STOCHASTIC / PROBABILISTIC MODELLING OF MULTIPLE ADAPTIVE PROCESSES: SOME SUBTLE COMPLEXITIES

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ABSTRACT

The modelling of the adaptation of occupants' personal and environmental characteristics (e.g. use of lights and blinds; use of windows, doors and fans; adjustment of clothing and activity levels) has become a vibrant area of research activity, with several prototype models already available. However, a certain degree of caution should be exercised when using these models. Firstly, many of them are far from complete – being based on a small subset of the family of stimuli which fully describe the adaptive process in question. Secondly, they tend to focus *exclusively* on a given process, so that possible inter-relationships with other processes are generally ignored i.e. the probability of opening a door may be higher is a window has already been opened.

Following a brief review of the state of the art, we present experimental evidence of the non-independence of adaptive processes and propose a more general framework for the development and integration of comprehensive adaptive models.

INTRODUCTION

In general, models of occupants' adaptation of their personal and environmental characteristics may be classified (Robinson and Haldi, 2008) as being stochastic (they account for random fluctuations of the process under study and the dependence of this process on time) or probabilistic (similar to stochastic, but with no direct temporal dependence).

Thus far researchers have tended to focus on the development of probabilistic models of adaptive actions.

The earliest contributions were made by Hunt (1979, 1980), who developed a model for predicting the probability of manually switching on lights upon entering a room given the minimum internal illuminance, based on measurements in four school classrooms. This model has since been integrated into the dynamic simulation programs SERI-RES [now SUNREL] (Haves and Littlefair, 1982) and ESP-r (Clarke, 2001) as well as with Reinhart's (2001, 2004) Lightswitch-2002 Wizard and more recently with Daylight 1-2-3 (Reinhart et al, 2007). The former use a standard occupancy profile to determine the time of arrival whereas Lightswitch-2002 includes some randomness into these schedules whilst also integrating functions for manual intermediate switch-off and switch-off at departure. The latter are based on the observations of Pigg et al (1996) that occupants are more likely to switch their lights off if they expect to be away from their room for longer periods of time. Finally Lightswitch-2002 also includes a simple manual blind control function using a threshold incident direct shortwave irradiance of $50Wm^{-2}$.

In summary then, switching lights on at arrival and subsequently switching them off prior to departure are based solely on minimum internal illuminance and switching off at departure is based solely on expected departure duration. This seems rather reasonable for the case of workplaces in which light use is dependent on visual tasks. In homes however users may also control lights according to preferences for ambience; for example whilst dining or watching television, so that some temporal element may be required.

The solely visual stimulus in Lightswitch-2002 for blind control (taking irradiance is a glare indicator) is somewhat at odds with results which indicate, through logistic regression analysis, that blind control is correlated with both internal (Nicol and Humphreys, 2004) and external (Nicol, 2001) temperature. In other words thermal as well as visual stimuli play a role here.

Nicol (2001) also presents logit functions for use of windows, heaters and fans as a function of external temperature; likewise for use of lights, with temperature being used as a surrogate for external illumination. Based on this work, Herkel et al (2005) developed an initial model for the control of window openings using presence and (solely) external temperature as an input. However as Robinson (2006) points out, this may lead to the unexpected result that windows within adjacent buildings of fundamentally different design will be opened with the same probability.

Rijal et al (2007) have since developed a model for window opening and closing, based on multiple logistic regression analysis, which takes both internal and external temperature into account. But Haldi and Robinson (2008) argue though that the inclusion of external temperature dampens the locally experienced (by occupants) indoor temperature as the key stimulus for opening windows; whilst accepting that outdoor temperature may well be a stimulus for the closing of them.

Following from the example set by Reinhart (2004), both Yun and Steemers (2008) and Herkel et al (2008) propose models which use solely indoor temperature as input to predict the probability of opening and closing window openings at arrival, departure and during intermediate periods.

In summary some good progress has been made in the modelling of window opening/closing behaviour, but these models are far from complete. Whilst it seems likely that internal stimuli as well as impending departures are the key stimuli for opening windows, external stimuli are likely either to act as a resistance to opening windows (e.g. in the case of noisy environments or during rainfall) or to determine the duration during which windows are opened (e.g. to limit cold draughts or general over-cooling)[1]. Haldi and Robinson (2008) present a framework for such a model in which each key variable is handled as part of a logical sequence; with closing at departure also considering the possible desire for nocturnal cooling.

Blinds and windows are perhaps a special case of adaptive action: since they regulate energy (and mass) transfers across the external envelope. As such they may be expected to be influenced by multiple stimuli, whereas lights, doors, fans and personal characteristics such as clothing and activity level are likely to be influenced by predominantly internal (visual or thermal) stimuli[2]. The results of Nicol (2001), Nicol and Humphreys (2004) and Haldi and Robinson (2008) in relation to use of fans, doors and personal characteristics may therefore be reasonably complete; in terms of the stimuli which have a direct impact on their adaptation by occupants.

One important remaining issue is whether exercising one type of adaptive action has an influence on the probability with which another type of adaptive action will be exercised. For example, are we more likely to open a door if the window has already been opened, to benefit from the increased flow rates due to cross ventilation? Are we more or less likely to open windows if blinds have already been lowered?

On a related note, the priority with which different adaptive actions are likely to be exercised has yet to be studied in any detail; although Haldi and Robinson (2008) have provided an indication of the order with which different actions are exercised, albeit based on results relating exclusively to thermal stimuli.

This paper aims to shed some light onto these issues with a view to proposing a general framework according to which models of adaptive actions should be developed and integrated with one another.

EXPERIMENTAL DESIGN

For the purpose of developing a model for overheating risk prediction a longitudinal thermal comfort 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 (see Robinson and Haldi, 2008a,b).

For each building in this temperate climatic region, volunteers were asked to complete a short electronic questionnaire which was installed on their PC. This questionnaire, 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 e-questionnaire was to produce time-series data regarding participants' adaptive actions and their evolving perception of the parameter(s) under examination.

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.

[1] Only Fritsch et al (1990) seem to have considered this issue in an explicit way; by modelling window status as a Markov chain.

[2] However evidence suggests (Nicol, 2001; Haldi and Robinson, 2008) that decisions regarding clothing level are better predicted using prevailing external weather conditions.

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.

RESULTS

For the purpose of inferring a probability distribution for the whole range of temperatures (indoor or outdoor), a theoretically justified statistical method is the logistic regression (Nicol, 2001). Using this method the proposed probability distribution $p(\theta)$ follows the relationship $p(\theta) = exp(a\theta+b) / (1+exp(a\theta+b))$, with θ being the temperature. This has several directly interpretable 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 $\theta=\theta_{50}$, and high values of a enable more deterministic predictions.

To determine whether the probability of exercising a given adaptive action is independent of whether other adaptive actions have been exercised, we perform logistic regressions on the whole dataset as well as upon subsets of the dataset, corresponding to events when it is known that another specific action has taken place.

Variations of the above parameters between conditional (when another action has taken place) and unconditional cases are of particular interest. A statistical summary of these is presented in Table 1 and detailed regression analysis relating to unconditional case is available in Haldi and Robinson (2008).

In each of the four charts in Figure 1 we have *unconditional* logistic regression curves relating to the switching on of fans (in grey); whereas, clockwise from upper left we have conditional regression curves relating to the probability of switching fans on given that windows have been opened, blinds have been lowered, doors have been opened and cold drinks have been consumed, respectively. We can observe that regression parameters for the use of fans remain almost unchanged with use of windows, blinds, doors and cold drinks; so that the black curves are almost superimposed over the grey ones. This result is relatively unsurprising, as there is no obvious physical relationship between the effects on parameters effecting thermal comfort arising from use of fans and other actions. Furthermore, fans are generally switched on as a last resort at high temperatures, where other adaptive actions have generally already been exercised and found to have been insufficient.

The two sets of curves are also rather closely related to one another in respect of blind use (Figure 2); although we do find that for all indoor temperatures, there is a slightly higher probability that blinds will be lowered if either windows and/or doors have already been opened. The same is also true with respect to use of fans, but the confidence interval is large in this case. This effect can be quantified by the difference in θ_{50} caused by concomitant action, defined as $\Delta\theta_{50} = \theta_{50,cond} - \theta_{50,ncond}$. The difference is around -1.5°C for all cases related to blinds use.

The results are somewhat more interesting in respect of window openings (Figure 3). When blinds have been lowered the dataset size is of similar magnitude to the inverse case (blinds lowered given that windows have been opened), but *P(windows open | blinds lowered)* is practically insensitive to indoor temperature, with parameters a and b being statistically insignificant. However the probability of this occurring is consistently high, so that if blinds have been lowered prior to opening windows, there is a high probability that windows will be opened soon after, to avoid overheating. Thus, the fact that blinds are lowered implies a rather systematic opening of windows, independently of temperature, but the reverse is not observed. There is also a slightly higher probability, at elevated temperatures, that windows will be opened if doors have already been opened ($\Delta\theta_{50}$ = -1.4°C); as the benefits of this action are accentuated (by the prior opening of doors). We can furthermore note a clear increase in the parameter a. There is relatively little difference with respect to the (non)conditional probabilities relating to switching on of fans and the consumption of cold drinks.

There is a consistently higher probability that doors will be opened if windows have already been opened (Figure 4), particularly at intermediate temperatures ($\Delta\theta_{50}$ = -3.7°C); to further improve the efficiency of this means of physiological cooling. The reverse trend is observed with respect to use of fans and the consumption of cold drinks; but interestingly, a stronger more deterministic relationship with indoor temperature is observed.

IMPLICATIONS FOR MODEL DEVELOPMENT

It seems clear from the above analysis that, in some cases, there are relatively complex interrelationships between different types of adaptive action. Some actions have a higher priority than do others and the fact that one type of action has taken place can have an impact on the probability with which subsequent adaptive actions will be exercised. It follows therefore that any *general* model of adaptive actions should consider these interrelationships. A framework by which this might be achieved is presented in Figure 5.

From initial or subsequent simulation results, the necessary environmental stimuli (e.g. internal / external air temperature, sun position and beam irradiance, wind speed and direction, rain presence, noise level) as well as non environmental stimuli (e.g. time, clothing and activity level) from time *t-1* are parsed to the model of adaptive actions at time *t*. Taking possible action in turn, the status of other actions is determined (status of adaptive actions may be locally stored). This data is then parsed to each action-specific sub model (indicated in bold in Figure 5). Results regarding actions which influence the building simulation tool may then be used to initialise the relevant models (e.g. in respect of a mass flow network for window openings). Once all possible actions have been evaluated, the environmental response may be simulated.

Following from the earlier discussion regarding the partial nature of current (independent) models of adaptive actions, Haldi and Robinson (2008) describe a comprehensive framework within which window opening and closing may be modelled, considering the set of environmental stimuli. If such an approach is followed for the range of adaptive actions, a complete environment for the modelling of adaptive actions should result. Such an environment could then be implemented within a standard platform for integration with the modelling of physical responses to adaptive actions within building simulation programs, such as SHOCC (Bourgeois, 2005).

CONCLUSIONS

From the review of literature and analyses of field survey data presented in this paper we conclude that:

- Current models of occupants' actions to adapt their environment to optimise their comfort tend to be based on a small subset of the stimuli which describe these actions.
- Current models do not consider feedback mechanisms between different types of adaptive action, which in some cases are important.
- Experimental evidence suggest important interrelationships between actions on windows and blinds and between windows and doors.
- A general and comprehensive model of occupants' adaptive actions should respond to the above limitations. A framework for such a model is suggested within this paper.

Furthermore, more complete field survey campaigns would be extremely valuable (considering visual, thermal, olfactory and possibly aural parameters, both internal and external) both to better define the nature of interrelationships between different types of adaptive actions as well as to provide for a comprehensive basis for modelling them. Real-time measurements of adaptive actions would provide more reliable data for this analysis, as relationships between stimuli and actions in our database could be dampened by poor temporal resolution due to self-reporting. This is also a potential source of error. These more precise data would also support a better understanding of the temporal evolution of interactions between adaptive processes as well as the influence of mobility (specifically, arrival to and departure from a room) on both individual and correlated actions.

Concerning this latter point, and as observed by Reinhart (2004) and Yun and Steemers (2008), the probability of occupants performing adaptive actions is different at arrival/departure than during occupation. We suggest that this is related to differences in the rate of change of perception of stimulus than to the act of arrival itself ($dx/dt|_{arrival} >> dx/dt|_{occupation}$). Considering (either implicitly or explicitly) the environmental history both of the occupants' room occupation and journeys to and fro might thus provide for a more general form of model.

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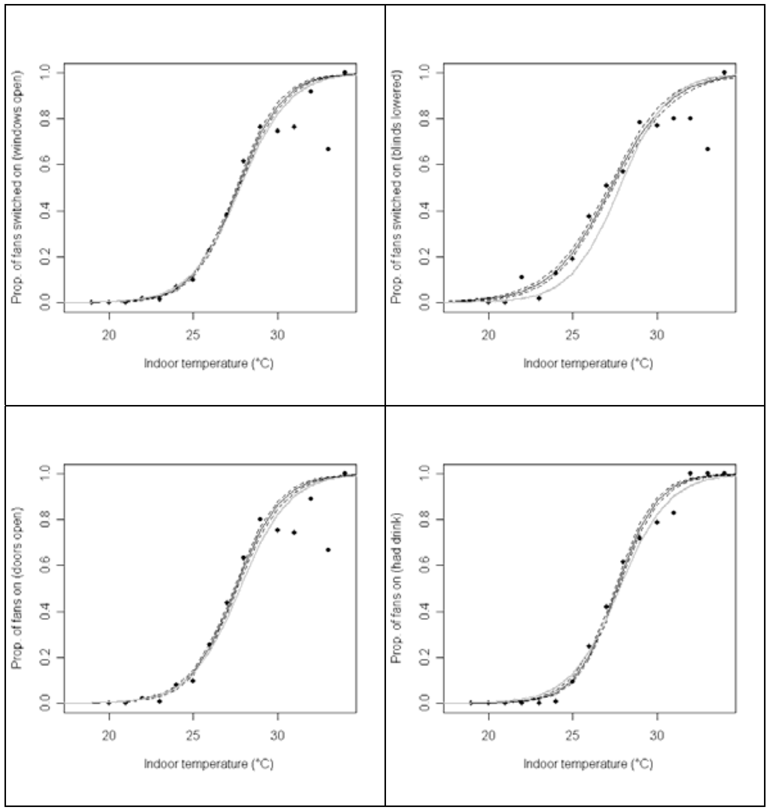

Figure 1 Unconditional (grey) and conditional (black with dashed error band) logistic regression with respect to fans

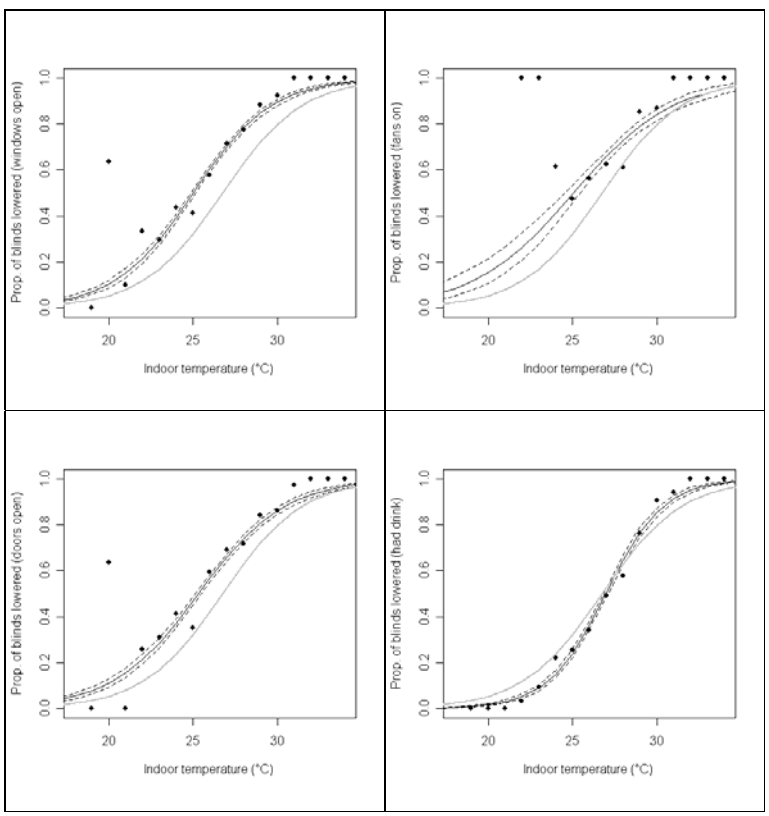

Figure 2 Unconditional (grey) and conditional (black, with error band) logistic regression with respect to blinds

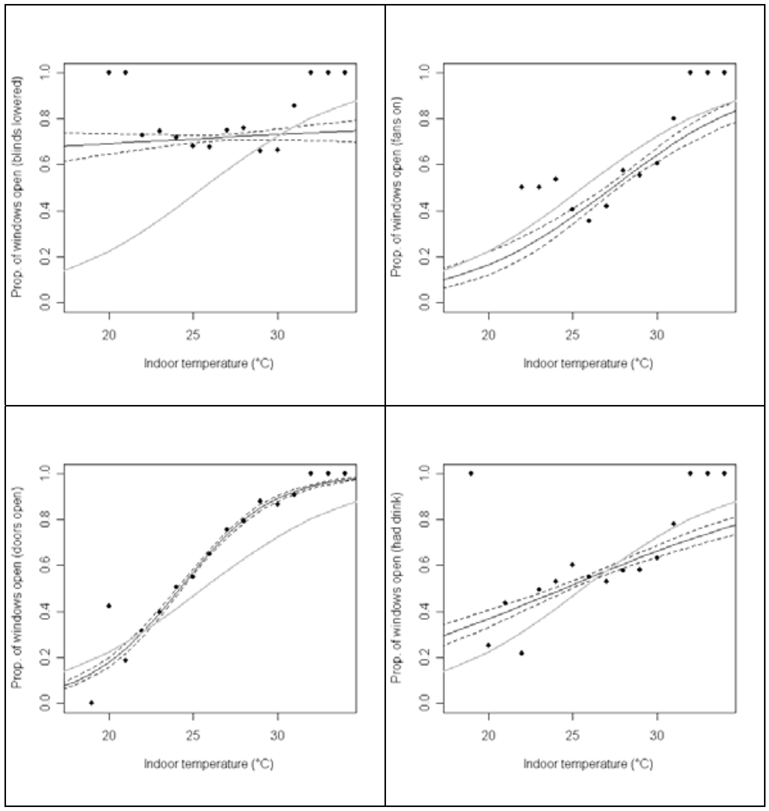

Figure 3 Unconditional (grey) and conditional (black, with error band) logistic regression with respect to windows

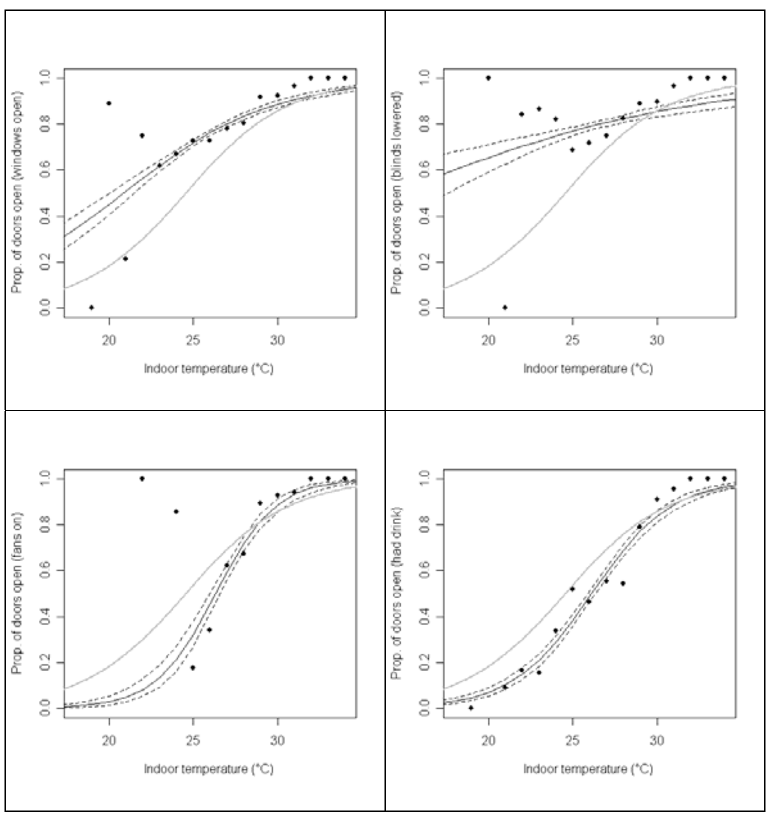

Figure 4 Unconditional (grey) and conditional (black, with error band) logistic regression with respect to doors

Control	Cond.	Nb. entries	a	b	θ_{50}	G	Resid. dev.	R^2	a_{nc}	$\theta_{50,nc}$	a/a_{nc}	$\Delta\theta_{50}$
Fans	W***	2049	0.759 ± 0.036	-20.97 ± 0.98	27.6	737.2	1834.5	0.42	0.696	27.8	1.09	-0.2
Fans	B	1138	0.569 ± 0.039	-15.52 ± 1.05	27.3	305.7	1258.6	0.32	0.696	27.8	0.82	-0.5
Fans	D	1602	0.745 ± 0.040	-20.50 ± 1.07	27.5	595.2	1490.2	0.43	0.696	27.8	1.07	-0.3
Fans	d	1266	0.839 ± 0.049	-23.16 ± 1.34	27.6	521.1	1140.2	0.46	0.696	27.8	1.21	-0.2
Blinds	W	1470	0.431 ± 0.030	-10.79 ± 0.77	25.0	270.2	1724.6	0.23	0.425	26.8	1.01	-1.8
Blinds	F	499	0.338 ± 0.056	-8.47 ± 1.52	25.1	41.2	584.16	0.11	0.425	26.8	0.79	-1.7
Blinds	D	1281	0.392 ± 0.030	-9.93 ± 0.77	25.3	217.8	1542.8	0.21	0.425	26.8	0.92	-1.5
Blinds	d	1000	0.589 ± 0.040	-15.88 ± 1.07	27.0	321.4	1049.6	0.37	0.425	26.8	1.39	0.2
Windows	B	1098	0.020 ± 0.030*	0.42 ± 0.80*	-21.4	0.4	1305.3	0.00	0.220	25.6	0.09	-47.0
Windows	F	601	0.222 ± 0.045	-6.06 ± 1.26	27.3	25.3	808.54	0.06	0.220	25.6	1.01	1.7
Windows	D	1787	0.364 ± 0.026	-8.81 ± 0.65	24.2	243.8	2141.9	0.17	0.220	25.6	1.65	-1.4
Windows	d	1209	0.122 ± 0.025	-2.98 ± 0.64	24.5	25.5	1640	0.03	0.220	25.6	0.55	-1.1
Doors	W	1212	0.226 ± 0.031	-4.72 ± 0.81	20.9	56.2	1294.1	0.07	0.331	24.6	0.68	-3.7
Doors	B	742	0.114 ± 0.040**	-1.63 ± 1.05*	14.4	8.3	739.12	0.02	0.331	24.6	0.34	-10.2
Doors	F	265	0.564 ± 0.092	-14.85 ± 2.51	26.3	51.6	291.49	0.24	0.331	24.6	1.70	1.7
Doors	d	598	0.424 ± 0.044	-11.08 ± 1.14	26.1	124.6	705.69	0.25	0.331	24.6	1.28	1.5

* $p > 0.1$, ** $p < 0.01$, ***W=Windows open, B=Blinds lowered, D=Doors open, d=drinks consumed, F=Fans on.

Table 1 Conditional (a, b, θ_{50}) and unconditional (a_{nc}, $\theta_{50,nc}$) logistic regression parameters ($p<0.001$ except else stated), with G-statistic, residual deviance and Nagelkerke's R^2.

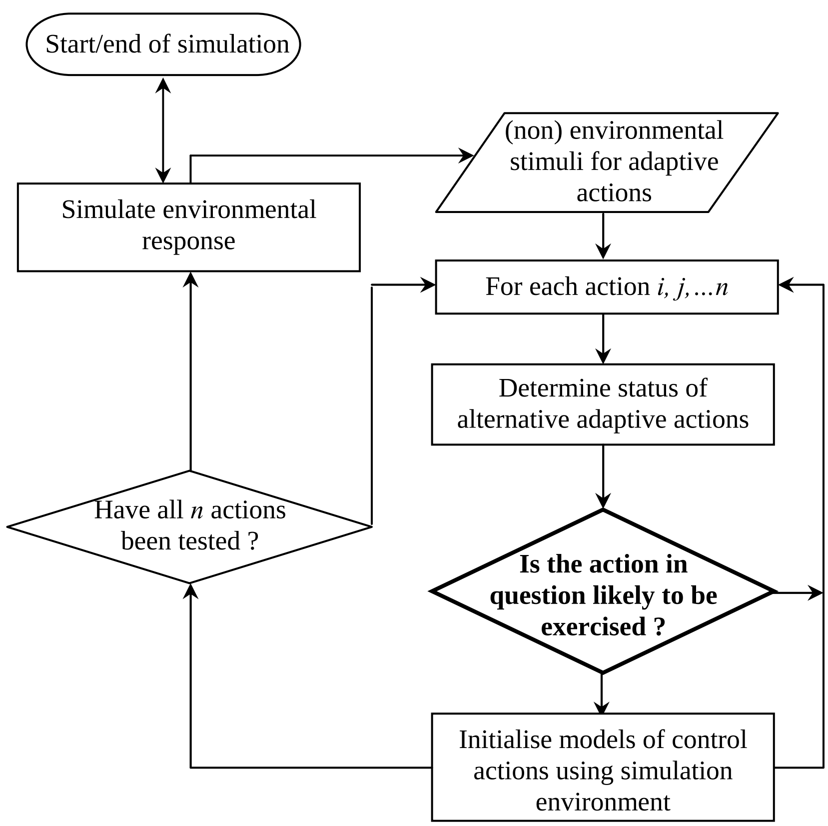

Figure 5 Proposed general framework for the integration of models of occupants' adaptive actions: the decision box in bold indicates calls to individual models of adaptive actions, taking the time, physical stimuli and the status of other possible actions as an input.