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Light switch behaviour: occupant behaviour stochastic models in office buildings

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Abstract
It is common knowledge that occupants' behaviour on building control systems plays a significant role to achieve comfortable indoor environmental conditions. Moreover, different research studies have shown how occupants' behaviour also has a huge influence on energy consumption. Consequently, since the building sector still consumes nearly half of the total amount of energy used in Europe and because occupants' comfort should be one of the major aim of a building construction, this influential factor should be further investigated. Reliable information concerning occupants' behaviours in a building could help to better evaluate building energy performances and design robustness, as well as, it could help supporting the development of occupants' education to energy awareness. Concerning occupant behaviour related to indoor lighting systems, many studies have been made regarding occupants' feelings and performances to certain visual stimuli due to different light systems. Nevertheless, occupants' interactions with lighting control systems needs further investigation also because few models to predict switching operations have been implemented in energy simulation programmes. This study proposes probabilistic models to describe occupants' switching on-off control over lighting. They have been developed using a multivariate logistic regression based on measurements of indoor climate parameters, outdoor environmental conditions and artificial lights "switch on/off" actions. Measurements were made over eleven months for three different office rooms. Two predictive light-switch behaviour models were inferred in relation to the number of actions carried out by the users (active or passive). The models are presented and critically discussed in this paper. The study extends the information on environmental parameters influencing occupants' manual control of the lighting system in offices and energy consumption.

Keywords: Occupant's behaviour; light switching; stochastic modelling

1 INTRODUCTION
To predict more realistic energy consumption as well as occupant's comfort requirements, human interaction with buildings and systems should be further investigated. The human behaviour has been studied by several experts from different study branches varying from social science to building science. Researchers tried to describe and forecast occupants' behaviour developing stochastic models based on environmental conditions, named drivers. Different models were carried out on how people adjust blinds, open and close windows, change temperature set point, switch on and off lights (Parys, 2011). The energy saving potential connected with the use of daylight has been the subject of an earlier study, resulting in a broad range from 20% to 80%, according to calculations (Bodart et al., 2002). The research of (Opdal et al., 1995) is of particular interest because calculated energy savings are compared against measurements. A saving potential of about 30% resulted from

measurements, whereas the simulations, without accounting for occupant behaviour, predicted a saving potential of about 40%.

In the study exposed in the current paper, occupants' behaviour towards manual lighting operational system is modelled for the case of office buildings. The aim is to enlarge the knowledge about indoor and outdoor environmental conditions influencing people's behaviour, as well as to predict their impact on electric energy use in buildings. The statistical models were inferred over field measurements recorded from an office building located in Prague for more than eleven months.

2 METHOD

In literature the main factors which influence the behaviour of occupants related to the light switching in office buildings are reported (Fabi et al., 2013). Models were developed following consolidated proposed methodology (Fabi et al., 2013), switching from standardized and deterministic methodologies, toward a probabilistic approach in energy modelling. Behaviour patterns for active and passive occupant's typologies were analysed in order to determine the influencing factors leading the office occupants to switch ON/OFF the lights. Some of the factors identified in the literature were then quantified in this study by means of long-term monitoring of behaviour and environmental variables in three offices, resulting indifferent user models, suitable to be implemented in an energy simulation software.

3 THE FIELD SURVEY

Data on light switching operations were gathered with a measuring campaign in eight identical offices of the Czech Technical University (CTU) in Prague within the framework of the EU Project "Clear-Up". Environmental parameters useful to model light-switching behaviour were monitored in two single offices (in the following called Room 2 and Room 5) and one shared office (in the following called Room 3).
The lighting equipment installed in the rooms is characterized both by manual and automatic control. Occupants can operate manually over each control with an individual pair of up/down buttons as summarized in Table 1.

Table 1. Summary of the possible operations over roller blinds, ceiling and floor standing lights.

	Roller Blinds	**Ceiling light**	**Floor standing light**
short	step move up/down,stop while moving	manual on/off	on/off
long	Move up/down completely		dimmer

The automatic system varies for each component. The ceiling light band and the floor standing lamp are controlled by a presence detector. In fact, after a configurable time period of non-occupancy (set to 15 minutes), the lights switch off automatically, while on re-occupancy, the system resumes lighting settings. The floor standing lamp can be, furthermore, constantly controlled with an integrated manual and dynamic set-point system. The automatic operation of the ceiling lights, which is triggered by the presence detector, was not implemented when the measures were taken, and so it was possible to analyse the data when the overhead lights were switched on and off manually.

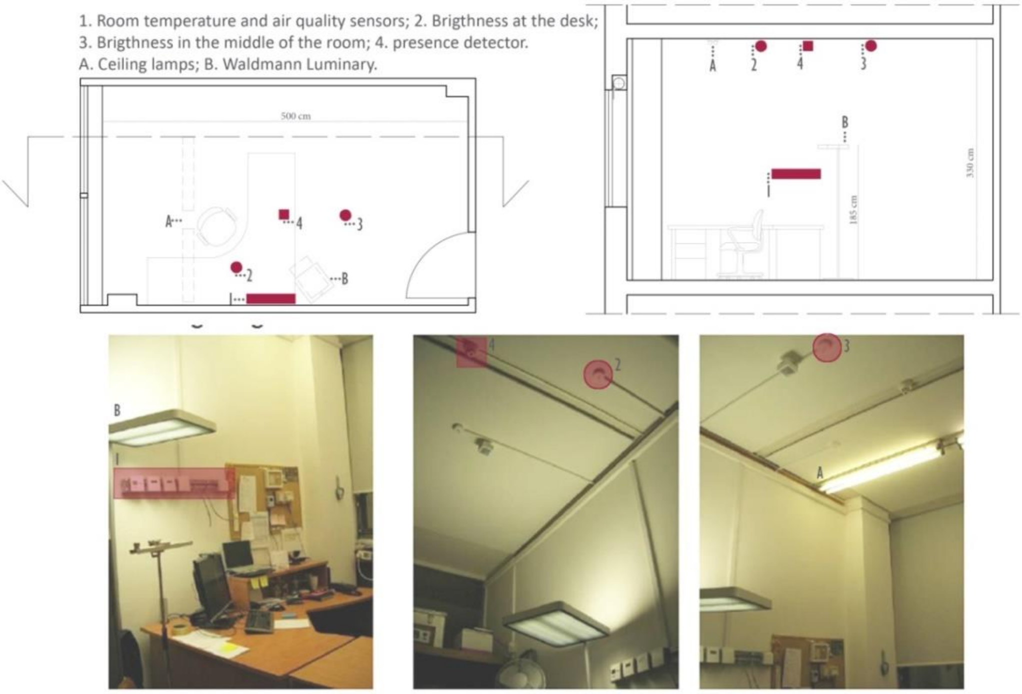

Figure 1. Installed sensors in office rooms.

Moreover, a series of variables concerning indoor and outdoor environmental conditions were monitored from February 2012 to January 2013.

The following variables were measured at 5 minute intervals in all 8 offices:

• *Indoor environment parameters*

- Temperature [°C]
- Set-point temperature [°C]
- Relative humidity [%]
- CO_2 concentration [ppm]
- VOC concentration [ppm]
- Illuminance (in the middle of the room, on desk, at window)

• *Outdoor environment parameters*

- Air temperature [°C]
- Relative humidity [%]
- CO_2 concentration [ppm]
- VOC concentration [ppm]
- Wind speed [m/s]
- Rain (yes, no)
- Wind speed [m/s]

Since several studies (Hunt, 1979, Love, 1998, Reinhart, 2001) demonstrated that occupants' actions on lighting are strictly connected to the fact that people are entering or leaving the space, the time of presence was included as possible behavioural influencing factor besides the measured variables. Considering Hunt's results, the authors settled the arrival period and the departure period as the first and last 15 minutes, when occupancy is recorded. The other period of occupancy was called intermediate (Table 2). Furthermore, previous studies on occupants' behaviour over lighting system already proposed a connection between the large spatial brightness gradient within the room and the use of artificial light (Halonen and Lehtovaara 1995, Begemann et al. 1997), consequently, the illuminance uniformity was derived in this case as a ratio between the lux levels measured by the sensors. The azimuth and elevation angle for the specific location were evaluated from the website http://www.sunearthtools.com/dp/tools/pos_sun.php?lang=it.

A stochastic model was developed from this data for the three rooms representing three different behavioural models.

3 STATISTICAL MODELLING

In the analysis the probability of switching on and off the lights was inferred for three behavioural models. The statistical software R was used for all data analysis and modelling.

The collected data shows that the users did not use the lights very much. It is interesting to see that the room with a lower occupational rate, presents the higher number of action over the light system. Generally this database confirms the findings of previous studies (Hunt, 1979, Love, 1998, Reinhart, 2001): the majority of switch on actions are taken when people arrive in the office. The collected data shows how the ceiling light stays on, even after the occupants leave the rooms: for Room 2 this condition happens for the 37% of time of the whole period during which the light is on, and it happens even more for the other two rooms (42% room 3, and 46% room 5). It also emerged that quite often the lights are turned off on arrival in the room (Table 2). It is interesting to see that this event happened more often in Room 2 than Room 3 and Room 5 (respectively 19%,17%,15%), and it means that the occupants of Room 3 and Room 5 left the light on for longer periods (not more often), and they might have not turn off the light suddenly at their arrival (Table 2).

Table 2. Actions on lighting related to the moment of presence

	Room 2			Room 3			Room 5		
	Arrival	Departure	Intermediate	Arrival	Departure	Intermediate	Arrival	Departure	Intermediate
Switch ON	102		22	10	1	1	18	0	9
Switch OFF	23	52	49	2	6	4	4	13	10

Switch off actions show high readings also during the intermediate moment of presence (Table 2), when users remain for long periods inside the office.

The database was divided depending on the state of the light (on/off) to infer the probability of switching on or off separately (the change from one state to another). Moreover, given the number of actions collected and the occupancy pattern, the users of the three rooms were divided into two groups:

- Active: representing an occupant profile that use frequently artificial light.
- Passive: representing an occupant profile that use less frequently artificial light.

Consequently, different models were built considering the data all together and the two categories separately. The monitored occupant' actions are summarised in Table 3:

Table 3. Actions on lighting related to the two categories moment of presence

	active models	**passive models**
SWITCH-ON	120	37
SWITCH-OFF	122	39

Occupant' actions on the control system were obtained by mean of logistic regression with interaction between variables accordingly to the following equation:

$$\mathrm{Log}\frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + c_{12}x_1x_2 + c_{13}x_1x_3 + \cdots \quad (1)$$

Where:

p is the probability of a switching on/off event

β_0 is the intercept

β_{1_n} are coefficients

x_{1_n} are explanatory variables such as illuminance, room temperature

c_{12_nm} are interactions coefficients

Backward and forward selections, based on the Akaike information criterion were used to infer the models. The AIC criterion was applied because it evaluates the relevance of each individual variable as well as the amount of parameters included by the model, decreasing the risk of over fitting (Schweiker and Shukuya, 2009).

In order to limit the complexity of the model, only interaction between continuous and categorical variables (e.g. lux level and moment of presence) was investigated. In particular, the categorical variables used to investigate correlations among parameters were: the time of presence (arrival/intermediate/departure period), the door switching and the room indicator.

The analysis results were models able to predict probabilities of turning on and off the lights, and they confirmed that there is not a unique valid model to characterize the user and its behaviour, but only a dedicated model according to the used database and goal of the analysis. The scales of the variables was taken into account: Schweiker and Shukuya (2009) suggested to multiply the scale of the variable with the coefficient, to get an indication of the magnitude of the impact from each variable.

Logistic regression requires independent variables. Specifically, two kinds of correlations were taken into consideration: variables should be independent from the office they were recorded in and among each other. In this case, lighting variables still had high dependency between each other because some of them were inferred from the other. To overcome this problem, models where inferred with diverse explanatory variables and, also in this case, the different models were selected using AIC criterion. Its use was assumed reasonable because the model were developed from almost the same subset of database.

These preliminary cautions depend on the fact that correlations between explanatory variables might result in inflation of the estimated variance of the deducted coefficient and consequently in too wide confidence intervals. Confidence intervals were considered to assess the significance of the models and generalized variance inflation factors (GVIF) were calculated for coefficients of all explanatory variables to estimate the size of the inflation due to multi-co linearity among all explanatory variables.

4 RESULTS

Stochastic models estimate how an occupant's action varies as a function of the different independent variables. It can reasonably be assumed that occupants make actions just when they are in the room, so when the presence detector records the occupancy of the space. For this reason models were built considering only time-steps when occupant presence is observed. The main variables resulted as influencing factors for the three different models are presented in Table 4 and in Table 5 with their magnitudes.

Even if the statistical analysis include the interaction terms among the variables, it results that selected models do not present any reciprocal influence among the considered factors.

The confidence intervals reveals that the majority of the variables selected in the models are significant. Only the time of presence in the active switch-on model presents inflated intervals. Obviously, the departure period displays a lower significance (-975.04 – 944.09) as well as the intermediate time (-2,63 – 2.76). Nevertheless, even the arrival period do not result significant (-1,39 – 3.88).

Table 4. Influencing factors for energy-related behaviour with respect to switch ON/OFF lights for the investigated offices.

	Light switch on		*Light switch off*	
Infleuncing factor	***Active models***	***Passive models***	***Active models***	***Passive models***
Moment of presence	x	x		X
Illuminance at the windows	x	x		
Illuminace in the middle of the room	x	x	x	
Indoor temperature	x			x
State of the floor lamp	x			x
Elevation	x			
Illuminance ratio between ill. in the middle of the room and on the desk			x	x
Azimut				x

Table 5. Magnitudes of resulting influencing factors for energy-related behaviour with respect to switch ON/OFF lights for the investigated offices.

	Light switch on		*Light switch off*	
Infleuncing factor	***Active models***	***Passive models***	***Active models***	***Passive models***
Illuminance at the window	-2.46	-3.36		
Illuminace in the middle of the room	2.82	3.84	-10.76	
Indoor temperature	-2.59			8.58
State of the floor lamp	-4.08			-4.92
Elevation	-4.13			
Illuminance ratio between ill. in the middle of the room and on the desk			5.20	5.35
Azimut				-2.30

4.1 Active-user models

The daylight from the window, the room temperature, the dimming state of the floor standing light and the sun elevation were negatively correlated with the probability of switching on the ceiling lamp (figure 2). In fact it is reasonable to assume that the rise of this variable will reduce the odds of action over ceiling light. A higher indoor temperature presumably could be related to a warmer season with higher daylight levels (offices were not provided with cooling devices). The illuminance in the middle of the rooms, resulted, unexpectedly, a positive correlation: the probability increased when the lux level increased.

Sun elevation got a higher influence over switch on probability than lux level at the window, even if the two variables are strictly correlated (figure 2).

The time of presence influence on probability has been already defined in previous studies (Mahdavi et al., 2008; Reinhart 2004): it is higher when people arrive in the office while lower for departure and intermediate periods even if they result not significant coefficients with wide interval of confidence. Concerning the switch-off model, the main drivers resulted to be the illuminance in the middle of the room and the uniformity. The result is quite surprising as in previous researches (Pigg et al. 1996, Mahdavi et al. 2008) the chance of switching off actions were not related to lighting environmental conditions, but only to users presence patterns (specifically absence length was considered the main parameter that drives people to turn off the light).

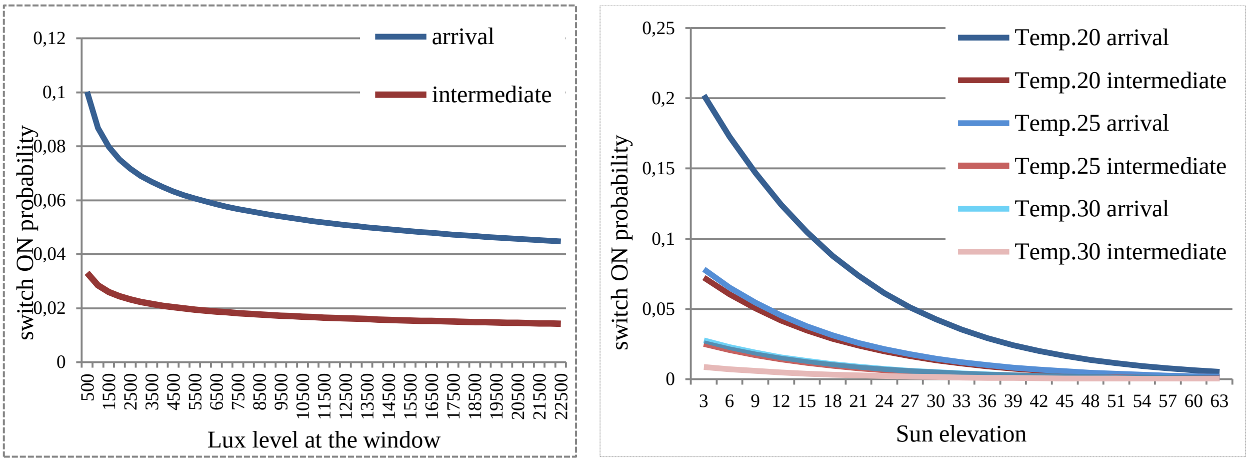

Figure 2. Switch-on probabilistic curves for active users related to different drivers (lux level at left and sun elevation at right)

4.1 Passive-user model

The switch-on model built from the data of the rooms occupied by what the authors defined as “passive” users, are characterized by a lower number of drivers than the active one. Only the illuminance is included with the same condition: the increase of illuminance level will diminish the probability of switch on action over the ceiling lamp while the illuminance inside is unusually positively correlated instead. Besides the continuous variables, the moment of presence affects the model with less significance in relation to the departure period. Only the uniformity parameter is included in switch-off model as lighting parameter. Even if its importance is quite high for the model according to the magnitude, it is not easy to determine its influence. In this case the uniformity was determined vice versa, since higher values were measured in the middle of the room than over the desk and more often they were higher than 1, meaning that higher ratio values do not definitively infer a better uniformity. Room temperature, the state of the dimming floor standing light and the azimuth were the other continuous variables that affected the model.

5 DISCUSSION

Generally, all the probabilities inferred by the various models show really low values (figure 2). It depicts of course the conditions emerged from the preliminary observation: people are not used to act over lighting system. This will reflect in low energy consumption related to lighting system, but in any case it represent a real condition.

From all the models it emerges that the users’ behaviour is influenced by a superior number of parameters than the one presented in literature. In fact, even taking into account the most simplified switch-on model, two other environmental conditions are used to infer the probability of action: indoor temperature and sun elevation. Nevertheless, they represent two

other parameters related to daylight in the indoor space. Unfortunately, the daylight at the work plan, which is the main variables for the existing models (Hunt 1979, Reinhart 2001, Mahdavi et al. 2008), could not be included as a variable. Despite this limitation, the illuminance at the windows is displayed with a negative correlation in accordance to previous studies. On the contrary, higher lux level in the middle of the room increase the probability to turn on the light. This dissimilarity could probably deal with the presence of the floor standing lamp which influenced of course the illuminance measurements.
Switch-off models also recorded much more variables. Pigg et al. (1996) and Mahdavi et al. (2008) defined that the turning-off action over light was mainly related to the absence length of occupants. Here instead, occupant's actions are influenced by both lighting variables and the period factor. Nevertheless the absence length was not included as a possible factor so it is not possible to evaluate if it represents the main stimulus. A very surprisingly, as well as note-worthy, aspect is that occupants' behaviour over lighting system never results to be affected by the blinds' state. Haldi (2010) enhanced the possibility of interaction between the two systems that both imply occupants' action in his study and Reinhart (2004) added this relationship a priori in his model. However this condition does not result in this research and it might also mean that this strong relationship is well known by experts in the field but actually not adopted by real users, even if they are people of a high social education standard (civil engineers).
Another consideration regards the facts that all the switch-off models display a negative intercept while for the switch on models is always positive. This condition illustrates that users are more used to turn on lights than switch them off. They get the stimulus to turn on the light due to poor visual comfort while its non-necessity normally does not drive to turning off. They might not perceive its uselessness or are simply unwilling to operate the action since the controller is far away from where they are. This situation underlines how important it is to inform and educate people in relation to this matter.

6 CONCLUSIONS

Different behavioural models related to occupant preferences on artificial lighting were inferred from data gathered during a monitoring campaign in an office building. It was evaluated the probability that an action (switch on or off) may occur for different behavioural models (Active and Passive users), defined on the basis of the number of actions on occupational periods. From the resulted models it emerged that users' behaviour is influenced by many parameters, representing a step-forward with respect to the previous studies. In fact, even taking into account the most simplified switch-on model, two new environmental parameters are used to infer the probability of action: indoor temperature and sun elevation. It was understood that users are more used to turn on lights than to switch them off. This situation underlines how important it is to inform and educate people in relation to this topic.
A further point to specify is that the presence of active users does not imply less energy consumption: their chance to turn off the light is higher but also to switch it on. For this reason it is necessary to implement the model in energy simulation software. Expanding knowledge of the explanatory environmental conditions may help to better understand human comfort needs and habits, and their implementation in energy simulation software, will allow to better understand the impact of occupants' behaviour on energy consumption as well as on building indoor comfort.

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