a simulated temperature profile and a record of simulated actions). This integrated model then has the form (Figure 8):

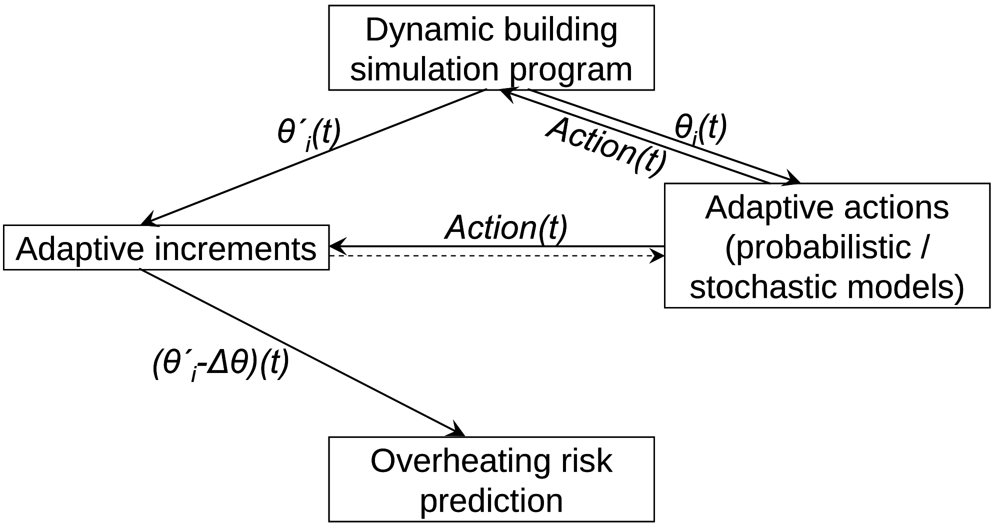

Figure 8 Schematic view of integrated model

In this model then, a dynamic thermal simulation program is coupled with a family of probabilistic / stochastic models of human interactions with personal and environmental characteristics. At time t a single or conjugation of adaptive actions takes place – a window is opened for example – in response to the input environmental stimuli, say internal air temperature θ_i at time t. This influences the target zone's heat balance which in turn influences the buoyancy pressures driving the mass flow through our newly opened window. When predictions from our thermal and airflow models have converged we have a new air temperature θ'_i. This may be used to calculate the corresponding degree hours of overheating stimuli, based on the difference between the converged air temperature, less the adaptive increments associated with the adaptive action(s) taken, and a given reference temperature θ^*. With this information the corresponding change in overheating risk from the previous timestep to the present one may be calculated[6].

The advantage of this approach is its considerable simplicity. All that is required is to gather enough statistically meaningful data from which to derive the models of adaptive actions and the adaptive increments which correspond to the typical physiological / psychological thermal relief associated with these actions.

An alternative to this wholly statistical approach might be to reformulate this integrated overheating model to take inputs from a deterministic thermal comfort model, such as the steady state model of Fanger (1970) or the detailed dynamic model due to Fiala (1998), which itself would take as input occupants' personal characteristics (perhaps probabilistically defined) and local environmental stimuli. A complication which now arises is that these

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[6] In fact, since there is no direct feedback from "adaptive increments" [at least in this model] and "overheating risk prediction" to either the "dynamic building simulation program" or the associated "adaptive actions", the former may in principle be handled as a separate post-process; so that the overheating model simply reads in time-series temperature and adaptive action data.

environmental stimuli should comprise the air and radiant temperature, shortwave radiation absorption, air velocity and relative humidity; which would be locally experienced following a particular simulated adaptive action. This is not terribly complicated in the case of temperature, humidity and radiation exchange (these are standard features – albeit somewhat weak in terms of radiation exchange (Robinson and Stone, 2004) – of dynamic building simulation programs); but local simulation of air velocity (and perhaps turbulent intensity) implies coupling the steady state or dynamic thermal comfort model with some form of computational fluid dynamics model, embedded within a bulk airflow model, itself coupled with a dynamic building simulation program[7].

Numerous studies have been conducted in recent years to test the validity of using the *steady state Fanger* model to test the thermal comfort of non air-conditioned spaces, by comparing measured Actual Sensation Vote (ASV) with Predicted mean Vote (PMV). Oseland (1997) provides a comprehensive review of such studies which consistently reveal significant discrepancies between ASV and PMV. As de Dear (1994) notes "the PMV…[is] appropriate in practice for climate controlled or air-conditioned buildings as a predictive tool. However, for naturally ventilated buildings, we need an adaptive model". There are several reasons for the observed discrepancies. Foremost is that treating the human heat balance as steady state introduces important errors when this modelled human is subjected to the highly transient conditions that are commonly experienced in passively designed buildings[8]. Another key source of error (referred to be de Dear) is that the physical consequences of adaptive actions (e.g. moderated local radiant temperature or air velocity), and the corresponding physiological responses, are ignored. See Humphreys and Nicol (2000, 2002) for more detailed discussions of the random and systematic errors associated with Fanger's PMV equation.

In principal, coupling a *dynamic* comfort model with models of adaptive processes and their consequences represents a sound way forward to account for the consequences of adaptive actions (which should themselves preferably be coupled with simulated responses to environmental stimuli). Bute as noted earlier, this would require detailed simulation of the indoor microclimate. The statistical approach of combining predicted adaptive actions (which use physical stimuli as an input) with the consequences of these actions on thermal satisfaction therefore seems to be an appropriate starting point, so that these are now each discussed in turn.

4.1 ADAPTIVE ACTIONS

Considerable progress has been made recently in simulating the presence of occupants in buildings and their interactions with personal and environmental characteristics in buildings. In the case of the modelling of occupancy presence this progress is reviewed by Page et al (2007), in which a comprehensive general model is also presented. Progress in the modelling of human behaviour in general is reviewed in Robinson (2006) and in more detail with respect to the modelling of the use of window openings and water/electrical appliances in Page (2007). In general, models of human presence and behaviour may be classified as being *stochastic* (they account

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[7] This however is not as yet a standard feature of building simulation programs, though Beausoleil-Morrison (2000) has achieved an initial implementation in the case of the integrated modeling environment ESP-r.

[8] The time constant of the body is essentially assumed to be zero, so that extrema in core temperature are over predicted…it is a pessimistic model.

for random fluctuations of the process under study and the dependence of this process on input stimuli, including time) or *probabilistic* (similar to stochastic, but with no direct temporal dependence).

In the following the probabilistic modelling of interactions which are intended to regulate occupants' thermal satisfaction is considered, whether this involves suppressing or diminishing discomforting stimuli or accentuating comforting stimuli.

4.1.1 PROBABILISTIC MODELLING OF BEHAVIOUR/ADAPTATION BY LOGISTIC REGRESSION ANALYSIS

In particular the influence of thermal stimuli on occupants' interactions with windows, blinds, fans and doors, their consumption of cold drinks as well as their use of light (<0.5 Clo) as opposed to heavy (>0.7 Clo) clothing levels are considered. More specifically, and inspired by the work of Nicol (2001) and Rijal et al (2007), distributions for the probability of occupants' adaptive actions are inferred as a function of indoor and outdoor temperature.

In order to infer a probability distribution for the whole range of temperatures, a statistical method already used for such purposes in Nicol (2001) and Rijal et al (2007) is logistic regression. The probability of a given event $p(\theta)$ then relates to input stimulus θ as follows: $\log\left(\frac{p(\theta)}{1-p(\theta)}\right) = a\theta + b$. The probability distribution is then given by the logit function: $p(\theta) = \frac{\exp(a\theta + b)}{1+\exp(a\theta + b)}$.

Parameters *a* and *b* are then obtained through regression using the binomial family of generalised linear models, specifying the logit as the link function. In the present work this regression analysis has been performed for the adaptive control options: opening windows, lowering blinds, switching on fans, opening doors, consuming cold drinks and choosing a low level of clothing insulation (Figure 9). In all cases (except for clothing) it is found that these actions are significantly better described by indoor rather than outdoor temperature or indeed the combination of indoor and outdoor temperature (Haldi and Robinson, 2007). Concerning the latter, which is based on multiple logistic regressions, it appears that because indoor and outdoor temperature are intrinsically correlated and that indoor temperature is a direct local stimulus, introducing outdoor temperature generally dampens the influence of indoor temperature and so degrades the quality of regressions. Nevertheless, the regression curves and associated error bands relating to both indoor and outdoor temperature (discretised into 1°C bins) for the range of adaptive actions mentioned above are presented Figure 9, with the regression parameters and those relating to goodness of fit presented in Table 1.

Conclusions regarding the validity of a given model models are inferred from the values obtained for the 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. From this the *G-statistic* can also be defined, as $G = D_{null} - D = -2 \log (\lambda_{null}/\lambda)$, 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[9] (Hosmer, 1989). 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 BIC = $-2 \log (\lambda/\lambda_S) + k \log N$, where *N* is the sample size. 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. In the present case, use of BIC is limited to the comparison between models for the same control, as the database sizes are different for different types of control.

Together with the above tests, it is also desirable to select models that provide good values for slope *a*, as these provide better (more deterministic) predictions in the context of building simulation.

Table 1 Logit function parameters for $p(\theta_i)$

Control	**Occupants, N**	**Thermal stimulus**	**a**	**b**	**G-statistic**	**Residual deviance**	**BIC**
Windows	40	Indoor	0.220 ± 0.015	-5.64 ± 0.38	238.1	5209.9	5227
		Outdoor	0.049 ± 0.006	-1.12 ± 0.15	57.4	5390.5	5408
Blinds	31	Indoor	0.425 ± 0.021	-11.37 ± 0.54	535.1	3438.0	3455
		Outdoor	0.139 ± 0.008	-3.54 ± 0.19	313.1	3660.0	3677
Fans	37	Indoor	0.696 ± 0.026	-19.32 ± 0.70	1110.1	3081.3	3099
		Outdoor	0.311 ± 0.011	-8.18 ± 0.28	1132.5	3058.9	3076
Doors	26	Indoor	0.331 ± 0.022	-8.14 ± 0.55	273.7	2817.5	2835
		Outdoor	0.026 ± 0.009	-0.35 ± 0.19	9.4	3081.8	3099
Drinks	60	Indoor	0.243 ± 0.013	-6.94 ± 0.34	366.3	7181.8	7199
		Outdoor	0.108 ± 0.006	-3.10 ± 0.14	366.7	7181.3	7199
Clothing	60	Indoor	0.248 ± 0.013	-6.11 ± 0.33	407.8	7723.4	7741
		Outdoor	0.162 ± 0.006	-3.33 ± 0.14	817.7	7313.5	7331

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[9] Although p-values are not presented, they are consistently highly significant

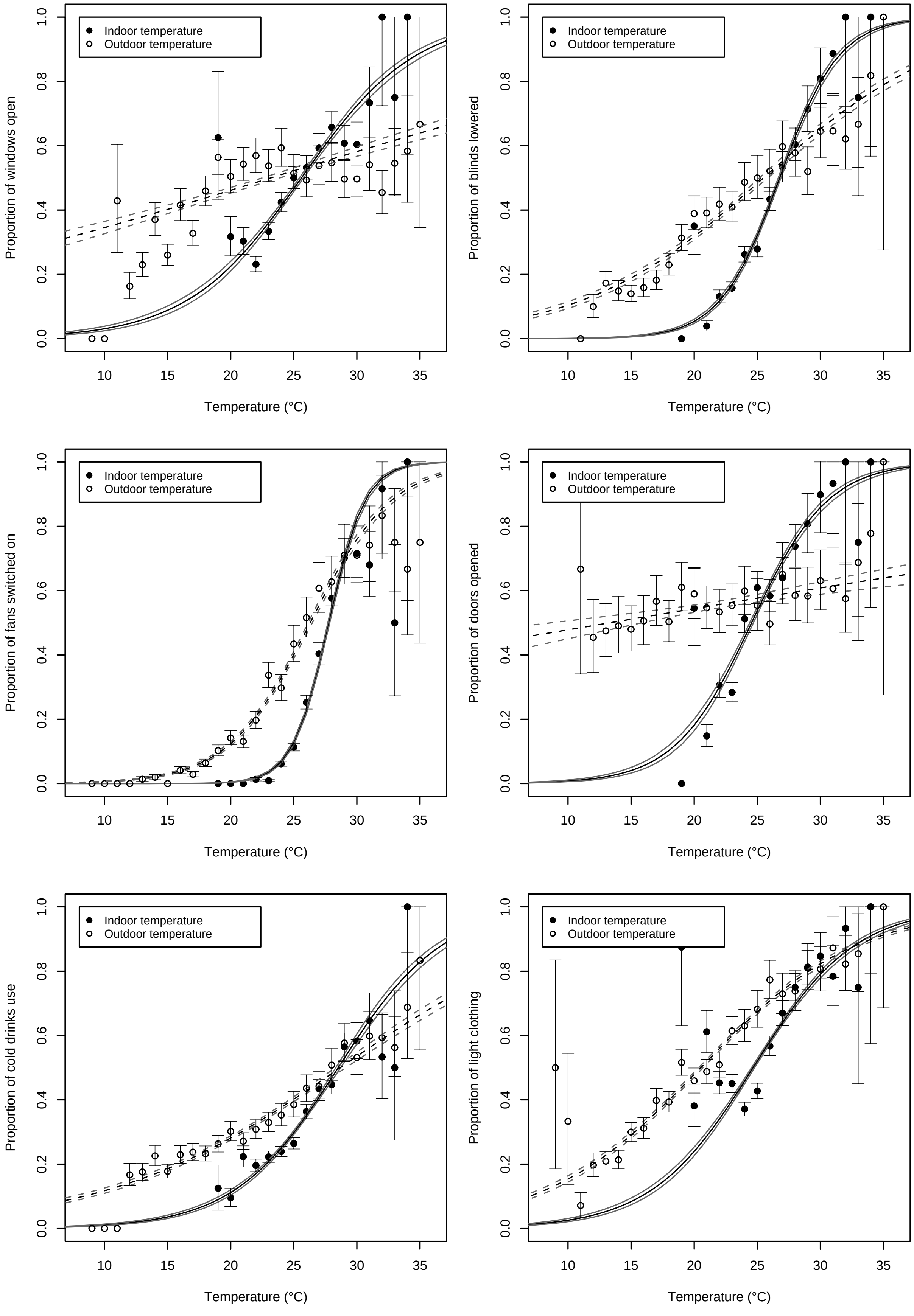

Figure 9 Action probability as a function of indoor and outdoor temperature for the studied adaptive actions, with gray lines denoting standard errors of fits

For comparison purposes, the regression curves relating to all six adaptive actions that were studied in this work are presented in Figure 10, with respect to indoor and outdoor temperature.

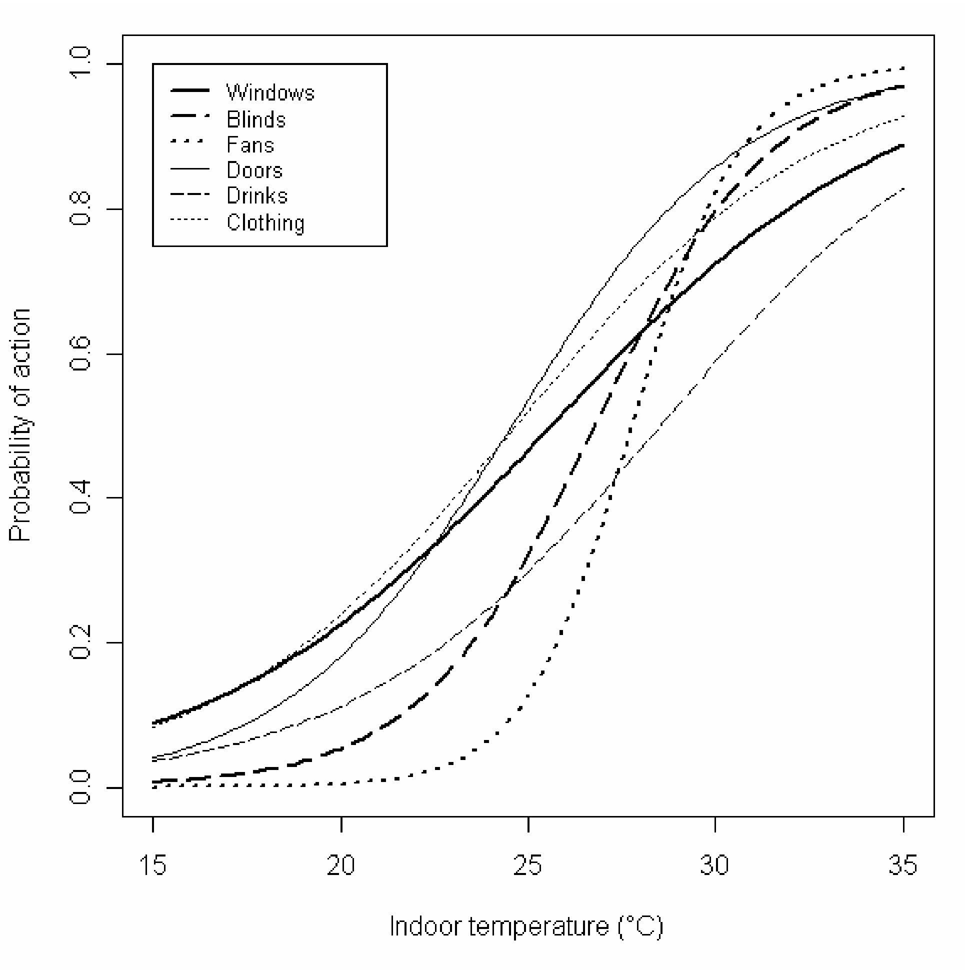

Figure 10 Probability distributions for the studied adaptive actions

4.2 EMPIRICAL ADAPTIVE INCREMENTS

As noted earlier, when adaptive opportunities have been exercised by occupants their neutral temperature (that at which they feel neither cool nor warm) tends to be elevated, for example due to *real* physiological cooling resulting from the action exercised, or the psychological perception that such cooling has been realised. This should be evident in comparisons of mean temperature for cases when a particular adaptive action has and has not been exercised. In Figure 11 for example it can be seen that for all categories of reported thermal sensation the median temperature is higher when windows have been opened. This trend is followed for all control actions.

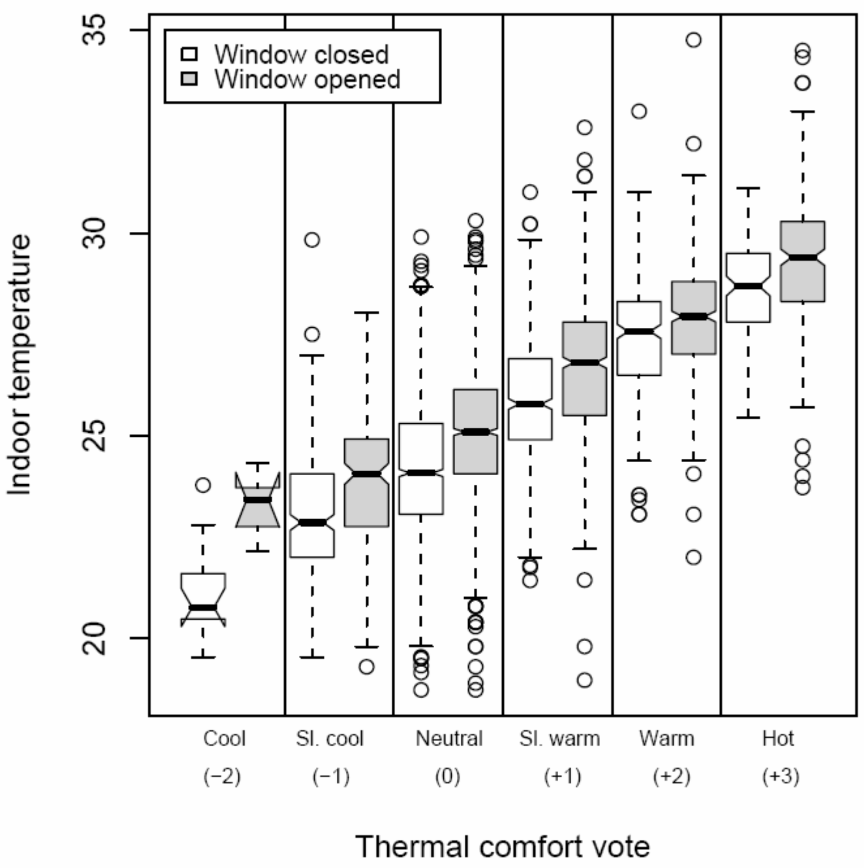

Figure 11 Influence of window opening on temperature distribution[10]

Following from the above rationale, *empirical* adaptive increments can thus be deduced; these corresponding to the offset in indoor temperature (say for neutral thermal sensation) associated with a given adaptive action, as the median temperature when a given action (and no other) has been exercised, less that when no adaptive action has been exercised. The corresponding results for all single and conjugations of adaptive action are presented in Table 3 below (see Haldi and Robinson (2007) for a detailed discussion of these empirical adaptive increments).

Unfortunately for certain categories of adaptive action the population size is very small (very few instances of this action were recorded) so that the error bands are correspondingly large and the p-values rather high. Furthermore, due to the limited size of the dataset from which they were derived, each category has not been further differentiated according to light / heavy clothing level; so that these results are in fact a mélange of clothing adjustments and other adaptive actions. Clearly this further differentiation would be possible, and with reasonable uncertainties, if we had a larger database. Likewise certain conjugations of adaptive actions which have not been presented due to limited data.

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[10] Tails correspond to minima and maxima, whereas the range of the bars corresponds to the two central quartiles. The extent of the notches within these bars is proportional to the statistical error in defining the median at which the notches converge (the bold line). White box plots correspond to cases in which the window has not been opened and grey to cases in which it has; so that the difference in median temperatures represents the adaptive increment. Unfilled circles represent statistical outliers.

Table 2 Reported comfort temperatures and increments for ***exclusive*** *control actions and their conjugates*

Controls	Comfort temperature	N	Adaptive increment	t value	p-value	Interaction constant
N*	23.98	777	0.00 ± 0.06	430.60	p < 0.001	
W	24.56	348	0.58 ± 0.10	5.82	p < 0.001	
B	24.44	28	0.46 ± 0.30	1.55	0.12	
F	25.37	16	1.39 ± 0.39	3.55	p < 0.001	
D	24.13	339	0.15 ± 0.10	1.51	0.13	
d	24.67	204	0.69 ± 0.12	5.65	p < 0.001	
WB	25.78	83	1.80 ± 0.18	10.05	p < 0.001	1.72 ± 0.83
WF	26.80	10	2.82 ± 0.49	5.71	p < 0.001	1.43 ± 0.61
WD	24.89	301	0.92 ± 0.11	8.69	p < 0.001	1.25 ± 0.48
Wd	24.77	189	0.79 ± 0.13	6.31	p < 0.001	0.62 ± 0.21
BF	25.27	14	1.30 ± 0.42	3.10	1.99E-03	0.70 ± 0.49
BD	24.95	49	0.97 ± 0.23	4.25	p < 0.001	1.58 ± 1.40
Bd	25.84	10	1.86 ± 0.49	3.76	p < 0.001	1.61 ± 1.02
FD	25.43	**1**	1.45 ± 1.55	0.93	0.35	0.94 ± 1.31
Fd	27.31	4	3.33 ± 0.78	4.28	p < 0.001	1.60 ± 0.77
Dd	24.09	103	0.11 ± 0.16	0.65	0.51	0.13 ± 0.23
WBD	25.36	219	1.38 ± 0.12	11.65	p < 0.001	1.16 ± 0.58
WBd	24.64	45	0.66 ± 0.24	2.78	5.51E-03	0.38 ± 0.25
WFD	26.55	25	2.57 ± 0.32	8.14	p < 0.001	1.21 ± 0.49
WFd	25.43	**1**	1.45 ± 1.55	0.93	0.35	0.54 ± 0.71
WDd	25.09	153	1.11 ± 0.14	8.06	p < 0.001	0.78 ± 0.27
BFD	26.14	**1**	2.16 ± 1.55	1.39	0.16	1.08 ± 1.20
BFd	26.58	4	2.60 ± 0.78	3.34	p < 0.001	1.02 ± 0.63
BDd	25.59	8	1.61 ± 0.55	2.92	3.54E-03	1.23 ± 0.92
FDd	26.67	4	2.69 ± 0.78	3.46	p < 0.001	1.20 ± 0.68
WBFD	26.79	58	2.81 ± 0.21	13.29	p < 0.001	1.08 ± 0.46
WBFd	26.14	**1**	2.16 ± 1.55	1.39	0.16	0.69 ± 0.70
WBDd	25.61	41	1.63 ± 0.25	6.57	p < 0.001	0.87 ± 0.42
WFDd	27.09	11	3.11 ± 0.47	6.60	p < 0.001	1.10 ± 0.45
WBFDd	26.83	14	2.85 ± 0.42	6.82	p < 0.001	0.87 ± 0.40

*N = **N**one, W = **W**indows, B = **B**linds, F = **F**ans, D = **D**oors and d = Cold **d**rinks. Controls designated by multiple letters correspond to conjugations of these control options (e.g. **WB** = **W**indows + **B**linds).

4.2.1 ADAPTIVE ALGORITHMS: AN AGGREGATION OF ADAPTIVE INCREMENTS?

An interesting by-product of the above work is a possible improvement in the understanding of the reason why, during summer months, internal comfort temperature tends to be positively correlated with outside temperature. One hypothesis is simply that, in line with the above arguments, when subjected to warm indoor conditions occupants are more likely to exercise the adaptive opportunities available to them and that these actions bring physiological and psychological relief [so that neutral temperatures are elevated]. If this statement is true then, by deducting the empirical adaptive increments associated with the adaptive opportunities exercised from each coincident record of air temperature in our database, the strength of correlation between indoor neutral and air temperature should reduce (Figure 12). Indeed, if this database was very large (so that statistical errors are small) and increments for all types of adaptive opportunity had been deduced, the correlation should either be completely nullified, or at least substantially reduced. In this latter case, the remaining slope would represent other factors such as occupants' acclimatisation to warmer summertime weather.

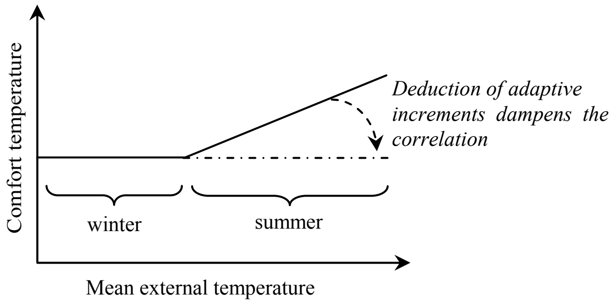

Figure 12Winter and summertime dependence of indoor comfort on some running mean of outdoor temperature

Irrespective of the method used to average outside temperature [monthly mean (de Dear and Brager, 2002); exponentially weighted running mean over seven days (Humphreys, 1978) or over four days (Van der Linden, 2006)], we find that for (an albeit incomplete and sometimes rather uncertain set of) adaptive increments associated with the actions recorded, the correlation is indeed reduced, but not nullified (Table 3).

Table 3 Adaptive algorithms using both the raw data and that adjusted according to the adaptive actions taken, formulated according to the methods of de Dear and Brager, Humphreys and Van der Linden.

	de Dear-Brager	**Humphreys**	**van der Linden**
a (observed)	0.113 ± 0.012	0.246 ± 0.007	0.287 ± 0.008
a (observed, adjusted)*	0.095 ± 0.011	0.197 ± 0.007	0.233 ± 0.007
a (originally published)**	0.31	0.44	NA
b (observed)	22.394 ± 0.242	19.873 ± 0.146	19.078 ± 0.153
b (observed, adjusted)	22.092 ± 0.222	20.155 ± 0.139	19.444 ± 0.146
b (originally published)	17.8	15	NA
r2	0.03	0.26	0.31
r2 (adaptive)	0.02	0.20	0.25

*Statistics relating to datapoints for which the neutral temperature has been adjusted in accordance with the increments relating to the adaptive actions exercised.

**The slope (a) and intercept (b) originally published by the authors. Other results relate to the use of the data obtained from the field survey described in this paper.

5 CONCLUSIONS

A new integrated model for predicting overheating risk in offices in temperate climates has been proposed. This model predicts:

- the probability with which occupants will adapt their personal and environmental characteristics in response to thermal stimuli,
- the effects of adaptive actions, when exercised, on occupants' comfort temperature. Indeed it is suggested that the commonly used adaptive algorithms (e.g. of Humphreys (1978) and de Dear and Brager (2002)) are nothing more than an aggregation of individual adaptive processes; which can each be isolated in the form of empirical adaptive increments (provided of course that sufficient data exists),
- the probability of a population perceiving an environment to have overheated (or alternatively the probable proportion of a population to perceive this) in response to the above.

Finally it is interesting to note that, due to the symmetric nature of the problem, the model for predicting *over*heating risk may in principle also be reformulated to predict *under*heating risk.

There are however many weaknesses to this new integrated model for overheating risk prediction. For example:

- only responses to indoor *air* temperature are currently considered, rather than a more comprehensive measure such as *operative* temperature,
- the overheating model has also been calibrated to exclusively temperate climate conditions. Its relevance to e.g. warm humid climates may be questionable,
- also due to field survey constraints, it has not yet been possible to calibrate the charge of tolerance to overheating stimuli β,
- the probabilistic models of adaptive actions should also consider non-thermal stimuli, e.g. visual for blind use and olfactory for window openings. In this the closing of windows and raising of blinds (and switching off of fans) should also be considered; likewise the prioritisation of different control actions,
- certain of the suggested adaptive increments suffer from rather high uncertainties, although these may be reduced with larger datasets (so that further field surveys would be useful).

Nevertheless, this new integrated model does represent a promising direction for the development of a complete model for predicting occupants' adaptations of their personal and environmental characteristics and the associated consequences for their overall (long term) satisfaction with the indoor thermal environment. This long term satisfaction (specifically the risk that a space may overheat) is, after all, the key test for whether a space is generally acceptable or not.

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