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Representing Behaviour and Adaptation of Office Occupants in Building Simulation

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REPRESENTING BEHAVIOUR AND ADAPTATION OF OFFICE OCCUPANTS IN BUILDING SIMULATION

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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 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 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 and for integration in dynamic building thermal simulation programs.

INTRODUCTION

The deterministic features of building simulation programs are now relatively mature and these programs are today increasingly used by practitioners to inform building design. But their accuracy is undermined by a poor representation of human interactions with environmental controls; to the extent that predictions of like buildings may, in Baker's estimation, vary by a factor of two [1]. 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 of human behaviour within the building simulation community in recent years.

This paper presents results linked 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 [2], who proposed a probabilistic approach for the prediction of the use of windows, lights, blinds, heating systems and fans. Following from this rationale, Nicol related the probability for actions on controls 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.

But as Robinson [3] points out this may lead to the absurd result that occupants of adjacently located buildings based on fundamentally different designs would interact with controls with similar probability. Rijal et al [4] have subsequently published an interesting refinement to Nicol's probabilistic model for the opening of windows, using multiple logistic regression to define a probability distribution for window opening based on both indoor and outdoor temperature, mentioning application results within the dynamic simulation program ESP-r. However, 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.

In this paper we test separately the ability of both internal and external temperature to describe the probability of occupant interactions with a range of personal and environmental characteristics. We also discuss the effects of control actions on occupants' comfort temperature and in this we also define a set of adaptive increments, which we define as the increase in temperature at which occupants report the same sensation vote compared to those that have not.

FIELD SURVEY METHODOLOGY

This work is a by-product of a field survey conducted during the summer of 2006, to develop a new model of overheating risk (see [5]). As part of this field survey, volunteers were asked to complete a short electronic questionnaire which was installed on their personal computer. This longitudinal questionnaire, 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 and adaptive actions exercised.

With respect to adaptive actions, 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 hour preceding the prompt. 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, temperature measurements were recorded from sensors installed in close proximity to each participants workstation. Furthermore, local simultaneous climate data was obtained from the Swiss Federal Office of the Environment.

In total, a dataset of some 5928 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.

PREDICTION OF OCCUPANTS' ADAPTIVE ACTIONS

Our results 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.

With similar methods to those used by Nicol et al [2] and Rijal et al [4], we attempt to infer a distribution for the probability of occupants' adaptive actions as a function of indoor and outdoor temperature. The database is first filtered so that we consider only those occupants for whom a given adaptive action under investigation was personally available. Measured temperatures are then rounded to the nearest unit, and for each unit temperature, an empirical probability of adaptive action is computed from the occurrences reported for each action.

In order to infer a probability distribution for the whole range of temperatures, a statistical method already used for such purposes in [2] and [4] is logistic regression. The proposed probability distribution $p(\theta)$ is given by the logit function $p(\theta) = exp(a\theta + b) / (1+exp(a\theta + b))$. The parameters a and b are then obtained through weighted linear regression. The corresponding regression curves are shown in Fig. 1 and a summary of the regression parameters obtained is given in Table 1.

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

The former property allows us to interpret θ_{50} as an indicator of the temperature at which half of the occupants will use a given control, if available. Furthermore, the parameter a measures indirectly the sensitivity of occupants' behaviour to temperature changes around this value. In particular if $a = 0$ the distribution becomes independent of θ, and for large a, $p(\theta)$ tends to a step function. We can therefore interpret low values of a as a sign that θ is irrelevant to explain a given action, and large values as increases in the deterministic degree of predictions.

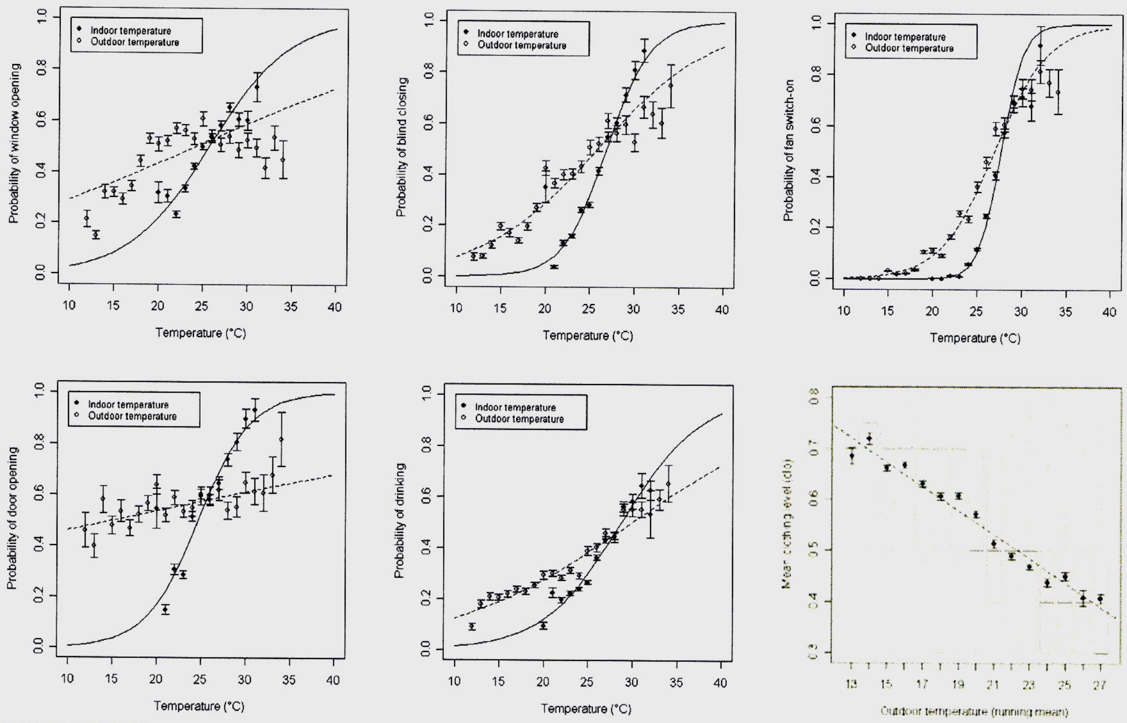

Figure 1: Probabilities of actions on controls as functions of indoor and outdoor temperature

	a_{in}	b_{in}	$\theta_{50,in}$	r_{in}^2	a_{out}	b_{out}	$\theta_{50,out}$	r_{out}^2
Windows	0.224 ± 0.027	-5.77 ± 0.68	25.8	0.86	0.063 ± 0.015	-1.52 ± 0.34	24.2	0.43
Blinds	0.416 ± 0.040	-11.17 ± 1.01	26.9	0.91	0.158 ± 0.011	-4.07 ± 0.26	25.8	0.89
Fans	0.828 ± 0.074	-22.88 ± 1.87	27.6	0.93	0.336 ± 0.020	-9.02 ± 0.43	26.9	0.94
Doors	0.342 ± 0.050	-8.45 ± 1.22	24.7	0.81	0.031 ± 0.008	-0.47 ± 0.17	15.4	0.41
Drinks	0.227 ± 0.019	-6.54 ± 0.48	28.8	0.92	0.098 ± 0.007	-2.93 ± 0.15	30.0	0.90

Table 1: Regression parameters for fits with indoor and outdoor temperature

Our results strongly support the conclusion that indoor temperature offers better predictions than outdoor temperature for all controls. Moreover, regression results indicate that the use of this latter is clearly inappropriate for windows and doors.

The high value of the slope a for fans indicate that their use is particularly well described through a logit function. This strong sensitivity to indoor temperature is an expected result, as actions on fans seem to be mostly driven by local thermal conditions, which is not necessarily the case for other controls.

Although the adaptive actions observed in this study are better related to indoor than to outdoor thermal stimuli, thermal conditions do not exclusively explain these actions. For instance, window openings are also related to olfactory stimuli (pollutant concentration), blind use should be related to visual stimuli (glare, illuminance) and door openings may be linked with non-physical variables, such as privacy considerations. Nevertheless, our approach gives reliable predictions concerning thermally-driven actions, although the closing of windows and doors, the raising of blinds and the switching off of fans are not currently considered.

Concerning personal characteristics, we have not been able to find any convincing relationship between thermal stimuli and metabolic activity; which is largely dictated by the office activity in question. Similarly, the small amount of observed "within-day" changes in clothing level does not enable the application of logistic regression methods. However, we have observed adaptations in clothing level from one day to another, i.e. as a predictive strategy. In particular, we notice a clear relationship between the exponentially weighted running mean outdoor temperature[1] $\theta_{out,rm}$ and the level of clothing insulation during that day (see Figure 1), as was also observed in [6]. We obtain from a linear regression on these data that clo = -0.0236 $\theta_{out,rm}$ + 1.0276, with good agreement (r^2 = 0.97).

EMPIRICAL ADAPTIVE INCREMENTS

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 [7]. 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 median 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 [8].

Our results are summarised in Fig. 2 with box plots of increments for all observed combinations of controls for which sufficient data is available; and in Table 2 with the associated increments.

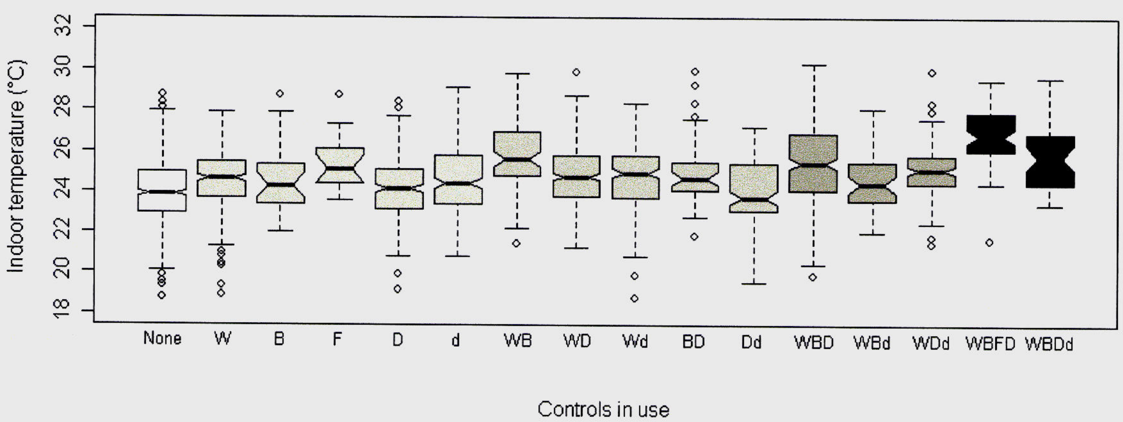

Figure 2: Joint influence of all controls on comfort temperature, with notches along the median denoting the extent of statistical uncertainty (W: windows, B: blinds, F: fans, D: doors, d: drinks)

Contr. in use	Comfort temperature	Occur-rences	Offset from none	Contr. in use	Comfort temperature	Occur-rences	Offset from none
None	23.90 ± 0.11	779		**Wd**	24.93 ± 0.24	189	1.03 ± 0.35
W	24.62 ± 0.15	349	0.72 ± 0.26	**BD**	24.68 ± 0.33	49	0.78 ± 0.44
B	24.30 ± 0.58	28	0.40 ± 0.69	**Dd**	23.72 ± 0.37	103	-0.18 ± 0.48
F	25.10 ± 0.67	16	1.20 ± 0.78	**WBD**	25.43 ± 0.30	221	1.53 ± 0.41
D	24.14 ± 0.17	339	0.24 ± 0.28	**WBd**	24.40 ± 0.45	45	0.50 ± 0.56
d	24.41 ± 0.26	204	0.51 ± 0.38	**WDd**	25.09 ± 0.18	153	1.19 ± 0.29
WB	25.58 ± 0.38	83	1.68 ± 0.49	**WBFD**	26.78 ± 0.37	60	2.88 ± 0.49
WD	24.74 ± 0.18	301	0.84 ± 0.30	**WBDd**	25.75 ± 0.60	41	1.85 ± 0.72

Table 2: Increments in comfort temperatures for the simultaneous use of several controls

[1] The exponentially weighted running mean outdoor temperature is defined as (with α = 0.8)

$$\theta_{out,rm} = (1-\alpha)\cdot\sum_{i\geq 1}\alpha^{i-1}\theta_{dm-i} \cong (\theta_{dm-1} + 0.8\cdot\theta_{dm-2} + 0.6\cdot\theta_{dm-3} + 0.5\cdot\theta_{dm-4} + 0.4\cdot\theta_{dm-5} + 0.3\cdot\theta_{dm-6} + 0.2\cdot\theta_{dm-7})/3.8$$

Concerning isolated use of controls, our observed empirical adaptive increments are particularly evident in the case of windows and fans, although the limited amount of data does not enable us to draw precise conclusions in all cases. Conjugate actions on controls generally induce higher increments, as expected. It is interesting though that 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. See [9] for further discussion.

DISCUSSION

Based on analysis of the results from our field survey 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. We observe that, in all cases, control actions are considerably better described by indoor than by outdoor temperature. However, our results do not allow us to totally discard outdoor temperature influences. For example, although actions on windows seem mainly 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. Moreover, as mentioned above, it would be useful to integrate non-thermal stimuli in order to improve the accuracy of predictions. Indeed a possible approach to the development of a general basis for the modelling of occupants' adaptive actions is discussed in [9].

Empirical adaptive increments have also been defined for individual as well as conjugations of control action. The integration of both these increments and the probabilistic models of adaptive actions with dynamic building simulation programs may be achieved by an iterative procedure proposed below (Fig. 3).

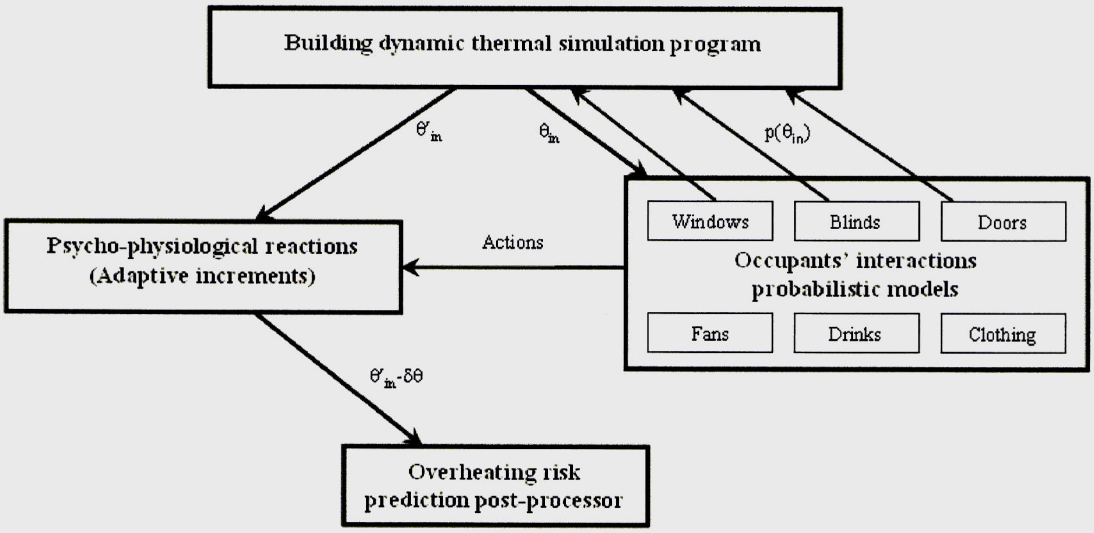

Figure 3: Integration of probabilistic models for actions on controls and adaptive increments into dynamic building simulation (after [10])

At the start of a proposed iterative process, an initial indoor temperature θ_{in} provided by a dynamic simulation environment is taken as input for the set of probabilistic models, which compute probabilities of control actions $p(\theta_{in})$. Among the controls available, only actions on windows, blinds and doors have an impact on indoor thermal conditions and give an output to the simulation program. An iterative feedback between indoor temperature and action probabilities produces a converged temperature θ'_{in}. This is then influenced by the adaptive increment $\delta\theta$ derived from observed psycho-physiological effects of occupant actions. Finally, a post-processor uses as input the adaptive indoor temperature $\theta_{in,ad} = \theta'_{in} - \delta\theta$ for the prediction of overheating risk [10].

ACKNOWLEDGEMENTS

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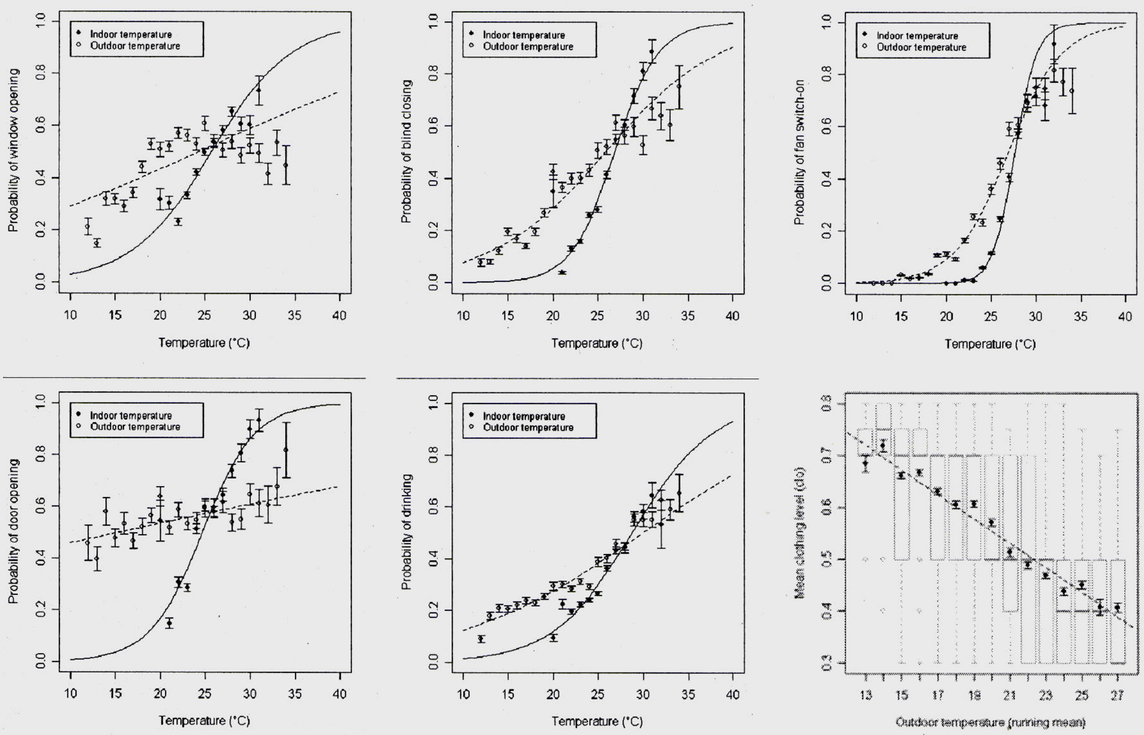

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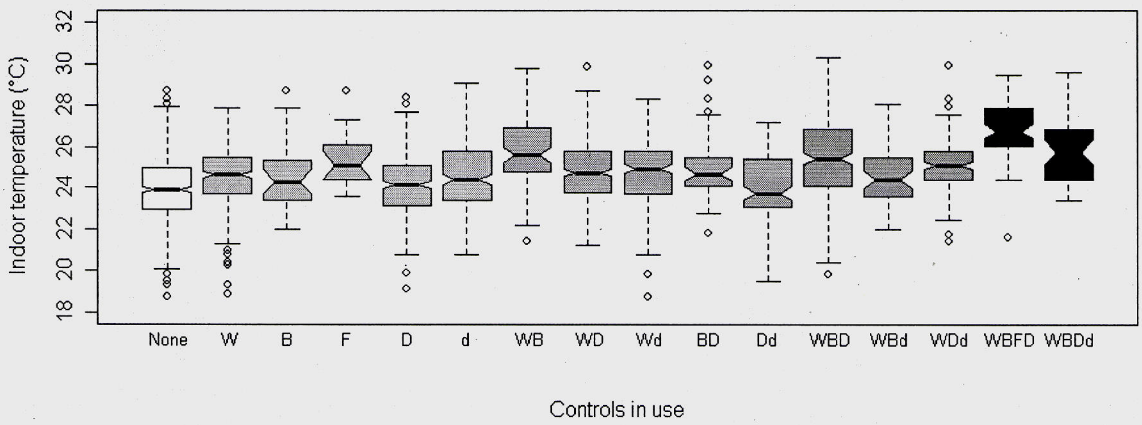

Figure 2: Joint influence of all controls on comfort temperature, with notches along the median denoting the extent of statistical uncertainty (W: windows, B: blinds, F: fans, D: doors, d: drinks)

Contr. in use	Comfort temperature	Occur-rences	Offset from none	Contr. in use	Comfort temperature	Occur-rences	Offset from none
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Concerning isolated use of controls, our observed empirical adaptive increments are particularly evident in the case of windows and fans, although the limited amount of data does not enable us to draw precise conclusions in all cases. Conjugate actions on controls generally induce higher increments, as expected. It is interesting though that 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. See [9] for further discussion.

DISCUSSION

Based on analysis of the results from our field survey 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. We observe that, in all cases, control actions are considerably better described by indoor than by outdoor temperature. However, our results do not allow us to totally discard outdoor temperature influences. For example, although actions on windows seem mainly 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. Moreover, as mentioned above, it would be useful to integrate non-thermal stimuli in order to improve the accuracy of predictions. Indeed a possible approach to the development of a general basis for the modelling of occupants' adaptive actions is discussed in [9].

Empirical adaptive increments have also been defined for individual as well as conjugations of control action. The integration of both these increments and the probabilistic models of adaptive actions with dynamic building simulation programs may be achieved by an iterative procedure proposed below (Fig. 3).

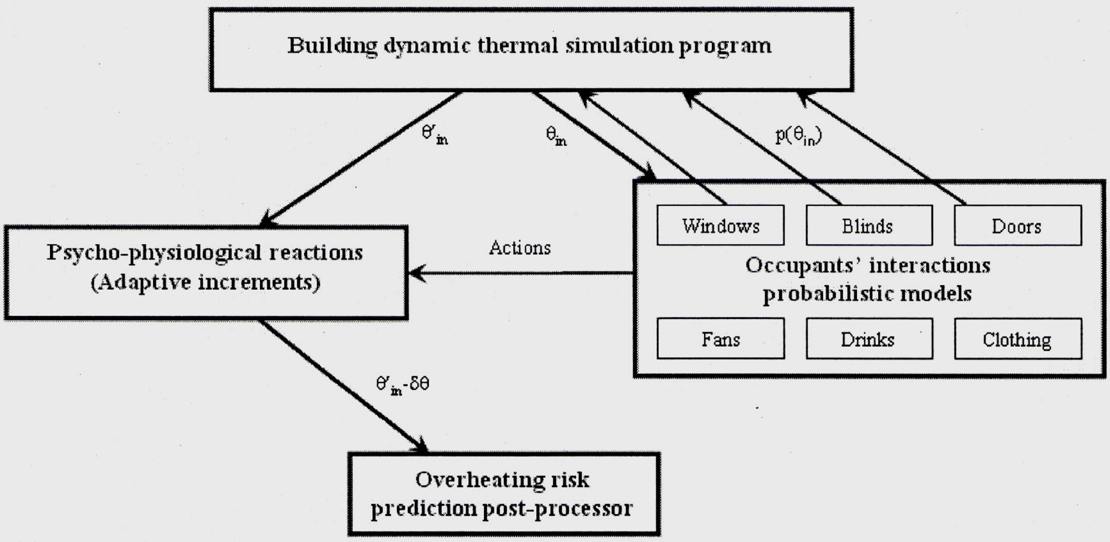

Figure 3: Integration of probabilistic models for actions on controls and adaptive increments into dynamic building simulation (after [10])

At the start of a proposed iterative process, an initial indoor temperature θ_{in} provided by a dynamic simulation environment is taken as input for the set of probabilistic models, which compute probabilities of control actions $p(\theta_{in})$. Among the controls available, only actions on windows, blinds and doors have an impact on indoor thermal conditions and give an output to the simulation program. An iterative feedback between indoor temperature and action probabilities produces a converged temperature θ'_{in}. This is then influenced by the adaptive increment $\delta\theta$ derived from observed psycho-physiological effects of occupant actions. Finally, a post-processor uses as input the adaptive indoor temperature $\theta_{in,ad} = \theta'_{in} - \delta\theta$ for the prediction of overheating risk [10].

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