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Thermal performance of a naturally ventilated building using a combined algorithm of probabilistic occupant behaviour and deterministic heat and mass balance models

Authors:

Geun Young Yun[a], Paul Tuohy[b], Koen Steemers[a]

Affiliation:

[a] The Martin Centre for Architectural and Urban studies, Department of Architecture, University of Cambridge, 1-5 Scroope Terrace, Cambridge, UK.

[b]The Energy Systems Research Unit, Department of Mechanical Engineering, University of Strathclyde, Glasgow, UK.

Abstract:

Natural ventilation is an established passive cooling technique with the potential to reduce building energy demands through the avoidance of air conditioning. However there has been uncertainty about the potential of natural ventilation in practice due to a lack of knowledge about the occupant interactions with windows for any given situation. This study explores the role of occupant behaviour in relation to natural ventilation and its effects on the summer thermal performance of naturally ventilated buildings. A behavioural algorithm is developed (the Yun algorithm) representing probabilistic occupant behaviour and implemented within a dynamic simulation tool. A core of this algorithm is the use of Markov chain and Monte Carlo methods in order to integrate probabilistic window use models into dynamic energy simulation procedures. The comparison between predicted and monitored window use patterns shows good agreement. Performance of the Yun algorithm is demonstrated for active, medium and passive window users and a range of office constructions. Results show for example, that in some cases, the temperature of an office occupied by the active window user in summer is up to 2.6°C lower than that for the passive window user. A comparison is made with results from an alternative behavioural algorithm developed by Humphreys (Rijal et al., 2007). In general, the two algorithms lead to similar predicted results, but the results suggest that the Yun algorithm better reflects the observed time of day effects on window use (i.e. the increased probability of action being taken on arrival).

Keywords:

Natural ventilation, Occupant behaviour, Behavioural algorithm, Window use, Energy efficiency, Thermal performance, ESP-r, Dynamic building simulation

Corresponding author:

Geun Young Yun

The Martin Centre for Architectural and Urban Studies, Department of Architecture, University of Cambridge, 1-5 Scroope Terrace, Cambridge, UK.

Phone:+44 (0)1223 760127; Fax: +44 (0)1223 332960 Email: gyy20@cam.ac.uk

Co-authors:

Paul Tuohy

Energy Systems Research Unit, Department of Mechanical Engineering, University of Strathclyde, Glasgow, UK.

Phone:+44 (0)141 548 3747; Fax: +44 (0)141 552 5105 Email: tuohy@esru.strath.ac.uk

Koen Steemers

The Martin Centre for Architectural and Urban studies, Department of Architecture, University of Cambridge, 1-5 Scroope Terrace, Cambridge, UK.

Phone:+44 (0)1223 760127; Fax: +44 (0)1223 332960 Email: kas11@cam.ac.uk

1. Introduction

Naturally ventilated buildings are common across many regions of the world. There is an increasing interest in the comfort and energy performance of these buildings due to a range of factors including higher recent summer temperatures and also legislative requirements for building energy use and carbon emissions such as enshrined in the EU directive [1]. One area of concern is the increasing use of air conditioning in UK buildings and its associated energy and emissions. Avoidance of air conditioning will require buildings to be designed, built (or re-designed and upgraded) and operated to passively maintain a comfortable indoor environment. In current UK building regulations, domestic dwellings require a summer overheating calculation to be carried out using the Governments standard assessment procedure [2] or similar, for non domestic dwellings the guidance is to use CIBSE TM37 [3]. These methods for demonstrating compliance are simplistic, set static thresholds and take no explicit account of outside daily or hourly temperature variations or of detailed building ventilation paths and their dynamic interaction with the external climate. Other allowed methods include dynamic simulation which can account for dynamic climatic variation. Although dynamic simulation has the potential to investigate building performance in great detail and include airflows, ventilation openings, climate and building and occupant detailed behaviour, it is common practice to represent occupant behaviour either by using fixed ventilation rates as in the more simple methods [2,4] or to model using an indoor temperature threshold to trigger window opening and apply proportional control above that threshold. The ventilation rates or temperature thresholds are generally derived from an amalgamation of historical survey data from buildings of a given type to define "typical" values which could be viewed as representing some typical or average behaviour of occupants. While these values may well represent behaviour in a historical notional average building they have no ability to accurately represent or explain the range of behaviours seen in survey data and do not provide insight into the actual behaviour and resultant effects on energy and comfort that will prevail in a specific situation. This is especially a concern in the current and future contexts where building regulations, building design, work patterns and climate are changing and historical assumptions may not be valid.

In a typical naturally ventilated building the performance is highly dependent how the building responds to climatic and internal variations and on how and when the occupants respond to their conditions (i.e. what adaptive actions they take and under what conditions will they take them) and in turn how the people's adaptive actions alter the buildings performance and so on. In order to model in detail the performance of naturally ventilated buildings it is desirable to be able to model the occupant's behaviour within a dynamic simulation environment. ESP-r is open-source dynamic simulation software developed by ESRU at the University of Strathclyde [5]. Its open-source nature makes ESP-r a particularly suitable vehicle for the development and dissemination of new algorithms for adoption in other commercial and non-commercial simulation tools. Many control modes are already implemented in ESP-r, most represent controls as would be executed by a building management system (i.e. proportional control, integral control, on/off control and optimum start control). Some controls have also been implemented to represent occupant behaviour. The Hunt model [6] for the switching on and off of office lighting, the stochastic Lightswitch 2002 algorithm developed by Reinhart to predict dynamic personal response and control of lights and blinds from field study data [7] and Newsham et al [8]'s original Lightswitch model are available. The SHOCC module developed by Bourgeois et al [9] is also available which enables sub-hourly occupancy modelling coupled with the occupant behavioural algorithms.

Among the most common adaptive actions in a naturally ventilated building is the adjustment of the window position. Recently the Humphreys adaptive algorithm for window opening behaviour was implemented in ESP-r and its application illustrated in summer overheating and annual energy use calculations for a range of different office designs [10, 11]. The Humphreys algorithm is a stochastic algorithm based on adaptive thermal comfort theory which has evolved over a number of years [12, 13]. The survey data behind the Humphreys algorithm was gathered in the 1990s for a number of offices across the UK for which window opening was recorded four times per day.

There have been several other studies of window opening behaviour [14, 15, 16, 17, 18] and several different approaches have been taken in the formulation of algorithms to represent this behaviour. Of particular interest is the study by Fritsch et al [15]. They performed field measurements of occupants' use of windows in four offices during a heating season and proposed Markov chains to create a time series of window angle as a function of outdoor temperature. The comparison of the monitored and generated time series of window angles confirmed the validity and reliability of the model based on Markov chains.

Yun and Steemers [19,21] recently carried out a detailed monitoring study at sub-hourly frequency gathering window use and other environmental data for a number of modern UK offices and developed occupant window use models based on Markov chains which includes time of day (or more specifically - time of arrival) as a factor. These models are designed to be applied in Monte Carlo method in order to capture the non deterministic nature of the window opening behaviour. Time of day effects (i.e. increased probability of action on arrival etc) on window opening have been recognised by another study [18] and are also found in other non window behavioural models such as the manual lighting algorithms by Hunt [6] and Reinhart [7] but are not included in the Humphreys algorithm, possibly due to the time resolution of the survey data.

In this paper a new algorithm (the Yun algorithm) for occupant window-control behaviour in a cellular office with single-sided natural ventilation and its implementation in dynamic building simulation software for potential application to building design is described. Predicted behaviour is compared with the monitored data. The algorithm is then used to demonstrate the effects of a range in user behaviour and various building design parameters on thermal performance in summer. A comparison is made between the results from the Yun algorithm and those generated from use of the alternative Humphreys algorithm. The results, similarities and differences between two approaches are then discussed and some conclusions are developed.

2. Non-homogenous Markovian model of window states

Yun and Steemers [19] revealed that the previous state of a window strongly influences the current window state, i.e. the current window state is more likely to stay the same as the previous one, irrespective of the previous window state. This study has selected a Markov chain model for the representation of occupant use of a window as a Markovian model is the chance process where the past results have an influence on the outcomes of successive predictions. The Markovian model has been applied to the simulation of building performance [22,23,24] and the representation of occupant behaviour [25,26] and occupancy [27]. Tanimoto et al [26], in particular, proposed a method to predict the maximum residential cooling load based on Markovian models of air-conditioning use and a new algorithm generating the daily activity schedules of residents. A brief description of the Markov chain is now explained.

2.1 Markov chain

A Markov chain is a sequence of random states, $S = \{S_{0,} S_{1,} ..., S_r\}$, which meets the following conditions:

$$\Pr(S_{t+1} \mid S_t, S_{t-1}, ..., S_0) = \Pr(S_{t+1} \mid S_t) \quad (1)$$

This definition represents that the distribution of S_{t+1} given the past depends only on the value of the previous state S_t [28]. This Markovian property does not indicate that S_{t+1} is independent of the previous states, $S_0, S_1, ...S_{t-1}$, but it means that any dependency of S_{t+1} on the past is stored in the value of S_t [29].

The Markovian process begins in one of the states, S, and proceeds from one state to another in one step. The transition probability that the chain moves from state i to state j is defined as follows:

$$P_{i,j} = \Pr(S_{t+1} = j \mid S_t = i) \quad (2)$$

The event that a state remains the same occurs with probability of $P_{i,i}$. If a Markov chain consists of r states, the equation to calculate the transition probability shifted from state i to state j in m steps is given by:

$$P_{i,j}^{m} = \sum_{k=1}^{r} P_{i,k} P_{k,j}^{m-1} \quad (3)$$

2.2 Representing a time series of window states

A time series of the binary state of a window (i.e. open or closed) at time intervals of one-hour has been constructed using a Markov chain. For the sake of convenience, 0 stands for a window being closed and 1 for a window being open. Figure 1 illustrates the sequence of a window state. $P^{i}_{\lambda,\phi}$ represents the transition probability of a window state in i time step from λ to ϕ, where the window state in i time step θ^{m} is λ or ϕ. As only two window states are considered here, a window state in m time step is $\lambda, \phi \in S = \{0,1\}$. The transition probability is calculated by using the existing occupant behaviour models of window-control derived from logistic regression analysis [19, 21]. Table 1 summarises occupant behaviour models as a function of time of day and types of occupants. This Markovian model is inhomogeneous as the transition probability changes according to the time of day. For instance, the transition probability of a window state from closed to open on arrival is much higher than the likelihood of the change of a window state during the subsequent occupation period under the same thermal stimulus. The subsequent occupation period is defined here as the occupied hours except arrival and departure times.

Insert Figure 1 and Table 1

3. Combined algorithm of probabilistic and deterministic building performance

This study develops an algorithm for probabilistic occupant behaviour integrated with deterministic building physics models. It aims to comprehend the probabilistic characteristic of the Markovian model of a window state in the analysis of building performance. The behavioural algorithm borrows the concepts of stochastic simulations or Monte Carlo methods. A brief explanation of the Monte Carlo methods is now given.

3.1 Monte Carlo method

The Monte Carlo method is defined as a statistical analysis based on artificially recreating chance process with random numbers, repeating the chance process many times and directly estimating the values of important parameters [29]. Thus, it provides not just point estimates of interest, but the statistical characteristic of estimates like average, maximum, minimum, standard deviation, etc. The Monte Carlo method is based on the law of large numbers, expressed in Equation (4):

Take $X_1, X_2, ... X_n$ to be independent random variables, with a finite mean (μ). Let $S_n = X_1 + X_2 + \cdots + X_n$. For every positive real number ε

$$\lim_{n \to \infty} P\left(\left| \frac{S_n}{n} - \mu \right| \geq \varepsilon \right) = 0 \tag{4}$$

It indicates that the average of the individual outcomes of random process, (Sn/N), is unlikely to be far from the true mean (μ), when n is large enough. Therefore, we can obtain the outcome which can be predicted with a high degree of certainty, by taking averages of independent random processes [30].

3.2 Combined behaviour algorithm of probabilistic occupant behaviour and deterministic heat and mass balance models

Figure 2 illustrates a combined algorithm of probabilistic and deterministic algorithm of building performance, developed and subsequently implemented into a building simulation tool, ESP-r. ESP-r is an integrated modelling tool that simulates a thermal and fluid flow phenomenon in a building, by solving the thermal model and a fluid flow network. Previous validation studies have shown that ESP-r can accurately predict thermal and airflow behaviour [31].

The first stage in the estimations of indoor thermal conditions and energy demands is to initialise a window state at a time step of 1 (Figure 2). An initial window state might be randomly chosen from $S = \{0,1\}$ in the general case. However, the longitudinal field studies [19,21], which provided the transition probability functions, showed all the windows were closed as occupants left their offices. Thus it is assumed that a window is closed at the start of a simulation. The algorithm stages from 2 to 5 are carried out at a simulation time step of i. The second stage assigns a candidate state of a window at the current time step (i), which is different from the previous time step ($i-1$). If there are more than two window states, the candidate state has to be chosen randomly. In this specific case, the candidate state can be simply calculated by:

$$\phi = |\lambda - 1| \tag{5}$$

Where ϕ is a candidate state at the current time step of i,

λ is a window state at the time step of $i-1$.

Stages 3 and 4 update a window state (θ^i) with probability ($P^i_{\lambda,\phi}$). In other words, they generate a binary distribution of window states from the transition probability functions in Table 1. In stage 3, the transition probability of a window state from λ to ϕ is calculated. If the previous window state is closed (λ=0), then the equation for the transition probability of a window state to open (ϕ=1) at the current time step is given by

$$P_{0,1}^{i} = P_{0,0}^{i-1} P_{0,1} + P_{0,1}^{i-1} P_{1,1} \quad (6)$$

Stage 4 is a typical process in Monte Carlo methods [32]. A uniform random variable between 0 and 1 is created using the pseudo random generator. This random number is compared with the transition probability calculated in Stage 3. If the transition probability is equal or over the random number, we accept the trial state (i.e. a window state for the current time step is changed to the trial state). This evaluation result is then reflected in a time series of a Markovian window states.

Once the window state at the current time step is determined, the iterative solution process of the existing deterministic thermal and airflow model in ESP-r is started [31]. When the model has converged in Stage 5, we can attain the point estimate of indoor conditions such as air and mean radiant temperatures, relative humidity and energy demand. To obtain a window state and other parameters of interest at the next time step (i+1), repeat the Stages 2 to 5. This is repeated until it reaches the last simulation time step (Stage 6).

Stage 7 is an iteration process (i.e. multiple simulations as a function of a binary distribution of the window state). It aims to attain the statistical distribution of parameters of interest. Stage 6 is repeated until it meets the last number of the Monte Carlo or predefined iteration. Each simulation during the iteration process produces point estimates of indoor thermal conditions and energy demand at each simulation time step. The final estimates of parameters of interests at each time step in the simulation using the combined algorithm is the result of the average of point estimates obtained from each of the iterations. Other useful estimates from the combined algorithm include standard deviation, maximum and minimum values of interest.

Insert Figure 2 here

4. Model description

Simulation studies were conducted on a theoretical south facing cellular office (Figure 3). It is assumed that the office is located within an office building and the thermal conditions of the adjacent space are specified to be similar to those of the modelled office. The simulations use the climate data set for Cambridge, UK, obtained from the weather database program, Meteonorm 5.1 [33]. Meteonorm creates hourly weather data from monthly average values for periods of at least ten years using stochastic methods [33]. The simple theoretical office model and the climate dataset used in the simulations were chosen to be somewhat similar to the office types and climate of the monitoring study. Precise details of the monitored buildings such as thermal and optical properties of constructions, internal gains from equipment and the actual local climate (including sheltering, ground reflectance and overshading etc.) were not available [19, 21] and so values have been assumed here to allow the algorithm operation to be demonstrated.

The simple office model whose only external wall faces due south has a width of 3m, a depth of 4.5m and ceiling height of 3m. The glazing ratio to the total south-facing external wall area is 35% or $3.2m^2$ and double glazing with a U-value of $2.8W/m^2K$ was selected. The casual gains in the model are detailed in Table 2. The modelling study employs different construction types to allow analysis of the effect of thermal mass. Table 3 shows the specification of each construction type. The simulation period selected to represent a warm summer period from the Meteonorm climate file is from 21 August (Monday) to 25 August (Friday). This warm summer period was chosen to represent the type of climatic conditions where a poor building performance could potentially lead to the adoption of air-conditioning. The simulation time step used is one hour and the occupied period is from 9 am to 6 pm. The hourly time-step was chosen as being consistent with the frequency in the monitoring data [19,21].

The design light level is 400 lux on a horizontal work plane 0.8m above the floor. For the calculation of illuminance level on the work plane by daylighting an analytical daylight factor method is selected. The model has two photocells in the back and front of the space and the average of two photocells illuminance is used for lighting control to complement the level of daylighting illuminance (Figure 4). An artificial light is switched off when the daylight level at the height of the work plane is over 600lux (i.e. 1.5 times higher than design light level).

Two kinds of airflow modelling methods were used. First, an airflow network model, consisting of airflow components of a large opening, infiltration and external wind pressure, was set up. It was employed for the simulation of the passive, medium and active behaviour models of window-control. As a comparison the use of fixed airflows was also evaluated, in this case a fixed constant background infiltration of 0.33 air change rate per hour (ac/h) was assumed and fixed ventilation rates of 2, 4, or 6ac/h were set during occupancy, these values were chosen to be within the range specified by CIBSE [4].

Initially the model of the south-facing office with a medium-thermal mass and occupied by the medium occupant type for window-control was chosen as a base case to allow effective comparison and to highlight the effects of the various parameters.

Insert Figures 3 and 4 and Tables 2 and 3

5. Results

5.1 Effects of the number of iterations

The estimates of indoor conditions are obtained from the average of point estimate results from multiple simulations (i.e. iterations) as a function of the binary distribution of the window state. Thus, the number of iterations is of significant importance. To determine the number of iterations required for a stable and accurate estimation, we investigated the change in indoor operative temperature from the value at the immediately preceding repetition (Figure 5).

It is observed that variance in the change of the indoor temperature tends to go up as the day goes on. For instance, the maximum variance is 0.10°C at 10 am, 0.38°C at 12 pm, 0.68°C at 2 pm and 1.00°C at 4 pm. It seems to be attributed to the cumulative effects of probabilistic functions of the window-control behaviour models at a higher simulation time step. As the time series of window states is represented by Markov chains, the range of outcomes becomes wider the later the particular simulation step occurs within the simulation period.

Figure 5 illustrates that only a marginal change in the indoor temperature occurs after 80 iteration simulations (i.e. 80 numbers of multiple simulations as a function of binary distribution of the window state). This is in line with previous studies which used Monte Carlo analysis in the uncertainty analysis in building simulations [33,35]. After 160 iterations the changes in indoor temperature are in most cases less than 0.01°C and the largest change is equal or less than 0.03°C. This study has chosen the iterations of 300 to improve and guarantee the accuracy of the simulation results.

Insert Figure 5 here

5.2 Comparison with monitoring data

Due to the lack of some detailed data such as actual local weather conditions, precise thermal properties of the actual building constructions, and accurate internal heat gains from IT equipment in the field studies [19,21], a direct comparison of indoor thermal conditions between simulation results and monitoring data was not possible. Instead, we evaluated the Yun algorithm by comparing the predicted window state to the measured window state across a range of indoor temperatures. The window state data from simulation results and the field studies were classified using a temperature bin of 1°C and the probabilities of a window being open were then calculated according to time of day (i.e. on arrival and during subsequent occupation period).

The comparison of predicted probabilities using the Yun algorithm with the field monitoring results shows good agreement (Figure 6), and the monitored and predicted window state probabilities show similar trends. The difference between the predicted and monitored probabilities is 3.1% for the subsequent occupation period, which includes all of the occupied period except occupant's first arrival times. The Yun algorithm appears to slightly overestimate the probability of a window being open on arrival (the mean deviation on arrival is 8.6%). However, the difference is not significant considering the unknowns between the model and the real office.

Insert Figure 6 around here

5.3 The effects of occupant behaviour of window-control

Figure 7a shows the effects of the modelled occupant window opening behaviour on indoor thermal conditions for a medium window user and also for the case where the window is not opened. The reduction in the indoor temperature due to window opening behaviour compared to the case where the window is always closed spans from 1.66°C to 9.00°C, with an average reduction of 6.18°C. The cooling effects of opening a window become more apparent towards the end of the week due to the cumulative effect of the closed window, ambient temperature and solar and internal gains (figure 7b). For instance, the maximum temperature difference between when a window is controlled with a medium occupant model of window-control and when a window is assumed to be closed, takes place on Friday when the peak solar radiation reaches 669 W/m^2. While this model is somewhat simplistic (e.g. it assumes all adjacent spaces in the building have similar temperatures) it clearly illustrates window opening behaviour as a possible method for cooling of the indoor environment.

Figure 7a also illustrates for the medium window user case the range of indoor temperatures with standard deviations at each simulation time step, the highest standard deviation of the indoor temperature is 0.91°C for the unoccupied period; 1.73°C for the occupied period. Figure 7b demonstrates the likelihood of window-control activity for the medium window user model. The proportion of iterations when a window is open (i.e. the likelihood of a window being open) ranges from 66% to 82% on arrival and from 60% to 96% during the subsequent occupation period. This is closely related with indoor temperature distributions. For example, on arrival, the proportion of the iterations with a window being open is 66% at the indoor temperature of 24.36°C and 82% at the indoor temperature of 26.12°C, when during the subsequent occupation period the operative temperature gradually increases from 27.03°C to 28.52°C the likelihood of a window being open rises from 78% to 89%.

Insert Figures 7 and 8 here

The models of manual window control in this study enable different window use patterns to be considered in the prediction of indoor thermal conditions (Figure 8). Figure 8b shows the wide variation in window-control patterns as a function of active, medium and passive user behaviour models. The average likelihood of a window being open on arrival is 99% for the active window user, 76% for the medium window user, 43% for the passive window user. During the subsequent occupation periods the figures are 83% for the active window user, 75% for the medium window user, 67% for the passive window user.

It is clear that individual differences in the interaction with a window play an important role in building thermal performance (Figure 8a). The operative temperature inside an office, where an occupant most actively controls the window in response to the intensity of indoor thermal stimulus, remains the lowest, while the room temperature for the passive user of a window is the highest. The temperature of an office of an active user of a window is up to 2.64°C lower than that for a passive user of a window. The largest difference between the two cases occurs at one hour after the occupant arrival on Wednesday. The likelihood of a window being open at this simulation time step is 84% for the active window user and 44% for the passive window user. As the weather conditions and internal heat gains remain the same between the two cases, the temperature difference results from the difference in the window-control patterns of occupants. The mean temperature difference between the two offices during occupied period is 1.15°C.

5.4 Effects of thermal mass and occupant behaviour

Figure 9 demonstrates the variation in indoor temperature distribution as a function of light, medium and heavy-weight construction with the medium user behaviour model of window-control. The results show that the thermal responses of a light weight structure are most sensitive to the change in heat gains and weather conditions. On average, the temperature in a light-weight office during occupancy is 1.75°C higher than that in a heavy-weight office.

As identified by Baker [36], the appropriate use of heavy or medium thermal mass and its effective distribution in a building is an effective design strategy to moderate the extremes of thermal conditions. Thermal mass combined with solar shading, night cooling and good ventilation is recommended design practice for maintaining comfortable summer temperatures [4, 37]. The maximum and minimum office temperatures among the three offices analysed are all observed in a light weight office. The maximum temperature of 34.28°C (at 2 pm on Friday) and the minimum temperature of 22.79°C (at 10 am on Tuesday) occur for the light-weight office. The largest temperature difference of 5.14°C between light and heavy-weight offices happens at 2 pm on Friday.

Insert Figure 9 here

5.5 Fixed ventilation rate methods and occupant behaviour models of window-control

Figure 10 compares indoor temperature results obtained using the Yun algorithm with those obtained using a fixed ventilation rate. It suggests, as expected, that the simplified fixed ventilation rate representation of window-control does not well represent the variation experienced in the performance of natural ventilation. An ac/h of 10 or higher is commonly applied in evaluation of summer temperatures [4] which would in this case give predicted indoor temperatures even lower than for the 6 ac/h results shown here which could lead to an underestimate of the actual room temperatures that would be experienced in practice.

It should be mentioned that the window-control activities, ventilation rates from an open window and cooling effects of natural ventilation are dependent on various factors such as wind speed and direction, ambient temperature, indoor thermal conditions and the detailed design of a window system. These factors are not explicitly accounted for when fixed ventilation rates are assumed. Thus, a detailed simulation incorporating user behaviour, ventilation paths and local climate conditions as carried out in this study has potential to provide more robust prediction of the airflow rate and the thermal performance of naturally ventilated buildings.

Insert Figure 10 here

5.6 Comparative simulation with the Humphreys model

The research team led by Fergus Nicol and Michael Humphreys have recently proposed the Humphreys algorithm for window opening in naturally ventilated buildings [10,11]. This algorithm is based on window opening being an adaptive response to thermal discomfort and has also been implemented in ESP-r. As a comparison to the new algorithm (the Yun algorithm) developed in this work and described in earlier sections, the same office was simulated but with the Humphreys algorithm controlling the window opening behaviour. The Humphreys algorithm [10] is also stochastic and it has a thermal comfort 'dead-band' which could be viewed as having the effect of making the probability of a window change event dependent on the previous setting of the window as the window setting from the previous time step directly affects the thermal comfort conditions of the current time step. Unlike in previous studies using the Humphreys algorithm, here a Monte Carlo approach was employed to generate a statistical distribution. The results for this application of the Humphreys algorithm are shown in Figure 10a. In general the operative temperature ranges predicted are similar for both the Yun (22.2°C to 30.8°C) and Humphreys (24.4°C to 30.2°C) algorithms as both predict the windows will generally be open for this warm period. However differences between the two algorithms are also highlighted particularly with respect to the predicted behaviour on the cooler days of the week. On these days the Humphreys algorithm predicts that the occupants will be comfortable on arrival and will not open the windows until outdoor temperature, solar and internal gains cause the internal temperature to exceed the comfort band and the occupant experiences some mild thermal discomfort. This occurs around 11am for the more moderate Tuesday, Wednesday and Thursday conditions in this example. This behaviour is shown in the increasing trend in the operative temperature for the mornings of these cooler days which is opposite to the prediction from the Yun algorithm where window opening on arrival causes the office temperature to drop initially due to the influx of cooler outside air. On days where the room temperatures have already exceeded the Humphreys comfort band by arrival time then the performance of the two algorithms is more consistent (Monday, Friday). Figure 11b shows the average value for the probability function calculated in the Humphreys algorithm. The Humphreys algorithm has been assigned a value of 0 when the comfort band is not exceeded (i.e. a window is closed). In comparison to the earlier chart (Figure 11a) for the Yun algorithm, it can be seen that while in general the maximum probabilities for the window being open on each of the days are similar the difference in predicted behaviour on arrival is again highlighted.

Insert Figure 11 here

6 Discussion

This study reports the development of a behavioural algorithm of manual window-control (i.e. the Yun algorithm) using Markov chain and Monte Carlo methods from a longitudinal monitoring campaign and its implementation into a dynamic energy simulation tool, ESP-r. The Yun algorithm generates a time series of window states as a function of the indoor thermal stimulus, the previous window state and time of day in order to simulate occupant behaviour of window-control observed in the monitoring campaign. Thus, the algorithm would potentially contribute to more realistic predictions of thermal performances of naturally ventilated buildings, compared with conventional simulation methods which deal with the use of windows based on certain assumptions such as a predefined schedule, fixed ventilation rate and threshold method. These assumptions are often without evidence from the field and attributed to discrepancy between predicted and actual building performance [10]. We envisage that the application of the Yun algorithm in dynamic simulation processes would allow us to better understand the roles of occupant behaviour in building performance and develop more reliable and robust design strategies.

The Yun algorithm classifies building occupants into active, medium and passive users of windows and is capable of quantifying the effects of the difference in occupant interactions with windows on thermal performances. This study also provides evidence that the effects of occupant behaviour of window-control patterns can be of the same order as the influence of thermal mass. The mean variation in indoor temperature is 1.75°C due to the different construction types and the variation caused by different user behaviour of window-control is 1.15°C. This also suggests that taking account of occupant behaviour in building simulation tools is essential to ensure the accuracy and reliability of their simulation results.

Another outcome of this study is the comparison of the Yun algorithm with the Humphreys adaptive algorithm of manual window-control. The two algorithms result in generally similar prediction results. The differences in indoor temperatures between the algorithms over the occupied hours are in most cases less than 0.5°C. Particularly the temperature difference is minimal during the warmer days of the week (Monday and Friday) when the indoor temperatures by the occupant’s arrival time of day go already over the comfort band in the Humphreys algorithm.

The Humphreys algorithm was based largely on a 12 building survey (6 Aberdeen, 6 Oxford) carried out in the 1990s. Buildings covered Educational, Local Authority and Commercial offices of both cellular and open plan office types. Longitudinal and transverse studies were carried out [10]. The observations were made only 4 times per day. Building fabric and building locations were varied. The Yun algorithm is based on more comprehensive and more frequent observations across a smaller number of observation sites and a narrower range of buildings and occupations. The Humphreys algorithm as it was published and evaluated here does not distinguish between arrival times and later times of day. This may have been influenced by factors such as the four-a-day sampling period, the occupant activities, the surrounding environments etc. The thermal comfort basis for the Humphreys algorithm is not sensitive to non thermal factors such as ‘stuffiness’, contaminants, odours or other hypothetical desires for air movement or freshness. Sources of ‘poor air’ that could trigger non thermal window opening could possibly include high levels of dust, IT equipment left running overnight, building materials that emit contaminants, odours, low humidity, un-emptied bins containing organic materials, toilets, cleaning materials, etc. These non thermal triggers could alter window opening behaviour and tend to increase window opening with (in the UK climate) some associated increase in energy use for the enhanced ventilation rates in winter time and possibly some reduction in peak summer temperatures [11].

Monitoring data that forms the basis of the Yun algorithm may be influenced by the specific situational and contextual factors of the offices on campus such as pleasant surroundings (visual and aural), single occupancy, easily operable windows, educational employee types etc. These may lead to enhanced window use in these monitored offices. The educational employees in a campus setting may routinely open the windows because it is pleasant to do so. This will not always be the case (e.g. road noise outside) and other situations may lead to windows remaining closed until some thermal discomfort is experienced.

The Yun algorithm similarly to the Humphreys algorithm, may not be directly sensitive to the other non thermal factors which may drive window opening events although it may indirectly capture these by its separate treatment of window opening events upon arrival. The Humphreys approach directly incorporates adaptive thermal comfort criterion based on rolling mean external temperatures which is now included in standards to be applied to free running buildings [4,38] while the Yun algorithm is dependent on internal temperatures only. The Yun algorithm approach, of defining different user types may offer some advantages in identifying the critical roles of occupant behaviour in naturally ventilated buildings, similarly, the incorporation of time of day or event driven effects (i.e. arrival, occupied periods) has advantages and better reflects the occupant window-control behaviours discovered in the monitoring activities.

Future work can be carried out in a number of areas in order to make the methodology more robust. Further surveys, algorithm development and validation studies should be carried out in order to answer the open questions. Both Humphreys and Yun methodologies have merits and it is expected that further data gathering and analysis may lead to a solution containing elements of both. Both methodologies lend themselves to being embedded in building design software and would give advantages over current standard methods for design of comfortable and low energy buildings. The simulation methodology illustrated here has comprehended occupant window opening behaviour and its stochastic variability. Other occupant behavioural models such as occupancy models, blind, shade and light use models [9] can also be integrated in future with the window algorithms in dynamic simulation to more fully represent the occupant experience and impact on comfort, energy use and carbon emissions. Other uncertainties in parameters such as internal gains and building fabric (thermal bridges etc) should also be comprehended in the methodology and combined with the occupant models in order to give a realistic range of building performance (comfort and carbon) under realistic operational conditions at the design stage [35].

Comprehending occupant behaviour and its effect on energy is recognised as one area where simplified models are weak. Dynamic simulation relies on the same assumptions of behaviour used in the simplified models. There is scope for the current and future work in this field to both develop robust human behaviour models for use in dynamic simulation and to improve the simplified methods.

7. Conclusions

A newly developed algorithm (The Yun algorithm) for occupant window-control behaviour including Markov chains and Monte Carlo methods and its implementation in dynamic building software for potential application to building design has been described in detail. The Yun algorithm applied to a naturally ventilated office was used to illustrate the predicted effect of user behaviour on the summer thermal performance for a range of different building constructions. It was shown that variation between active and passive window user behaviour can have a significant effect on thermal performance, the difference between active and passive window use behaviour being of the same order as the difference between low and high thermal mass constructions. A comparison was made between the Yun algorithm results and the results from the alternative Humphreys algorithm. The similarities and differences between the two approaches are discussed and areas for further work identified. The algorithm has been implemented in open source simulation software to facilitate its dissemination and adoption in other simulation software or by other researchers. An argument is presented for the incorporation of occupant behaviour models in building design.

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List of Figures

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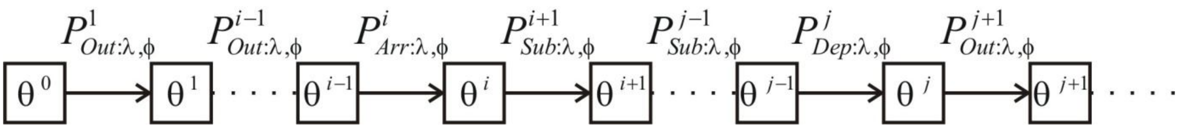


Figure 1. Representation of a time series of binary window states using Markov Chain

A combined behaviour algorithm

Stage 1: Initialisation

i. Set initial window state: $\theta^{(1)} = \lambda = 0$

Stage 2: Trial State

i. Choose a new trial state: ϕ where $\phi \in S = \{Closed, Open\} = \{0,1\}$

Stage 3: Transition Probability

i. Calculate the probability of the state changing to ϕ : $P^{(i)}(\phi)$

Stage 4: Evaluation

i. Generate random variable: $U \sim U[0,1]$

ii. Compare $P^{(i)}(\phi)$ with U

- if $P^{(i)}(\phi) \geq U$ then, accept the trial state ϕ
- if $P^{(i)}(\phi) < U$ then, reject the trial state ϕ

iii. Set the state of Markov chain at simulation time step i: $\theta^{(i)}$

- if the change is accepted, set $\theta^{(i)} \leftarrow \phi$
- if the change is rejected, set $\theta^{(i)} \leftarrow \theta^{(i-1)}$

Stage 5: Computation

i. Solve thermal and mass balance equations

Stage 6: Internal Repetition

i. Repeat from Stages 2 to 5 until it reaches the last simulation time step

Stage 7: Iteration

i. Repeat Stage 6 until it satisfies the predefined Monte Carlo iteration number

Figure 2. Diagram of the Yun algorithm

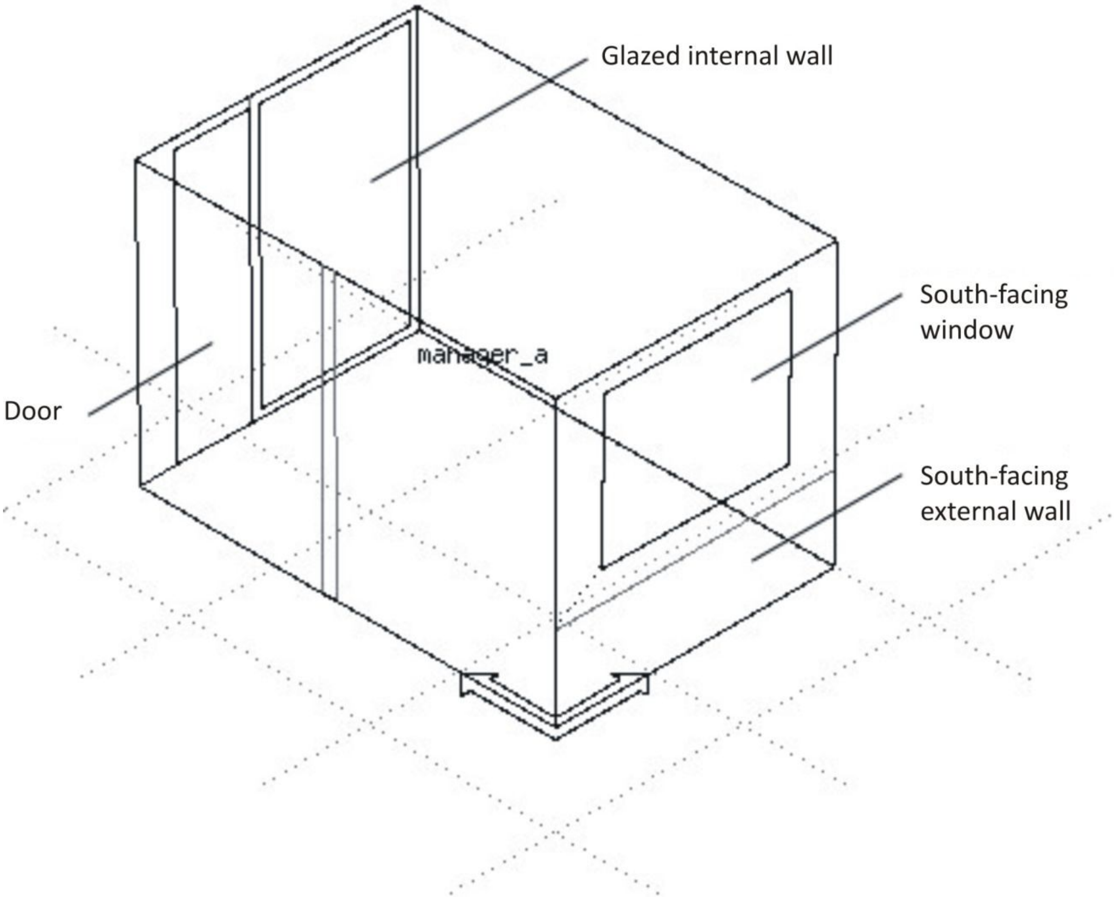


Figure 3. Modelling image of a theoretical cellular office

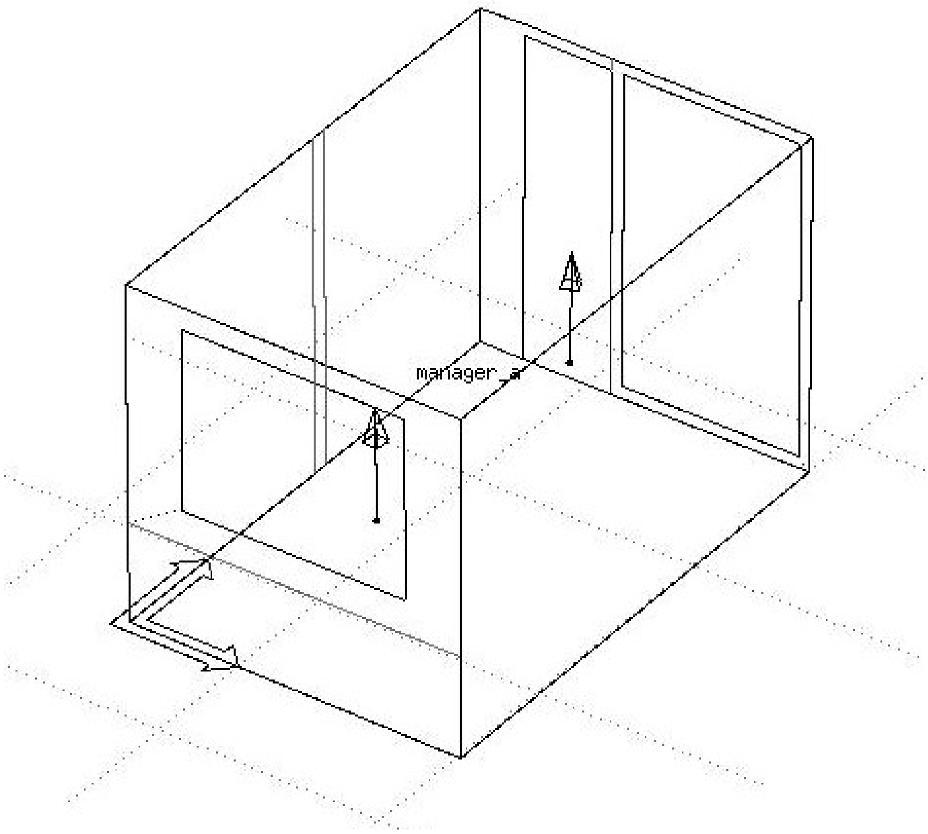


Figure 4. Position of photocells in a cellular office

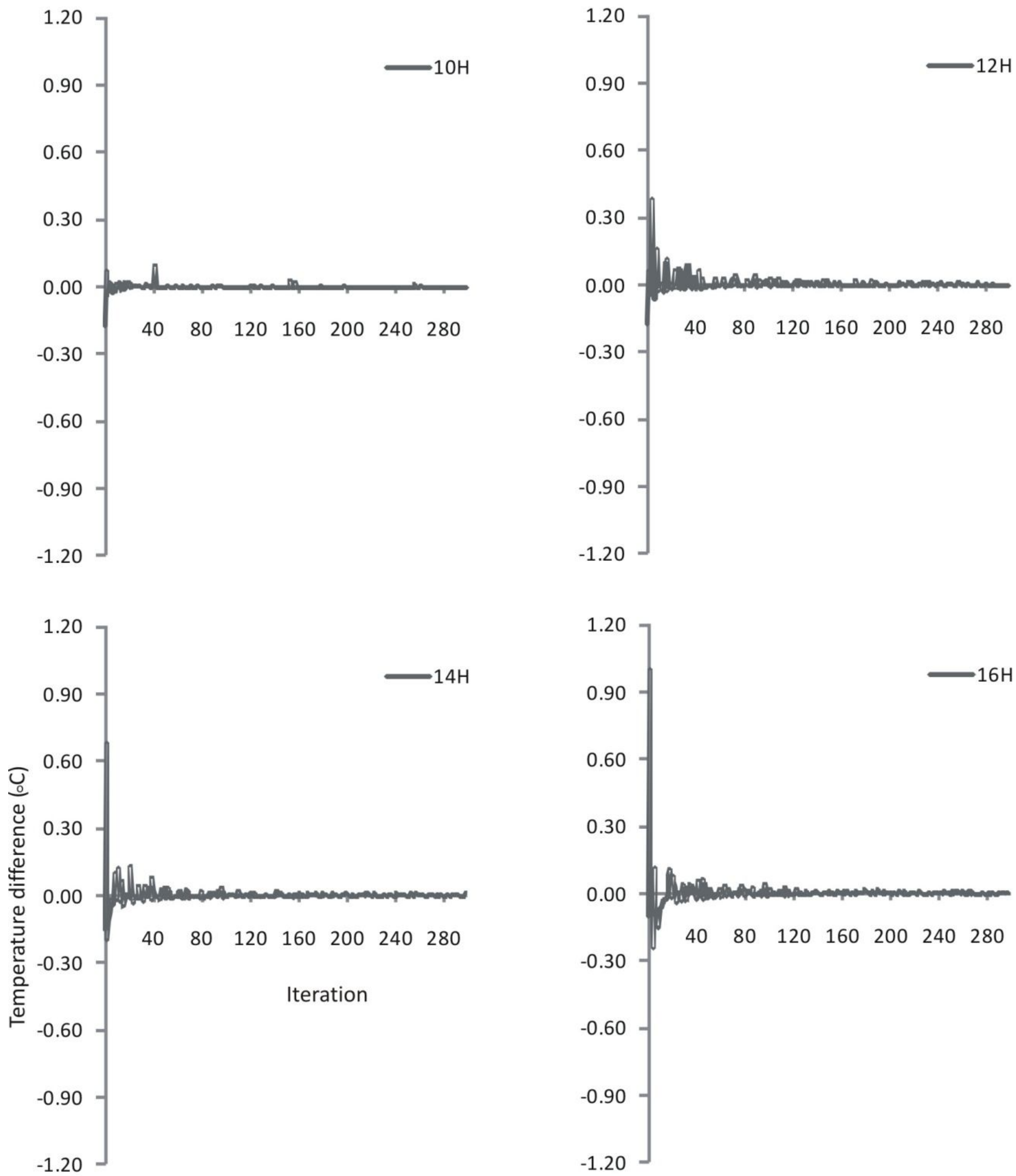


Figure 5. Change in indoor temperature from the value at the immediately preceding iteration as the iteration proceeds

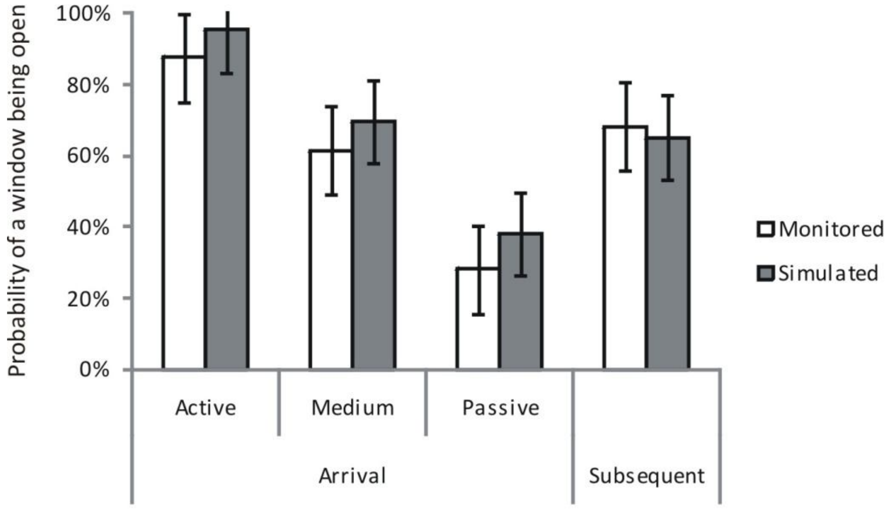
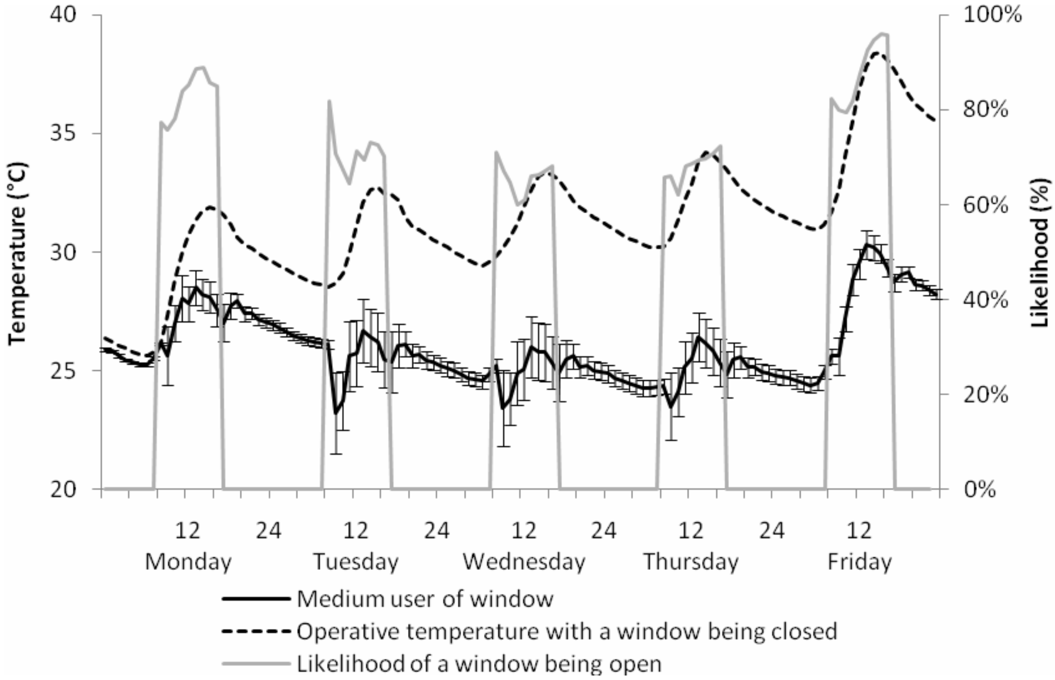


Figure 6. Comparison between predicted and monitored probabilities of a window being open

(a)


40
35
30
25
20
Temperature (°C)
100%
80%
60%
40%
20%
0%
Likelihood (%)
12
24
Monday
Tuesday
Wednesday
Thursday
Friday
Medium user of window
Operative temperature with a window being closed
Likelihood of a window being open

(b)

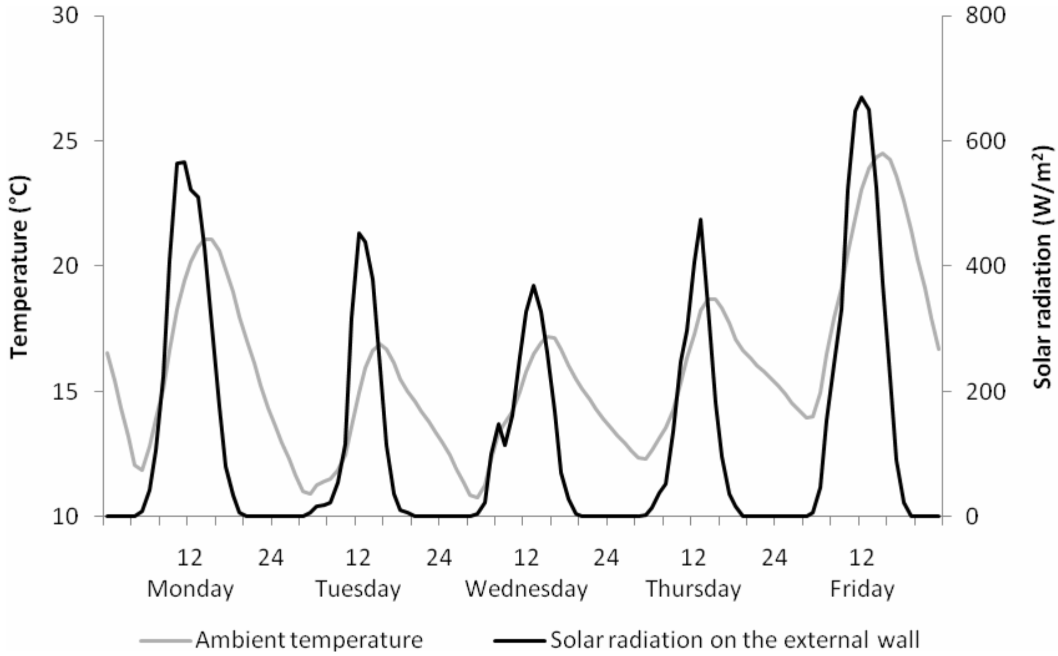
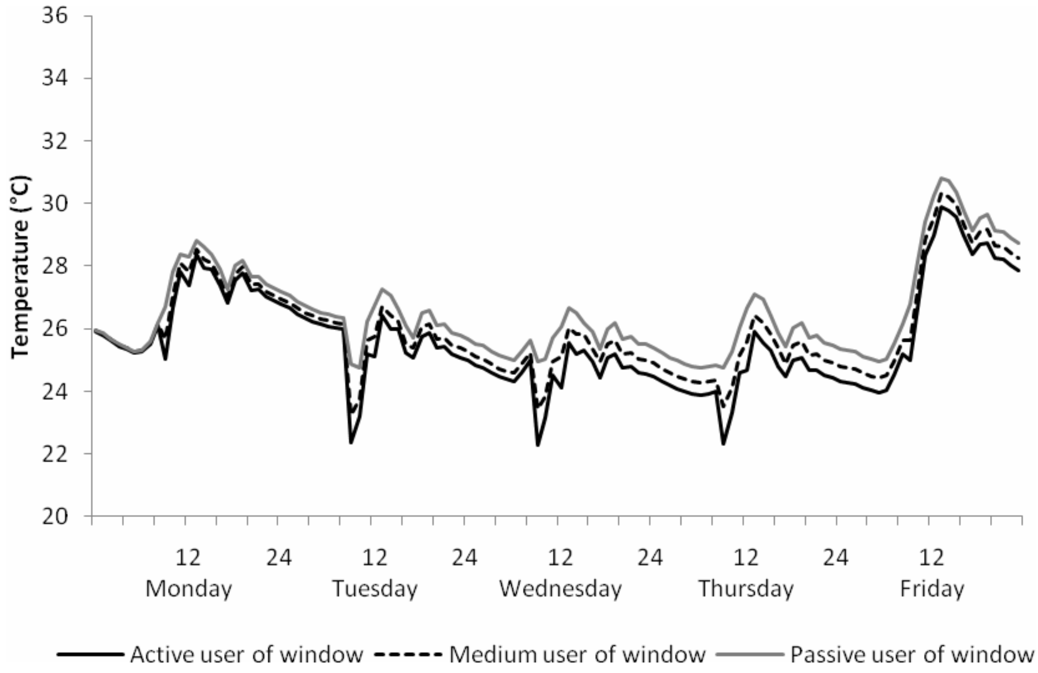


Figure 7 Effects of occupant's window-control behaviour on indoor temperature in medium weight thermal mass structure

(a) Indoor temperature with standard deviation using the medium user behaviour models of window-control for the simulation period, along with the likelihood of a window being open

(b) Ambient conditions

(a)


Temperature (°C)
36
34
32
30
28
26
24
22
20
12
24
Monday
Tuesday
Wednesday
Thursday
Friday
Active user of window
Medium user of window
Passive user of window

(b)

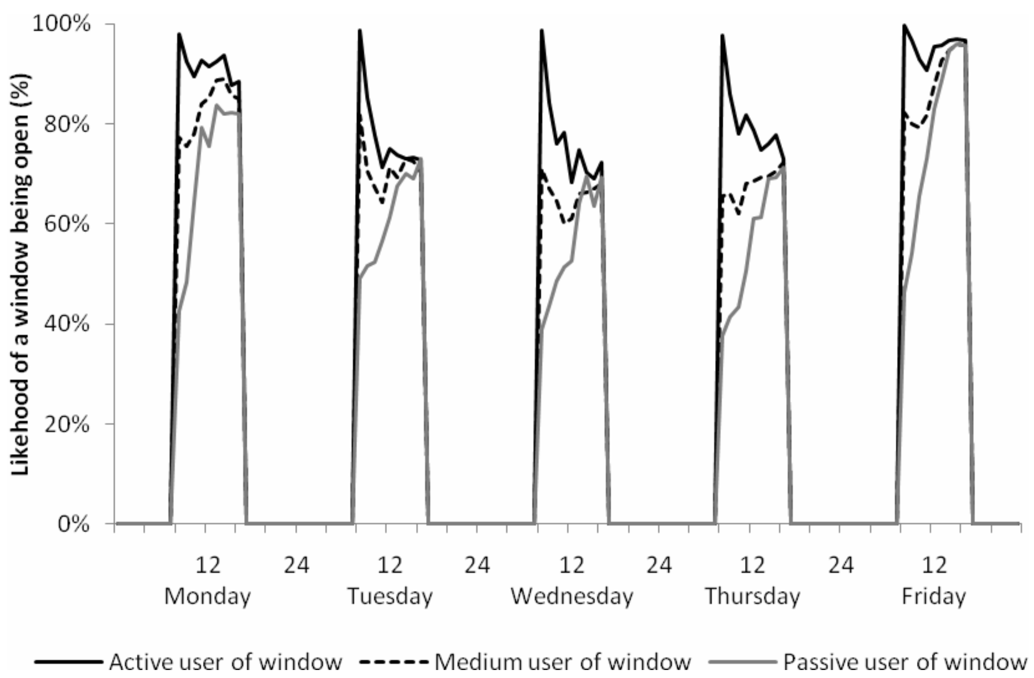

Likehood of a window being open (%)
100%
80%
60%
40%
20%
0%
12
24
Monday
Tuesday
Wednesday
Thursday
Friday
Active user of window
Medium user of window
Passive user of window

Figure 8 Indoor operative temperatures in an office with medium weight construction mass as a function of passive, medium and active user behaviour models of window-control

(a) Indoor operative temperatures

(b) The likelihood of a window being open (i.e. the ratio of the number of iteration when a window is open to the total number of iteration)

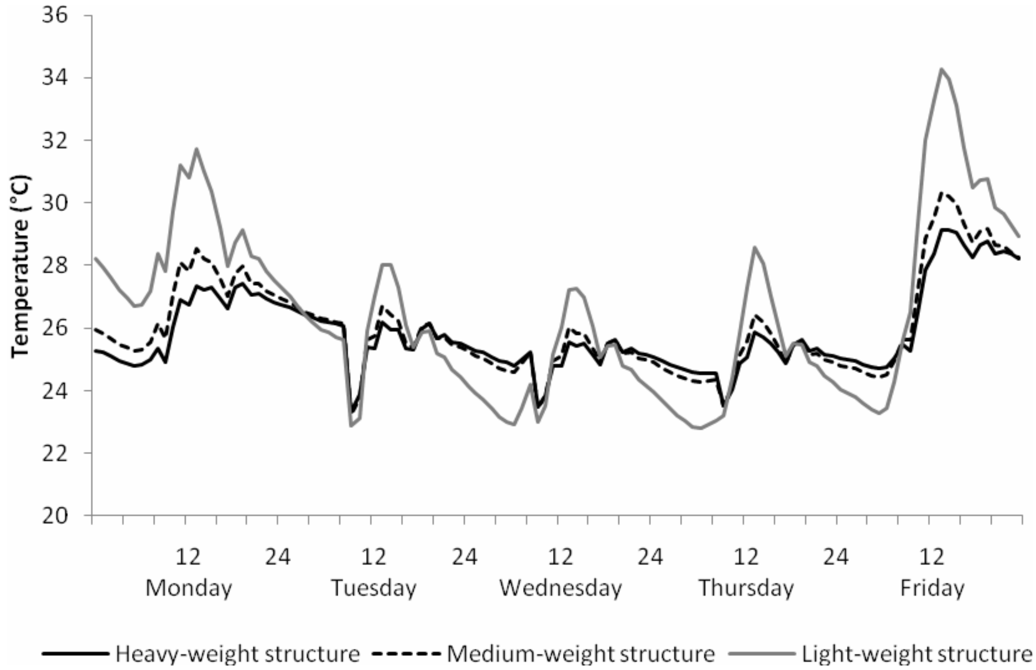


Figure 9 Indoor temperatures in an office with light, medium and heavy weight construction using a medium user behaviour model of window control

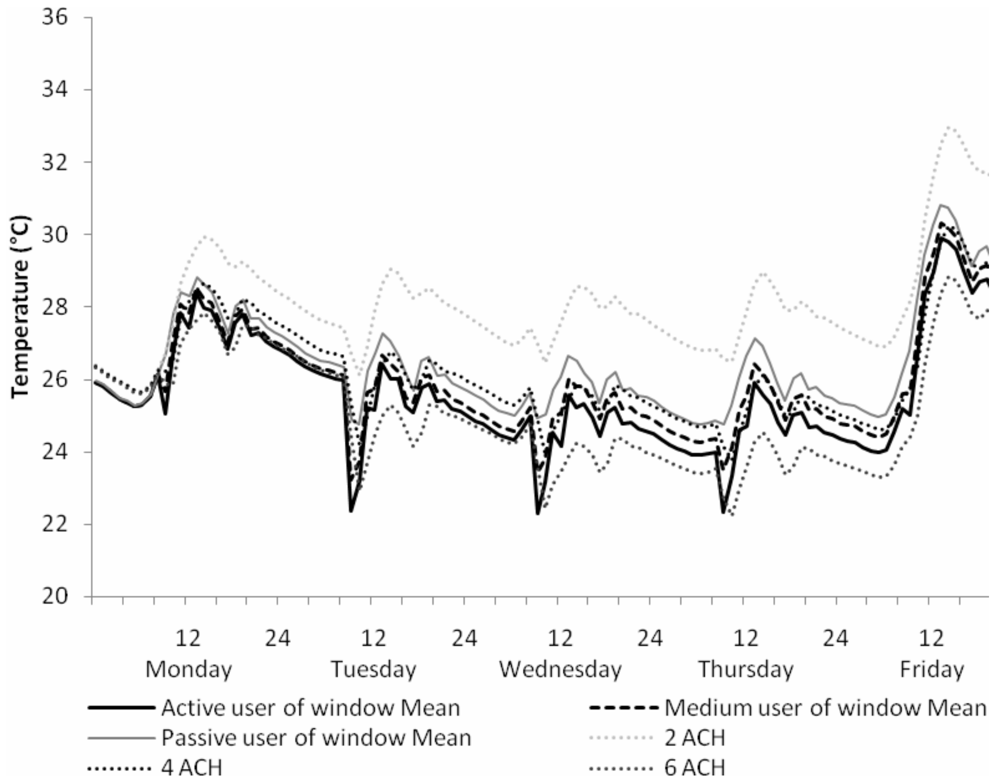
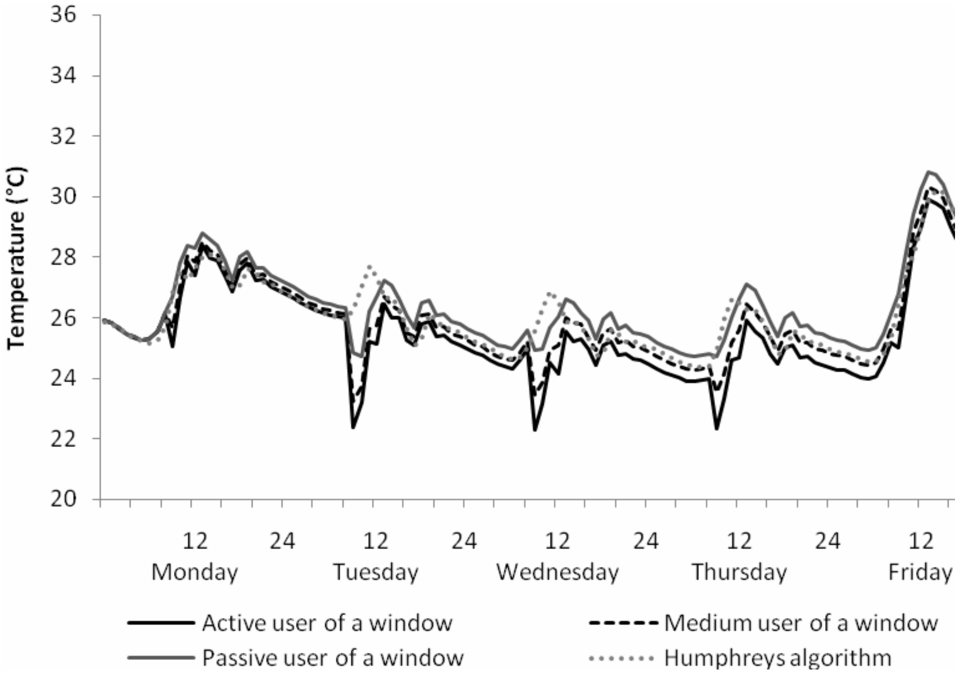


Figure 10 Comparison of indoor temperature as a function of passive, medium and active user behaviour models of window-control with indoor temperature with fixed ac/h of 2, 4 and 6 in an office with a medium-weight construction

(a)


36
34
32
30
28
26
24
22
20
Temperature (°C)
12
24
12
24
12
24
12
24
12
Monday
Tuesday
Wednesday
Thursday
Friday
Active user of a window
Medium user of a window
Passive user of a window
Humphreys algorithm

(b)

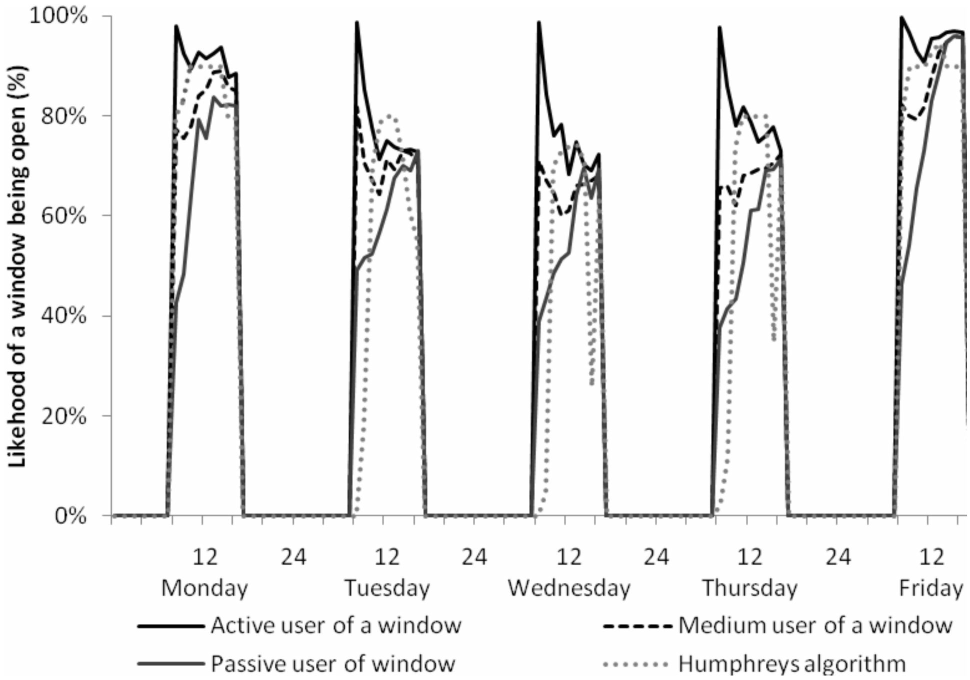


Figure 11 Comparison of the results between the Yun and Humphreys algorithms

(a) Indoor operative temperatures

(b) Likelihood of a window being open (i.e. the ratio of the number of iteration when a window is open to the total number of iteration)

Tables:

Logistic transition probability function

$$P_{(i,j)} = \frac{e^{a+bT_{in}}}{1+e^{a+bT_{in}}}$$

where $P_{(i,j)}$ is the probability of a window state transition from i to j and T_{in} is indoor temperature

Regression results

Time of day	Occupant type	State transition	a (SD)	b (SD)
Arrival	Active	Closed to open	-14.094 (9.195)	0.717 (0.428)
Arrival	Medium	Closed to open	-7.989 (1.856)	0.359 (0.080)
Arrival	Passive	Closed to open	-7.777 (4.292)	0.293 (0.183)
Subsequent	Medium	Closed to open	-11.383 (2.669)	0.365 (0.108)
Subsequent	Medium	Open to closed	3.748 (2.462)	-0.289 (0.103)

Table 1. Transition probability functions: logistic regression coefficients for the user behaviour models of window control (SD refers to standard deviation)

Gain/Floor area (W/m^2)	Selected heat gain in the model
Occupancy	12
Lighting	12
Small power	8

Table 2. Internal heat gains during the occupied period

Floor						
Thermal mass	Material	Thickness (mm)	Conductivity W/(m.°C)	Density kg/m^3	Specific heat J/(kg.°C)	R (m^2.K)/W
Heavy	Heavy mix concrete	150	1.400	2100	653	0.11
Medium	Heavy mix concrete	150	1.400	2100	653	0.11
	Wilton	10	0.060	186	1360	0.17
Light	Aerated concrete block	100	0.240	750	1000	0.42
	Air	200				0.17
	Chipboard	20	0.150	800	2093	0.13
	Wilton	15	0.060	186	1360	0.25
Ceiling						
Thermal mass	Material	Thickness (mm)	Conductivity W/(m.°C)	Density kg/m^3	Specific heat J/(kg.°C)	R (m^2.K)/W
Heavy	Heavy mix concrete	150	1.400	2100	653	0.11
Medium	Heavy mix concrete	150	1.400	2100	653	0.11
	Light plaster	10	0.160	600	1000	0.06
Light	Aerated concrete block	100	0.240	750	1000	0.42
	Air	200				0.17
	Mineral ceiling	15	0.030	290	2000	0.50
External wall						
Thermal mass	Material	Thickness (mm)	Conductivity W/(m.°C)	Density kg/m^3	Specific heat J/(kg.°C)	R (m^2.K)/W
Heavy	Cement screed	10	1.400	2100	650	0.01
	Polyurethane foam	100	0.030	30	837	3.33
	Light mix concrete	100	0.380	1200	653	0.26
	Gypsum plaster	10	0.420	1200	837	0.02
Medium	Cement screed	10	1.400	2100	650	0.01
	Polyurethane foam	100	0.030	30	837	3.33
	Aerated concrete block	70	0.240	750	1000	0.29
	Gypsum plaster	10	0.420	1200	837	0.02
Light	Cement screed	10	1.400	2100	650	0.01
	Polyurethane foam	90	0.030	30	837	3.00
	Aerated concrete	50	0.160	500	840	0.31
	Air	200				0.17
	Light plaster	10	0.160	600	1000	0.06
Internal wall						
Thermal mass	Material	Thickness (mm)	Conductivity W/(m.°C)	Density kg/m^3	Specific heat J/(kg.°C)	R (m^2.K)/W
Heavy	Cement screed	10	1400	2100	650	0.01
	Light mix concrete	100	0.380	1200	653	0.26
	Gypsum plaster	10	0.420	1200	837	0.02
Medium	Cement screed	10	1.400	2100	650	0.01
	Aerated concrete block	70	0.240	750	1000	0.29
	Gypsum plaster	10	0.420	1200	837	0.02

Light	Cement screed	10	1.400	2100	650	0.01
	Aerated concrete	50	0.160	500	840	0.31
	Air	200				0.17
	Light plaster	10	0.160	600	1000	0.06

Table