Fourth National Conference of IBPSA-USA
New York City, New York
August 11 – 13, 2010

WINDOW OPENING BEHAVIOUR IN A NATURALLY VENTILATED SCHOOL

Spencer Dutton[1, 2], Li Shao[3]
[1]Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley, USA
[2]University of Nottingham, University Park, Nottingham, UK
[3]De Montfort University, Leicester, UK

Author contact: smdutton@lbl.gov

ABSTRACT

Several studies have highlighted the significant disparities between the predicted performance of new buildings and their post occupancy measured performance. Occupant window opening behaviour has been shown to have a significant impact on both classroom indoor air quality and building energy use; and is currently poorly represented in building simulation tools.

A post occupancy assessment of a new primary school was performed over a period of over one year. Concurrent measurement of window open state, CO_2 concentration, temperature, and exterior environmental conditions were taken at a frequency of two minutes. In addition, classroom daily occupancy levels and monthly building energy usage were recorded.

A probabilistic model of the proportion of windows open throughout the day as the occupants interact with the windows was developed based on the results of multinomial logistic regression analysis. The model was used to schedule window opening in the EnergyPlus simulation program.

Predictions of both CO_2 concentration and building energy performance, using the occupant behaviour model, were shown to give more accurate predictions than a model based on temperature set points.

INTRODUCTION

The use of natural ventilation in temperate climates has the potential to reduce building energy use. However these improvements in energy performance often come at the expense of indoor air quality (IAQ). Studies in the UK have shown that many naturally ventilated schools, including buildings built to 2004 building standards, are not achieving recommended levels of ventilation. The Building Research Establishment studied the IAQ of eight schools across the UK (BRE 2006). This report showed ventilation levels below 3 l/s in all of the measured schools, and found 60% experienced average CO_2 levels of above the recommended concentration of 1000ppm (BB101 2006). Maintaining minimum air quality standards is particularly important in schools; where carbon dioxide build up in class rooms is known to reduce the ability of students to concentrate, and influence absenteeism (Daisey 2003, Shendell et al. 2004). Suggestive evidence also links low ventilation rates with student work performance (Wargocki et al, 2005).

Typical school buildings in the UK utilize either single sided, or cross natural ventilation through the use of occupant controlled windows. Under these conditions, wind driven natural ventilation is the dominant ventilation driver (Dutton 2009). The variable nature of this ventilation can result in periods of both insufficient ventilation and periods of unnecessarily high ventilation. This over-ventilating of heated spaces can lead to increased heating energy costs, particularly when over-sized; thermostatically controlled hydronic heating systems successfully maintain thermal comfort in the space. A key contributor to the energy losses of modern school buildings is the ventilation losses caused by intentional venting of class rooms to improve air quality during heated periods (Dutton 2009). This can lead to a conflict of interest for the occupants, between the need to improve energy efficiency and the requirement of a safe and comfortable learning environment.

Designers of hybrid and naturally ventilated buildings, which can include schools, need reliable ventilation and energy performance tools if the dual goals of improved IAQ and energy efficiency are to be achieved. Building energy simulation software such as EnergyPlus and ESP-r combine the ventilation modelling of a network flow model with thermal energy simulation. As thermal effects influence the performance of natural ventilation systems, and ventilation performance impacts building energy performance, logic dictates that the combination can provide both more realistic building thermal performance and improved ventilation prediction.

Occupant window opening behaviour has been shown to have a significant impact on both classroom IAQ and building energy use. Window open behaviour has been shown to be poorly represented in commonly used building simulation tools such as EnergyPlus, in part due to inherent limitations in the tools themselves (Dutton 2009). The work presented in this paper aims to improve the prediction of building performance through improved understanding of occupant behaviour and the factors that influence behaviour.

METHOD

A post occupancy study was performed for a naturally ventilated elementary school in the UK. Indoor and external environmental conditions, carbon dioxide concentration, occupant behaviour and building energy were monitored over a 1-year period.

Work published by UC Berkeley CBE (Zhang 2003, Huizenga 2001) showed that long wave radiation heat exchange between the window and occupant can influence thermal comfort, and these comfort effects differ during winter and summer months (CBE 2006). Previous studies (Rohles and Nevins 1971), (Humphreys 1998), highlighted the importance of partial vapour pressure, internal, and external temperature, and, to a limited extent, wind speed as factors influencing thermal comfort; and were therefore included as potential drivers of occupant window intervention behaviour. Early work by Warren (1984) showed that solar radiation can have a direct impact on window opening. Work by Hausler and Berger (2002), Zhang (2006) and LBNL (1984), showed that, in unheated periods, solar radiation is a significant contributor to thermal comfort, and was therefore included as a potential driver of window opening behaviour. Work by Inkarojrit (2004) demonstrated a relationship between operative temperature and window open proportion.

Measurement of environmental conditions

Internal environmental conditions and window state were measured in two out of the six teaching classrooms. The position of sensors in the classroom was constrained by the requirement that they were neither visually intrusive nor distracting for the students. CO_2 sampling was taken from a fixed, single position in the room located centrally at a height of 2 meters, using a WMA-3 CO_2 monitor, accurate to 1% of span concentration over the calibrated range.

A Davis Pro 2 weather station centrally located 3m above the roof line was used to monitor the external horizontal irradiation, air temperature, humidity, barometric pressure, wind direction/speed, rainfall. Environmental variables measured in the classrooms include the dry bulb temperature, CO_2 concentration and humidity levels. Temperature sensors were located throughout the building, with three located in each of the two main classrooms where CO_2 sampling occurred. The air temperature measurement was an average of three PT100 thermistors (±0.15°C @ 0°C) located at the working plane. Building management system heating schedule information was logged.

Magnetic contact sensors on the classroom windows provided a detailed picture of window opening behaviour. Each classroom contained four lower and four upper, bottom hung windows.

In addition to measured environmental variables, several derived variables were assessed during the analysis including the window transmitted solar radition; the window boundry wind pressure and the classroom vapour pressure.

An EnergyPlus model of the school that accurately represented the building geometry and window form was used to calculate the window transmitted solar radiation. Measured global horizontal radiation data was split into its constituent diffuse and direct components, using a diffuse ratio model (Muneer 1986). Muneer's model has been shown to be sufficiently accurate in determining this diffuse ratio for sites in the UK (Dutton 2008). These radiation components were used together with measured data to produce a local weather file. Post processing of the results of simulations of the school building provided a measure of window transmitted radiation.

A measure of the wind pressure at the window boundary for each simulation time step was calculated with equation 1, using the measured wind speed, wind direction and wind pressure coefficients calculated using the CP Generator software. The Dutch Building Research Institute (TNO 2008) provides a web based interface to its software CP Generator to calculate wind pressure coefficients of buildings.

$$P_w = C_p \rho \frac{V_{ref}^{2}}{2} \qquad \text{(1) (LBNL 2007)}$$

RESULTS

Window usage and temperature measurements were recorded for 436 days continuously from April 14th 2007 to June 23rd 2008, which coincided with measured weather data. Figure 1 shows the relationship between the outdoor temperature and the number of open windows during free running, occupied periods during the unheated season. The heating season was defined as days when the school daytime average outdoor air temperature was exceeded by the indoor air temperature by more than 10 ˚C. This definition translated to an approximate November 1st to May 1 st heating season, which corresponded well with BMS heating schedule data.

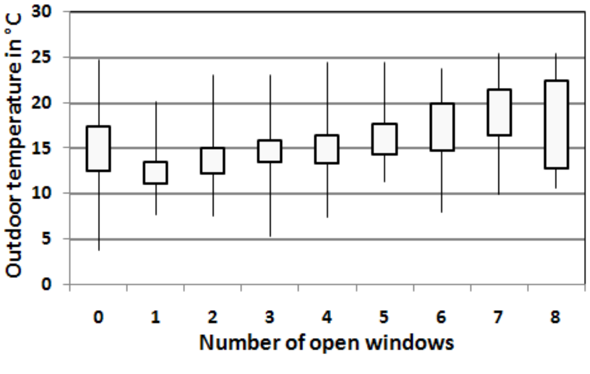

Figure 1 Outdoor temperature v open windows

Classroom measurements of carbon dioxide were recorded every 2 minutes over a total period of 137 days from March 13th 2007 until June 22nd 2007 and then again from September 26th 2007 to November 3rd 2007.

Analysis of the building's gas and electricity usage showed that it achieved lower than current good practice energy use compared to comparable naturally ventilated school buildings. However, measured CO_2 occupant exposures indicated that the air quality appeared to have suffered as a consequence. Carbon dioxide concentrations of over 1000 ppm were seen for 10%, 4.7% and 45.7% of the occupied time for March, June and October, respectively.

Occupant window usage

Several recently published models of window intervention, including those of Haldi et al (2009) and Humphreys (Rijal 2008) are based on the presumption that the main driver of occupant window intervention is occupant discomfort. Humphrey's adaptive thermal comfort model, suggests that the occupants' thermal comfort range shifts to a lower temperature in the winter (Humphreys and Nicol 1998). Occupants are therefore expected to be more tolerant of cooler environmental conditions in the winter.

Humphrey observed in studies of naturally ventilated offices the existence of a temperature dead band between which occupants rarely interacted with their windows. Rijal (2008) proposed a method of implementing Humphrey's observations of occupant window opening behaviour in a building simulation model, the basis of Rijal's model being that occupants only interact with their windows when they are thermally uncomfortable (defined as ± 2 ˚C either side of the adaptive comfort temperature).

A validation of this basic principle was attempted based on the measured occupant window data. A calculation was made of the average temperature in the classroom immediately preceding closing and opening interventions; with heated and unheated periods again considered separately. Table 1 shows the mean room air temperature immediately preceding window interventions for both unheated and heated periods. These results indicate that the average temperature in the classroom preceding closing interventions was warmer during the heated periods than the unheated periods. This result indicates that either the occupants are no more tolerant of cooler indoor environmental conditions during the winter heating periods, or that an alternative driver is overwhelmingly influencing their closing actions. Cold draughts would be an obvious candidate driver of window closing; later analysis could not find a significant correlation between window closing and either wind speed or wind direction, thought potential exists for buoyancy driven draughts.

Table 1 Average classroom temperatures preceding intervention.

Intervention period	Unheated mean classroom temp °C / std dev.	Heated mean classroom temp. °C/ std dev.
Window opening before 9am	19.1	18.9
Openings after 9am and before 3pm	20.5 / 1.8	21.3 / 1.4
Closings after 9am and before 3pm	19.8 / 2.1	20.6 / 1.7
End of class closing	20.4	20.1

Window openings were shown to be preceded by lower average temperatures in unheated periods than heated periods. Table 2 gives the percentage of window opening and closing interventions classified by occupant adaptive thermal comfort.

Table 2 Thermal comfort classification of window interventions between 9am and 3pm.

	Cold discomfort	Comfortable	Hot discomfort
Humphreys			
Openings	7.7%	86.3%	6.0%
Closings	18.7%	80.5%	0.8%
Brager/de Dear			
Openings	0.9%	59.2%	39.9%
Closings	3.3%	76.4%	20.3%

The assessment of thermal comfort was based on both Humphrey's (1998) and de Dear's (90% comfortable) (2002) adaptive comfort criteria; results show the majority of interventions occurred when occupants were comfortable.

Although later analysis demonstrated a correlation between comfort temperature, and the proportion of open windows, these results would appear to show that, in this case at least, discomfort is not the primary driver of intervention. A more accurate characterization of observed behaviour would be that occupants opened windows for fresh air, when thermal condition allowed for it.

These results suggest that any possible occupant adaptation to external environmental conditions did not result in a corresponding shift in window intervention behaviour, indicative of adaptation to cooler winter temperatures.

ANALYSIS

Drivers of window intervention

Multinomial logistic regression analysis was used to determine the dominant contributing environmental factors that influenced the likelihood of window intervention. A window intervention was defined as the change of state of a window.

Considering only periods immediately preceding an intervention to either open or close a window, several candidate variables were assessed for their influence on occupant window intervention. Candidates included both measured environmental conditions and variables derived from measured data. Environmental variables assessed included internal classroom air temperature, external air temperature, CO_2 and wind speed. The derived variables included the window transmitted solar radiation, wind pressure at the window boundary, and vapour pressure. Candidate variables were used, as predictors in the logistic regression analysis. Each variable was assessed both individually and collectively to produce regression models of behaviour. The pseudo R-Square correlation between window open models based on individual variables and the measured data was used as the basis for determining the significance of each variable.

Regression analysis showed that the type of window intervention (either an opening or closing of windows), determines the relative importance the environmental conditions hold in influencing the likelihood of intervention. Table 3 gives correlations between the window interventions and a model based on either indoor or outdoor temperature. The pseudo R-Square relation between window closings and internal temperature was 0.29, compared to an R-Square of 0.12 to external temperature. This result supports Haldi's analysis (2009) that of the variables assessed, the likelihood of window closing intervention is most closely correlated with internal temperature.

The temperature based model was extended to include either window transmitted solar radiation (WTSR) or CO_2. The majority of the 137 days of measured CO_2 data fall in the unheated season. Consequently CO_2 was excluded from the heating season intervention analysis. A significant number of unheated season days experienced levels of CO_2 in excess of 1000 ppm, particularly in October, justifying the inclusion of CO_2. Although Table 3 shows CO_2 to be a statistically significant factor in window opening, the window open proportion model selected for more detailed assessment in this paper does not include CO_2 as an independent variable. Results where inclusion of additional variable did not significantly change model correlation are indicated by *NS.

Table 3 Window intervention pseudo r-square.

Behaviour description	**Covariant parameters**	**Cox and Snell Pseudo R-Square**		
		Temperature only	**Temp. and WTSR**	**Temp. and CO_2**
Heated Class Window closing	Internal T	0.055	*NS	-
	Outside T	0.364	*NS	-
Heated Class Window opening	Internal T	0.014	0.11	-
	Outside T	0.154	0.222	-
Unheated Class Window closing	Internal T	0.299	*NS	0.33
	Outside T	0.125	*NS	0.13
Unheated Class Window opening	Internal T	0.134	0.173	0.17
	Outside T	0.141	0.207	0.215

During unheated periods, analysis of both classrooms showed that window closing interventions were significantly influenced by in internal temperature. However, window opening interventions were marginally closer correlated to the outside temperature. For heated periods, external temperature was shown to be a significantly more important driver of window closing behaviour. Results for window openings in heated periods showed that outside temperature and WTSR did demonstrate some correlation but were not found to be highly significant.

A significant correlation was found between the measured CO_2 and window opening, but not with window closing. No significant correlation was found between the calculated wind pressure variable with either window opening or closing. A correlation was found between the vapour pressure and window opening, but not closing.

Development of a window open proportion model

Previously published probabilistic models by Frédéric Haldi et al (2009) and Humphreys (Rijal 2008) predict the probability of interaction with an individual window. These models however do not consider the state or quantity of adjacent windows in the room in their prediction of window state. An alternate approach was proposed for spaces with multiple operable windows that aim to predict the proportion of open windows in the room. A measure of the fraction of operable windows open (number of windows open at any given time) was found to be ideally suited to the scheduling of window open state in the building simulation tool EnergyPlus.

The independent environmental variables were each assessed to determine the correlation between the variable and the proportion of opened windows. Unheated and heated periods were considered separately, with separate models produced for each. Regression analysis was performed for each independent variable in isolation, producing a model based solely on that variable. The pseudo R-Square correlation of each of those models to the measured dependent variable indicates the relative significance of each variable shown in Table 4 and Table 5.

Table 4 Heated period drivers.

Heated periods	**Pseudo R-Square Cox and Snell**
Outside temperature	0.19
Vapour pressure	0.10
Solar transmitted radiation	0.09
Internal temperature	0.06

Table 5 Unheated period drivers.

Unheated periods	**Pseudo R-Square Cox and Snell**
Outside temperature	0.29
Internal temperature	0.28
Solar transmitted radiation	0.11
Vapour pressure	0.10
CO_2	0.10

Model development method

A range of candidate models was developed, using different combinations of environmental input variables. All of the models differentiate between heated and unheated periods. Table 6 and Table 7 give candidate models and their pseudo R-Square relation to the measured data. Analysis was performed for both independent classrooms, main and control, to allow comparison between the two independent test rooms.

Table 6 Unheated candidate models.

Model ID	Input independent variables used.	Cox and Snell
UN-0	Outside temperature	0.28
UN-1	Outside temp., solar trans. radiation	0.31
UN-2	Outside temp., vapour pressure, solar transmitted radiation	0.35
UN-3	Outside temp., vapour pressure, solar transmitted radiation, hour	0.37
UN-4	Outside temp., solar transmitted radiation, CO_2	0.45
UN-5	Outside temp., solar transmitted radiation, vapour pressure, CO_2	0.47

Table 7 Heated candidate models.

Model ID	Input independent variables used.	Cox and Snell
H-0	Outside temperature	0.19
H-1	Outside temp., vapour pressure	0.25
H-2	Outside temp., solar trans. radiation	0.27
H-3	Internal temp., solar transmitted radiation, vapour pressure	0.26
H-4	Outside temp., vapour pressure, solar transmitted radiation	0.32
H-5	Outside temp., vapour pressure, solar transmitted radiation, hour day	0.40

The candidate multinomial logistic models produced a series of probabilities of occurrence for each of the model outcome categories. Model coefficients are used to form nine equations, giving the probability of each outcome category occurring P_{ik}.

$$P_{ik} = \frac{e^{z_{ik}}}{e^{z_{i1}} + e^{z_{i2}} + \ldots + e^{z_{iK}}}$$

Where:

$$z_{ik} = b_{k0} + b_{k1}x_{i1} + \ldots + b_{kJ}x_{iJ}$$

These categories represent the number of open windows, ranging from 0 to 8. The sum of the probabilities of all of the possible outcomes is 1. A binomial function roll was used to generate the model prediction. This was deemed a preferable approach to the method employed in much of the previous research, which used a binary Logit model of a single window.

To represent the binary function role, the probabilities of all outcomes were cumulatively summed up to a total of 1, with each category representing a range of values. For each category, the range of values covered is therefore proportionate to its likelihood of occurring. A binary function role between 0 and 1 is compared to cumulative probabilities of the outcomes.

Comparisons were made between candidate models (based on main test classroom data) against the measured results of the independent classroom. Models UN-2 and H-5 were selected and they did not require CO_2 and an input variable. In addition, comparisons were made between predicted and measured window open proportions for alternating days of the main test classroom, splitting the data into two halves (odd and even days). Periods of occupied time were segmented into ten-minute blocks; the number of measured occurrences of a particular window open fraction is shown in Figure 2 and Figure 3.

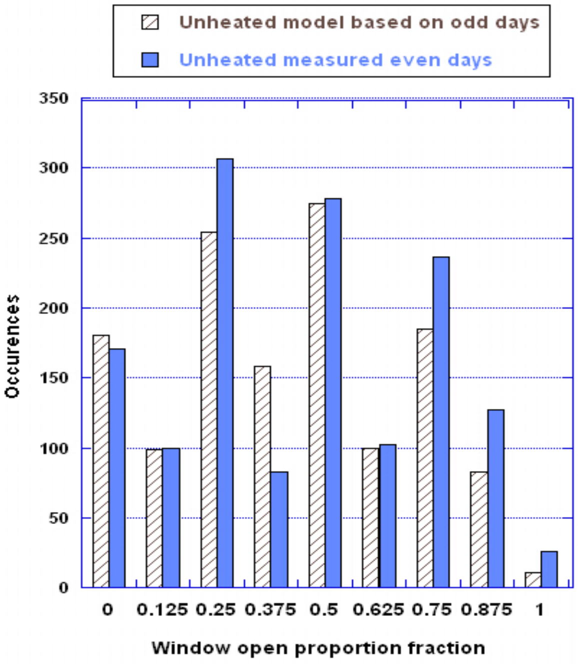

Figure 2 Unheated period comparison.

During unheated periods occupants demonstrated a preference for opening pairs of adjacent windows together, leading to the bias towards 2, 4 and 6 open windows. These results demonstrate that in these eight-window teaching spaces, the probability of an individual window being opened is related to the number of windows already opened.

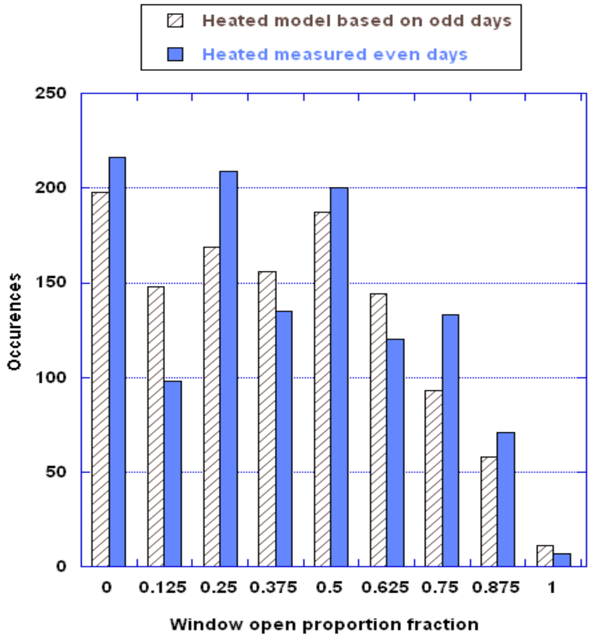

Figure 3 Heated period comparison.

Prediction of classroom CO_2 concentration

Models of window opening behaviour were used to schedule windows in an EnergyPlus model of the school building. Ventilation rates as predicted by EnergyPlus were used together with measured occupancy numbers from class registers to calculate CO_2 concentrations, using the calculation method as specified in AM10 (1997). A stepped steady state approximation was assumed, with the steady state level being recalculated each time a significant change in conditions occurred. A comparison was made between calculations of CO_2 concentrations, based on three different window opening schedules.

Generation of metabolic CO_2 by pupils and teachers was, from work by Coley and Beisteiner (Coley 2002) given by:

$$Q_{CO_2,\text{Adult}} = 0.0054\ \text{l/s}^{-1}$$

$$Q_{CO_2,\text{Pupil}} = 0.0041\ \text{l/s}^{-1}$$

Three predictions of classroom carbon dioxide concentration were generated, using three sources of window open data—firstly, using the measured window opening state; then using window opening predictions based on the UN-2 and H-5 probabilistic models; and finally, using window opening behaviour based on temperature set-points. Table 8 shows the R-Square relation between 4 weeks of measured CO_2 data and the three CO_2 concentration predictions; the accuracy of CO_2 was notably constrained by the accuracy of the air flow network flow coefficients.

Table 8 Measured and predicted CO_2 R-Square

Model ID	**Correlation with measured CO_2**
Measured window data	0.54
UN-2 model predicted	0.53
Temperature step model	0.48

Figure 4 presents the three predicted CO_2 concentrations for four days in May.

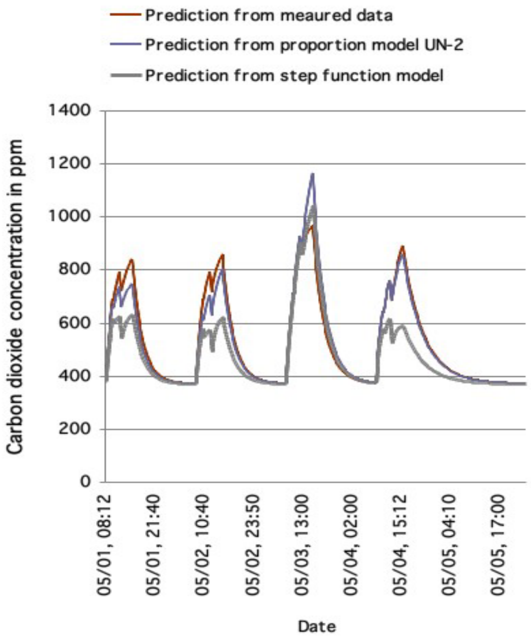

Figure 4 CO_2 prediction comparison.

The air temperature set point model used was a step function that incrementally increased the proportion of open windows, as the temperature in the space increased. Below 17 ° C, the number of open windows was zero, increasing by one window per degree up to 24 ° C, where all the windows were open.

CONCLUSIONS

The stochastic nature of human behaviour limits the applicability of regression analysis to define window-opening behaviour based solely on environmental variables. Despite this, a multinomial regression analysis-based model has been produced, which provides a significantly more realistic picture of window opening behaviour than a temperature set point based step function model. Ventilation rate results produced by the EnergyPlus airflow network model were used to produce predictions of CO_2. With further development this approach has significant potential for use in both building energy, and carbon dioxide exposure prediction.

Many of the recently published stochastic models of window opening have been derived from data from single window cellular offices. Analysis showed that probability of an individual window being opened is related to the number of windows already opened; therefore binary models as proposed by Rijal (2008) and Haldi (2009) are limited in their application to spaces with multiple windows. This work proposes that for spaces with multiple windows, an alternative approach should be taken that considers the state of adjacent windows.

Environmental factors such as temperature and humidity were shown to influence both the likelihood of window intervention, and the number of windows opened. However the presumption that discomfort drives the majority of window interventions was found to be invalid for this case study. Occupants were found to be within the bounds of common measures of thermal comfort for the majority of window intervention events, and opened windows most of at the beginning of the day to provide fresh air. During unheated periods, windows were most often opened early in the mornings, both for ventilation but also to prevent anticipated overheating later in the day. Consequently, stochastic models that are triggered by a discomfort threshold were found to significantly under-predict occupant window usage for buildings that are able to maintain satisfactory thermal comfort levels.

Work to develop this model further are ongoing, recent developments include the use of the current window state in determining the outcome of an intervention, and the development of a sub model to predict morning openings before students arrive. Further analysis to include a larger number of classrooms, in multiple schools including classrooms with a range of orientations would significantly improve the general applicability of the model. Additionally, further work will be conducted to compare the results of this study to other previously published probabilistic models of window opening. Although none of the previously published models are based on data collected in school buildings, a comparison between models would still be a beneficial.

COEFFICIENT TABLES

Table 9 UN-2 model B-Coefficients

	Intercept	Vapour pressure hPA^{-1}	Outside Temperature °C^{-1}	Solar T. Power W^{-1} m^{2}
0	-1.00	0.82	-0.72	0.02
0.125	-2.86	1.10	-0.89	0.02
0.25	-3.34	1.15	-0.87	0.02
0.375	-6.51	0.97	-0.51	0.02
0.5	-6.98	1.12	-0.58	0.02
0.625	-8.16	0.93	-0.27	0.01
0.75	-11.17	1.09	-0.33	0.02
0.875	-14.34	0.91	0.03	0.02
1	Reference	-	-	-

Table 10 H-5 model B-Coefficients

	Intercept	Vapour pressure hPA^{-1}	Solar T. Power W^{-1} m^{2}	Hour h^{-1}	Outside Temp °C^{-1}
0	8.37	1.06	0.006	-0.48	-1.29
0.125	1.54	0.50	0.009	0.26	-0.96
0.25	0.48	1.15	0.012	0.28	-1.65
0.375	6.36	0.37	-0.001	0.12	-0.97
0.5	4.54	0.68	-0.001	0.11	-1.04
0.625	0.89	0.52	0.001	0.22	-0.60
0.75	-0.02	0.63	0.002	0.28	-0.78
0.875	-2.22	0.87	0.003	0.30	-0.88
1	Reference	-	-	-	-

NOMENCLATURE

Pw = Wind surface pressure relative to static pressure in undisturbed flow [Pa]

Cp = Wind surface pressure coefficient.

P = Air density [kg/m3]

V_{ref} = Ref. wind speed at local height [m/s]

ACKNOWLEDGMENTS

Kind thanks go to Prof. Li Shao, Prof. Saffa Riffat, UC Berkeley CBE, and the Indoor Environment group at LBNL. Funding provided by the UK EPSRC.

REFERENCES

AM10 1997, CIBSE, Applications Manual 10: Natural Ventilation in Non-Domestic Buildings. The Chartered Institution of Building Services Engineers,

BB 101 2006, Ventilation of School Buildings—Version 1.4, Department of Education and Skills (DfES), London.

BRE, 2006, Ventilation and Indoor Air Quality in Schools Guidance Report 202825, Building Research Establishment, Technical Report.

Coley, D.A., A. Beisteiner, 2002, Carbon dioxide levels and ventilation rates in schools, International Journal of Ventilation 1 p45–52

DFES. 2003. Building Bulletin 87, Guidelines for Environmental Design in Schools, London: DFES.EU. 2002.

de Dear R.J. and Brager G.S., 2002, Thermal Comfort in naturally ventilated buildings: revisions to ASHRAE standard 55. Energy and Buildings 34 6 (2002), pp. 549–561

Daisey, J.M., Angell, W.J. and Apte, M.G., 2003, Indoor air quality, ventilation and health symptoms in schools: an analysis of existing information, Indoor Air, 13, 53–64.

Dutton, Spencer, Li Shao, Robert Clear, 2008, Assessment of the accuracy of diffuse irradiation ratio models and their potential impact on building simulation, eSim 2008 Montreal.

Dutton Spencer, 2009, Window opening behaviour and its impact on building simulation: a study in the context of school design. PhD thesis submission Dec. 2009 University of Nottingham, UK

Haldi F, Robinson D. 2008 On the behaviour and adaptation of office occupants. Building and Environment 2008;43(12):2163–77.

Hausler, T. and Beregr, U. 2002, "Determination of Thermal Comfort and Amount of Daylight". Air Conditioning, Air Protection & District Heating, Szklarska Poreba, Juni 2002, Zusammenfassung.

Huizenga, C., Zhang H., Arens E. and Duan T. 2001, "A Model of Human Physiology and Comfort for Assessing Complex Thermal Environments". Building and Environment 36(6): 691 - 699.

Humphreys, M.A., Nicol, J.F.,1998, Understanding the adaptive approach to thermal comfort, ASHRAE Transactions 104 (1) (1998) 991–1004.

LBNL 1984, Window Performance for Human Thermal Comfort, Charlie Huizenga,Hui Zhang, Pieter Mattelaer, Tiefeng Yu, Edward Arens, University of California, Berkeley CA 94720-1839

LBNL,2007, EnergyPlus Engineering Reference, November 6, 2007 p384 and p381

Muneer and Saluja, 1986 T. Muneer and G.S. Saluja, Correlation between hourly diffuse and global solar irradiation for the UK, Building Services and Engineering Research and Technology 7 (1986), pp. 37–43.

Rijal HB, Tuohy P, Nicol JF, Humphreys MA, Samuel A, Clarke J. 2008 Development of an adaptive window-opening algorithm to predict the thermal comfort, energy use and overheating in buildings. Journal of Building Performance Simulation 2008;1(1):17–30

Shendell, D.G., Prill, R., Fisk, W.J., Apte, M.G., Blake, D. and Faulkner, D., 2004, Associations between classroom CO2 concentrations and student attendance in Washington and Idaho, Indoor Air, 14, 333.

Warren 1984, P.R., and L.M. Parkins. 1984. Window-opening behaviour in office buildings, ASHRAE Transactions 90(1B): 1056-1076.

Zhang, H., C. Huizenga, E. Arens, P. Lyons. "Window Performance for Human Thermal Comfort." Report to National Fenestration Rating Council. November 2005.

Inkarojrit, V., Paliaga, G., 2004 "Indoor climatic influences on the operation of windows in a naturally ventilated building", Plea 2004, the 21st Conference on Passive and Low Energy Architecture, Eindhoven, The Netherlands, September 2004.