

VALIDATION OF MODELS OF USERS' WINDOW OPENING BEHAVIOUR IN RESIDENTIAL BUILDINGS

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ABSTRACT

The characterisation of window opening behaviour is crucial for suitable prediction of building performance (energy consumption, indoor environmental quality, etc.) by means of simulations. In this paper, data from a measurement campaign was used to validate three models of window opening behaviour. Data from the measurement campaign was used as input in the models to calculate the probability of opening and closing windows. Afterwards, the validation was carried out by comparing the predicted probabilities with the actual measured state of the windows in the dwellings.

INTRODUCTION

Dynamic building thermal simulation programs are increasingly used to develop efficient solutions for predicting and optimising energy and environmental performance of buildings. However, some key processes are often not taken into account by these tools, leading to potentially significant errors. Most noteworthy is the influence of building occupants, whose actions, such as the use of windows and shading devices, have an important impact on the indoor environment and the overall energy performance of a building.

Window opening behaviour has been investigated by several researchers (Andersen et al., 2009; Fabi et al. 2012; Haldi and Robinson 2009; Nicol, 2001; Nicol, Humphreys, 2004, Roetzel et al., 2009). This has led to a variety of logistic regression models expressing the probability with which actions will be performed on windows, as a function of indoor temperature, outdoor temperature or both. In this paper, some of these models have been validated to test their effectiveness. This involves using the models to calculate probabilities of window interactions using a dataset (the validation set) containing input variables and the window position. A comparison between observed and simulated window opening proportions is provided as validation. This allows for a direct unbiased assessment of the predictive power of the developed models.

Validation of behavioural models

Generally, the published statistical models of occupant's behaviour are not validated. To our

knowledge, only two papers about the validation of behavioural models are published, regarding respectively office buildings and residential buildings. In 2009, Haldi and Robinson proposed a cross-validation procedure to perform the evaluation of the predictive power of window opening behaviour models developed for office buildings. Applying the suggested validation criteria, in 2011, Schweiker et al. tested the accuracy of window opening behaviour models using different datasets in a double-blind way. Although these two papers represent an important milestones on the way of assessing the predictive accuracy of stochastic models of occupants' interactions with the built environment (in particular with windows), considerable space for further research work still remain. In this paper, models of window opening and closing behaviour inferred from a measurement campaign in Denmark (Andersen et al. 2013) were validated taking into account the suggestions of the two published paper using a similar dataset from another measurement campaign in residential buildings.

VALIDATION PROCEDURE

The use of stochastic models for the simulation of occupants' interactions with the built environment has greatly affected the modelling approach in the last years (Haldi and Robinson, 2009, Rijal et al. 2007, Rijal et 2008, Andersen et al., 2011, Herkel et al. 2008, Yun et al. 2008, Yun et al. 2009, Fabi et al., 2012). The increased derivation of stochastic models of occupant behaviour leads to the natural question – how accurate is the model? Traditionally, modellers have tested their models against experimental data whenever possible.

The issue of model validation is very complex and there are probably as many opinions on model validation as there are workers in the field. In the present work, focus will be on one aspect of model validation - the actual process of comparing model predictions to measured data.

The validation process is primarily a way of measuring the predictive performance of a statistical model. One way to measure the predictive ability of a model, is to test it on different dataset than the model was inferred from. The main idea behind the validation is to have two datasets, one used as a

“training set”, to generate the algorithm, and the other dataset, the “validation set”, is used for estimating the accuracy of the algorithm.

The training dataset

Measurements of window opening and closing behaviour along with indoor and outdoor environmental variables were conducted in 15 dwellings located in the area of Copenhagen, Denmark, during the period from January to August 2008.

The following variables were measured at 10 minute intervals in all 15 dwellings.

- Indoor environment parameters:
 - Temperature [°C]
 - Relative humidity [%]
 - CO2 concentration [ppm]
- Outdoor environment parameters
 - Air temperature [°C]
 - Relative humidity [%]
 - Wind speed [m/s]
 - Solar radiation [W/m²]
- Window state (open/closed)

Models formulation

Andersen et al. (2013) used the training dataset to define standardised occupant behaviour patterns, suited for simulation purposes. Since the 15 models were different and did not show similarities, the authors decided to group the buildings according to their ventilation principle and ownership: the 15 dwellings were divided into 4 groups depending on the ownership (owner-occupied or rented) and the type of ventilation (natural or mechanical) in the following way:

- a) Group 1 (G1, NatOw): Owner-occupied, natural ventilation – (3 dwellings)
- b) Group 2 (G2, MechOw): Owner-occupied, mechanical ventilation – (2 dwellings)
- c) Group 3 (G3, NatRent): Rented-occupied, natural ventilation - (5 dwellings)
- d) Group 4 (G4, MechRent): rented-occupied, mechanical ventilation - (5 dwellings)

Multivariate logistic regression with interactions between selected variables was used to infer the probability of a window opening and closing event. The method relies on the probability function described on equation 1. The models predict the probability of an action (opening or closing) using equation 1, where p is the probability of opening/closing a window, a and b_n are the coefficients in the tables and x_n are the associated variables (temperature, CO₂ concentration etc.). Moreover, this equation takes into account the interactions between variables by adding interaction terms to the model.

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

Models 1 (G1, NatOw), 2 (G2, MechOw) 3 (G3, NatRent) and 4 (G4, MechRent) were inferred from merged data from several dwellings (Andersen et al. 2013). Moreover, in three of the cases the actual opening angle of the window was also measured, so a model that predicts the size of the degree of opening was inferred using linear regression.

By merging the dwellings in groups, inner dynamics of a single dwelling were lost and the specific behaviour was flattened in the groups. The dwellings were grouped due to the high complexity and large variety between the individual models, but in an attempt to check for singularities in an appropriate way, the authors studied the dwellings also separately. The authors conducted further analyses by inferring models from data from each apartment (resulting in a total of 15 models). In this way, it was possible to look for similarities in influential variables for window opening and closing. Logistic regression was then carried out for every dwelling. The analysis showed very different user patterns with different combinations of influential variables and no obvious parallel between dwellings.

These models were then validated using the validation dataset described below. The validation of the singular dwelling model was done in two successive step. First, the dwellings of both dataset were categorized on the basis of the window opening frequency in three occupants' types representing high (active users), medium (standard users) and low (passive users) frequency.

In this way, the performances of active user's models resulting from the training dataset (7 models) were validated using active users' dwellings of the validation dataset, and in the same way passive users' models (5 resulting models) were validated against passive users' dwelling.

The validation dataset

Ten residential buildings were selected for a long-term monitoring of indoor and outdoor conditions and actions on windows in Copenhagen, according to the characteristics of the measured data in the first dataset. Measurements took place for periods of three months (February-April) 2010. During this period, the following variables were measured at 10 minute intervals in all 10 dwellings.

- Indoor environment parameters:
 - Temperature [°C]
 - Relative humidity [%]
 - CO2 concentration [ppm]
- Outdoor environment parameters
 - Air temperature [°C]
 - Relative humidity [%]

- Wind speed [m/s]
- Solar radiation [W/m²]
- Window state (open/closed)

The validation criteria

The aspects used by Haldi and Robison (2009) and by Schweiker et al. (2011) to assess the predictive power of the models were used for assessing the effectiveness of the developed window opening behaviour models. 10 simulations were repeated using a 10-min time step for the whole period with available measurements for the 10 measured dwellings, producing 10 x 10 = 100 sets of simulated window states, to be compared with the sets of observed data of windows.

The first aspect taken into account according to Haldi and Robinson (2009) and Schweiker et al. (2011) is the *discrimination criteria*.

This issue is related to the ability to reproduce the window states, by comparing the observed window states and the predicted window states. Defining the state of the window as positive, when open and negative, when closed, the predicted outcomes could be defined true (positive, i.e. the windows is really open, or negative, i.e. the window is really closed) or false (positive, i.e. the window is not really open, or negative, i.e. the window is not really closed). In this way, the True Positive Rate (or sensitivity, proportion of actual open windows that correctly predicted open) and the False Positive Rate (the proportion of actual closed windows that are correctly predicted closed) could be defined. Models with a strong predictive value are described by true positive rates significantly higher than the false positive rate. Finally, the accuracy of the models gives the proportion of correct predictions weighting the proportion of true outcome (positive and

negative) on the total amount of window states measured.

Since the developed models predict the probability of an action (opening or closing) occurring using a logistic regression (equation 1), an important aspect to be taken into account is the *number of actions* on windows. The comparison between the observed window opening actions and the predicted openings could give the overview of the performance of the models. Table 1 provides the overall observed and predicted window openings.

RESULTS OF MODELS VALIDATION

Simulations were performed using the coefficient of the four models presented in Andersen et al (2013) using measured data from the validation dataset. Ten repeated simulations were completed. The results were then analysed to compute the indicators introduced in the previous section, which are presented for each simulated model in table 3.

Even if the accuracy values of the four models was quite high, only Group 2 (G2, MechOw), had a substantial difference between the TPR and FPR in the bedroom. Interestingly, Group 2 also had similar number of predicted and real actions on windows. Since the purpose of the developed models is to infer the probability of the action of opening and closing windows and not to directly predict the state, the number of actions is a significant indicator of the performance of the models. Model G1 (G1, NatOw) predicted no actions in winter season. Figure 1, presents the proportion of actions on windows for each of the dwelling of the validation dataset tested with the window opening and closing behaviour model G2 (G2, MechOw). This model is characterized by any dependence on the time of the day or season.

Table 1.

Validation parameters for the validation dataset: true positive rate, false positive rate, accuracy, average number of opening action per bedroom and living room.

Model	TPR		FPR		ACC		Actions	
	Bedroom	Living room	Bedroom	Living room	Bedroom	Living room	Bedroom	Living room
EXACT	100%	100%	0%	0%	100%	100%	244	259
G1	17%	9%	18%	7%	59%	82%	2	-
G2	30%	1%	14%	1%	81%	90%	204	249
G3	4%	1%	1%	0%	65%	91%	178	108
G4	10%	12%	8%	4%	70%	78%	15	206

Looking at figure 1 the model predicts the real opening actions in the living room accurately. This is especially true for dwelling 1 and 2, where there was 29 predicted actions vs. 30 real actions for dwelling 1

and 86 predicted actions vs. 80 real actions for dwelling 2.

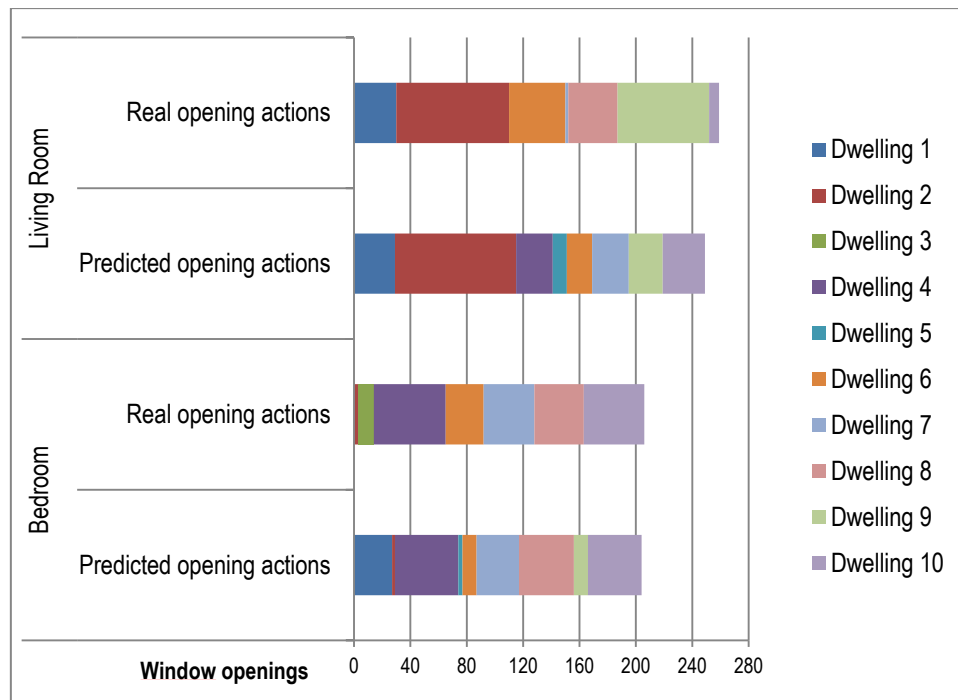


Figure 1. Comparison between predicted and observed number of actions on windows for each dwelling tested with the G2 model.

The results of the validation of the models derived from data from the single dwellings are presented in table 2. The average accuracy of the models was not high, since the difference between TPR and FPR was small, with the exception of the active models tested in the living room, where TPR values were quite different from FPR values. Even if the state of the window was predicted quite good in the active dwellings with the active models (74% of correct prediction in the bedroom and 72% in the living room), the indicator of the comparison of the number of actions on windows did not reflect this trend. On the other hand, although passive models in passive users' dwellings did not perform well in terms of prediction of the state of the window (see Accuracy value in table 2), they performed well on predicting the window opening/closing actions.

Since the aim of the validation process was to scale up the effectiveness of the window opening

behaviour models for simulation purposes, it was important to find a model that performed well without defining a priori the type of occupant. As a consequence, the stochastic model of the single behaviour of each dwelling was tested in order to obtain an accurate model of user behaviour, then these different behaviours that could be randomly simulated in order to better represent users' variability.

For this reason, further analyses were performed to check the performances of the singular model of dwellings, without considering the characterization of the users' typology in active standard and passive. In this case the aim was to see how well a model suited for a specific kind of user (active or passive) will be accurate on predicting both the windows opening and closing and the state of the window. The results of the simulations are given in table 3.

Table 2. Validation parameters for the active and passive users' dwellings: true positive rate, false positive rate, accuracy, average number of opening action per bedroom and living room.

Model	TPR		FPR		ACC		Actions	
	Bedroom	Living room	Bedroom	Living room	Bedroom	Living room	Bedroom	Living room
EXACT	100%	100%	0%	0%	100%	100%	237	250
Active (average)	34%	41%	35%	25%	74%	72%	29	56
d1	80%	100%	100%	100%	18%	17%	1	1
d4	21%	20%	20%	4%	70%	77%	8	22
d6	6%	64%	7%	23%	78%	70%	39	215

d7	22%	31%	20%	3%	72%	81%	77	49
d8	53%	1%	57%	1%	54%	82%	22	8
d13	12%	21%	76%	8%	4%	81%	30	45
d14	44%	51%	31%	30%	72%	59%	29	55
Model	TPR		FPR		ACC		Actions	
	Bedroom	Living room	Bedroom	Living room	Bedroom	Living room	Bedroom	Living room
EXACT	100%	100%	0%	0%	100%	100%	7	9
Passive (average)	15%	20%	36%	37%	52%	63%	7	6
d3	0%	0%	0%	0%	89%	100%	9	1
d5	4%	0%	27%	0%	59%	97%	12	9
d9	0%	40%	21%	67%	48%	33%	9	1
d10	36%	1%	59%	18%	31%	82%	4	18
d11	37%	60%	72%	100%	34%	2%	2	1

Table 3.

Validation parameters for the dwellings' models: true positive rate, false positive rate, accuracy, average number of opening action per bedroom and living room.

Model	TPR		FPR		ACC		Actions	
	Bedroom	Living room	Bedroom	Living room	Bedroom	Living room	Bedroom	Living room
EXACT	100%	100%	0%	0%	100%	100%	244	259
d1	70%	80%	0%	0%	14%	9%	12	9
d3	31%	10%	10%	0%	80%	91%	66	15
d4	30%	19%	10%	5%	79%	86%	55	178
d5	23%	30%	8%	0%	65%	90%	109	61
d6	3%	30%	7%	23%	81%	74%	489	219
d7	11%	6%	18%	20%	73%	72%	758	625
d8	54%	21%	33%	1%	46%	90%	241	55
d9	51%	72%	13%	61%	63%	30%	180	9
d10	60%	9%	47%	1%	41%	82%	29	147
d11	65%	80%	48%	60%	45%	20%	22	8
d13	24%	4%	29%	5%	70%	88%	283	449
d14	53%	33%	41%	39%	61%	56%	282	497
d15	8%	9%	16%	19%	72%	74%	865	724
d16	22%	25%	4%	13%	83%	77%	248	266

In table 3 the performances of more or less complicated (for the number of variable included in the model) logistic window opening behaviour models are represented. The best performing model in terms both of accuracy and of prediction of number of action on windows, was the model of dwelling 16, characterized by a probability of opening windows positive correlated with the CO₂ concentration, solar radiation and Illumination level depending on the time of the day and season, and by a probability of closing windows positive correlated with the solar hours during the day and negatively correlated with the illumination level (see table 2 for the variables in the models).

The simulations of the performance of this model for each dwelling of the validation dataset are

represented in figure 2 in terms of accuracy on the prediction of opening action on windows.

As it resulted also in the table 5, the capacity of the model to predict the number of action on windows was good especially in the bedroom, even if in the case of the test on dwelling 4 completely it was not able to predict the action on window, and overestimates the actions occurring.

The most accurate models on predicting both the state of the window (open or closed) and the number of actions on windows were characterized by a positive correlation between the probability of opening and CO₂ concentration and illumination values (Group 2 and dwelling 16 models) and a negative correlation with sun hours and illumination level for closing windows.

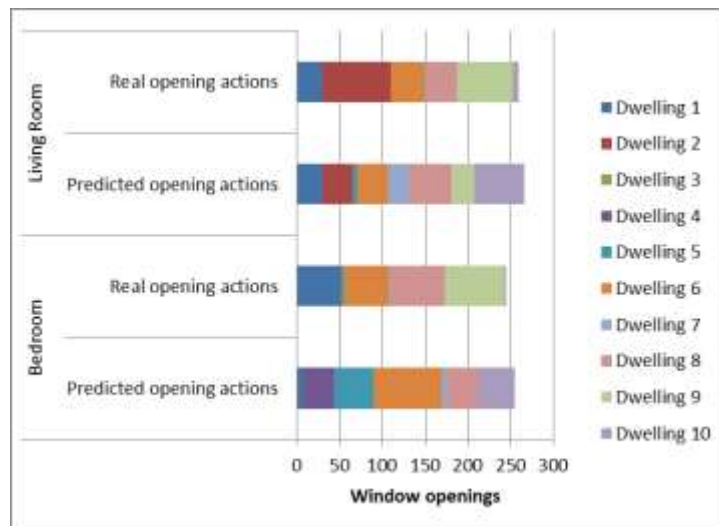


Figure 2. Comparison between predicted and observed number of actions on windows for each dwelling tested with the d16 model.

DISCUSSION

Rijal et al. (2007) describes three different assumptions (fixed schedules, fixed rules based on indoor and/or outdoor conditions, fixed ventilation/infiltration rates) that designers have made in the past when modelling window opening behaviour. It is clear that these strategies of modelling occupant behaviour will lead to differences in the simulated indoor environment and in the simulated energy consumption of the building. An implementation of stochastic models proposed in this paper into a simulation program would significantly improve the validity of the simulation results in two ways. First of all, it would enable comparability of results from different models, since they would be based on the same behaviour patterns. Secondly, because the behaviour in the model is based on real behaviour it has a better chance of mimicking the behaviour of the occupants in the building and thus predicting the indoor environment and energy consumption correctly.

In this work only the models developed by the authors was tested and validated, but further research should deepen also other window opening behaviour models already existing in literature. This is an important issue to be faced, to ensure the generalization of the results by testing the ability of a model to be independent from the context where it is built (i.e. climatic conditions, cultural habits, building construction). An important aspect to be faced is discrepancy about the actual and simulated indoor climate conditions when that the model doesn't predict the window opening that happens in the measured dataset. This is especially true for the indoor temperature values, that could drop down when the window is open in the first dataset but not in the validation dataset.

Impact of unknown occupancy patterns

The occupancy of the dwellings was determined using the monitored CO₂ concentration. This method was better than not taking the occupancy into account but may have lead to uncertainties since short changes in the occupancy may have passed unnoticed. This could lead to a lower accuracy on prediction then aspected.

Applicability of stochastic behavioural models

Since the validation is performed on two separate dataset coming from different dwellings and users, the assumption of independency of observation from the habits of inhabitants of the individual dwelling is a particular important topic. Modeling the window opening behaviour this topic was faced by removing from the models all the variables depending from the individual dwelling having an influence on opening and closing the windows. Looking at the validation results, the quality of the built environment and other factors (psychological, social, contextual or biological) that are not taken into account in the measurement campaign could have a determinant influence on occupant's behaviour, so that appropriate models need to consider the most important of these factors.

CONCLUSION

Models for the prediction of occupants' interactions with windows in residential environment calibrated for a specific dataset were validated externally on a second distinctive dataset. The method used was conducted for several modelling approaches of varying complexity with respect to the number of variables included in the models.

The models that most accurately predicted the state of the window (open or closed) and the number of

actions on windows were characterized by a positive correlation between the probability of opening and CO₂ concentration and illumination values (Group 2 and dwelling 16 models) and a negative correlation with sun hours and illumination level for closing windows.

Although this paper describes an analysis of the predictive accuracy of models of occupant's interactions with windows in residential context, there remains lot of aspects to be deepened and investigated with further work. A more comprehensive study on relationship with individual variables (psychological and biological) and occupants' activities and occupancy integrated with longer environmental measurements would improve the validity of the results. Additional information on building envelope and usage of other system (e.g. radiators) would be helpful on building the behavioural models.

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