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Simulating Window Behaviour of Passive and Active Users

Sara Torabi Moghadam[a,*], Federica Soncini[a], Valentina Fabi[a], Stefano Corgnati[a]

[a]Politecnico di Torino - Corso Duca degli Abruzzi, 24 - 10129 Torino, Italy

Abstract

People usually spend most of lifetime within buildings and so they need to make the indoor environment comfortable by heating, cooling, ventilation and illumination. Assessing the energy consumption with a certain level of accuracy is a key factor in the research for sustainability and efficiency in buildings. This study attempts to analyze window behavioural models in office buildings, comparing "Active" and "Passive". The outcomes quantify the effects of natural ventilation on energy loads, leading to the conclusion that a probabilistic occupant behaviour schedule may reproduce in a more realistic way the actual energy use.

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Keywords: Opening Window Behaviour; Thermal Performance Simulation; Office Building.

1. Introduction

Window opening behaviour can have a significant influence on variation in energy consumption and indoor environment. Therefore, it is important to contemplate the uncertainty related to window opening behaviour, when designing and realizing the energy efficiency in buildings. Currently, computational simulation is one of the most widespread analysis tools of a building's energy performance. Its complexity is connected to miscellaneous disciplines in the scientific area and concerning human behaviour. Therefore, it is not easy to combine these aspects and ensure that the building performance simulation maximizes its potential. Commonly, occupant behaviour is simplified through the implementation of standardized schedules in simulation [1,2]. By contrast, human interaction with building control systems is governed in a stochastic manner, e.g. the influence of human behaviour on window operation and shading devices [3]. Since the sense of comfort varies from person to person, the probability of performing an action to restore the comfort conditions is different for every individual [4]. For this reason, recent

* Corresponding author. Tel.: +39 011 090 7467; fax: +39 011 090 7499.
E-mail address: sara.torabi@polito.it

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developments in this area have focused on some detailed aspects of occupancy. Regarding the definition of Reinhart [5], through the delineation of representative active and passive users, the individual variability, which characterizes human behaviour, should be incorporated in building simulations. Specifically, Reinhart classified occupants as active or passive daylighting users [5]. He defined as active the user who prefers to use natural light as much as possible, while a passive user tends to favor only artificial light. Moreover, the same definition is applied to the use of window blinds, where someone who operates the blinds in order to maximize daylight availability or avoid discomfort due to glare is active, whereas a passive user manages blinds with the intention of eliminating daylight [5].

Taking its cue from the above-mentioned study by Reinhart, the current research examines the implications of different types of building occupants related to the use of windows. The purpose is to understand how the distinction between active and passive users can influence the predicted energy loads in an office building. To this end, first the model defined by Haldi and Robinson [6] is considered as a reference stochastic window model. Subsequently, the model elaborated by Parys [7] defining active and passive users is implemented. Finally, the comparison between the different user types is carried out for each scenario for the performance indicators – energy use for cooling and heating and the ventilation rates.

2. Implemented window opening behaviour

In this framework, the regression parameters describing the probability functions of the occupants observed in an office building, based on Haldi and Robinson's observation [6], are elaborated to obtain active and passive behaviour. However, since this research is a genuine effort to reflect the notion of active and passive users, the reference model of Haldi and Robinson is not discussed in detail. The entire model's analysis can be found in [8], while here only the main sections are considered.

Parys' model relating to the description of active and passive users with regard to control options is taken into account in this paper [7]. This approach is adopted since it defines the variability among users in an intuitive way. Going into the specifics of the distinction between users, the work carried out by Parys [7] is selected as a stochastic window behavioural model, where active and passive users are described as the quartiles of the data related to the people observed. As reported by Haldi and Robinson [9], when the probability of action is 50% (A_{50}), it can be defined as the comparing indicator of individuals. Parys defines "*active behaviour as the 25th percentile and passive behaviour as the 75th percentile of the set of individual A_{50}-values, where A is the most influential driving variable of the respective probability function*" [7]. Moreover, the model associated with the differentiation within users, along with the aggregated model of Haldi and Robinson [6], is a Markov chain consisting of three sub-models of window operation (arrival, intermediate and departure, for both opening and closing).

The following variables are measured by Haldi and Robinson [6] at 5 minute intervals as an adequate frequency to record short-term occupancy patterns: indoor temperature (°C), outdoor temperature, daily mean outdoor temperature (°C), rainfall (binary variable), ongoing presence duration (min), preceding absence longer than 8 hours (binary), following absence longer than 8 hours (binary), window higher than ground floor (binary). Parys, starting from the same recorded variables, used the data obtained to create individual models. Both models [6,7] predict the probability of action (open or close the window) using the logistic regression which infers the interaction between variables according to the following equation:

$$\log\left(\frac{p}{1-p}\right) = a + b_1 \cdot x_1 + b_2 \cdot x_2 + \ldots + b_n \cdot x_n + c_{12} \cdot x_1 \cdot x_2 + c_{13} \cdot x_1 \cdot x_3 + \ldots \tag{1}$$

- p : probability; a : intercept; b_{1-n} : coefficients ; x_{1-n} : variables ; c_{1-n1} : coefficients for the interaction terms

3. Proposed methodology

The case study implemented for the simulations is a medium sized office building [10] featuring 15 individual heating zones, of which eight have north facing windows and the others are south façade oriented. Each office cell is equipped with an operable window. In this layout, each thermal zone is considered separately in a multi-zone context which allows more detailed results to be obtained. The pre-set temperatures for heating and cooling are considered 20°C and 26°C†[1]. 1 ACH is provided via the mechanical ventilation system during the working hours, i.e. from 8:00 to 18:00, with a lunch break from 12:00 to 14:00. The installed lighting power is assumed to be 10 W/m^2, while the internal gains due to the equipment (during occupied period) are supposed to be 15 W/m^2. The overall area, given by the set of thermal zones modelled within the building simulation software, is 242.10 m^2 and the height is 2.90 m. The external wall facing north has a total window area of 71.77 m^2, while the other, oriented to south amount to 85.84 m^2. The thermophysical properties of the transparent components is double pane glazing with U =1.00 [W/m^{2}K] and opaque components are described in the tables below (Table 1). Procedurally, a Monte Carlo analysis with 90 runs is performed, implementing the individual behavioural model (active, passive users and the reference one) as presented previously, in IDA ICE.

Table 1. Thermophysical properties of the transparent components.

	Material	Density	Specific heat	Thermal	U value	Thickness
		[kg/m^3]	[J/kgK]	conductivity [W/mK]	[W/m^{2}K]	[m]
External wall	Thermal Plaster	421	836	0.088	0.15	0.527
	Biomattone (Hemp and Lime)	435	1883	0.088		
	Biomattone (Hemp and Lime)	435	1883	0.088		
	Titanium Zinc	7200	389	110.000		
Roof	Mineral Panel	246	916	0.330	0.22	0.274
	Galvanized Steel Sheet	7800	477	52.000		
	Concrete	400	837			
	Kraft Paper	50	1883	0.018		
	Rockwool	100	1046	0.035		
	Bitumen	1200	920	0.170		
	Greenbiz (Green Roof)	611	837	0.123		
External floor	Concrete	900	477	52.000	0.14	0.395
	Rockwool	100	837	0.220		
	Natural Beton (Hemp and Hydraulic Lime)	200	1200	0.053		
	Clay Panel	280	1498	0.053		
	Stone Panel	2800	1800	0.090		

4. Simulation results

In order to verify the final energy performances due to the action on windows by different user types, it is fundamental to analyse how behavioural models under similar weather conditions perform. Their effect on ventilation rates, cooling and heating loads is verified. In particular, the results of each performance indicator are presented, seasonally, with the aim of examining the discrepancy between three types of models: Reference window opening model [6], Active and Passive users [7].

4.1. ACH

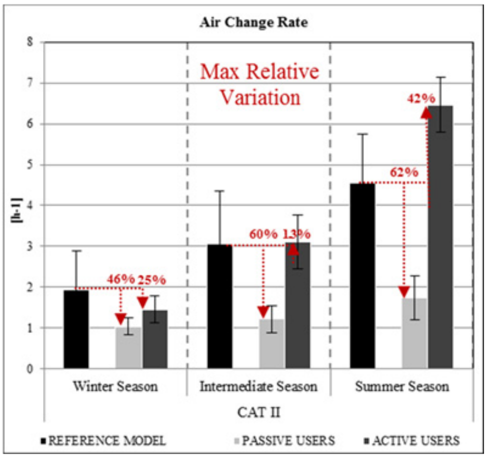
The constant mechanical air change rate is assumed 1h^{-1} as a fixed assumption, while, it is variable in a probabilistic algorithm's model for window opening. Since window opening is governed by indoor and outdoor temperature, when comparing different users it can be noticed that with the highest air change rate recorded in

[1] This category is defined in Standard EN 15251:2006 for office buildings; Minimum operative temperature for heating: 20°C and Maximum operative temperature for cooling 26°C.

summer season, there is a remarkable variation between models. ACH is even three times higher in the model with the active users (i.e. $ACH_{Active,summer} = 6.6\ h^{-1}$) compared to the passive users (i.e. $ACH_{Passive,summer} = 1.74\ h^{-1}$) (Fig. 1(a)). The active users are clearly the ones who actively seek to open the window.

A common pattern in the intermediate and winter seasons comes out from the analysis of air change rates values. With regard to the comparison between the reference model and those active and passive, the reference model ensures the highest ventilation rate in winter (i.e. $ACH_{Reference,winter} = 1.94\ h^{-1}$), while in summer and during the intermediate seasons it is 4.56 h^{-1} and 3.06 h^{-1} respectively.

The air change rate value of the reference model during the cold winter months fits with heating energy use in this season, when the air change rate is higher and the heating system uses more energy to restore the heat losses due to human interaction with windows. Result fluctuations in the same office building caused by changing occupant patterns (active, passive and reference) are presented in the following figures 1-3. To address the sensitivity of the performance indicator respect to fluctuations in occupant behaviour, the statistical indicator CV (Coefficient of Variation) is applied. This indicator is a normalized measure of dispersion of a probability distribution or frequency distribution and it is defined as the ratio of the standard deviation to the mean. The relation between the percentages of CV is shown in major detail in Fig. 1(b). It is observed that the same value of CV appears in the winter and intermediate season for both active and passive, while in summer there is a variation. Passive users are the ones who vary more than the others ($CV_{Active,summer} = 30\%$). It is important to consider Standard Deviation and Coefficient of Variation together. For instance, even if the CV value is generally the lowest, this could be not true for standard deviation. Fig. 1(a) shows the corresponding SD values, which are indicators of the results' fluctuation deriving from the probabilistic approach.



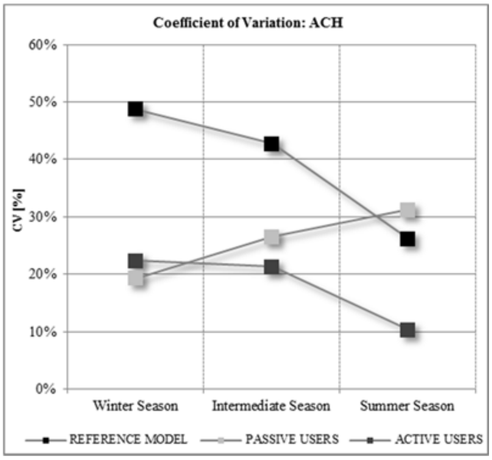


Fig. 1, (a) Mean values and standard deviation; (b) CV values deriving from the probabilistic approach for ACH

4.2. Heating

The constant mechanical air change rate is assumed 1h^{-1} as a fixed assumption, while it is higher in a probabilistic algorithm's model for window opening. Thus, the variations in ACH between the different approaches highlighted what should be expected. Varying the implementation of occupant behavioural models within the building simulation tool, it results in a more or less energy use. A "manual" (stochastic) window control, for active and passive users, increases with a variation, of 9.47% and 2.47% respectively, in the winter season ($E_{Heating,standard,summer}$= 33.88 kWh/$m^2$). Consequently, the variation between different users has an impact on the heating energy load (see Fig. 2(a)).

Models defined by an active usage of the window registered a value higher than passive, in all seasons, with a maximum difference of 5.52kWh/m^2 in the intermediate time of year.

When compared with the reference model, the heating energy load is elevated with respect to active (Δ= 8.5 kWh/m^2) and passive (Δ= 10.87 kWh/m^2) control of the window. Actually, open windows during winter lead to an increase in heating energy demand, as a result of high transmission losses.

From the analysis of Standard Deviation and CV values (Fig. 2(a),(b)), it is deduced that all behavioural models (reference model, active and passive) present very low percentage of variation.

4.3. Cooling

The lowest energy use for cooling in changing window operation (user type active) is observed in summer probably because window opening encourages the natural ventilation of the indoor environment.

As a consequence of the climatic characteristics of the selected weather zone, the difference in handling window control system is less evident during the winter and intermediate seasons.

Cooling loads are forcefully affected by window opening. Once probabilistic control is permitted, summer reductions in cooling loads are in the order of 15.35% for active users, and 2.53% for passive (i.e. $E_{Cooling,standard,summer}$ = 14.20 kWh/m^2).

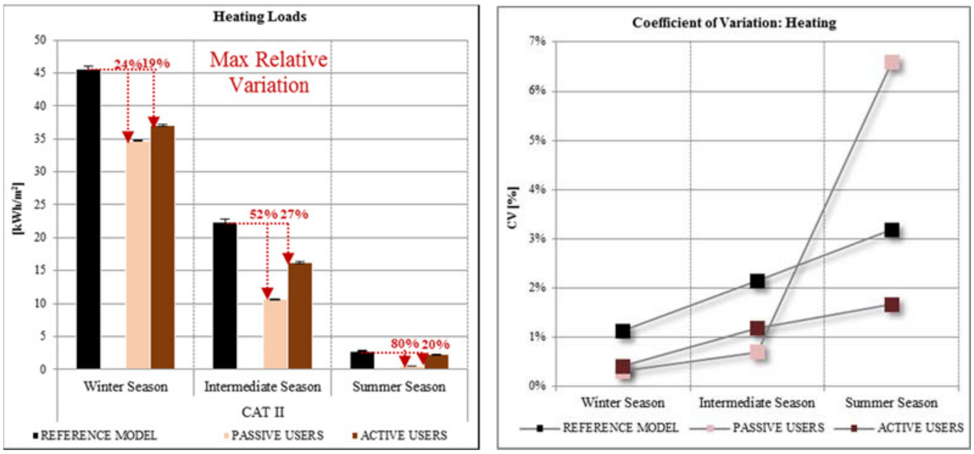


Fig. 2, (a) Mean values and standard deviation; (b) CV values deriving from the probabilistic approach for Heating.

The results shown in Fig. 3 highlight that the reference model is always between the other types of users (active and passive) with a value of 12.35 kWh/m^2 during the summer, decreasing to 1.12 kWh/m^2 and to slightly more than zero (0.20 kWh/m^2) in the intermediate and winter season respectively.

The CV of all types of implemented user models has the same trend (Fig. 3(b)). Moreover, looking at the standard deviation numerical values, SD is almost similar in all cases (Fig. 3 (a)) as proved by SD values, passing from just 0.02 kWh/m^2 for active and passive to 0.03 kWh/m^2 for reference in summer.

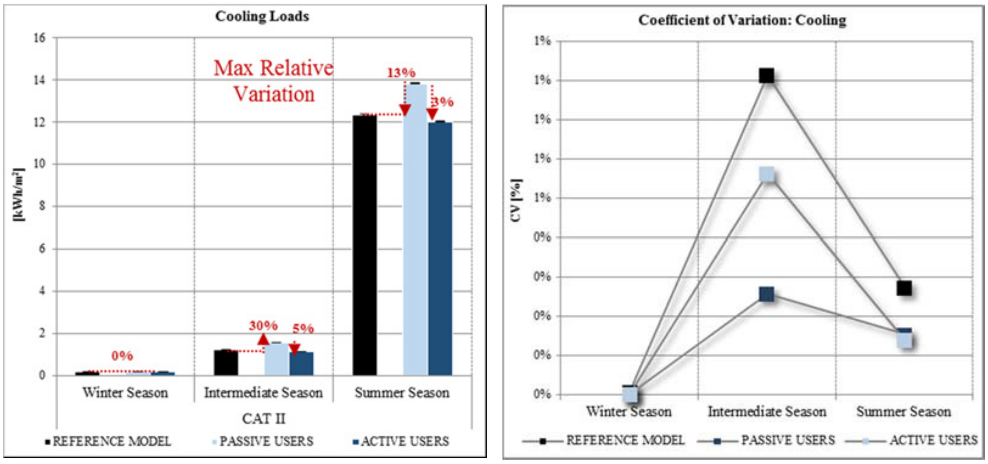


Fig. 3, (a) Mean values and standard deviation; (b) CV values deriving from the probabilistic approach for Cooling.

5. Conclusion and future work

The set of models presented in this paper are an attempt to simulate the impact of individual behaviour, by implementing the logistic regression models intended for active and passive [7] and generalized window behaviour [6] on building energy simulation.

The investigations carried out in this research, demonstrate the importance of taking into account window opening behaviour for a better understanding of the energy use patterns of office buildings.

Therefore, a generalized model of user behaviour may underestimate or overestimate the predicted energy consumption of a building, consequently resulting in a wrong estimation of expected energy consumption.

Following the current research, future studies should focus more on the distinction between users when considering occupant behaviour, in order to provide a more precise representation of reality by simulation tools prediction methods. Although the proposed methodology aspires to improve energy efficiency in new buildings during an earlier phase of design, this can also be applied to retrofitting projects in existing buildings.

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