Occupant behaviour in naturally ventilated and hybrid buildings.

ABSTRACT

Adaptive thermal comfort criteria for building occupants are now becoming established. In this paper we illustrate their use in the prediction of occupant behaviour and make a comparison with a non-adaptive temperature threshold approach. A thermal comfort driven adaptive behavioural model for window opening is described and its use within dynamic simulation illustrated for a number of building types. Further development of the adaptive behavioural model is suggested including use of windows, doors, ceiling fans, night cooling, air conditioning and heating, also the setting of opportunities and constraints appropriate to a particular situation. The integration in dynamic simulation of the thermal adaptive behaviours together with non-thermally driven behaviours such as occupancy, lights and blind use is proposed in order to create a more complete model of occupant behaviour. It is further proposed that this behavioural model is implemented in a methodology that includes other uncertainties (e.g. in internal gains) so that a realistic range of occupant behaviours is represented at the design stage to assist in the design of robust, comfortable and low energy buildings.

INTRODUCTION.

The experience of a building can have a large impact on an individual's productivity and their feeling of well-being. The behaviour of occupants can have a large effect on energy use. To be successful, a building should satisfy the reasonable requirements of its occupants while minimising the energy needed to do so.

Building simulation is now being increasingly used in all aspects of building design including option appraisal, virtual prototyping, visualisation, building energy performance assessment and comfort evaluation. One challenge for building simulation is to correctly comprehend people's comfort requirements and how people behave in order that those requirements are met. This is especially important in naturally ventilated or hybrid buildings where occupant behaviour rather than mechanical systems provides the environmental control.

Significant research has been ongoing for some time in this area (deDear et al. 1997, Humphreys and Nicol 1998) and has resulted in adaptive criteria for thermal comfort in free running buildings being included in several international standards (CEN 2007, ASHRAE 2004). Research into adaptive behaviour has also been significant (Nicol and Humphreys 2004, Rijal et al 2007, Yun and Steemers 2007, Haldi and Robinson 2008, Herkel et al 2008, Mahdavi 2008) and progress is being made, but this work has yet to result in adaptive behavioural algorithms being widely adopted.

Current practice in building design and building simulation is to assign standard fixed parameters to represent occupant behaviour, such as fixed ventilation rates or window opening schedules (see Rijal et al 2007). While these parameters may represent some averaged typical behaviour they are not sensitive to the effects of any specific environment on occupant behaviour, or to the effect of that behaviour on the environment, occupant comfort and on energy use.

In this paper we first review the criteria for thermal comfort in free running buildings as described in the recent CEN standard EN15251 (CEN 2007), illustrate its application to a range of buildings, and draw comparison with the alternative non-adaptive criteria. We then give details of behavioural algorithms that are based on adaptive comfort criteria and survey data and have been developed to represent window opening and other adaptive occupant behaviours. We also describe how these algorithms are being further developed. We discuss non-thermal adaptive behaviours and occupancy patterns and how these can be combined with the thermal behavioural algorithms to create a more comprehensive model of occupant behaviour. We illustrate how uncertainty is built into the thermal behavioural algorithms and propose the combination of this uncertainty with other uncertainties in order to generate a realistic range of building performance which can then be used to assess the robustness of a design. We suggest how this distribution can be related to the comfort criteria and discuss the possible use of a capability parameter to describe and optimise the comfort performance of a climate adaptive building.

This area of research is clearly developing rapidly. Our intention here is to provide a summary of our approach so far and an indication of our thoughts on a possible future direction. We also discuss how the results so far can usefully be applied.

The building simulation tool used for this work is the ESP-r program originally developed by Clarke (Clarke 2001) of the University of Strathclyde but now being used and developed by commercial and

research organisations worldwide. The open-source nature of ESP-r makes it a suitable vehicle for development and also facilitates the dissemination of the behavioural algorithms.

ADAPTIVE COMFORT CRITERIA IN BUILDING DESIGN.

The recent CEN standard EN15251 (CEN 2007) gives the "indoor environmental input parameters for design and assessment of energy performance of buildings addressing indoor air quality, thermal environment, lighting and acoustics". Contained within this document are the cooling season thermal comfort criteria to be applied to mechanically cooled buildings as well as the alternative adaptive thermal comfort criteria that may be applied to naturally ventilated office buildings or dwellings in free-running mode (outside the heating season) "where there is easy access to openable windows and occupants may freely adapt their clothing to the indoor and/ or outdoor thermal conditions".

The adaptive comfort temperature (T_{comf}) is defined as the optimal operative temperature and is related to the running mean of the outdoor temperature (T_{rm}) and given by equation 1.

$$T_{comf} = 0.33T_{rm}+18.8 \tag{1}$$

where
$$T_{rm} = (1-\alpha).\{ T_{ed-1} + \alpha. T_{ed-2} + \alpha^2 T_{ed-3}\dots \} \tag{2}$$

and
T_{rm} = Running mean temperature for today

T_{ed-1} is the daily mean external temperature for the previous day

T_{ed-2} is the daily mean external temperature for the day before and so on.

α is a constant between 0 and 1. Recommended to use 0,8

This relationship was derived from surveys of environment and behaviours in offices across the European Union (Nicol and McCartney 2001, McCartney and Nicol 2002). Upper and lower temperature limits are then defined with reference to this adaptive comfort temperature for different categories of building as shown in table 1.

	TABLE 1 categories of buildings in EN15251 (Source CEN 2007)
Category	**Explanation**
I	High level of expectation and is recommended for spaces occupied by very sensitive and fragile persons with special requirements like handicapped, sick, very young children and elderly persons.
II	Normal level of expectation and should be used for new buildings and renovations.
III	An acceptable, moderate level of expectation and may be used for existing buildings.
IV	Values outside the criteria for the above categories. This category should only be accepted for a limited part of the year.

For each of these categories then upper and lower limits are set for the operative temperature (T_{op}) by the following equations and illustrated in figure 1. The upper limits are applicable for $10 < T_{rm} < 30$ and the lower limits for $15 < T_{rm} < 30$. It may be useful to describe the conditions between the lower and upper limits as the 'comfort band'.

Category I	upper limit:	$T_{op,max} = 0,33\ T_{rm} + 18,8 + 2$	(3)
	lower limit:	$T_{op\ min} = 0,33\ T_{rm} + 18,8 - 2$	(4)
Category II	upper limit:	$T_{op\ max} = 0,33\ T_{rm} + 18,8 + 3$	(5)
	lower limit:	$T_{op\ min} = 0,33\ T_{rm} + 18,8 - 3$	(6)
Category III	upper limit:	$T_{op\ max} = 0,33\ T_{rm} + 18,8 + 4$	(7)
	lower limit:	$T_{op\ min} = 0,33\ T_{rm} + 18,8 - 4$	(8)

where $T_{op\ max\,/\,min}$ = limit value of indoor operative temperature, ^{o}C
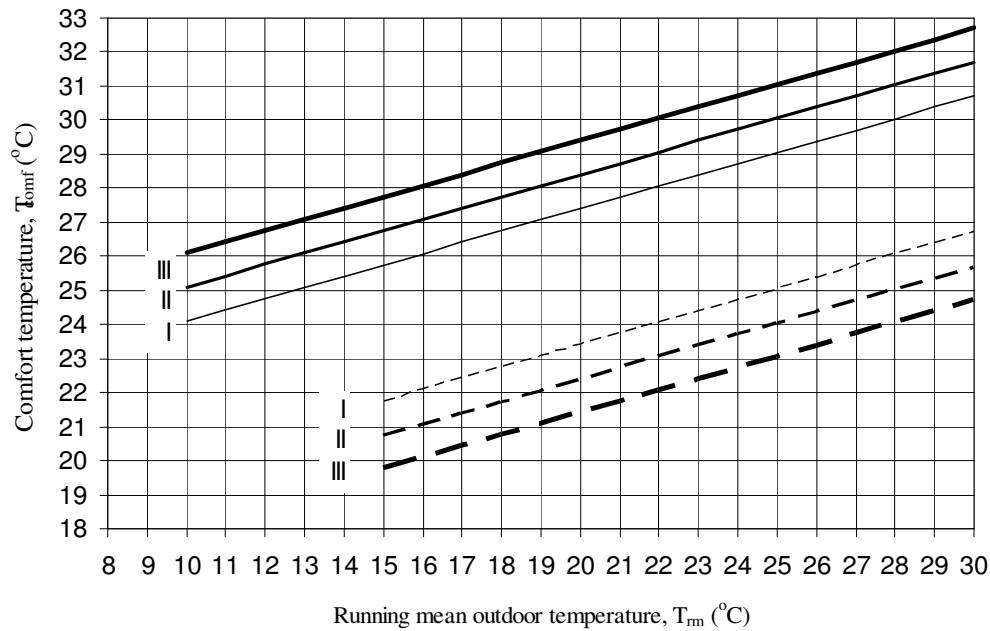

Figure 1 *Adaptive comfort criteria for building category I, II and III from EN 15251 (CEN 2007).*

According to the CEN standard these limits can be further extended for the case when increased air movement can be achieved through the use of fans under occupant control with the extent of this temperature extension being dependent on the air velocities achieved.

A comparison of these adaptive criteria with the non-adaptive criteria for each category of building is given in Table 1 for the case where the running mean outdoor temperature is $20^{o}C$. The adaptive criteria

give significantly higher indoor comfort temperature limits for climates with running mean temperatures greater than 13 or 14 degrees, the amount depending on the building category.

TABLE 2. Comparison of adaptive and non adaptive comfort criteria					
Building category	Non-adaptive PPD criteria	Non-adaptive design T_{max} (^{o}C)	Non-adaptive energycalc T_{cool} (^{o}C)	Adaptive design T_{max} (^{o}C) (T_{rm}=20°C)	Adaptive design T_{max} (^{o}C) (T_{rm}=20°C, Fan 0.6m/s)
I	< 6%	25.5	24.5	27.4	29.4
II	< 10%	26	24.5	28.4	30.4
III	< 15%	27	24.5	29.4	31.4

The adaptive criteria can be easily applied in building design to assess comfort performance of design options. As an illustration the building performance was assessed using the dynamic simulation tool ESP-r for 3 variants of a simple south facing office located in Dundee, Scotland (Figure 2).
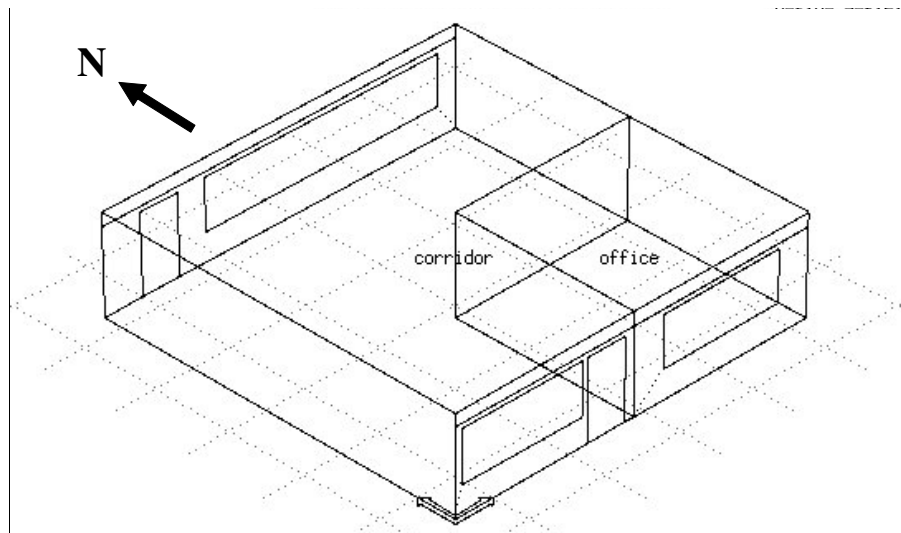

Figure 2 *The Dundee cellular office (labelled 'office') within a larger open plan office used to evaluate design options (Rijal et al. 2007).*

The three variants consisted of a base case office with typical 1990's UK building standards and thermally lightweight construction and two variants, one with external shading applied and the other with an exposed concrete ceiling to add thermal mass. A more detailed description of these building variants has been given in a prior publication (Rijal et al 2007). The performance of the office design variants is easy to extract from simulations, the performance plotted against the adaptive comfort criteria is shown in Figure 3 and summarized in Table 3.
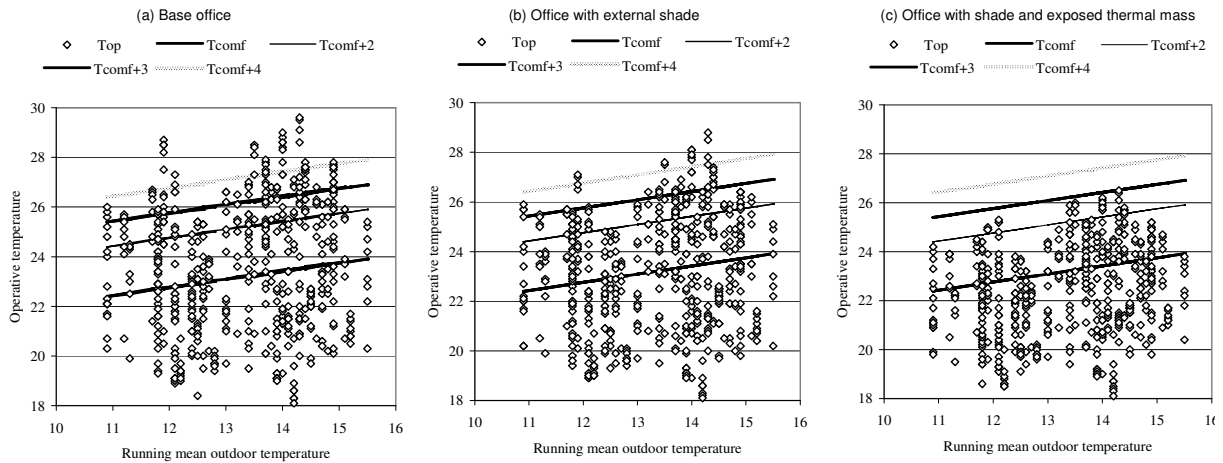
Figure 3 *The summer performance of the three office design variants (Rijal et al. 2007) is compared against the adaptive comfort criteria, the left graph (a) shows the baseline office, the center graph (b) shows the baseline office with an external shade added, the right graph (c) shows the baseline office with an external shade and an exposed concrete ceiling. All axis units are °C.*

TABLE 3. Design variant results for adaptive comfort criteria			
Building design variant	**Occupied hours > Tcomf+2 (category I)**	**Occupied hours > Tcomf+3 (category II)**	**Occupied hours > Tcomf+4 (category III)**
Base case - typical south facing office.	32 %	17 %	5.5 %
Base case with external shading.	22 %	7.2%	2.3 %
Base with shading and exposed mass.	5.3 %	0	0

THERMAL COMFORT DRIVEN WINDOW OPENING BEHAVIOUR MODEL.

The applicability of the adaptive criteria for thermal comfort depends on the individual being able to take adaptive actions when they experience discomfort, specifically freedom to adjust clothing, open windows and possibly increase air movement by turning on fans.

The Humphreys algorithm (Rijal et al 2007) has been developed for modelling window opening adaptive behaviour and builds on the adaptive comfort theory behind the CEN standard. The algorithm was derived from the data gathered in the European surveys used to define EN 15251 (see above) as well as in other surveys in the UK (see Rijal et al 2007) which included occupant comfort responses as well as a range of internal and external environmental parameters including the window status (open or closed). The

available data were analysed and a logit function extracted with a good fit to the survey data. The logit describes the probability of the window being open (Pw) based on both the indoor (T_{op}) and outdoor (T_{out}) temperatures.

Where: $$logit(Pw) = 0.171T_{op} + 0.166T_{out} - 6.4 \qquad (9)$$

and $$Pw = exp^{(Logit(P))}/(1 + exp^{(Logit(P))}) \qquad (10)$$

The Humphreys algorithm incorporates a comfort band similar to that in the CEN adaptive comfort standard. In the algorithm the occupant will not take adaptive action while conditions are 'comfortable', i.e. within 2 degrees of the adaptive comfort temperature, but will allow the status quo to remain unaltered. Out-with the 'comfort band' the logit is used to generate the probability that the window would be open if 'warm' or closed if 'cool'. To represent the fact that window opening is stochastic and that there would be a spread in window opening behaviour, the logit generated probability is compared to a random number to determine the actual window condition. Figure 4 illustrates the probability of window open for one specific set of circumstances.
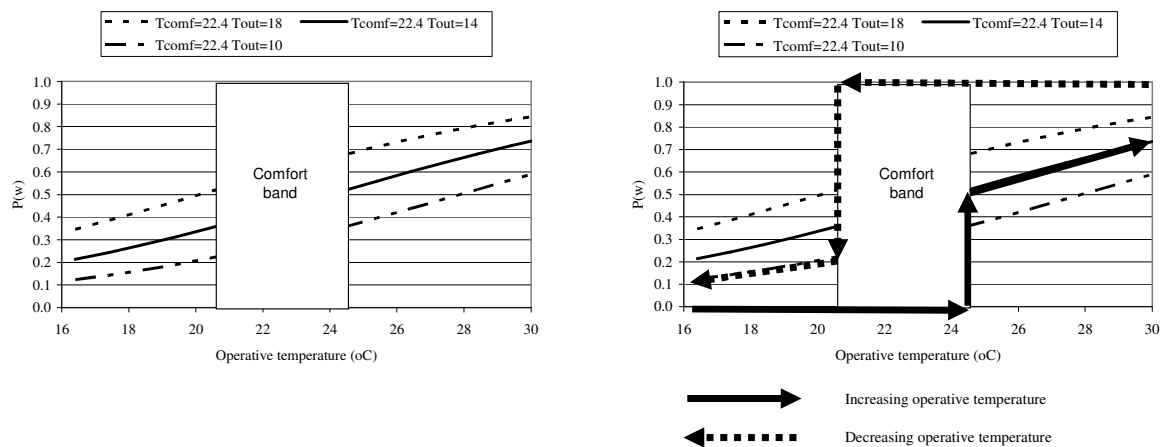

Figure 4 *The left figure shows the comfort band and window opening probability function (Pw) for the Humphreys algorithm for a day with a comfort temperature (T_{comf}) of 22.4 ^oC and three outdoor temperatures (T_{out}) of 10, 14 and 18 ^oC. The right graph illustrates the probability of window being opened (Pw) for the case of the window being initially closed and indoor operative temperature increasing (for the case shown T_{out} = 14 ^oC) and also Pw for the case where the window is initially open and the indoor operating temperature is decreasing (for the case shown T_{out} = 10 ^oC).*

The comfort temperature underlying the Humphreys algorithm during the free running part of the year is the same as for the CEN standard (Equation 1) but where the running mean outdoor temperature is less

than 10 degrees then the building is assumed to be heated and the heating season comfort temperature applied (CIBSE 2006) which has a lower dependence on outside running mean conditions (Equation 11). It should be noted that application of the Trm < 10 ^{o}C criteria to identify the heating being on represents seasonal occupant behaviour with respect to heating systems.

$$T_{comf} = 0.09T_{rm} + 22.6 \tag{11}$$

The window opening algorithm has been implemented in ESP-r and been shown (Figure 5) to give similar results to that found in the survey data when applied to the typical office described above.
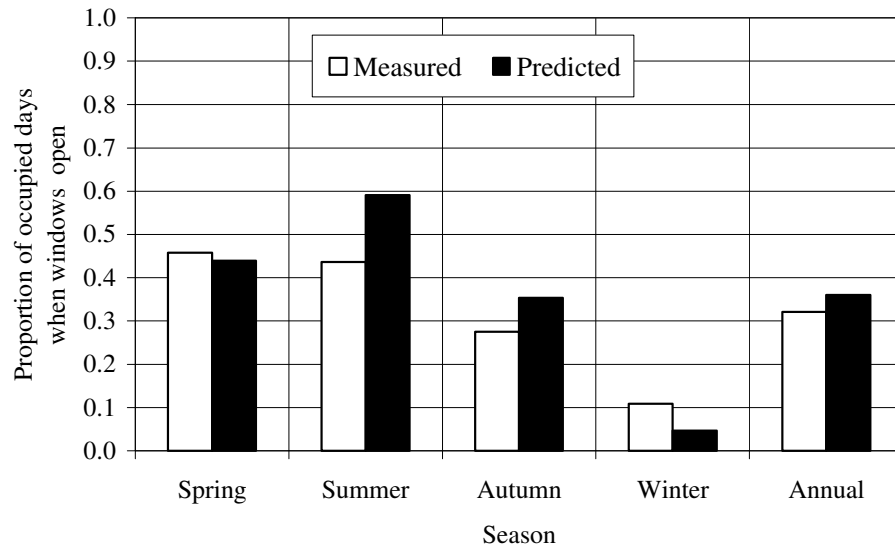

Figure 5 *Predicted window opening behaviour of the south facing Dundee office compared to the measured average of the UK survey data.*

The same office design variants as in the previous section were analysed for window opening behaviour and heating energy use. The more comfortable building variants (shaded and shaded with exposed thermal mass) had correspondingly fewer window openings due to overheating (Figure 6). This model of window opening behaviour predicted higher winter heating energy use in the shaded office compared to the base case (shading reduced solar gains) but lower winter heating energy requirement in the shaded with exposed thermal mass case (Figure 7). In part this reduction in heating energy use in the most comfortable office was due to the reduction in ventilation heating load due to fewer window opening events triggered by overheating discomfort especially in the transitional seasons.
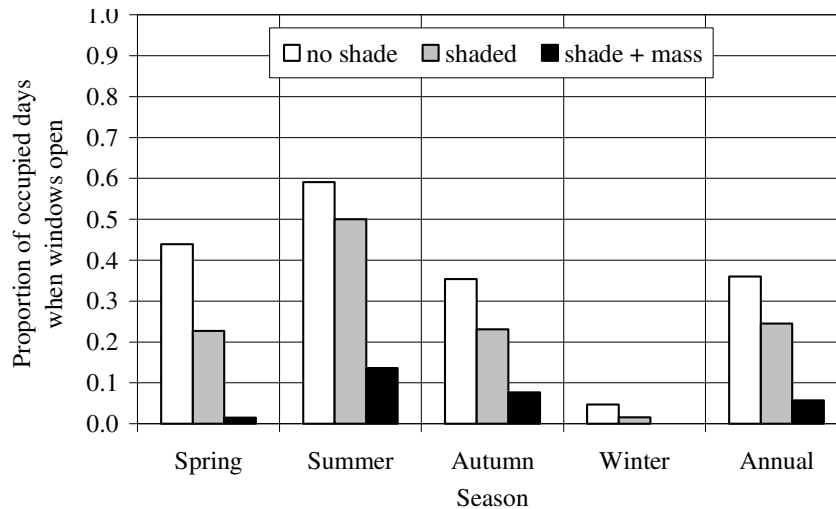
Figure 6 *Predicted window opening behaviour for the three design variants of the Dundee office.*
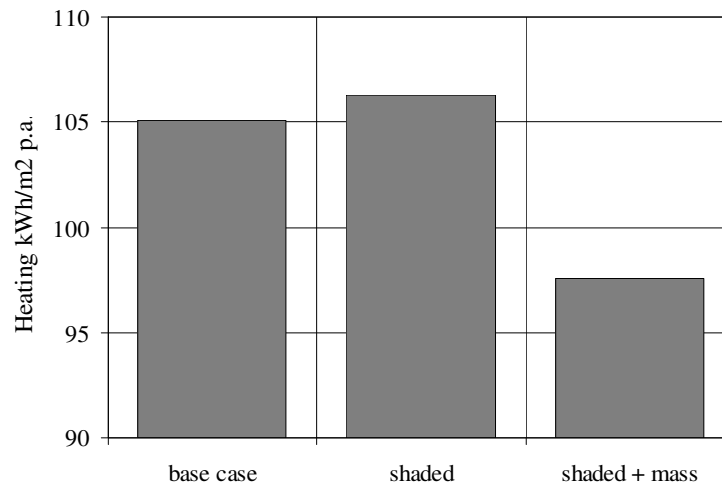

Figure 7 *Predicted annual heating energy demand in kWh/m² per year for each of the three design variants.*

The Humphreys algorithm integrated within building simulation software allows the adaptive thermal comfort to be established for any given set of conditions and represents occupant window opening adaptive behaviour which is taken in an attempt to restore thermal comfort when some discomfort is experienced. The algorithm integration allows this behaviour to be included in all aspects of the simulation including energy use calculations, airflow calculations, CFD calculations etc.

WINDOW, FAN AND DOOR THERMAL ADAPTIVE BEHAVIOURS.

The adaptive behaviour model was further developed based on a Pakistan dataset (Nicol et al 1999). The data from the warmer climates of the Pakistan study is complementary to the UK and EU datasets and has usefully extended the range of climates across which adaptive behaviour and comfort experiences have been collected. The Pakistan survey was of office buildings across several regions of Pakistan. Data gathered included temperatures, humidity, air movement, and use of window, ceiling fan, door, heating systems and local air conditioners.

Window opening behaviour was again modelled using an extracted probability function, additional probability functions were developed for the use of doors (additional ventilation) and ceiling fans (air movement). In this version of the algorithm a modified approach was taken to represent the thermal comfort band and adaptive behaviour (Rijal et al. 2008). Rather than modelling the probability function and comfort zone separately the comfort zone was incorporated into the equation through the comfort temperature (T_{comf}) and comfort or 'dead' bands for window and fan use (WD, FD) as shown in Equations 12, 13 and 14 for windows, fans and doors respectively.

Windows open: $\text{Logit}(Pw) = 0.525\{T_{op} - T_{comf} + (S_w - 0.5)\,WD\}$ (12)

Fans on: $\text{Logit}(Pf) = 0.595\{T_{op} - T_{comf} + (S_f - 0.5)\,FD\}$ (13)

Doors open : $\text{Logit}(Pd) = 0.081 T_{op} - 1.34$ (14)

Where Pw = Probability of window being open

Pf = Probability of fan being on

Pd = Probability of door being open

S_w = window status (1 = open, 0 = closed)

S_f = fan status (1 = on, 0 = off)

The effect of fan use on comfort temperature has been incorporated as a 2K increase (Nicol 2004b) when the ceiling fan is turned on which is consistent with approximately 0.6 m/s air velocity (CEN 2007). So when a fan is turned on the probability of a further adaptive action such as door or window opening is retarded by 2K from the probability that action would have been taken were the fan not on. This shift could be modelled in more detail in future to represent different fan settings and their associated air movements. The fan energy consumption is accounted for in the simulation code and adds to the internal gains in the space when in operation.

It would be possible in future to also represent local heating and air conditioning use in the same way as for windows, doors and fans.

'Heating on' seasonal behaviour related to the running mean outdoor temperature was again found and similar seasonal criteria extracted from the dataset were used to represent local air conditioner use ($T_{rm} >$ 28.1 ^{o}C), use of night ventilation ($T_{rm} >$ 28.1 ^{o}C), a 'fan inhibit' ($T_{rm} <$ 23.6 ^{o}C) to represent the non-use of fans in the winter. Additionally for this warmer climate dataset a 'window inhibit' was applied when outside air temperature is greater than 5K above the indoor operative temperature (no thermal comfort benefit from opening windows).

Again this approach gave reasonable agreement with the survey data when applied to a simulation model of a 'typical' office run for a Pakistan climate (Rijal 2008).

To allow the algorithm to capture the appropriate range of adaptive opportunities in any given situation, the availability of each opportunity was explicitly set, for example if window opening outside occupied hours was not allowed for security reasons then 'Night cool available?' was set to 'no', if a local air conditioning unit was available then 'AC available?' was set to 'yes'. Figure 8 shows the operation of the algorithm for the case where night ventilation is possible and where this is not possible due to some circumstance such as security risk. The extension of the behavioural algorithm based on the warmer climate dataset and a wider range of adaptive opportunities has allowed a more complete model to be constructed.
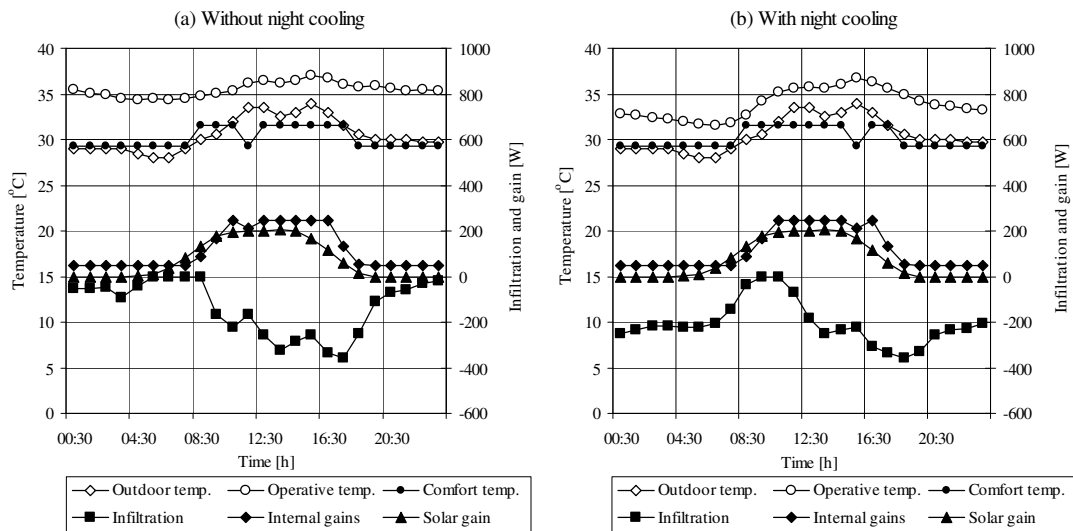

Figure 8 *Temperatures and energy flows for a summer day with and without night cooling. The lines represent the outdoor air temperature, the indoor operative temperature (open symbols), the comfort temperature (varies with fan use) and the energy flows from the convective cooling*

by the incoming air, the heat gains from occupants, equipment and lights and the incoming solar heating absorbed in the surfaces of the office. The night cooling is indicated by the cooling due to infiltration of around 200W overnight.

INTEGRATING THERMAL ADAPTIVE BEHAVIOURS WITH OPPORTUNITIES AND CONSTRAINTS.

A further development of the adaptive behavioural model is proposed which offers enhanced functionality.

It has been observed that where there are circumstances such that an adaptive action has some adverse impact then the occupant may tolerate a degree of thermal discomfort before taking this action (Humphreys 1973). This would be the case for example where opening a window led to excessive indoor noise, or opening a door led to loss of security. This effect could be viewed as a constraint that affects behaviour. The effect of a constraint would be to shift the probability function associated with that adaptive action further away from the comfort temperature than would be the case where the constraint did not exist (Figure 9).
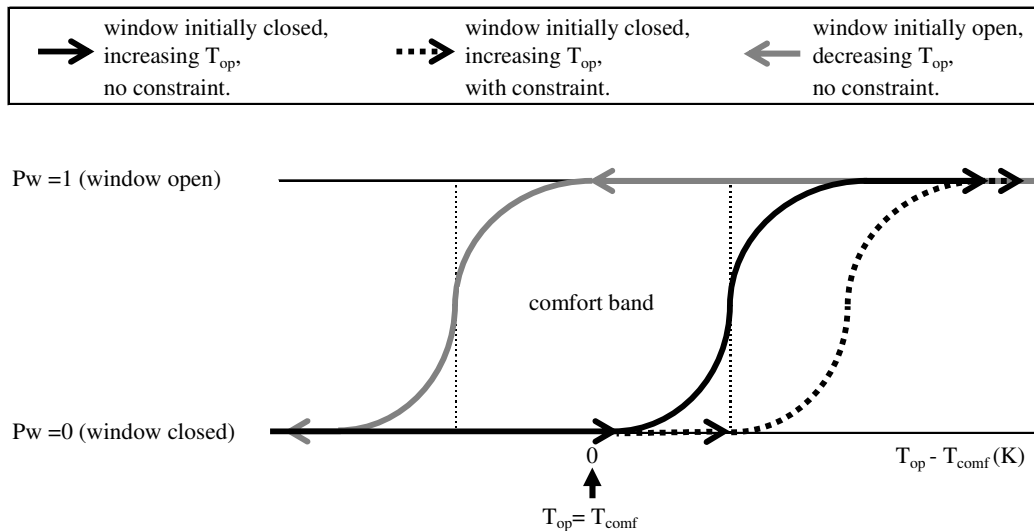

Figure 9 The incorporation of constraints within the window opening algorithm. The illustration shows the unconstrained window opening case (window initially closed, increasing operative temperature, no constraint) and the case where some negative consequence of window opening has the effect of retarding the occupants use of the window until their thermal discomfort has more weight than the negative effect of window opening (window initially closed, increasing operative temperature, with constraint).

It has been suggested that negative constraints can also exist where the probability of taking an action may be increased where there is some positive incentive to do so or the occupants recognise the advantage of the action before they actually become uncomfortable. The constraints could then be expressed as a temperature offset applied to the equation for the unconstrained case. This system of constraints could for example be used to differentiate between sets of windows in a building. Smaller secure, weather proof windows may be unconstrained while the main window units may be less secure and therefore have some constraint associated with opening them. The constraints themselves need not be fixed but could be dependent on time of day (e.g. rush hour traffic) or some other parameter or combination of parameters. There may, for example, be a modified thermal experience on arrival that could be included as a negative constraint at that time. An example of how adaptive opportunities and constraints could be specified for inclusion in simulation is shown in Table 4.

TABLE 4. Opportunities and constraints.			
Behaviour	**Opportunity available?**	**Constraint description?**	**Constraint function.**
Small window daytime opening	Yes	Unconstrained.	None.
Large window daytime opening	Yes	Constrained by noise, pollution, dust etc outside and incident rainfall.	+1.5 K generally and +99 (closed) if incident rainfall.
Door opening	Yes	Constrained by noise inside.	+2.5 K.
Fan use	No (no fan)	Not applicable	Not applicable
Heating use	Yes	Unconstrained	None.
Night cooling through large window	Yes	Constrained by security concerns.	+99 (closed).
Night cooling through small window	Yes	Unconstrained	None.

This system of constraints allows further customisation of the adaptive behaviour to particular situations. Ideally a building should allow sufficient unconstrained adaptive opportunities for the occupant to maintain comfortable conditions.

INTEGRATION OF THERMALLY ADAPTIVE BEHAVIOUR WITH OCCUPANCY AND NON-THERMALLY DRIVEN BEHAVIOURS.

The discussion so far has considered thermal comfort driven adaptive behaviour, but there are other drivers for adaptive behaviour such as visual and air quality conditions. For all of the adaptive behaviours, patterns of occupancy play a fundamental role and also should have a place within the model.

Visual drivers for adaptive behaviour can be viewed as being of two types, the first relates to the illuminance level required to perform the appropriate tasks in the environment and the second relates to visual discomfort due to glare or illuminance asymmetry. These visual parameters drive adaptive behaviours such as blind use, external shutter use, use of general lighting and of task lighting. The relationships between visual conditions and occupant adaptive behaviours have been investigated by a number of researchers and algorithms have been developed and incorporated in simulation programs. Hunt (1979) derived probability functions for manual operation of lighting from survey data from schools and offices, he observed that the probability of switching on lights depends strongly on the desk-plane illuminance and the arrival time of an occupant into the space, with much lower frequency of switching occurring during occupied periods. Reinhart (2004) built on work by Hunt, Newsham et al (2001) and others to create the 'Lightswitch-2002' algorithm. This algorithm incorporates stochastic adaptive behaviour for occupancy and the use of lights and blinds.

The air quality drivers (pollutants including particulate, olfactory and non-olfactory emissions) of adaptive behaviour are less developed in the building simulation environment than are the thermally and visually driven behaviours. Page et al. (2007) has proposed an olfactory trigger for window opening behaviour, building primarily on work by Fanger and proposing that sensitivity to this trigger is heightened on arrival. Other authors have noted enhanced probability of window opening on arrival which may be an expression of an olfactory trigger or may be due to some other factor. The 2007 CEN standard (CEN 2007) includes categorisation of buildings into 'very low polluting', 'low polluting' and 'not low polluting'. The very low and low polluting buildings use materials having low emissions of noxious or unpleasant substances. The CEN standard specifies higher ventilation rates during occupancy for the poorer building types and either that the ventilation system supplies two air changes prior to the start of occupancy or that background ventilation rates are ensured during unoccupied hours sufficient to disperse the pollutants. The inclusion of ventilation modelling in building simulation is available through both CFD and air-flow network methods (Clarke 2001) and the modelling of pollutant sources, dispersal and resulting

concentrations is also available (Samuel and Strachan 2007). What is less well defined is a library of materials available to the simulation tool with defined pollutant and odour emission rates, and also models of equipment and personal pollution emission rates associated with occupants and the equipment located in a space. Page and Robinson (2008) have also developed a probabilistic occupancy algorithm which it is claimed has benefits over that proposed by Reinhart.

Bourgois, Reinhart and Macdonald (2006) have created the facility in their sub-hourly occupancy model (SHOCC) to manage occupancy patterns, behavioural algorithms and associated heat gains or losses across the multiple zones of a building within a dynamic simulation. They illustrated this facility using the algorithms of Lightswitch-2002 and predicted the effect of occupant and automatic control of blind and lights on lighting energy use. The SHOCC module has been implemented in conjunction with ESP-r and its framework is extendable and could in future include the thermal and olfactory behaviours mentioned above.

INCLUSION OF OCCUPANT BEHAVIOUR MODEL IN UNCERTAINTY ANALYSIS.

One difficulty in designing a building is the large number of uncertainties that apply. These include variation in future occupancy patterns, variation in occupant activities and behaviours, variation in future internal gains due to equipment, uncertainty in future climates, uncertainty in construction processes, uncertainties in future pollution sources (e.g. printers and copiers) etc. The risks due to these uncertainties can be viewed by designers and clients as being increased in the case of naturally ventilated buildings due to the reliance on natural and therefore variable means of cooling and ventilation.

Building simulation software allows the possibility of quickly investigating building performance across a large range of possible conditions. Macdonald and Strachan (2001) developed a methodology for carrying out uncertainty analysis in simulation which is currently implemented within ESP-r but can be readily applied in other simulation tools. This methodology allows the variation in simulation input parameters (such as internal gains, climate, or building construction) to be specified and then allows Monte-Carlo or other statistical methods to be used to generate the corresponding range in building performance output parameters. The variation in inputs can be specified in detail. This capability is illustrated here by running the Humphreys window opening algorithm within a Monte-Carlo method for a UK summer, in this case only the variation due to the stochastic nature of the behavioural algorithm itself is

included – all other simulation input parameters are kept constant. Figure 10 shows the predicted variation in performance for one particular summer day and Figure 11 shows the distribution of internal temperatures relative to the comfort temperature for that day.
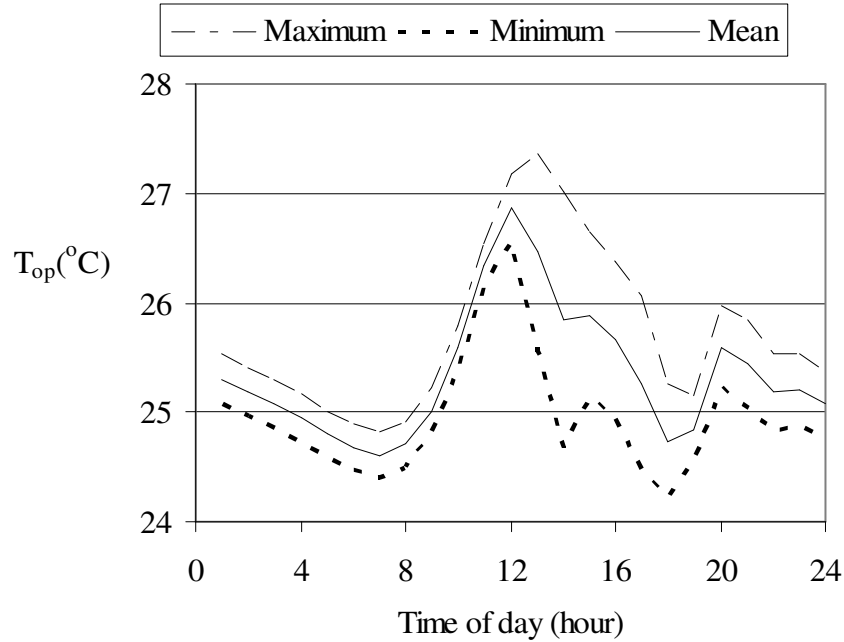

Figure 10 *The predicted range in operative temperature for a single day in summer day due to the variation in window opening behaviour represented by the stochastic nature of the Humphreys algorithm run in a Monte-Carlo mode.*
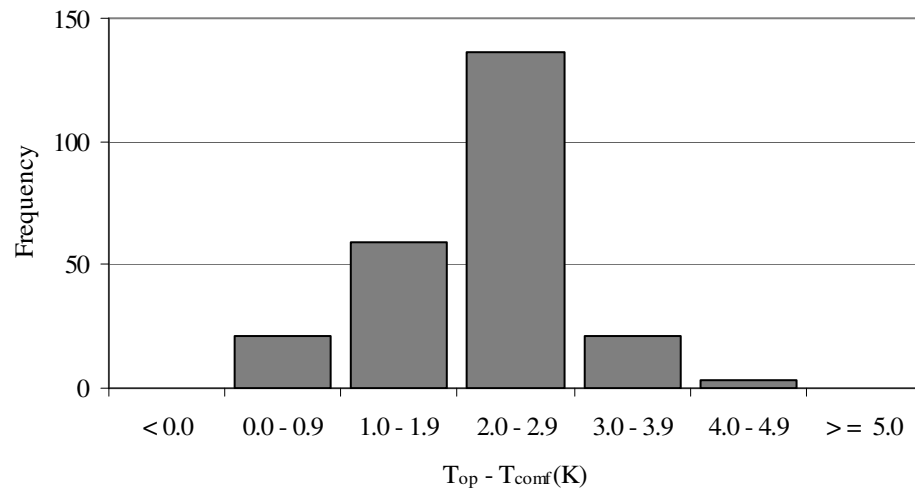

Figure 11 *The predicted distribution of the deviation from optimal thermal comfort temperature ($T_{op} - T_{comf}$) for the same summer day as in Figure 10 due to the variation in occupant behaviour as embedded in the Humphreys algorithm.*

The resulting distribution illustrates the predicted impact that variation in occupant window opening behaviour can have on the internal comfort conditions in the naturally ventilated space with higher temperatures resulting from windows being open less frequently and lower temperatures being associated with more frequent window opening. This distribution could be seen as representing the variation in user behaviour between more and less sensitive or more or less active individuals.

By incorporating variations in other simulation input parameters such as occupancy, internal gains from equipment, climates, construction properties etc. together with the variation due to occupant adaptive behaviour then a resulting prediction of the overall distribution in building performance for the range of possible conditions would be calculated. A simplified illustration of the predicted comfort performance for two design variants is given in Figure 12.
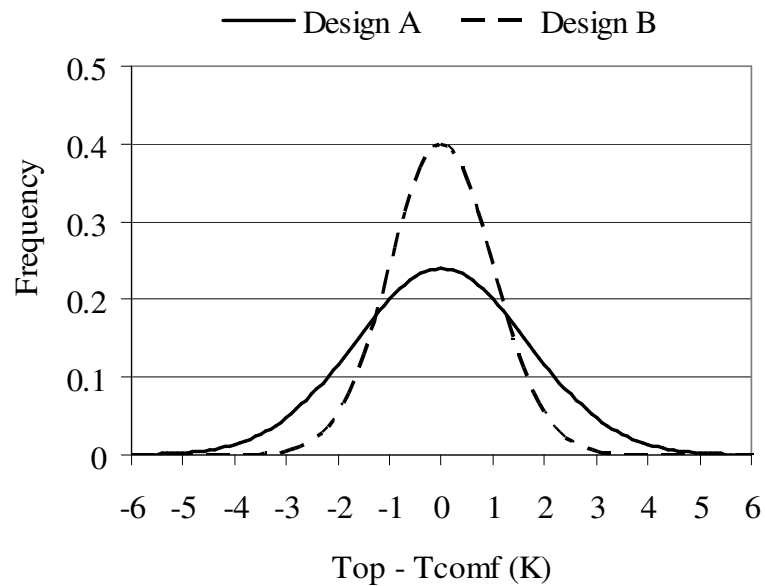

Figure 12 *Distributions representing the comfort performance of Design A and Design B for a range of input parameters representing variation in climate, internal gains, occupant behaviour, construction etc. Design A has a comfort capability of C = 1 when compared to the T_{comf} + 3K limit for a category II building, Design B has a comfort capability of C = 0.6.*

This illustration shows the two design variants to have similar average performance. However option A has poor performance for some combinations of possible input parameters that may result in significant overheating while option B is clearly more robust for the modelled changes in patterns of use, climate etc. This type of analysis can be carried out for any of the comfort or energy use outputs from the simulation.

In other fields of engineering 'six sigma quality' statistics (Pyzdek 2003) are applied to describe this type of analysis of design quality, here 'six sigma' refers to the ultimate goal that a process or system should perform outside specification only 3.4 times out of a million i.e. the sigma of the distribution is less than a sixth of the separation of the mean from the specification and the variation in the mean is less than 1.5 sigma. While this ultimate goal does not translate directly to the design of free running buildings, elements of the 'six sigma quality' approach can be applied. In 'six sigma' a capability parameter (C) can be used to describe the robustness of a design or process, where C can be defined (in its simplest form) as in equation 15.

$$C = (\text{specification limit} - \text{mean}) / (3 \times \text{sigma}) \tag{15}$$

In these terms building design A would have a comfort capability of C = 1 while building design B would have a capability of C = 0.6. This approach may be useful to use in the analysis of building designs as an alternative to exceedance criteria based on fixed input parameter sets.

To enable uncertainty analysis to be meaningful, the distributions describing input variation need to be defined from sources such as survey data and climate projections. A similar analysis could also be applied to measured performance data.

DISCUSSION AND CONCLUSIONS.

This paper has reviewed the approach being taken by the authors to developing a model of occupant comfort and behaviour for use in the simulation of buildings that rely on this adaptive behaviour for cooling and ventilation.

The approach to thermal adaptive behaviour is built on the established adaptive thermal comfort criteria. The algorithms have been developed from existing thermal comfort survey data and will continue to be developed as they are tested against further datasets. The behavioural algorithms are being implemented within the building simulation environment and the simulation results checked back against the measured data as a validation. It may be that further targeted surveys will be required to fully establish robust values for some of the parameters across a full range of contexts.

Combination of these thermal adaptive behavioural algorithms with existing and future visual comfort adaptive behavioural algorithms, occupancy algorithms and pollutant / olfactory algorithms is proposed and it is suggested that a framework to facilitate this already exists in the simulation environment.

The behavioural algorithms attempt to represent the variation in behaviours and comfort experiences of the overall population. It is proposed that this variation is treated together with other uncertainties influencing building performance such as internal gains from equipment and lighting, variation in possible climates, uncertainties in building fabric etc. It is proposed that these uncertainties should be treated within a Monte-Carlo methodology to generate a performance distribution. The framework for this uncertainty analysis already exists in simulation. This performance distribution would then allow a capability score to be established for the design, and the score could be used to compare different design options.

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