# User behaviour regarding natural ventilation – state of the art and research needs

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***SUMMARY:***
*This paper gives an overview of user behaviour regarding opening windows for natural ventilation and the methods to model this behaviour as input for building simulation. Influencing factors are summarized and evaluated. Temperature conditions are the most significant influences but most models base only on measurements in office buildings. Residential buildings are not well represented so far. Mathematical methods, which already have been used for this purpose, are mentioned and their ability for modelling user behaviour will be discussed. It is shown that all models applied so far are somewhat limited. A possible new method to overcome existing methods will be proposed.*

## 1. Introduction

Windows are used as controls for indoor climate in almost all climate zones. The users operate the windows to control the interior temperature and the well-being of the user by providing the necessary fresh air volume. There are several factors that influence the user in operating the windows. Some users open the windows very regularly depending just on the time of the day. Others prefer to maintain constant ventilation by a permanent slight opening of the window. Again others open the windows depending on their personal feeling and well-being. Reported factors influencing the opening strategies are among others the exterior and interior temperature, the duration of stay in the room, the type of windows or the availability of mechanical ventilation systems.

This paper presents an overview off different strategies reported in the literature worldwide. Possible influencing factors on user behaviour will be summarized and assessed. There are several mathematical methods to predict window operation. Logistic Regression, Markov- Chains and continuous-time-random process have already been used for this appliance. The ability of these methods will be reviewed. Also the ability of Generalized Estimating Equations, which have not yet been applied for this purpose, will be examined.

## 2. State of the art

### 2.1 Chronological summary

The first observations regarding the use of windows have been held by Dick in 1951(Dick & Thomas 19951), Brundett from 1977 (Brundrett 1977) to 1979 and Lyberg in 1982 (Lyberg 1982). They all came to the conclusion that the user behaviour is influenced by outdoor temperature. Warren and Perkins investigated in 1984 (P.R.Warren & L.M.Parkins 1984) the impact of outdoor temperature, solar radiation and wind speed. Again outdoor temperature was the driving variable. In an additional survey it was found that most of the window activities are made while arriving or leaving the room. The two main reasons for this behaviour were:

- windows were opened to improve air quality
- windows were opened to improve thermal comfort

The first probability model to predict the user behaviour was developed by Fritsch in 1991 (R.Fritsch et al. 1990). The model was based on measurements carried out in offices in LESO building in Lausanne, Switzerland. The influence of outdoor temperature, wind speed, solar radiation and indoor temperature was reviewed. Again outdoor temperature was the driving variable. To calculate the next window state, an inverse function of outdoor temperature and time was developed.

In the late 90s the interaction between user behaviour and thermal comfort became more and more interesting and led to several observations in Pakistan (Fergus Nicol & Susan Roaf 1996), (Fergus Nicol et al. 1999), Great Britain (Iftikhar A.Raja, Fergus Nicol, & Kathryn J.McCartney 1998), (Iftikhar A.Raja et al. 2001) and other European countries (Kathryn J.McCartney & Fergus Nicol 2002).

Based on these preceding observations Nicol (Fergus Nicol 2001) developed in 2001 a stochastic model by using logistic regression with outdoor temperature as the main variable. In his opinion outdoor temperature describes the situation of window opening better than indoor temperature although they both have similar correlation coefficients with the user behaviour. He reasoned that outdoor temperature is an input in every building simulation whereas indoor temperature is an output and can be already flawed.

Reiß, Erhorn and Ohl (J.Reiß, H.Erhorn, & J.Ohl 2001) categorized the users regarding their window opening behaviour in rare, medium or frequent by analysing the longitudinal measurements made in 76 apartments. They also discovered the inhomogeneous window operation in different kind of rooms and the fact that with more available space per occupant the window operation decreases. In buildings with mechanical ventilation users operate likewise but on lower level than those ones in buildings without mechanical ventilation.

In conflict with preceding opinions, Nicol and Humphreys proceed in ASHRAE Transactions 2004 (Nicol & Michael A.Humphreys 2004) and Robinson in Windsor Conference (Darren Robinson 2006) that indoor temperature must be the main influencing factor. Otherwise building architecture and method of construction would be neglected.

After that Rijal (H.B.Rijal et al. 2007), (H.B.Rijal et al. 2008) released an improved model depending on outdoor and indoor temperature, also known as the Humpreys Algorithm. The user behaviour especially in summer times was analysed by Haldi and Robinson (Frédéric Haldi & Darren Robinson 2008) in 2006. They tested the acceptability of high indoor temperature with the possibility of personal adaption by clothing, activity, cool drink and environmental adaption by using blinds, windows and fans, with the cognition that those actions are more likely influenced by indoor conditions than outdoor conditions. Yun and Steemers developed an algorithm to predict the occupant behaviour in summertime (Geun Young Yun & Koen Steemers 2008). The observation was held in offices with and without night ventilation. They note that most window activities take place at arrival or departure. Due to this conclusion a separate sub-model was developed to simulate user presence according to time. The result of the sub-model is used as an input for the main window opening model which is based on Markov-Chains. As this model is based on observations made in summertime they state that the validity of that model in wintertime is doubtful.

Herkel, Knapp and Pfafferott developed a user model based on logistic regression (Sebastian Herkel, Ulla Knapp, & K.J.McCartney 2008), using a sub-model to predict user presence. By analysing the window opening data they found that the proportion of open windows is similar in autumn and spring, highest in summer and lowest in winter. A change in window user behaviours are indicated by the first warm day in spring and the first cold day in autumn. Andersen made a survey of occupants in Danish dwellings in 2009 (Rune Vinther Andersen et al. 2009). He discovered that besides outdoor temperature also gender, solar radiation, size of the dwelling, kind of ownership, noise and lighting influence the occupant behaviour regarding the use of windows.

Finally Haldi and Robinson (Frédéric Haldi & Darren Robinson 2009) created a model which implies personal behaviour of the occupants. Based on over seven years of measurement in the LESO building in Lausanne, the users were categorized in three levels: low, medium and high window activity. Three different mathematic methods (logistic regression, Markov-Chains and continuous-time random process) to simulate user behaviour were observed to their ability to present the window opening act. They conclude that a hybrid model combining discrete-time Markov process and continuous-time model predicted the data best.

It is obvious, that the presence or absence of the user is one of the most important variables by simulating user behaviour. To respect this some separate presence models have been developed.

Wang, Federspeil and Rubinstein (Danni Wang, Clifford C.Federspiel, & Francis Rubinstein 2010) created a model based on presence measurements in offices. The presence probability is calculated depending on the time for each calculation step. That model was improved by Page, Robinson and Scatezzini (J.Page et al. 2008). They take long periods of absence, for example holiday or meetings, into account. The results of these presence models can also be used for estimating inner loads caused by occupants, such as $CO_2$ emission or moisture production rates, respectively inner heat gains. Also it could be an input variable to determine the use of other building equipment, such as heaters, fans and air-conditioning.

## 2.2 Summary of influences on users behaviour regarding natural ventilation

Different influencing factors on the window opening behaviour of occupants are found in literature. These can mainly be categorized in external, internal and user/usage dependent values.

### *2.2.1 External influences*

Heat losses because of transmission decrease because of improvements in air tightness and insulation. Accordingly losses because of ventilation become more and more important and have to be minimized. The kind of the building and its use, mainly influence the user inside.

For predicting window opening behaviour, outdoor temperature seems to be one of the important influencing factors. Of the above mentioned observations found high correlation between outdoor temperature and window opening. Other weather conditions like wind, rain and solar radiation seem to be less important. Wind speed only influences behaviour avove 6 m/s. The impact of rain also depends on window shape and opening angle. Correlation between solar radiation and window opening has not yet been confirmed.

There are several influences that haven't been observed so far or are not a part of this literature review. Especially outdoor noise and air pollution are supposed to influence the occupant's behavior.

### *2.2.2 Internal Influences*

The main influencing parameter if people feel comfort inside is indoor temperature. Same high correlation like with outdoor temperature can be found. On the other side, indoor temperature is an output in building simulation and can be flawed.

Another parameter if people feel comfort inside is $CO_2$ concentration. Existing models do not take air quality into account. But it can be expected that especially in rooms with high usage, the $CO_2$ concentration as a measure for air quality is important. E.g. it is shown for schools, that windows are opened at high interior $CO_2$ concentrations despite the room temperature and the exterior temperature are low (Runa Tabea Hellwig et al. 2008).

It is shown that in rooms with mechanical ventilation occupants act the same way, just on a lower level as in rooms without mechanical ventilation. In contrast user behaviour in different rooms is found to be very inhomogeneous.

#### *2.2.3 User behaviour*

Besides all external and internal parameters the user itself has got the main influence on how often windows are open and for how long. This habit depends on things like time of the day, activity, origin and personal thermal comfort conditions. It might seem hard to respect this in a user model. But some observations showed that categorizing users into low, medium and frequent window user might make sense.

#### *2.2.4 Conclusions from Literature review*

Summarizing the above findings some conclusions can be drawn. Some of them are very similar as the ones drawn by Haldi (Frédéric Haldi 2010):

- Temperature conditions are shown to be the most significant influences for user behavior regarding window opening. Still under discussion is, if exterior or interior temperature should be used as covariate in the modeling.
- Time dependent effects, short time (day/night, weekday/weekend) or long time (seasons, adaptation, …) are not well being represented.
- Different habits in different regions of the earth are not taken into account.
- Existing models base on measurements in office buildings. Residential buildings with different usage patterns are not represented.
- A possible categorization of “user types” regarding window opening behavior is rarely used despite it is found that such a categorization improve the predictions.

## 3. Some mathematical methods to describe user behaviour

For building energy simulation the final input needs to be an air exchange rate between zones or between a zone and the outside. This air exchange rate is in many cases influenced by the user, as the user open doors and windows. This means, the action if a window was opened or closed needs to be represented by the model. The action itself depends on one or more influencing variables. The following chapter will give an overview of different mathematical methods for modelling user behaviour.

### 3.1 Markov- Chains

Markov-Chains are predicting the transition probability P from one state to another for each time step while considering only the previous time step. The probability of transition is again a function of different parameters.

For this method one has to choose a fixed calculation time step. This can lead to a loss of information if time step would be chosen too long or to unneeded calculation if the step is too short. Furthermore, as the transition probability only depends on the previous time step, the history of opening and closing the window is neglected.

### 3.2 Survival Analysis

This method estimates the time until a certain event takes place. It is often used in medicine and social science to predict the duration until for example death. The survival function is predicting the probability that the duration until death is longer than the actual time. In its basics the survival time analysis is meant to describe events which only occur once. However, window opening is a repeated event, which needs an enhancement of the method

### 3.3 Generalized Linear Models (GLM)

Linear models are assuming normal distribution of the target value. This limitation is generalized with the method of GLM. The correlations of a linear model is given by

$$Y_{is} = \beta_1 \times x_{i1} + \beta_2 \times x_{i2} + ..... + \beta_p \times x_{ip}$$

Where β estimated constant

$x_{is}$ variable in room i at time step s

$Y_{is}$ target variable in room i at time step s

The expected value *E(Y)* can than be described as $E(Y) = \mu = X\beta$ with *X* being the variable matrix. To change the distribution of the expected value, a transformation via a link-function is needed.

$$g(\mu) = x\beta$$

The relationship between *E(Y)* and $\eta = x\beta$ is defined by a monotone, inverse function $g(\mu)$, called link-function. Because of the monotony the function can be described as

$$g(\mu) = x\beta \qquad \text{Link-function}$$

$$\mu = g^{-1} \cdot (x\beta) \qquad \text{Inverse function}$$

This link-function can be converted in to several forms, depending on the application. Following table shows the Link- function and the related inverse function for a binomial distributed target value. It's also called Logistic Regression.

*TABLE 1. The binomial link- function*

| distribution | Link-function | Inverse function/ Expected value |
|---|---|---|
| Binomial | $\eta = \ln\left(\frac{\mu}{1-\mu}\right)$ | $\mu = \frac{e^{\eta}}{1+e^{\eta}}$ |

***Logistic Regression***

Logistic Regression can be used to predict the probability of an event to happen under diverse circumstances. Because of the logarithmic link, the target value can not exceed 0 or 1. The following graph shows this clearly.

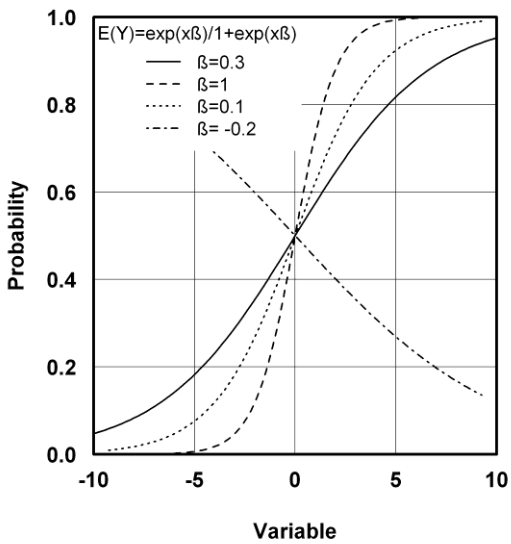


*FIG 1. Logistic Regression with different parameters*

A limitation of this method is the time independent consideration of the measuring values. But window opening data has a strong time dependency. Independence between single readings can not be assumed.

### *Generalized Estimating Equations (GEE)*

Window opening measurements are special. One of the main properties to respect is time dependence between single time steps. Such data is called longitudinal data. To consider this nature, measured window states of one day in one room have to be clustered. This approach can be made by using Generalized Estimating Equations. GEE's are again, a special kind of GLM, just with the feature of considering correlation between single measurements.

There are different kinds of autocorrelation. Correlation can be unstructured, equal in every clustered data set or can be a function of the distance between the single measurements in a clustered data set. To observe the correlation structure for window opening a correlation matrix was made to prove autocorrelation and the kind of correlation structure.

Window opening data from residential buildings in Germany were used. The whole dataset consists of measurements in 17 apartments and houses. Originally data was used for estimating performance of building technology and heat losses through ventilation. For this purpose outdoor and indoor climate, energy demand and window status were measured hourly for at least one year.

The matrix shows the correlation coefficients between opening duration in every single hour of the day. To illustrate the correlation trend through the day, the colour gets darker with higher coefficient. It shows clearly, that window openings are high correlated when they are close. The correlations values become smaller with rising distance. During night hours more previous hours correlate with the actual hourly window state.

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 0 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.00 | 0.93 | 0.89 | 0.87 | 0.86 | 0.84 | 0.81 | 0.74 | 0.66 | 0.60 | 0.55 | 0.51 | 0.49 | 0.47 | 0.47 | 0.45 | 0.44 | 0.45 | 0.45 | 0.46 | 0.48 | 0.51 | 0.55 | 0.59 |
| 2 | 0.93 | 1.00 | 0.97 | 0.95 | 0.93 | 0.92 | 0.88 | 0.80 | 0.69 | 0.61 | 0.55 | 0.51 | 0.49 | 0.46 | 0.46 | 0.44 | 0.44 | 0.44 | 0.44 | 0.45 | 0.46 | 0.49 | 0.53 | 0.58 |
| 3 | 0.89 | 0.97 | 1.00 | 0.99 | 0.97 | 0.96 | 0.91 | 0.83 | 0.71 | 0.61 | 0.55 | 0.50 | 0.48 | 0.45 | 0.45 | 0.43 | 0.42 | 0.43 | 0.43 | 0.43 | 0.45 | 0.48 | 0.51 | 0.56 |
| 4 | 0.87 | 0.95 | 0.99 | 1.00 | 0.99 | 0.97 | 0.93 | 0.85 | 0.72 | 0.62 | 0.55 | 0.50 | 0.47 | 0.45 | 0.45 | 0.43 | 0.42 | 0.42 | 0.42 | 0.43 | 0.44 | 0.47 | 0.50 | 0.56 |
| 5 | 0.86 | 0.93 | 0.97 | 0.99 | 1.00 | 0.99 | 0.94 | 0.86 | 0.73 | 0.62 | 0.55 | 0.51 | 0.47 | 0.45 | 0.45 | 0.43 | 0.42 | 0.42 | 0.42 | 0.43 | 0.44 | 0.47 | 0.50 | 0.55 |
| 6 | 0.84 | 0.92 | 0.96 | 0.97 | 0.99 | 1.00 | 0.96 | 0.88 | 0.74 | 0.63 | 0.56 | 0.51 | 0.47 | 0.45 | 0.45 | 0.43 | 0.42 | 0.42 | 0.42 | 0.42 | 0.44 | 0.47 | 0.50 | 0.55 |
| 7 | 0.81 | 0.88 | 0.91 | 0.93 | 0.94 | 0.96 | 1.00 | 0.91 | 0.76 | 0.65 | 0.57 | 0.52 | 0.48 | 0.45 | 0.45 | 0.43 | 0.42 | 0.43 | 0.43 | 0.44 | 0.45 | 0.48 | 0.51 | 0.56 |
| 8 | 0.74 | 0.80 | 0.83 | 0.85 | 0.86 | 0.88 | 0.91 | 1.00 | 0.86 | 0.71 | 0.63 | 0.56 | 0.52 | 0.49 | 0.49 | 0.48 | 0.46 | 0.47 | 0.47 | 0.47 | 0.48 | 0.50 | 0.52 | 0.56 |
| 9 | 0.66 | 0.69 | 0.71 | 0.72 | 0.73 | 0.74 | 0.76 | 0.86 | 1.00 | 0.85 | 0.72 | 0.64 | 0.59 | 0.56 | 0.56 | 0.54 | 0.53 | 0.53 | 0.52 | 0.52 | 0.53 | 0.54 | 0.54 | 0.56 |
| 10 | 0.60 | 0.61 | 0.61 | 0.62 | 0.62 | 0.63 | 0.65 | 0.71 | 0.85 | 1.00 | 0.85 | 0.73 | 0.67 | 0.63 | 0.63 | 0.60 | 0.58 | 0.57 | 0.57 | 0.56 | 0.56 | 0.56 | 0.56 | 0.57 |
| 11 | 0.55 | 0.55 | 0.55 | 0.55 | 0.55 | 0.56 | 0.57 | 0.63 | 0.72 | 0.85 | 1.00 | 0.87 | 0.76 | 0.70 | 0.70 | 0.65 | 0.62 | 0.61 | 0.60 | 0.59 | 0.59 | 0.58 | 0.57 | 0.56 |
| 12 | 0.51 | 0.51 | 0.50 | 0.50 | 0.51 | 0.51 | 0.52 | 0.56 | 0.64 | 0.73 | 0.87 | 1.00 | 0.87 | 0.77 | 0.77 | 0.71 | 0.67 | 0.65 | 0.64 | 0.62 | 0.61 | 0.60 | 0.57 | 0.55 |
| 13 | 0.49 | 0.49 | 0.48 | 0.47 | 0.47 | 0.47 | 0.48 | 0.52 | 0.59 | 0.67 | 0.76 | 0.87 | 1.00 | 0.88 | 0.88 | 0.78 | 0.73 | 0.69 | 0.67 | 0.65 | 0.62 | 0.60 | 0.57 | 0.54 |
| 14 | 0.47 | 0.46 | 0.45 | 0.45 | 0.45 | 0.45 | 0.45 | 0.49 | 0.56 | 0.63 | 0.70 | 0.77 | 0.88 | 1.00 | 1.00 | 0.88 | 0.79 | 0.73 | 0.71 | 0.67 | 0.64 | 0.61 | 0.57 | 0.54 |
| 15 | 0.47 | 0.46 | 0.45 | 0.45 | 0.45 | 0.45 | 0.45 | 0.49 | 0.56 | 0.63 | 0.70 | 0.77 | 0.88 | 1.00 | 1.00 | 0.88 | 0.79 | 0.73 | 0.71 | 0.67 | 0.64 | 0.61 | 0.57 | 0.54 |
| 16 | 0.45 | 0.44 | 0.43 | 0.43 | 0.43 | 0.43 | 0.43 | 0.48 | 0.54 | 0.60 | 0.65 | 0.71 | 0.78 | 0.88 | 0.88 | 1.00 | 0.89 | 0.80 | 0.75 | 0.70 | 0.67 | 0.63 | 0.58 | 0.54 |
| 17 | 0.44 | 0.44 | 0.42 | 0.42 | 0.42 | 0.42 | 0.42 | 0.46 | 0.53 | 0.58 | 0.62 | 0.67 | 0.73 | 0.79 | 0.79 | 0.89 | 1.00 | 0.89 | 0.81 | 0.74 | 0.69 | 0.65 | 0.59 | 0.55 |
| 18 | 0.45 | 0.44 | 0.43 | 0.42 | 0.42 | 0.42 | 0.43 | 0.47 | 0.53 | 0.57 | 0.61 | 0.65 | 0.69 | 0.73 | 0.73 | 0.80 | 0.89 | 1.00 | 0.90 | 0.80 | 0.73 | 0.67 | 0.61 | 0.57 |
| 19 | 0.45 | 0.44 | 0.43 | 0.42 | 0.42 | 0.42 | 0.43 | 0.47 | 0.52 | 0.57 | 0.60 | 0.64 | 0.67 | 0.71 | 0.71 | 0.75 | 0.81 | 0.90 | 1.00 | 0.89 | 0.79 | 0.71 | 0.64 | 0.58 |
| 20 | 0.46 | 0.45 | 0.43 | 0.43 | 0.43 | 0.42 | 0.44 | 0.47 | 0.52 | 0.56 | 0.59 | 0.62 | 0.65 | 0.67 | 0.67 | 0.70 | 0.74 | 0.80 | 0.89 | 1.00 | 0.88 | 0.76 | 0.67 | 0.60 |
| 21 | 0.48 | 0.46 | 0.45 | 0.44 | 0.44 | 0.44 | 0.45 | 0.48 | 0.53 | 0.56 | 0.59 | 0.61 | 0.62 | 0.64 | 0.64 | 0.67 | 0.69 | 0.73 | 0.79 | 0.88 | 1.00 | 0.87 | 0.75 | 0.65 |
| 22 | 0.51 | 0.49 | 0.48 | 0.47 | 0.47 | 0.47 | 0.48 | 0.50 | 0.54 | 0.56 | 0.58 | 0.60 | 0.60 | 0.61 | 0.61 | 0.63 | 0.65 | 0.67 | 0.71 | 0.76 | 0.87 | 1.00 | 0.87 | 0.73 |
| 23 | 0.55 | 0.53 | 0.51 | 0.50 | 0.50 | 0.50 | 0.51 | 0.52 | 0.54 | 0.56 | 0.57 | 0.57 | 0.57 | 0.57 | 0.57 | 0.58 | 0.59 | 0.61 | 0.64 | 0.67 | 0.75 | 0.87 | 1.00 | 0.87 |
| 24 | 0.59 | 0.58 | 0.56 | 0.56 | 0.55 | 0.55 | 0.56 | 0.56 | 0.56 | 0.57 | 0.56 | 0.55 | 0.54 | 0.54 | 0.54 | 0.54 | 0.55 | 0.57 | 0.58 | 0.60 | 0.65 | 0.73 | 0.87 | 1.00 |

*FIG 2. Correlation matrix for window opening action for all hours of a day*

This observation proves time dependent autocorrelation between single window openings. For modelling proper user behaviour this dependency has to be taken into account.

## 4. Conclusions

After reviewing literature and analysing autocorrelation in window opening data, following results and research needs can be concluded:

- User behaviour regarding natural ventilation can be modelled via statistical methods. All models applied so far are somewhat limited. More sophisticated methods may overcome some of the limitations and improve the models.
- Window states during a day are correlated. GEE seem to be a good way by respecting autocorrelation of the data. Further analysis and application of this method to real measured data can result in a more sophisticated model.
- Most of the models are based on measurements in office buildings and can only be applied to office buildings. There are no window opening models for residential buildings or combined ones. An assessment of residential building behaviour would allow a more comprehensive model.

Designing a building and the inner climate of buildings requires a detailed understanding of the interaction of user and usage with building structure and systems. Understanding the driving parameters that make users open or close windows could allow to design buildings that reduce negative impacts of users on building energy use. This means also to improve the inner climate conditions to ranges where the user does not feel any stimulus to open windows. A comprehensive user model for whole building hygrothermal modelling seems possible. It requires a broader data analysis and incorporation of measured conditions in rooms with different usage types in different climate zones all over the world.

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