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Development of Stochastic Models of Window State Changes in Educational Buildings

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Abstract. How people would like to interact with surrounding environment will subsequently influence indoor thermal conditions and further impact building energy performance. In order to understand occupants' adaptive behaviours in terms of environmental control utilization from the point of view of quantification, an investigation on windows operation was carried out in non-air-conditioned educational buildings in the UK during summer time considering the effects of occupant type (active and passive) and the time of a day. Outdoor air temperature was a better predictor or window operation than indoor air temperature. Window operation was found to be time-evolving event. The purpose or criteria of adjusting window states were different at different occupancy stages. Active occupants were more willing to change windows states in response to outdoor air temperature variations. Sub-models predicting transition probabilities of window state for different occupant type and occupancy stages were developed. The results derived from this field study are helpful with improving building simulation accuracy by integrating sub-models into simulation software and further providing guideline on building energy reduction without sacrificing indoor thermal comfort.

1. Introduction

The behavioural adaptation of occupants plays a significant role in enabling subjects to achieve thermal comfort and consequently influences building energy consumption [1-2]. Adaptive behaviours in terms of personal (e.g., adding an item of clothing) and technological (e.g., turning on air conditioner, opening windows) dimensions induce a change in the heat balance of the human body [3]. Occupants' interaction with environmental controls in turn impact building energy performance. Brager *et al* [4]. concluded that behavioural adaptation could be viewed as the immediate and conscious feedback loop, where the discomfort played the role of start point rather than end point. Therefore, in order to satisfy most of people with indoor thermal environment in an environmental-friendly way, the understanding of people's responses with respect to environmental controls utilization is essential

Due to the observable characteristic of behavioural adaptation, the investigations on adaptive behaviours, particularly the environmental controls operation, attract more attention in world-wide. The researches in this field can mainly be classified into qualitative and quantitative aspects. The qualitative studies focus on revealing the utilization of environmental controls under real environment [5-7], restrictions[8] and impact factors [9-10] including both physical and non-physical factors. In terms of

quantitative dimension, researchers tend to develop models for predicting occupants' adaptive behavior [11-14] and consequently influences on energy consumption [15-17].

As aforementioned, the current models mainly focus on the probability that a certain performance (opening of closing) has been taken under a given thermal condition. The probabilities of window state transitions (e.g. from closed to open or from open to closed) are seldom considered. Nowadays, in order to improve the software simulation accuracy of building energy consumption and further to provide guidelines on regional thermal comfort conditions and building energy reduction, simulation considering time-evolving dynamic process of window state changing is vital. Therefore, this study aims to address: (1) an attempt to understand occupants' interaction with window control, particularly the window state transitions, is made by conducting a field study; (2) the effect of occupant type on the behavioural of occupants is clarified; (3) the influence of time of a day is also verified; (4) a stochastic model which can be integrated into building performance simulation software is developed.

2. Methodology
A filed study was performed in naturally ventilated office buildings in University of Reading, UK during summer season and comprised environmental parameter measurement and questionnaire survey.

2.1. The basic information on Surveyed Buildings
The surveyed buildings were located on the Whiteknights campus of the University of Reading. All of them were south-north orientation, of brick-concrete structure, single-glazed with aluminium alloy frames and non-air-conditioned with heating supplied in winter. Figure 1 demonstrates the façades of the surveyed buildings.

Figure 1. Surveyed buildings.

2.2. Environmental Parameters Measurement
In order to reflect the real-time variation of thermal conditions in the studied workplaces, TinyTag (TGU-4500), which recorded temperature and relative humidity using self-contained sensors, was employed to perform successive 24-hour indoor thermal environmental monitoring at 5-minute intervals.

2.3. Questionnaire Survey
The thermal diary used in this field study aimed at collecting information on clothing levels and mean thermal sensation, and gathering detailed information on the performance of window operation in real workplace environments and then for the further development of predictive models.

2.4. Experiment Procedure

Subjects were requested to report their arrival time and thermal sensation on-arrival first and then to record the initial states of windows in their offices. After that, they needed to observe and recorded the start and end time of window operation behaviour and report their mean thermal sensations on an hourly basis until departure.

3. Behaviour Models

3.1. Data Processing

Based on the literature review, the pattern of environmental control using was different from people to people[18-20]. Happle et al [21]. considered using of distinct models for distinct person types (e.g. active and passive subjects) to account for inter-individual diversity of occupant behaviour on the person-level. Therefore, occupants in this study were divided into two classifications, active and passive, respectively, on the basis of responses to the question 'if you could adjust the window, how often would you do so?'. Subjects whose answers were '0-never, 1- rarely' or '3-frequently or 5-always' on 5-point scale were regarded as 'passive' or 'active' subjects. Meanwhile, the time of a day was also found by many researcher to be crucial factor influencing occupants' adaptive behaviour. The whole occupancy period on working hours was consequently divided into three stages, at arrival, during occupancy and departure, respectively.

In order to present the real dynamic window use behaviour, Markov process is applied to both indoor and outdoor temperatures. 5 minutes time step is set up in agreement with environmental parameters measurement intervals of both University of Reading atmospheric observatory and TinyTag. The probabilities of windows state changes are represented by P_{ij}. The whole datasets are allocated to each sub-stage.

3.2. Models based on Markov Process

3.2.1. Sub-models on Arrival Stage. The first 30 minutes after occupant arriving at their offices is regarded as at arrival stage. Since all subjects closed when they left their offices on the previous working day for security reason. Then, there are two possible windows state changing during the on-arrival stage, from closed to open or keep closed, respectively. The predicted models for active and passive subjects with either outdoor or indoor air temperature as predictor at on-arrival stage are:

$$\text{For active subjects: } P_{0-1,arrive} = \frac{e^{-6.406+0.447 t_{out}}}{1+e^{-6.406+0.447 t_{out}}} \quad (1)$$

$$P_{0-1,arrive} = \frac{e^{-8.567+0.432 t_{in}}}{1+e^{-8.567+0.432 t_{in}}} \quad (2)$$

$$\text{For passive subjects: } P_{0-1,arrive} = \frac{e^{-9.510+0.522 t_{out}}}{1+e^{-9.510+0.522 t_{out}}} \quad (3)$$

$$P_{0-1,arrive} = \frac{e^{-6.145+0.235 t_{in}}}{1+e^{-6.145+0.235 t_{in}}} \quad (4)$$

The values of each constant and corresponding statistical test results are shown in table 1.

Table 1. Summaries of statistical tests for window operation at the on-arrival stage.

Occupant type	Overall Test		Nagelkerke R^2	Variables	Independent variable test			
	χ^2	P-value			Coefficient	S.E.	Wald	P-value
Active	23.732	<0.001	0.382	T_{out} [a]	0.447	0.103	18.799	<0.001
				Constant	-6.406	1.646	15.15	<0.001

	17.255	<0.001	0.279	T_{in} [b]	0.432	0.113	14.732	<0.001
				Constant	-0.856	2.418	12.554	<0.001
	5.134	0.023	0.273	T_{out}	0.522	0.253	4.246	0.039
Passive				Constant	-9.51	4.304	4.882	0.027
	17.255	<0.001	0.279	T_{in}	0.235	0.298	0.623	0.43
				Constant	-6.145	6.81	0.814	0.367

[a] Outdoor air temperature.

[b] Indoor air temperature.

Figure 2 demonstrates the windows transition probabilities from closed to open at on-arrival stage. It is clear that passive subjects are reluctant to open their windows until outdoor air temperature increases up to 18°C. For active subjects, the temperature corresponding to 50% transition probability decreases to around 15°C.

Based on the results shown in table 1, outdoor air temperature is a better predictor than indoor air temperature. The significant relationship between window use behaviour and outdoor air temperature is confirmed by the greater values of Nagelkerke's R^2. The P-values for both $G(\chi^2)$ and Wald statistics imply that including outdoor air temperature in the transition probability model makes a significant contribution.
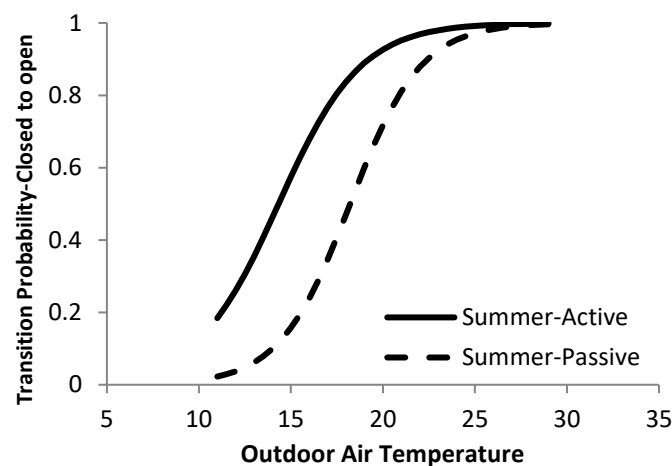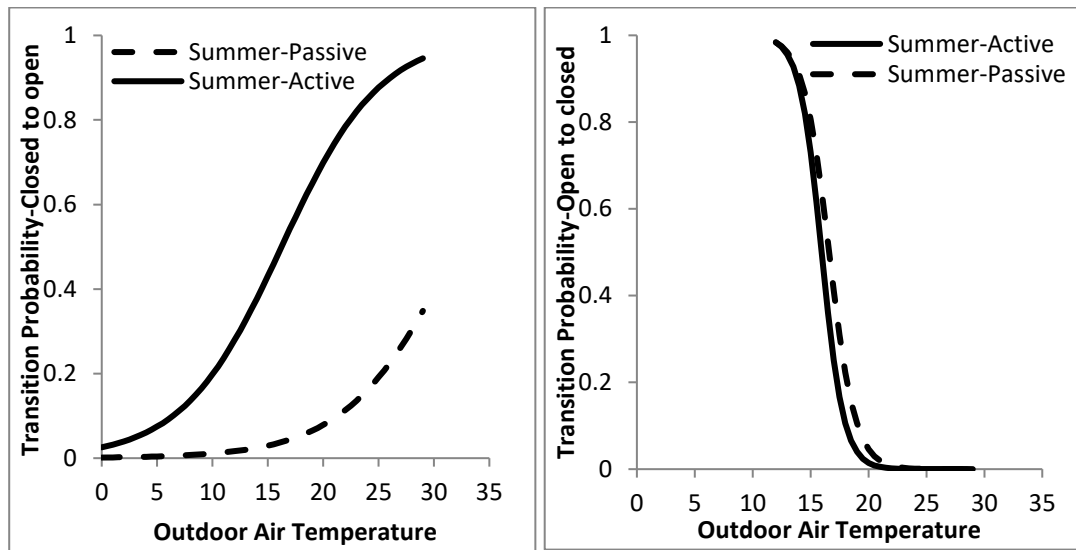

Figure 2. Transition probability of opening closed windows on Arrival.

3.2.2. Sub-models During Occupancy. Figure 3 depicts the windows transition probabilities from closed to open and from closed to open to closed. The probability of windows transition from closed to open is higher for active subjects in summer. With the increasing of outdoor air temperature, the transition probabilities accordingly goes up dramatically, especially the outdoor air temperature exceeds $10\,^{\circ}C$. The transition probabilities for passive subjects begin to increase significantly until the outdoor air temperature reaches $15\,^{\circ}C$. In terms of the transition probabilities of windows changes from open to closed are similar for active and passive subjects. In general, both two types of occupants are reluctant to close opened windows during occupancy in summer.

(a) From Closed to Open   (b) From Open to Closed
Figure 3. Transition probability of window state changing during occupancy.

The predicted models for active and passive subjects with either outdoor or indoor air temperature as predictor during occupancy stage are:

For active subjects (from closed to open):
$$P_{0-1,occupancy} = \frac{e^{-3.637+0.224\,t_{out}}}{1+e^{-3.637+0.224\,t_{out}}} \quad (5)$$

$$P_{0-1,occupancy} = \frac{e^{-8.567+0.432\,t_{in}}}{1+e^{-8.567+0.432\,t_{in}}} \quad (6)$$

For passive subjects (from closed to open):
$$P_{0-1,occupancy} = \frac{e^{-6.542+0.204\,t_{out}}}{1+e^{-6.542+0.204\,t_{out}}} \quad (7)$$

$$P_{0-1,occupancy} = \frac{e^{-21.558+0.825\,t_{in}}}{1+e^{-21.558+0.825\,t_{in}}} \quad (8)$$

For active subjects (from open to closed):
$$P_{1-0,occupancy} = \frac{e^{16.623-1.042\,t_{out}}}{1+e^{16.623-1.042\,t_{out}}} \quad (9)$$

$$P_{1-0,occupancy} = \frac{e^{22.738-1.122\,t_{in}}}{1+e^{22.738-1.122\,t_{in}}} \quad (10)$$

For passive subjects (from open to closed):
$$P_{1-0,occupancy} = \frac{e^{14.791-0.891\,t_{out}}}{1+e^{14.791-0.891\,t_{out}}} \quad (11)$$

$$P_{1-0,occupancy} = \frac{e^{-2.908+0.006\,t_{in}}}{1+e^{-2.908+0.006\,t_{in}}} \quad (12)$$

The values of each constant and corresponding statistical test results are shown in table 2 and table 3.

Table 2. Summaries of statistical tests of window operation
from closed to open during occupancy period.

Occupant type	Overall Test		Nagelkerke R^2	Variables	Independent variable test			
	χ^2	P-value			Coefficient	S.E.	Wald	P-value
Active	350.74	0.001	0.128	T_{out}	-1.042	0.094	123.61	0.001
				Constant	16.623	1.591	109.1	0.001
	110.68	<0.001	0.083	T_{in}	-1.122	0.096	137.99	0.001
				Constant	22.738	2.035	124.87	0.001
Passive	10.999	0.001	0.382	T_{out}	-0.891	0.324	7.571	0.006
				Constant	14.791	5.845	6.405	0.011
	17.255	<0.001	0.279	T_{in}	-0.006	0.012	0.209	0.647
				Constant	-2.908	0.216	180.74	0.001

Table 3. Summaries of statistical tests of window operation
from open to closed during occupancy period.

Occupant type	Overall Test		Nagelkerke R^2	Variables	Independent variable test			
	χ^2	P-value			Coefficient	S.E.	Wald	P-value
Active	23.732	<0.001	0.382	T_{out}	0.447	0.103	18.799	<0.001
				Constant	-6.406	1.646	15.15	<0.001
	17.255	<0.001	0.279	T_{in}	0.432	0.113	14.732	<0.001
				Constant	-0.856	2.418	12.554	<0.001
Passive	5.134	0.023	0.273	T_{out}	0.522	0.253	4.246	0.039
				Constant	-9.51	4.304	4.882	0.027
	17.255	<0.001	0.279	T_{in}	0.235	0.298	0.623	0.43
				Constant	-6.145	6.81	0.814	0.367

No matter active or passive subjects, the increasing of probabilities of windows state changing from closed to open in response to outdoor air temperature rising during occupancy are not as quickly as that at the on-arrival stage. That means at different occupancy stages the purpose of opening windows is different. Due to the initial state of closed, occupants open their window mainly for fresh air at on-arrival stage. But during occupancy, the thermal stimuli may predominate occupants' interaction with window operation.

3.2.3. Sub-models at Departure Stage. Since all windows will be closed on departure for security reason, the transition probabilities from open to closed or keeping closed are 100%. The development of any predictive models is thus not necessary.

4. Conclusions
The time-evolving window state changing process is mathematically demonstrated as several sub-models considering the factors of both person type and the time of a day by applying discrete-time Markov process. The findings obtained from this field study are summarized as below:

- Thermal stimuli, particularly the outdoor air temperature, are found to be the driving force for operating windows.
- The discrepancies of transition probability of window state between active and passive occupants are verified. Active subjects are more willing to adjust the windows state in response to the variations of outdoor air temperature.

- The purpose and criteria of window operation may different at various occupancy stages. For fresh air is the main purpose of window state changing from closed to open. But such criteria is promoted during occupancy and determined by thermal stimuli. The window states changing is found to be irrelevant to thermal environment but for security reason in this study.
- Windows operations are demonstrated as time-dependent events. The models considering the time of a day and subject type are developed.

References
[1]   Gabriel Happle G, Fonseca J A and Schlueter A 2018 *Energy Build.* **174** 276-92
[2]   Zhang Y, Bai X M, Franklin P and Mills F P 2018 *Energy Build.* **172** 279-94
[3]   Auliciems A 1986 *Architectural Science Review* **33**: 43-48
[4]   Brager G S and de Dear R J 1998 *Energy Build.* **27** 83-96
[5]   Indraganti M 2010 *Energy Build.* **42** 1019-25
[6]   Lai D Y, Jia S S, Qi Y and Liu J J 2018 *Build Environ.* **142** 234-43
[7]   Liu H, Zhang W Q, Li B Z and Tan M L 2011 *Journal of Central South University (English Edition)* **42** 1805-12
[8]   Indraganti M 2011 *Renewable Energy* **36** 1182-89
[9]   Humphreys M A and Nicol J F 1998 *ASHRAE Trans.* **104**: 991-1004
[10]   Zhou X, Liu T, Shi X, Jin X 2018 *Energy Build.* **165** 15-24
[11]   Jones R V, Fuertes A, Gregori E and Giretti A 2017 *Build Environ.* **118** 144-58
[12]   Li N, Li J C, Fan R J and Jia H Y 2015 *Renewable Energy* **73** 84-91
[13]   Haldi F and Robinson D 2010 *Build Environ.* **45** 2440-57
[14]   Pan S, Han Y Y, Wei S, Wei Y X, Xia L, Xie L, Kong X R and Yu W 2019 *Build Environ.* **149** 210-9
[15]   Wang L P and Greenberg S 2015 *Energy Build.* **92** 313-21
[16]   Sorgato M J, Melo A P, Lamberts R 2016 *Energy Build.* **133** 1-13
[17]   Rafsanjani H N, Ahn C R and Chen J Y 2018 *Energy Build.* **172** 317-327
[18]   O'Brien, William, Gunay H B, Tahmasebi F and Mahdavi A 2017 *J Build Performance Simulation* **10** 509-26
[19]   Haldi F 2013 *Proc. BS2013 (Chambéry)* p 1475
[20]   Haldi F, Davide C, Andersen R K and Wesseling M 2017 *J Build Performance Simulation* **10** 527-44
[21]   Happle G, Fonseca J A and Schlueter A 2018 *Energy Build.* **174** 276-292